Department of Economics and Business

Department of Electrical Electronic and Computer Engineering

Department of Mathematics and Computer Science

Master's Degree in Data Science

BIKE RIDER WORKLOAD DATA ANALYSIS USING XAI

MASTER DEGREE THESIS

Author
Syed Muhammad Khizar ALAM

Supervisor
Prof. Giovanni Gallo

Cosupervisor
Prof. Salvatore CAFISO

ACADEMIC YEAR 2024/2025
28th April, 2025

Syed Muhammad Khizar ALAM

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Master's Degree Thesis

UNIVERSITY OF CATANIA

April 2025

"*The greatest enemy of knowledge is not ignorance, it is the illusion of knowledge.*"

Stephen Hawking

UNIVERSITÀ DEGLI STUDI DI CATANIA

Dipartimento di Economia e Impresa

Data Science

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ABSTRACT

This thesis explores the use of Explainable AI, specifically Shapley Additive Explanations, to analyze the cognitive workload of a bicycle rider engaged in urban mapping. The study focuses on three cognitive states—ID Glance, Meditation, and Attention—using a dataset integrating EEG readings, GPS data, and geographic features. Principal Component Analysis was applied to map-related features, while machine learning models predicted cognitive states. Shapley Additive Explanations analysis provided interpretability, revealing that motion stability, road complexity, and environmental factors significantly influence cognitive workload. Structured environments enhanced relaxation and focus, while complex surroundings increased cognitive strain. These findings offer insights for urban planning, AI-assisted cyclist navigation, and transportation safety, demonstrating how Explainable AI can enhance AI-driven decision-making.

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List of Abbreviations

AI	**A**rtificial **I**ntelligence
XAI	**E**xplainable **A**rtificial **I**ntelligence
SHAP	**SH**apley **A**dditive ex**P**lanations
EEG	**E**lectro**E**ncephalo**G**raphy
GPS	**G**lobal **P**ositioning **S**ystem
PCA	**P**rincipal **C**omponent **A**nalysis
PC	**P**rincipal **C**omponent
RF	**R**andom **F**orest
SVM	**S**upport **V**ector **M**achine
XGBoost	**eX**treme **G**radient **Boost**ing
CatBoost	**Cat**egorical **Boost**ing
LightGBM	**L**ight **G**radient **B**oosting **M**achine
LIME	**L**ocal **I**nterpretable **M**odel-**A**gnostic **E**xplanations
R^2	**C**oefficient of **D**etermination
MAE	**M**ean **A**bsolute **E**rror

To my parents,
For their unconditional love, unwavering support, and endless encouragement. Your belief in me has been my greatest source of strength, and this achievement would not have been possible without your sacrifices and guidance. This work is a small tribute to the immense role you have played in my journey.

Chapter 1

Introduction

1.1 Background of the Study

Artificial Intelligence (AI) has revolutionized decision-making across various domains, including **transportation, healthcare, and human cognition analysis**. However, as AI models become increasingly complex, their **lack of transparency and interpretability** has raised concerns regarding **trust, reliability, and real-world applicability**. The ability to understand **how and why an AI model makes specific predictions** is crucial, particularly in scenarios involving human cognitive workload assessment.

Explainable AI (**XAI**) has emerged as a key solution to this challenge, providing techniques that **enhance model interpretability** and enable users to gain insights into decision-making processes. **SHapley Additive exPlanations (SHAP)** is one such XAI technique that offers a **game-theoretic approach** to interpreting machine learning models by assigning importance scores to each feature, explaining their contribution to individual predictions. This makes **SHAP an essential tool for understanding the impact of environmental and cognitive factors on human decision-making**.

This study applies **XAI techniques, specifically SHAP**, to analyze the cognitive workload of a cyclist engaged in **urban mapping activities**. The research focuses on three **key cognitive states**:

1. **ID_Glance** *(categorical)* – Represents different eye movement behaviors while cycling.
2. **Meditation** *(continuous)* – Indicates mental relaxation levels.
3. **Attention** *(continuous)* – Quantifies cognitive focus and engagement.

To achieve this, a dataset was collected from a **cyclist performing mapping tasks similar to a Google Street View vehicle**. This dataset integrates **EEG readings, GPS data, and urban geographic features**, allowing an in-depth analysis of how different **motion and environmental conditions** impact cognitive workload.

1.2 Motivation and Problem Statement

Understanding human cognitive workload in dynamic environments is crucial for improving urban mobility, cyclist safety, and AI-assisted navigation. In urban settings, cyclists often face complex decision-making scenarios influenced by road conditions, environmental features, and real-time physiological responses. However, existing studies lack transparent AI models that explain why and how specific environmental factors affect cognitive workload.

This research addresses the following key challenges:

- **How do environmental and motion-based factors influence cognitive workload while cycling?**
- **Can AI models effectively predict a cyclist's cognitive state based on EEG and geographic data?**
- **How can Explainable AI (SHAP) improve model interpretability and provide actionable insights?**

By integrating sensor data with AI-driven analysis, this study aims to bridge the gap between AI predictions and human understanding, ensuring real-world applicability of machine learning models.

1.2.1 Key Factors Affecting Cognitive Workload in Cycling

- **Road Complexity & Infrastructure** – intersections, dedicated cycling lanes, obstacles
- **Environmental Distractions** – traffic signs, moving objects, pedestrian crossings
- **Physiological State** – stress, mental fatigue, attention level

While AI-driven smart mobility solutions exist, they often fail to account for the cyclist's cognitive state. Current navigation systems provide route optimization based on speed and distance but lack intelligence regarding mental workload.

1.2.2 Problem Statement

> How can machine learning and Explainable AI (XAI) be utilized to analyze, interpret, and predict cognitive workload in urban cycling scenarios?

This research bridges the gap between AI-based cognitive analysis and real-world urban mobility, focusing on how environmental and physiological factors influence human cognition while cycling.

1.3 Objectives of the Study

The study aims to develop an AI-powered framework for analyzing cognitive workload using sensor data and Explainable AI techniques. The main objectives include:

Primary Objectives

The primary objectives of this research are:

1. **To develop AI models** capable of predicting cognitive states (ID_Glance, Meditation, Attention) based on EEG sensor readings and urban environmental data.

2. **To apply Principal Component Analysis (PCA)** for dimensionality reduction of geographic features, while retaining sensor data in its original form to preserve interpretability.

3. **To use SHAP analysis** to interpret model predictions and identify the most influential factors affecting cognitive workload.

4. **To provide insights into urban navigation strategies** by analyzing how different road conditions and motion factors influence cognitive states.

This study contributes to AI-assisted urban planning and cyclist safety by offering a transparent and interpretable framework for cognitive workload analysis.

1.4 Research Questions

This thesis is guided by the following research questions:

1. **How do different environmental and motion-based factors influence a cyclist's cognitive workload?**

2. **Which machine learning models are most effective for predicting cognitive states based on EEG and urban data?**

3. **How can SHAP-based explanations improve the interpretability of AI-driven cognitive workload models?**

4. **What insights can be derived from SHAP analysis to enhance AI-assisted cyclist navigation and urban safety?**

By answering these questions, this study aims to contribute to the fields of AI explainability, cognitive workload modeling, and urban mobility analysis.

1.5 Contributions of the Study

This research makes the following contributions:

- **Development of AI Models for Cognitive Workload Prediction** Trained machine learning models to predict **ID_Glance, Meditation, and Attention** based on EEG, GPS, and urban data.

- **Dimensionality Reduction via PCA** Applied Principal Component Analysis (PCA) to urban geographic data, ensuring model efficiency without compromising interpretability.

- **Application of SHAP for Explainability** Used SHAP values to interpret model decisions, identifying key factors influencing cognitive workload.

- **Insights for Urban Planning & AI-Assisted Cycling** Provided actionable insights on how **r**oad conditions, environmental complexity, and motion stability impact cyclist cognition.

These contributions enhance the transparency, applicability, and reliability of AI-based cognitive workload analysis.

1.6 Organization of the Thesis

This thesis is structured as follows:

Chapter 1: Introduction

- Provides background, motivation, and research objectives.
- Defines the problem statement and research questions.

Chapter 2: Literature Review

- Discusses related work in Explainable AI (XAI) and cognitive workload analysis.
- Covers SHAP, PCA, and AI models for cognitive state prediction.

Chapter 3: Data Collection and Preprocessing

- Describes the dataset (EEG, GPS, and urban geographic data).
- Explains feature engineering, data integration, and preprocessing techniques (including PCA on geographic features).

Chapter 4: Machine Learning Models for Cognitive State Prediction

- Details classification and regression models for ID_Glance, Meditation, and Attention.
- Includes model training, evaluation, and performance metrics.

Chapter 5: Explainable AI (SHAP) and Model Interpretability

- Uses SHAP analysis to interpret the influence of environmental and motion-based factors on cognitive workload predictions.

Chapter 6: Results and Discussion

- Presents the key findings, implications, and limitations of the study.

Chapter 7: Conclusion and Future Work

- Summarizes contributions and suggests directions for future research in AI-assisted navigation and cognitive workload modeling.

This study explores the **i**ntersection of AI, cognitive workload modeling, and urban mobility, providing an explainable and interpretable framework for predicting a cyclist's cognitive state. By leveraging SHAP-based explanations, this research ensures that AI models not only predict cognitive workload but also offer meaningful, human-interpretable insights that can improve cyclist safety, urban planning, and AI-assisted navigation.

The next chapter provides a comprehensive literature review on Explainable AI (**XAI**), SHAP, and machine learning techniques used for cognitive workload analysis.

Chapter 2

Literature Review

2.1 Introduction to Explainable AI (XAI)

Artificial Intelligence (AI) models are becoming increasingly complex, often operating as black-box systems that provide high accuracy but lack interpretability. This limitation poses significant challenges in applications where transparency, trust, and accountability are required, such as healthcare, finance, and cognitive workload analysis.

Explainable AI (XAI) addresses these concerns by providing techniques that make AI models more interpretable and their decision-making processes more transparent. The primary objectives of XAI are to:

- Enhance model trustworthiness by explaining how AI systems arrive at their predictions.
- Improve fairness and accountability by identifying potential biases in AI models.
- Enable human-AI collaboration by making AI decisions comprehensible to non-expert users.

For cognitive workload modeling, XAI can help researchers and practitioners understand which factors influence mental workload, how different environmental and physiological conditions affect cognitive states, and how AI models can improve decision-making in real-time applications.

This chapter discusses the importance of XAI in cognitive workload analysis, with a particular focus on **SHAP (Shapley Additive Explanations)**, followed by an overview of other explainability techniques.

2.2 SHAP (Shapley Additive Explanations) and its Importance

SHapley Additive Explanations (SHAP) is a widely used XAI technique that provides feature importance scores based on game theory. It assigns a contribution value to each feature, indicating how much it influences a model's prediction.

Key Features of SHAP:

- **Consistent Feature Attribution** – Ensures that features contributing more to predictions receive higher importance scores.
- **Local and Global Interpretability** – Can explain individual predictions (local) and overall feature importance across the dataset (global).
- **Model-Agnostic and Model-Specific Variants** – Works with different AI models, including decision trees, deep learning networks, and ensemble methods.
- **Bias and Fairness Detection** – Helps identify potential biases in AI predictions, making models more ethical and trustworthy.

2.3 Importance of SHAP in Cognitive Workload Analysis

SHAP is particularly valuable in cognitive workload modeling because it allows researchers to:

- Determine which environmental and physiological factors most impact cognitive states such as ID_Glance, Meditation, and Attention.
- Understand how road complexity, traffic density, and motion stability influence a cyclist's mental state.
- Improve AI-based assistive systems by ensuring transparent decision-making in workload predictions.

By leveraging SHAP, this study enhances AI-driven decision-making for cyclist safety and cognitive workload modeling.

2.4 Related Work in AI for Cognitive Workload Analysis

Cognitive workload estimation has been a significant research area in neuroscience, human factors, and AI. Several studies have explored AI-driven cognitive modeling using EEG signals, gaze behavior, and environmental data.

2.4.1 AI-Based Cognitive Load Estimation

1. **EEG-Based Cognitive Workload Models**
    - Various studies have used EEG signals to classify cognitive states, focusing on stress, attention, and relaxation levels.
    - Machine learning models such as **XGBoost, Support Vector Machines (SVM), and Neural Networks** have been applied to EEG-based workload classification.
2. **Cognitive Workload Prediction in Driving**
    - Researchers have developed AI models that assess driver workload using **gaze behavior, steering patterns, and physiological signals**.
    - These studies highlight the **importance of real-time monitoring** for safety-critical applications.
3. **Wearable Sensor Fusion for Mental Workload Assessment**
    - Some studies combine **EEG, eye-tracking, and environmental sensors** to model cognitive workload in dynamic scenarios.
    - The integration of **sensor fusion with machine learning** has shown promising results in predicting mental states.

2.4.2 Explainable AI for Cognitive Modeling

1. **SHAP for Brain Activity Interpretation** Recent research has applied SHAP to explain EEG-based AI models, helping identify **which brainwave frequencies contribute most to workload variations**.
2. **AI-Assisted Urban Mobility** Several studies have explored AI-driven route planning for cyclists, but **few integrate cognitive workload considerations**.

2.4.3 Gaps in Existing Research

- Most cognitive workload models do not integrate real-world cycling data.
- Few studies use SHAP to interpret AI-based cognitive models.
- There is limited research on combining **environmental and physiological factors** in cognitive workload analysis.

This thesis addresses these gaps by implementing SHAP-based explainability for cognitive workload modeling in urban cycling.

2.5 XAI Techniques Beyond SHAP

While SHAP is widely used for explainability, several alternative XAI techniques offer different approaches to model interpretation.

2.5.1 Local Interpretable Model-Agnostic Explanations (LIME)

LIME explains model predictions by creating locally interpretable approximations. It perturbs input data and observes how predictions change to approximate feature importance.

- **Advantages:** Simple, fast, and model-agnostic.
- **Disadvantages:** Less stable feature importance values compared to SHAP.

2.5.2 Feature Importance Methods

Feature importance techniques such as **Permutation Importance** and **Gini Impurity** rank features based on their contribution to reducing prediction error.

- **Advantages:** Intuitive and widely used in tree-based models.
- **Disadvantages:** Less effective for complex deep learning models.

2.5.3 Surrogate Models

Surrogate models approximate a complex AI model using a simpler, interpretable model (e.g., decision trees, linear regression).

- **Advantages:** Useful for explaining black-box models.
- **Disadvantages:** May lose accuracy compared to the original model.

2.5.4 Deep Learning Explainability

For neural networks, techniques like **Layer-wise Relevance Propagation (LRP)** and **Grad-CAM (Gradient-weighted Class Activation Mapping)** provide explanations for model decisions.

2.5.5 Comparison of XAI Methods

Method	Advantages	Disadvantages	Best Used For
SHAP	Consistent, Local & Global Interpretability	Computationally expensive	Tree-based & Deep Learning Models
LIME	Fast, Model-Agnostic	Less stable interpretations	Simple AI models
Feature Importance	Intuitive	Lacks deep model interpretability	Decision Trees, Random Forest
Surrogate Models	Approximates complex models	May lose accuracy	Black-box AI models
Deep Learning XAI	Works for Neural Networks	Complex to implement	CNNs, RNNs, Transformers

TABLE 2.1: Copmarison between XAI methods

This thesis **focuses on SHAP** due to its ability to provide both **global and local feature explanations** for cognitive workload prediction.

2.6 Summary

This chapter reviewed Explainable AI (XAI) methods, focusing on SHAP and its importance in cognitive workload modeling. Key takeaways include:

- AI models need explainability to improve **trust, fairness, and interpretability**.
- SHAP is an effective method for understanding **feature contributions** in cognitive predictions.
- Related studies focus on **EEG-based AI models**, but few integrate **urban cycling data**.
- Alternative XAI methods (LIME, Surrogate Models) provide different levels of interpretability.

The next chapter discusses **data collection, preprocessing, and feature engineering** used in this study.

Chapter 3

Data Collection and Preprocessing

3.1 Overview of the Dataset

This study utilizes two primary datasets that capture both **physiological and environmental factors** influencing a cyclist's cognitive state. Structured to provide insights into cognitive workload and mental engagement during urban cycling, these datasets integrate information from multiple sources. The data collection process involved synchronizing signals from various sensors, including electroencephalogram (EEG), an eye tracker, a camera, and the Global Navigation Satellite System (GNSS), alongside spatial data from OpenStreetMap. These datasets were previously developed at the Department of Civil Engineering and Architecture (University of Catania) and provided for this thesis. The following section details the dataset's structure and content.

3.1.1 Sensors Dataset

This dataset contains real-time sensor readings collected during the cyclist's ride. It includes three separate worksheets:

- **EEG Data** – Captures brainwave activity related to cognitive states.
- **Semantic Data** – Includes contextual information such as motion status, road conditions, and environmental features.
- **GPS Data** – Provides location-based tracking of the cyclist's movement patterns.

The **Sensors Dataset** comprises **11,104 entries across 73 columns**, offering detailed insights into cognitive responses based on environmental and physiological conditions.

3.1.2 Map Dataset

The Map Dataset provides **geospatial and environmental attributes** related to the cyclist's route. It consists of three layers:

- **Point Dataset** – Represents locations of specific features such as traffic signals, bike racks, and crossings.
- **Line Dataset** – Defines linear spatial elements, including road segments, cycling paths, and barriers.
- **Polygon Dataset** – Contains larger spatial features such as buildings, parks, and land use classifications.

The **Map Dataset** contains **12,853 rows across 68 columns**, providing geographic details such as **road types, intersections, and surrounding landmarks**.

3.2 Target Variables Overview

This study focuses on three target variables that represent distinct aspects of visual behavior and cognitive states:

3.2.1 ID_Glance (Categorical Variable - Eye Movement Classification)

ID_Glance categorizes the cyclist's **eye movements** into three distinct classes based on **glance duration**:

Class	Description	Glance Duration
Class 0 - Saccade	Rapid Eye Movement	Less than **150 ms**
Class 1 - Fixation	Brief Focus on a Point	**150 - 700 ms**
Class 2 - Long Fixation	Prolonged Focus	More than **700 ms**

TABLE 3.1: IDGlance Variable Interpretation

3.2.2 Meditation (Continuous Variable - Mental Relaxation Level)

Meditation measures **mental calmness and relaxation levels**, where higher values indicate reduced cognitive stress.

Range	Mental State	Description
0	Sensor Unable to Detect	No valid reading available
1 - 20	Strongly Lowered	High agitation, anxiety, or distractions
20 - 40	Reduced	Low relaxation, moderate mental activity
40 - 60	Neutral	Balanced cognitive state
60 - 80	Slightly Elevated	Increased relaxation, moderate focus
80 - 100	Elevated	Deep relaxation, minimal stress

Table 3.2: Meditation Variable Interpretation

Scale (0-100): Examples of activities that increase **meditation levels**:

- Deep breathing
- Mental relaxation exercises
- Rhythmic and stable motion

3.2.3 Attention (Continuous Variable - Cognitive Focus Level)

Attention quantifies the cyclist's **level of concentration** and **cognitive engagement** in a given task.

Range	Cognitive State	Description
0	Sensor Unable to Detect	No valid reading available
1 - 20	Strongly Lowered	High distractions, cognitive overload
20 - 40	Reduced	Low focus, wandering thoughts
40 - 60	Neutral	Balanced engagement
60 - 80	Slightly Elevated	Moderate concentration
80 - 100	Elevated	Deep focus, intense cognitive processing

Table 3.3: Attention Variable Interpretation

Scale (0-100): Examples of activities that increase **attention levels**:

- Focusing on a single idea or object
- Visual fixation on the road or traffic elements
- Active engagement in a task

By analyzing these three cognitive states, this study provides a **comprehensive framework** for understanding how **environmental and physiological factors influence mental workload in cycling**.

3.3 Feature Encoding

The **Map Dataset** contains several **categorical features** stored as **string values**, representing various **environmental attributes** such as **object types, road conditions, and scene descriptions**. Since most **machine learning models require numerical input**, categorical data must be transformed into a numerical format through an encoding process.

3.3.1 Identification of Categorical Features

The first step in feature encoding involved **identifying categorical attributes** within the **Map Dataset**, which were stored as **string values**. These categorical features typically represented:

- **Road Type and Surface Condition** (e.g., cycleway, paved, gravel)
- **Infrastructure Elements** (e.g., traffic signals, barriers, crossings)
- **Environmental Features** (e.g., vegetation, land use classification)

Since machine learning models do not process **text-based categorical features**, these variables were converted into numerical representations.

3.3.2 Label Encoding

To transform categorical features into numerical values, **Label Encoding** was applied using the `LabelEncoder` module from `sklearn.preprocessing`.

Encoding Process:

1. Each **unique string value** in a categorical feature was assigned a **numerical integer value**.
2. For example, a feature such as **Building_Type** with values [**"Residential", "Commercial", "Industrial"**] was encoded as [**0, 1, 2**].
3. This transformation ensured that all categorical attributes were **numerically formatted**, making them compatible with machine learning algorithms.

This encoding method preserves relative category importance without introducing artificial ordinal relationships between feature values.

Label Mappings for Categorical Features

The following tables summarize the **encoding scheme** applied to categorical features within the **Line, Point, and Polygon datasets** of the Map Dataset:

TABLE 3.4: Line Dataset Encoding

Column	Original Value	Encoded Value
osm_type	NULL Value	0
	way	1
highway	NULL Value	0
	cycleway	1
	path	2
	primary_link	3
	service	4
smoothness	NULL Value	0
	excellent	1
foot	NULL Value	0
	designated	1
bicycle	NULL Value	0
	designated	1
sidewalk_r	NULL Value	0
	separate	1
sidewalk_l	NULL Value	0
	no	1
service	NULL Value	0
	alley	1
	driveway	2
	parking_aisle	3
surface	NULL Value	0
	asphalt	1
	paved	2
	paving_stones	3
	sett	4
barrier	NULL Value	0
	bollard	1
	fence	2
	hedge	3
	retaining_wall	4
fence_type	NULL Value	0
	railing	1
wheelchair	NULL Value	0
	yes	1
segregated	NULL Value	0
	no	1
	yes	2
footway	NULL Value	0
	crossing	1
	sidewalk	2
cycleway	NULL Value	0
	crossing	1

TABLE 3.5: Point Dataset Encoding

Column	Original Value	Encoded Value
osm_type	NULL Value	0
	node	1
amenity	NULL Value	0
	bench	1
	bicycle_parking	2
	bicycle_rental	3
	waste_basket	4
waste	NULL Value	0
	trash;cigarettes	1
natural	NULL Value	0
	tree	1
traffic_si	NULL Value	0
	no	1
highway	NULL Value	0
	crossing	1
	traffic_signals	2
crossing	NULL Value	0
	marked	1
	traffic_signals	2
	uncontrolled	3
	unmarked	4
barrier	NULL Value	0
	gate	1
bicycle_re	NULL Value	0
	dropoff_point	1
	stands	1
	wall_loops	2
opening_ho	24/7	0
	NULL Value	1
crossing_i	NULL Value	0
	no	1
bicycle	NULL Value	0
	yes	1

TABLE 3.6: Polygon Datset Encoding

Column	Original Value	Encoded Value
osm_type	NULL Value	0
	way	1
building	NULL Value	0
	apartments	1
	yes	2
source_add	NULL Value	0
	Urząd Miasta Gdańsk	1
	survey	2
addr_stree	Aleja Grunwaldzka	0
	Księdza Leona Miszewskiego	1
	NULL Value	2
addr_postc	80-239	0
	80-241	1
	80-244	2
	NULL Value	3
addr_city	Gdańsk	0
	NULL Value	1
landuse	NULL Value	0
	grass	1

By applying feature encoding, the dataset was successfully transformed into a **numerically formatted** structure, ensuring **compatibility with machine learning models** used for cognitive workload analysis.

3.4 Data Integration and Cleaning

3.4.1 Merge Operations

To create a unified dataset for cognitive workload analysis, multiple datasets were merged based on **timestamps and ID columns**, ensuring proper alignment of sensor and environmental data.

Merging Sensor Data (EEG, Semantic, and GPS Data)

Objective: Integrate EEG sensor readings, semantic contextual information, and GPS location data into a single structured dataframe.

Process:

- **Step 1:** Merge **Semantic Data** and **EEG Data** using a common **ID column** via an **inner join**. This results in a dataset that contains both **contextual semantic information and cognitive EEG readings**.
- **Step 2:** Merge the resulting dataset with **GPS Data**, again on the **ID column**, using an **inner join**.

Outcome:

The final **merged_sensors_df** dataframe provides a holistic view of each unique ID, incorporating:

- EEG-based cognitive workload indicators

- GPS-based spatial tracking
- Semantic descriptors of environmental context

Merging Map Data (Line, Point, and Polygon Data)

Objective: Integrate multiple geographic feature layers into a **unified spatial representation**.

Process:

- **Step 1:** Prefixes ("line_", "point_", "polygon_") were added to the **column names** of each respective dataset to ensure feature distinction.
- **Step 2:** The **Line Dataset** and **Point Dataset** were merged using the **ID_Semantic** column with an **inner join**.
- **Step 3:** The resulting dataset was further merged with the **Polygon Dataset**, using **ID_Semantic** as the key.

Outcome:

The **merged map dataset** provides a comprehensive view of the spatial and structural characteristics of the rider's environment, integrating:

- **Road segments and barriers** (line data)
- **Fixed infrastructure elements** (point data, e.g., traffic signals, bike racks)
- **Larger spatial areas** (polygon data, e.g., parks, intersections)

Merging All Data (Sensors & Map Data)

Objective: Integrate **sensor-based cognitive workload data** with **environmental mapping data** to create a comprehensive dataset for machine learning.

Process:

The **merged sensor dataset (EEG, GPS, and semantic data)** was combined with the **merged map dataset** using the **ID_Semantic** column as a **common key**.

Outcome:

The final consolidated dataset provides a **complete representation of the rider's experience**, incorporating:

- **Physiological data** (EEG readings, cognitive states)
- **Geospatial tracking** (GPS trajectory, road conditions)
- **Environmental mapping** (urban features, infrastructure elements)

This dataset is **ready for use in machine learning models**, enabling a **detailed analysis of cognitive workload factors** during cycling.

3.5 Data Cleaning

To improve **data quality and model performance**, several preprocessing steps were applied to remove redundancy, handle missing values, and ensure consistency.

3.5.1 Column Removal

- Duplicate or **irrelevant metadata columns** (e.g., redundant timestamps, IDs) were **removed** to **reduce dataset complexity**.
- Non-contributing variables were **dropped** to improve model efficiency.

3.5.2 Handling Missing Data

- Rows where **ID_Glance (target variable)** was missing were **removed** to maintain analytical integrity.
- Columns with **a high percentage of missing values or containing only zeros** were **excluded** from model training.

3.5.3 Data Type Consistency

- Checked for **inconsistencies in data types** (e.g., **numerical values stored as strings**).
- Applied necessary **formatting corrections** to ensure **uniformity and compatibility** with machine learning models.

3.5.4 Feature Smoothing Using Moving Averages

- A **5-row moving average** was computed for **sensor-based variables** to reduce noise and enhance stability.
- **Raw sensor columns** were replaced with their **smoothed versions** to prevent redundancy.

By applying these **data integration and cleaning techniques**, the final dataset ensures **high-quality input for machine learning models**, leading to **more accurate cognitive workload predictions**.

Chapter 4

Machine Learning Models for Cognitive State Prediction

4.1 Introduction to AI Models Used

Machine learning models play a critical role in **cognitive workload prediction** by analyzing sensor and environmental data to determine **ID_Glance, Meditation, and Attention levels**. The dataset, comprising EEG, GPS, and environmental features, is processed using **classification models for ID_Glance** and **regression models for Meditation and Attention**.

To optimize model performance, **feature selection and dimensionality reduction techniques** were applied before training the models. The selection of machine learning algorithms was based on their ability to handle structured numerical data and their interpretability through Explainable AI (XAI) techniques such as SHAP.

4.2 Data Splitting and Scaling

To ensure robust model training and evaluation, the dataset was **split into training and testing sets** while maintaining an appropriate class balance.

- **Data Splitting:**
  - The dataset was divided into **90% training** and **10% testing** for classification and regression tasks.
  - Stratified sampling was applied to ensure **balanced representation of ID_Glance classes**.
- **Feature Scaling:**
  - **Standardization** (StandardScaler) was applied to EEG signals and numerical variables to ensure uniform feature distributions.

  - **Min-Max Scaling** was used for **Meditation and Attention values** to normalize the range between [0,1].

These preprocessing steps helped prevent **bias in model learning** due to differences in feature scales.

4.3 Classification Models for ID_Glance

ID_Glance (categorical variable) represents eye movement behavior and is predicted using classification models. The following models were selected based on their effectiveness in handling structured sensor data:

4.3.1 Logistic Regression

- **Baseline classification model** used to assess the dataset's linear separability.
- Provides **interpretability through feature coefficients** but is limited in non-linear problems.

4.3.2 Support Vector Machines (SVM)

- **Effective for high-dimensional feature spaces** and ensures maximum class separation.
- Uses the **Radial Basis Function (RBF) kernel** for non-linearity.

4.3.3 XGBoost Classifier

- **Gradient boosting model** optimized for structured data.
- Captures **complex feature interactions** and is robust against overfitting.

4.3.4 CatBoost Classifier

- **Handles categorical features efficiently** without requiring extensive preprocessing.
- Faster training compared to XGBoost and works well with limited data.

Each model's performance was **evaluated using accuracy, precision, recall, and F1-score**, ensuring an optimal selection for cognitive workload classification.

4.4 Regression Models for Meditation and Attention

The prediction of **Meditation and Attention** levels was formulated as a **regression problem**, where machine learning models were trained to estimate these continuous variables based on EEG, GPS, and environmental features. The selected regression models included **ensemble-based learners and distance-based methods** to ensure a balance between accuracy and generalization.

4.4.1 XGBoost Regressor

- A **gradient boosting framework optimized for structured data**, known for its high predictive accuracy.
- Uses **regularization and parallel processing** to prevent overfitting while maintaining efficiency.
- Well-suited for capturing **non-linear relationships** in EEG and environmental features.

4.4.2 Random Forest Regressor

- An **ensemble learning method** that constructs multiple decision trees and averages their outputs.
- Effective in handling **non-linear interactions** between features.
- Provides insights into **feature importance**, making it a useful tool for explainability.

4.4.3 Gradient Boosting Regressor

- A **sequential learning method** that builds trees iteratively, optimizing residual errors at each step.
- Well-suited for **medium-sized datasets** but can be computationally expensive.
- Works best with **careful hyperparameter tuning** to prevent overfitting.

4.4.4 LightGBM Regressor

- A **gradient boosting model optimized for speed and efficiency**, using a **leaf-wise splitting approach** instead of level-wise splitting.
- Handles **categorical features natively**, reducing preprocessing time.
- Well-suited for large datasets with **high-dimensional feature spaces**.

4.4.5 CatBoost Regressor

- A **gradient boosting model designed for categorical data**, requiring minimal preprocessing.
- Less sensitive to hyperparameter tuning and robust against **overfitting**.
- Performs well in scenarios with a mix of **numerical and categorical features**.

4.4.6 K-Nearest Neighbors (KNN) Regressor

- A **distance-based model** that predicts values based on the similarity to the nearest data points.
- Works well for **small datasets** but struggles with high-dimensional data.
- Computationally expensive when applied to **large feature spaces**, making it less suitable for real-time applications.

The selection of these models was aimed at **capturing complex relationships between EEG signals, environmental factors, and cognitive workload states**, allowing for an in-depth analysis of how external conditions impact mental focus and relaxation.

4.5 Feature Selection and Dimensionality Reduction

Before training the models, **feature selection and dimensionality reduction techniques** were applied to improve efficiency and interpretability.

4.5.1 Initial Feature Reduction

- **Removing Non-Informative Columns:**
  - A threshold was defined to **eliminate columns with low non-zero values**, reducing sparsity.
  - Features with little impact on **ID_Glance, Meditation, or Attention** were removed.
- **Dropping Additional Columns:**
  - Timestamp fields, redundant geographic identifiers, and highly correlated EEG components were removed.
  - This **reduced noise, improved computational efficiency, and enhanced feature interpretability**.

4.5.2 Principal Component Analysis (PCA)

To **reduce feature dimensionality while preserving variance**, **PCA was applied** to map-related features:

- **Dimensionality Reduction:**
  - PCA was used to transform **16 environmental features into 9 principal components** while retaining **95% variance**.
  - This mitigated **overfitting** and **reduced computational complexity**.
- **Preserving EEG and GPS Features:** PCA was only applied to **urban mapping features**, while EEG and GPS features were retained in their original form to maintain interpretability.

The application of PCA ensured that **highly correlated geographic variables were merged**, preventing redundancy in the dataset.

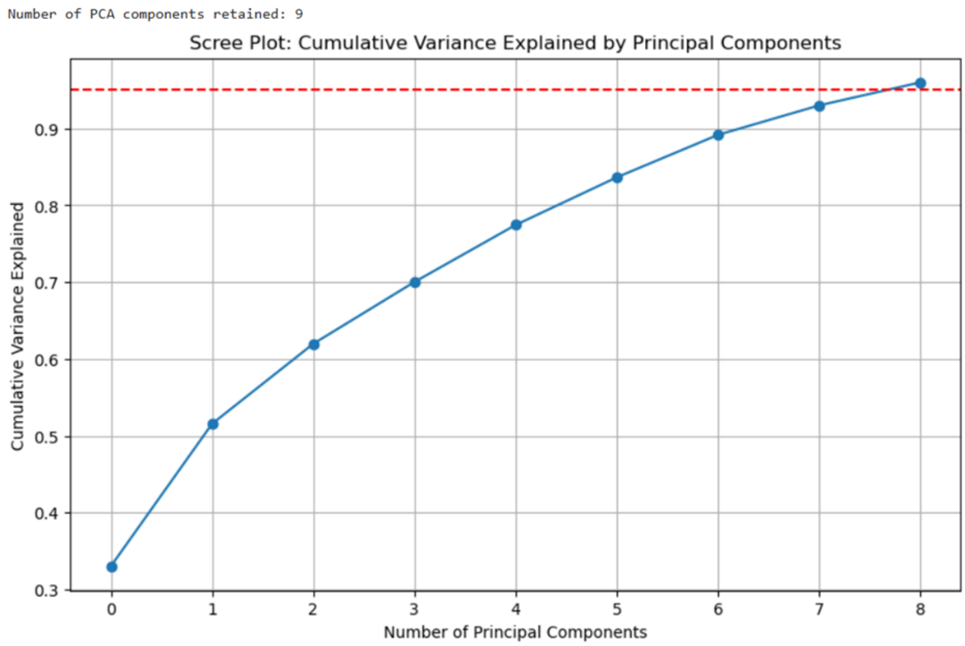

FIGURE 4.1: PCA Scree Plot

4.6 Model Performance Evaluation

Each classification and regression model was evaluated using standard performance metrics to assess their effectiveness in predicting **ID_Glance, Meditation, and Attention**.

4.6.1 Classification Model Metrics (ID_Glance Prediction)

The classification models were assessed using the following metrics:

- **Accuracy** – Measures the overall correctness of predictions.
- **Precision** – Determines the model's reliability in predicting specific gaze behaviors.
- **Recall** – Evaluates the model's sensitivity to each **ID_Glance** class.
- **F1-Score** – Provides a harmonic mean of precision and recall for a balanced evaluation.

4.6.2 Confusion Matrix for the training:

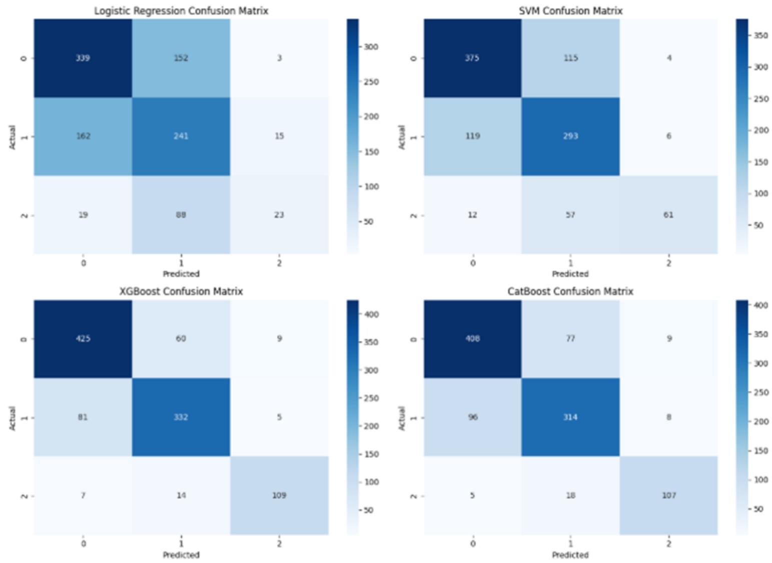

FIGURE 4.2: Confusion Matrix For IDGlance

4.6.3 Classification Model Results :

Model	Accuracy	Precision (Overall)	Recall (Overall)	F1-score (Overall)
Logistic Regression	**0.579**	**0.57**	**0.48**	**0.49**
Support Vector Machine (SVM)	**0.700**	**0.74**	**0.64**	**0.67**
XGBoost Classifier	**0.831**	**0.84**	**0.83**	**0.84**
CatBoost Classifier	**0.796**	**0.81**	**0.80**	**0.81**

TABLE 4.1: Classification Model Results for IDGlance

4.6.4 Performance Summary for ID_Glance Classification

- **Logistic Regression:** Achieved **57.9% accuracy**, but struggled with class imbalance, leading to a lower overall **F1-score (49%)**.
- **SVM:** Improved accuracy to **70.0%**, showing balanced performance across classes with an **F1-score of 67%**.
- **XGBoost:** The best-performing model with **83.1% accuracy** and the highest **F1-score (84%)**, excelling in all classes.
- **CatBoost:** Followed closely with **79.6% accuracy**, demonstrating strong handling of categorical features with an **F1-score of 81%**.

Final Model Selection for ID_Glance Prediction

XGBoost was selected as the best model due to its highest accuracy and balanced classification across all ID_Glance classes. CatBoost was chosen as a strong alternative due to its ability to handle categorical data efficiently.

4.6.5 Regression Model Metrics (Meditation & Attention Prediction)

For continuous target variables (**Meditation and Attention**), regression models were evaluated using:

- **R² Score** – Measures how well the model explains the variance in the target variable.
- **Mean Absolute Error (MAE)** – Assesses prediction accuracy by computing the average absolute error.

Model Training Heatmap:

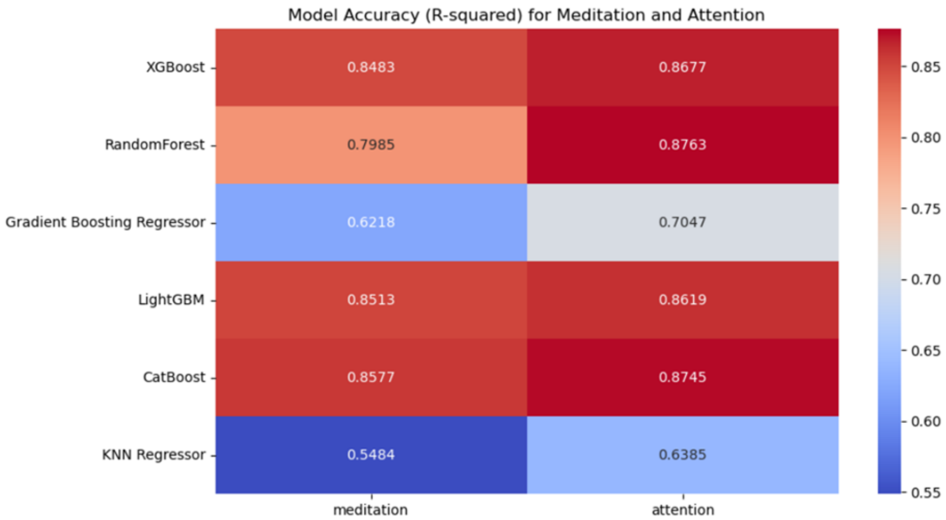

FIGURE 4.3: Heatmap for Regression Model Training

Regression Model Results

Model	Meditation (R^2)	Attention (R^2)
XGBoost Regressor	0.8483	0.8677
Random Forest Regressor	0.7985	0.8763
Gradient Boosting Regressor	0.6218	0.7047
LightGBM	0.8513	0.8619
CatBoost Regressor	0.8577	0.8745
K-Neighbors Regressor	0.5484	0.6385

TABLE 4.2: Regression Model Results for Attention and Meditation

4.6.6 Performance Summary for Meditation and Attention Prediction

- CatBoost achieved the highest performance overall, with $R^2 = 0.8577$ for Meditation and 0.8745 for Attention, making it the best-performing model.
- XGBoost (0.8483 for Meditation, 0.8677 for Attention) and LightGBM (0.8513 for Meditation, 0.8619 for Attention) closely followed, showing competitive accuracy.
- Random Forest performed well, particularly on the Attention dataset (0.8763).
- Gradient Boosting and K-Neighbors Regressors underperformed, with significantly lower R^2 scores, indicating limited predictive capability for these cognitive states.

Final Model Selection for Meditation and Attention Prediction

Given its superior predictive accuracy and stability, **CatBoost** was selected for Meditation prediction, while **Random Forest** was chosen for Attention prediction for further SHAP analysis. This will help interpret feature importance and understand how various environmental and physiological factors influence cognitive states.

4.6.7 Results Summary

This section presented the performance evaluation of classification and regression models for **ID_Glance, Meditation, and Attention**.

- For classification, **XGBoost** was the best model for ID_Glance prediction, followed closely by CatBoost.
- For regression, **CatBoost** was chosen for Meditation, and **Random Forest** was selected for Attention, based on R^2 scores.

The next chapter will discuss Explainable AI (SHAP analysis), which will help interpret the contributions of different features in predicting cognitive workload.

Chapter 5

Explainable AI (XAI) and Model Interpretability

5.1 Introduction to Explainability in AI

As AI models become more complex, their **lack of transparency** poses challenges in understanding their decision-making process. Explainable AI (**XAI**) techniques address this issue by providing **interpretability and insights** into model predictions.

For this study, XAI is crucial in analyzing how **physiological (EEG-based) and environmental (map-related) features influence cognitive workload predictions**. The use of **SHapley Additive Explanations (SHAP)** enables a detailed breakdown of the impact of different features on the predicted cognitive states (**ID_Glance, Meditation, and Attention**).

This chapter explores the application of **SHAP analysis** to improve model interpretability and examines feature contributions across different AI models.

5.1.1 SHAP for Feature Importance Analysis

SHAP is a powerful tool that assigns **Shapley values** to each feature, quantifying its impact on model predictions. It helps in:

- **Global interpretability** – Understanding which features influence predictions across the entire dataset.
- **Local interpretability** – Explaining individual predictions for specific data points.
- **Fairness and trust** – Ensuring AI models make decisions transparently and without bias.

By applying SHAP, we can determine the **most influential EEG, GPS, and environmental features** for predicting **ID_Glance, Meditation, and Attention**.

5.1.2 SHAP Analysis for ID_Glance (Eye Movement Classification)

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5.2 SHAP Analysis Approach

To analyze the interpretability of the models, SHAP values were used to determine the most influential features for each **target variable (ID_Glance, Meditation, and Attention)**. The approach followed these steps:

- **SHAP Value Computation:** SHAP values were calculated to determine which features contributed the most to model predictions.
- **Principal Component Mapping:** Since **PCA was applied to map features**, the most important **principal components (PCs)** were mapped back to their original features to improve interpretability.
- **Feature Contribution Visualization:** SHAP summary plots and bar charts were generated to illustrate the contribution of each feature to model predictions, highlighting the role of **environmental and sensor-based factors** in cognitive state estimation.

5.3 SHAP Analysis for ID_Glance

5.3.1 SHAP Summary Plot for XGBBoost (Class 0 - Saccade):

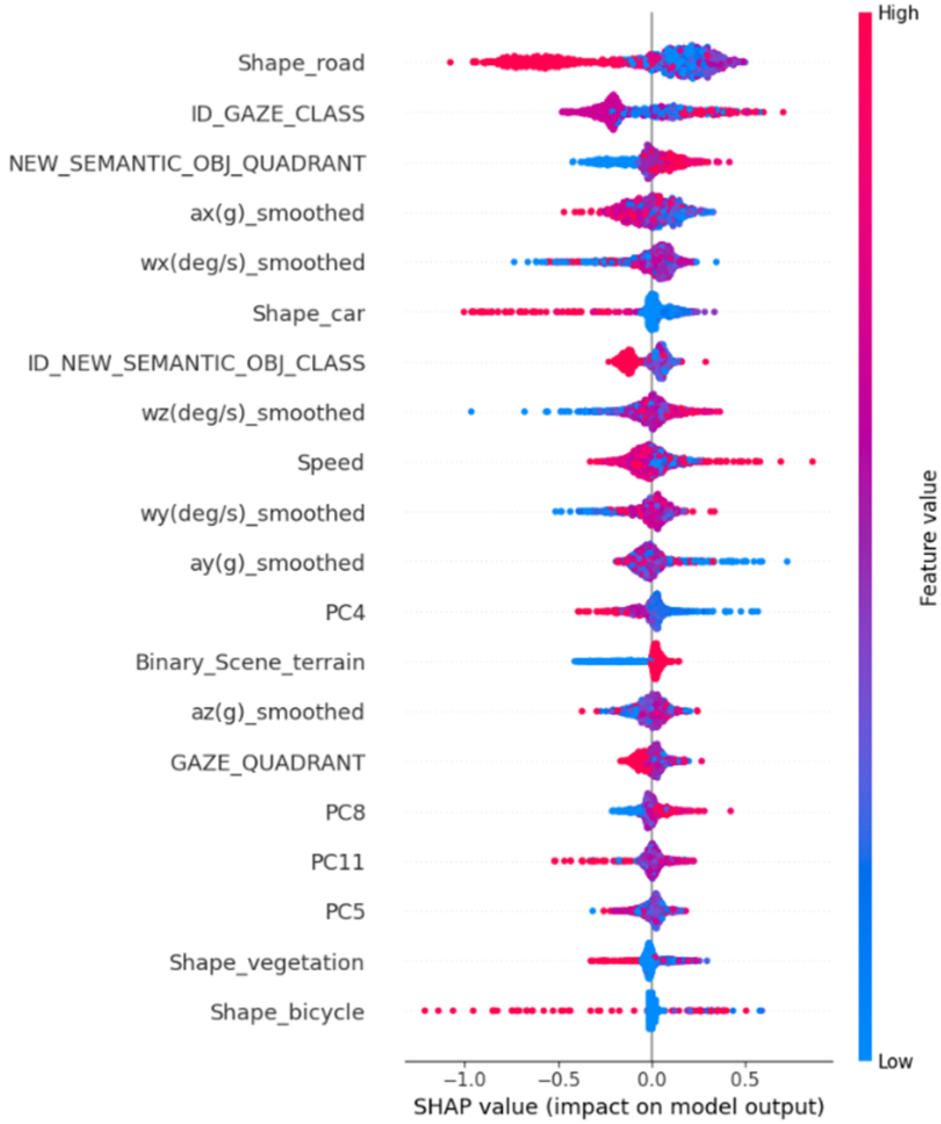

FIGURE 5.1: SHAP Summary Plot for XGBBoost (Class 0 - Saccade)

5.3.2 SHAP Summary Plot for XGBBoost (Class 1 - Fixation):

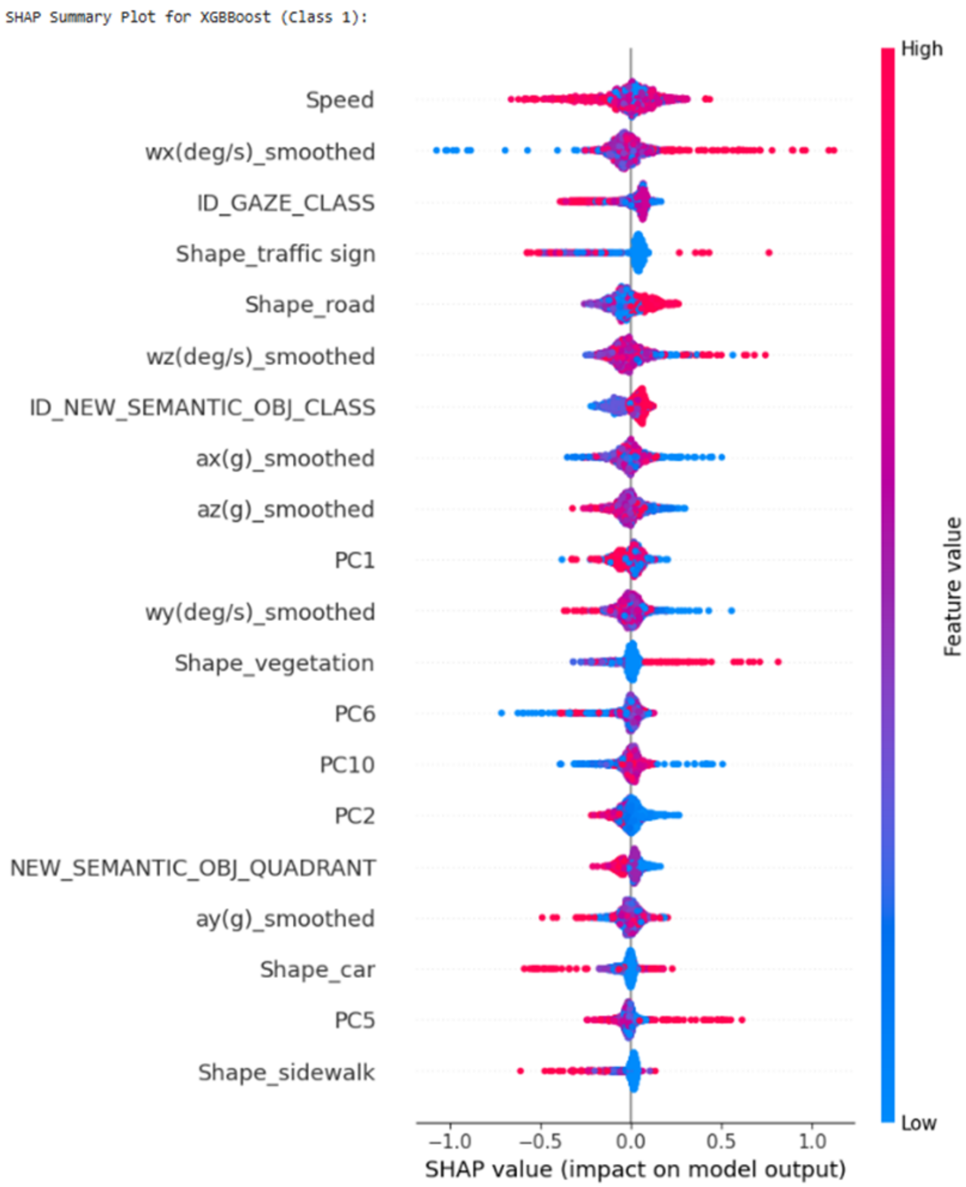

FIGURE 5.2: SHAP Summary Plot for XGBBoost (Class 1 - Fixation)

5.3.3 SHAP Summary Plot for XGBBoost (Class 2 - Long Fixation):

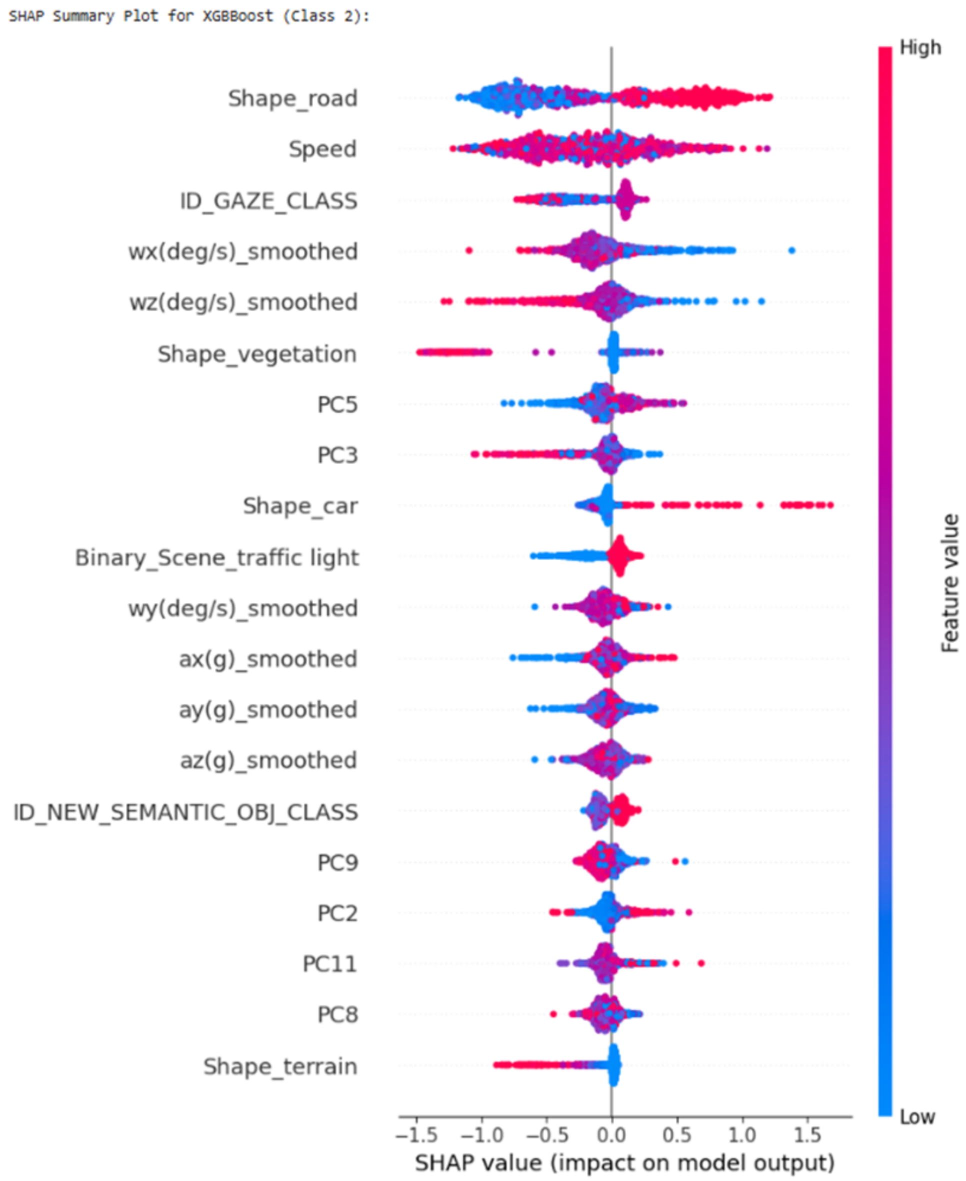

FIGURE 5.3: SHAP Summary Plot for XGBBoost (Class 2 - Long Fixation)

5.3.4 SHAP Analysis Results for ID_Glance

The SHAP analysis results showed key differences in feature influence across **three gaze behaviors (Class 0 - No Fixation, Class 1 - Fixation, Class 2 - Long Fixation)**:

Feature	**Class 0 (No Fixation)**	**Class 1 (Fixation)**	**Class 2 (Long Fixation)**
Shape_road	Complex roads increase no fixation (saccades)	Moderate influence	Straight roads promote long fixation
Speed	High variations increase gaze shifts	Moderate influence	Higher speed promotes long fixation
ID_GAZE_CLASS	Unstable gaze patterns reinforce saccades	Balanced fixation behavior	Stable gaze leads to long fixation
SEMANTIC_OBJ_QUAD	Peripheral objects increase gaze shifts	Objects in relevant quadrants aid fixation	Central objects promote long fixation
wx(deg/s)_smoothed	High angular velocity disrupts fixation	Moderate impact	Stable movement supports long fixation
Shape_traffic sign	Low influence	Fixation on traffic signs	Low influence
Shape_car	Car presence requires scanning, reducing fixation	Situational fixation on cars	Stable car presence encourages long fixation
Binary_Scene_traffic light	Low influence	Low influence	Presence of traffic lights encourages fixation
Shape_vegetation	Low influence	Low influence	Vegetation contributes to long fixation
Shape_terrain	Complex terrain increases gaze shifts	Moderate influence	Smooth terrain supports long fixation

TABLE 5.1: SHAP Analysis Results Table for ID_Glance

Note: Since **sensor features had the highest impact** on ID_Glance predictions, while **PCA was applied only to map features**, converting PCs back is unnecessary. Sensor data already provides clear insights, and reversing PCA would add complexity without improving interpretability

5.3.5 Final Interpretation and Conclusion

- **Class 0 (Saccade):** Frequent gaze shifts occur due to **c**omplex road structures, unstable movement, peripheral object placement, and high acceleration variations, making fixation difficult.
- **Class 1 (Fixation):** Represents balanced attention, where road design, object positioning, and speed allow for momentary but non-sustained fixations.
- **Class 2 (Long Fixation):** Prolonged visual focus is supported by straight roads, stable movement, and structured environments with clear reference points like cars and traffic lights.

These findings highlight how dynamic, unpredictable environments promote scanning behavior, while **s**tructured and stable conditions encourage sustained visual attention.

5.4 SHAP Analysis for Meditation

5.4.1 SHAP Summary Plot for CatBoost on MEDITATION:

FIGURE 5.4: SHAP Summary Plot for CatBoost on MEDITATION

5.4.2 Original Features Contribution to Influential PCs

Below is the bar chart showing the contribution of original map features to the most influential principal components (PCs 2, 1, 4, and 6) identified in the SHAP analysis for **Meditation**.

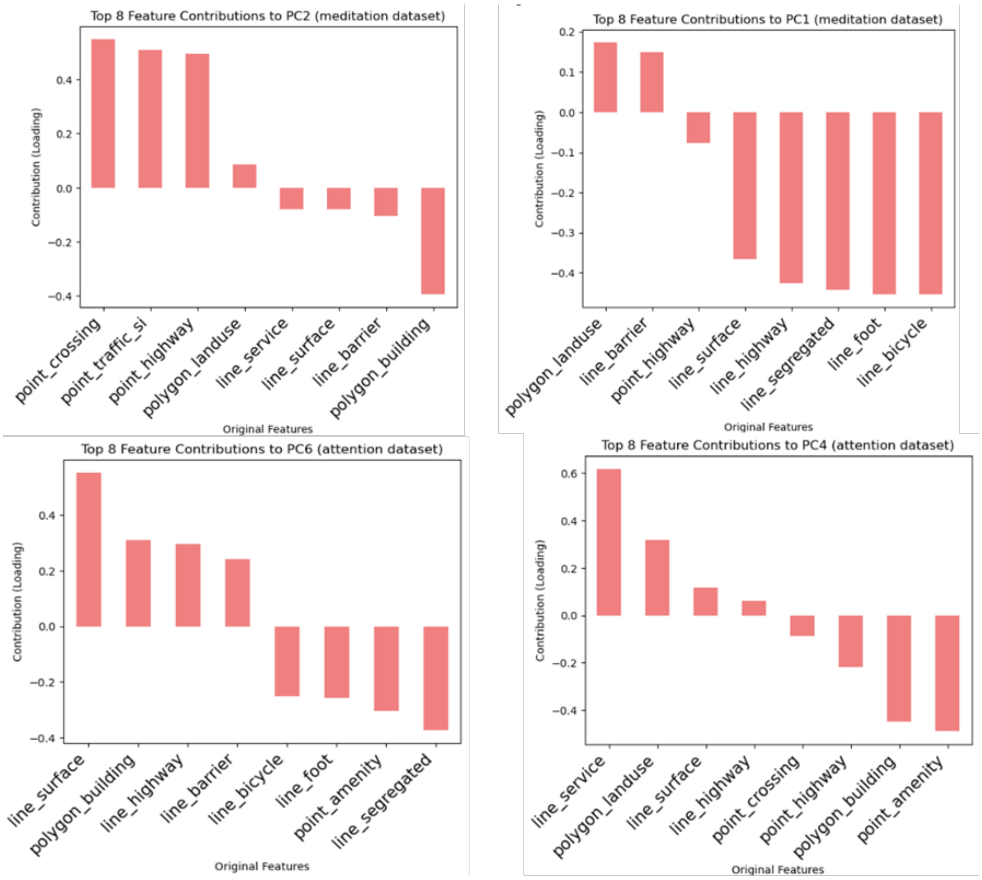

Figure 5.5: Bar Chart Original Features Contribution to Influential PCs - Meditation

5.4.3 SHAP Summary Plot for Original Features - CatBoost on MEDITATION:

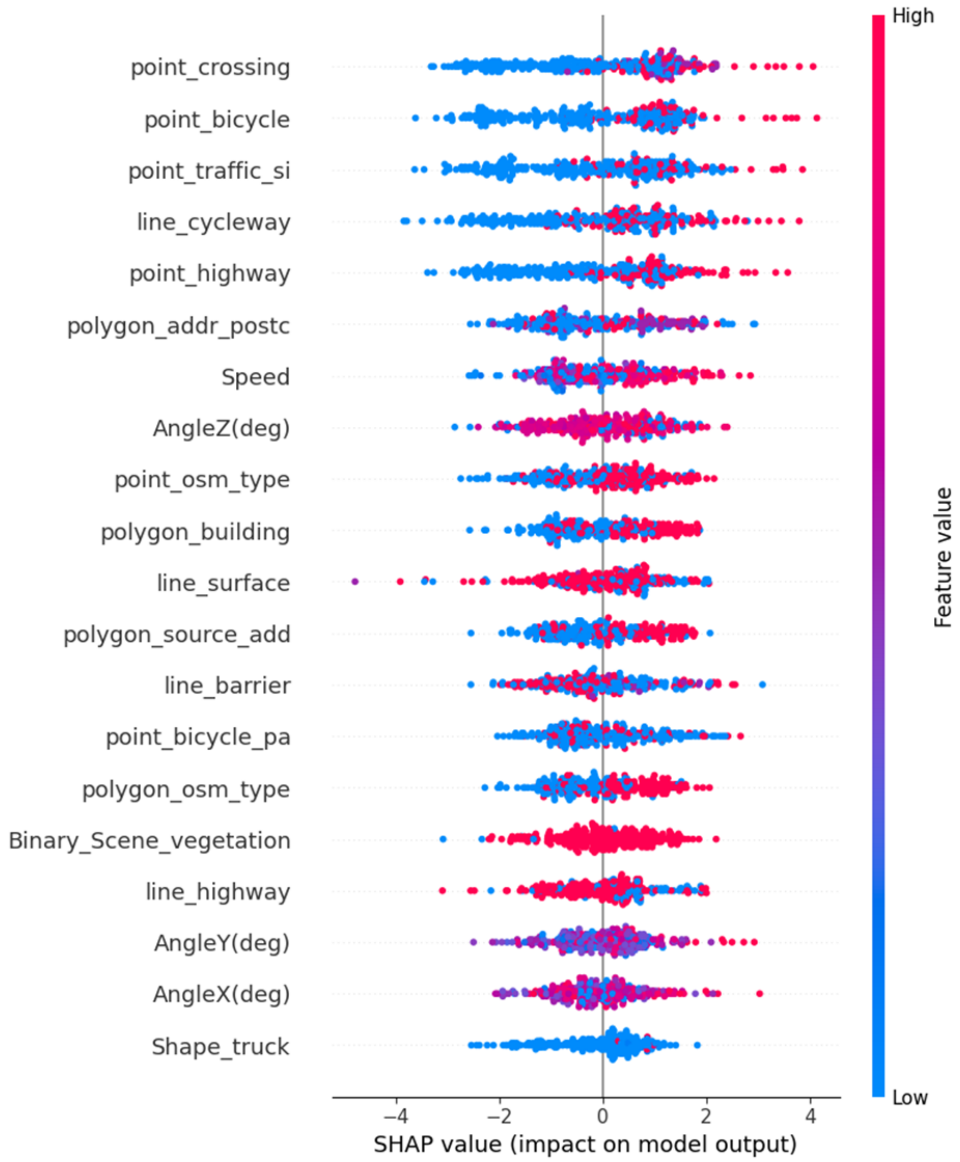

FIGURE 5.6: SHAP Summary Plot for Original Features - CatBoost on Meditation

5.4.4 SHAP Analysis Results for Meditation

Feature	Before Mapping (PC Influence)	After Mapping (Original Features)
Speed	High influence on meditation	Retained high influence
PC2, PC1, PC4, PC6	Key contributing PCs	Mapped to specific geographic features
ax(g)_smoothed, ay(g)_smoothed	Strong impact on meditation	Retained impact
Shape_road	Moderate impact	Replaced by line_highway, line_surface
Binary_Scene_fence	Indirect influence via PCA	Now line_barrier
wx(deg/s)_smoothed	Not a top factor	Lower impact after mapping
point_traffic_sign, point_highway	Previously embedded in PCs	Now directly interpretable
polygon_building, polygon_osm_type	Low impact before mapping	Now interpretable influences
AngleX(deg), AngleY(deg), AngleZ(deg)	Previously hidden in PCs	Directly influences meditation

Table 5.2: SHAP Analysis Results Table for Meditation

5.4.5 Final Interpretation and Conclusion

- **Before Mapping:** Principal components played a significant role, but their interpretability was limited. Sensor features (speed, acceleration, and angular motion) were dominant.
- **After Mapping:** The original geographic features (roads, traffic signs, barriers, and highway elements) emerged as important contributors to Meditation levels.
- **Conclusion:** Meditation is strongly influenced by movement stability (speed, acceleration) and environmental structure (roads, traffic signs, and highway attributes).

5.5 SHAP Analysis for Attention

5.5.1 SHAP Summary Plot for Random Forest on Attention:

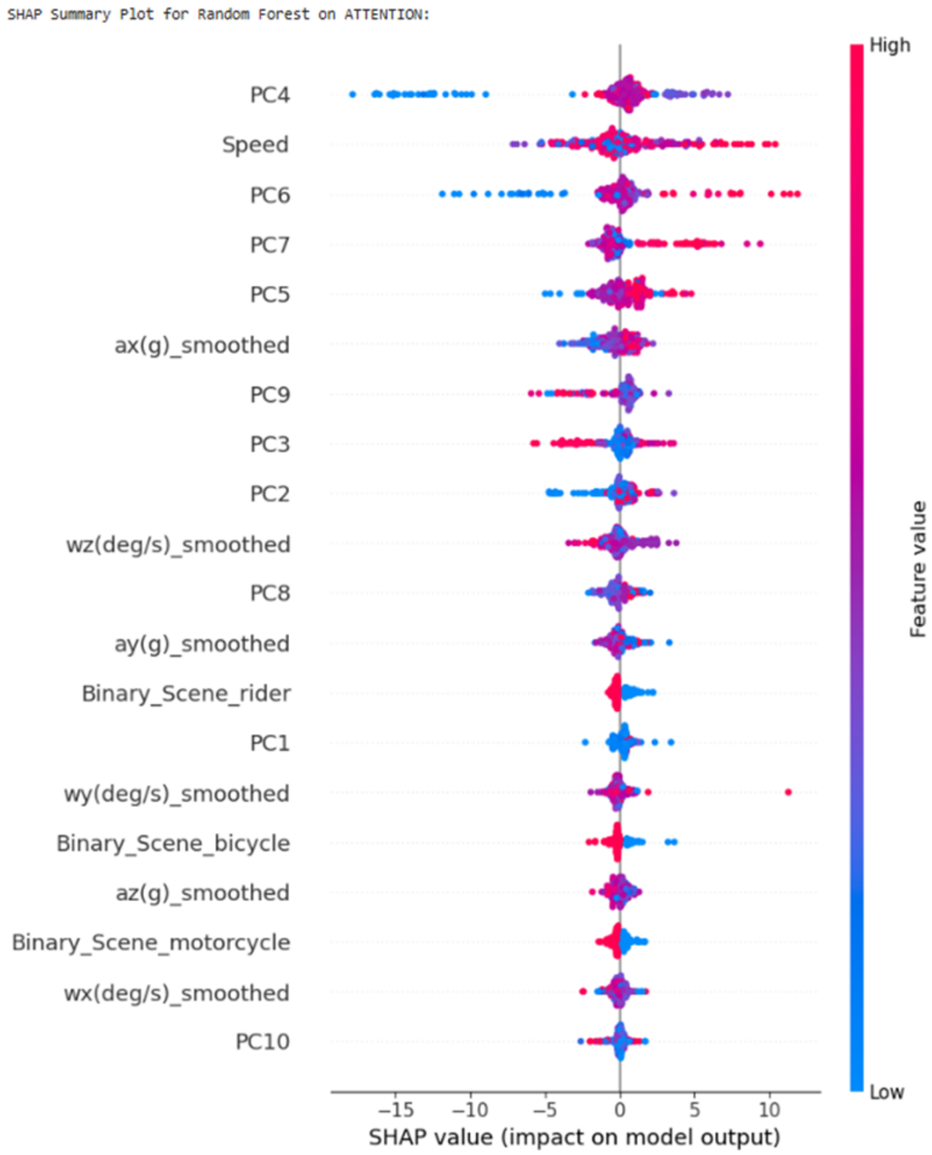

Figure 5.7: SHAP Summary Plot for Random Forest on Attention

5.5.2 Original Features Contribution to Influential PCs

Below is the bar chart showing the contribution of original map features to the most influential principal components (PCs 4, 6, 7, and 5) identified in the SHAP analysis for **Attention**.

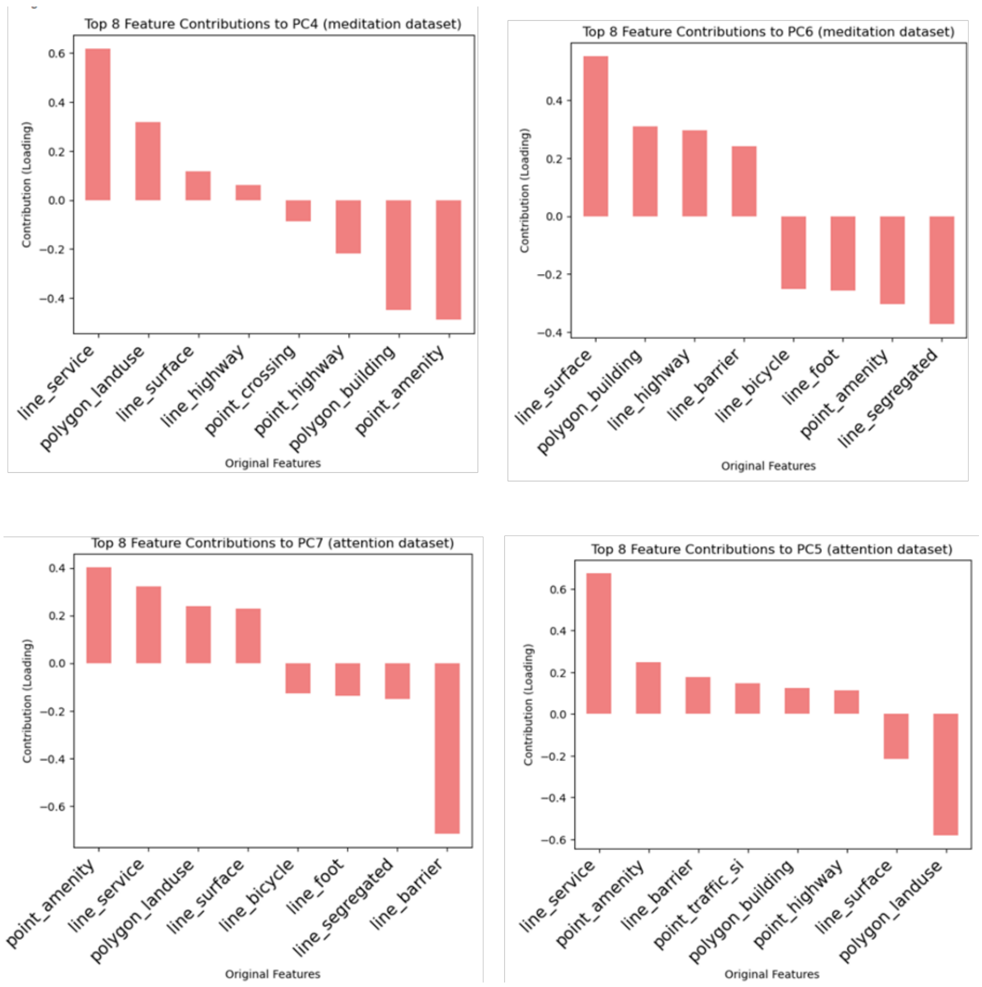

Figure 5.8: Original Features Contribution to Influential PCs - Attention

5.5.3 SHAP Summary Plot for Original Features - Random Forest on Attention:

FIGURE 5.9: SHAP Summary Plot for Original Features - Random Forest on Attention

5.5.4 SHAP Analysis Results for Attention

Feature	**Before Mapping (PC Influence)**	**After Mapping (Original Features)**
Speed	High influence on attention	Retained high influence
PC4, PC6, PC7, PC5, PC9	Key contributing PCs	Mapped to specific geographic features
ax(g)_smoothed, wz(deg/s)_smoothed	Strong impact on attention	Retained impact
Binary_Scene_rider, Binary_Scene_bicycle, Binary_Scene_motorcycle	Indirect influence via PCA	Now directly interpretable
ID_GAZE_CLASS	Not directly visible in first SHAP plot	Now a key feature influencing attention
Yaw, AngleX(deg), AngleY(deg), AngleZ(deg)	Previously embedded in PCs	Now directly linked to attention variability
line_barrier, line_surface, line_highway	Previously part of PCs	Now identifiable as influential geographic features

Table 5.3: SHAP Analysis Results Table for Attention

5.5.5 Final Interpretation and Conclusion

- **Before Mapping:** Principal components dominated, limiting interpretability.
- **After Mapping:** Specific environmental and motion factors emerged as key contributors.
- **Conclusion:** Attention is strongly influenced by **speed, yaw, acceleration, road barriers, and semantic objects**.

These insights enhance **AI-assisted navigation strategies** by incorporating real-world cognitive workload factors.

By integrating **SHAP analysis**, this study provides interpretability to AI-based cognitive workload modeling, helping improve cyclist safety and decision-making in urban environments.

Chapter 6

Results and Discussion

6.1 Overview

This chapter presents the results obtained from the analysis of cognitive workload in cyclists using Explainable AI (XAI) techniques, particularly SHapley Additive exPlanations (SHAP). The discussion is structured around the three cognitive states predicted in this study:

1. **ID_Glance (Categorical Variable**) – Represents visual attention behavior, categorized into Saccade, Fixation, and Long Fixation.
2. **Meditation (Continuous Variable**) – Indicates mental relaxation levels during cycling.
3. **Attention (Continuous Variable)** – Measures cognitive focus and engagement in a given environment.

The results highlight how environmental complexity, motion stability, and infrastructure design influence cognitive workload, offering critical insights into urban planning, AI-assisted cyclist navigation, and transportation safety.

6.2 Key Findings from Model Performance and SHAP Analysis

Machine learning models were trained to predict ID_Glance, Meditation, and Attention using EEG-based motion data (sensor features) and urban mapping data (environmental features). SHAP analysis was then applied to provide interpretable explanations for each cognitive state.

6.2.1 ID_Glance

The ID_Glance classification model (**XGBoost**) demonstrated that gaze behavior is influenced by a combination of motion stability, environmental structure, and cognitive state changes.

Key Influencing Factors for ID_Glance

- Gaze Classification (ID_GAZE_CLASS) – Determines whether the rider exhibits rapid eye movements (saccades) or prolonged fixations.
- Motion Stability (Acceleration & Angular Velocity) –
  - High acceleration variations and frequent angular velocity shifts increase gaze shifts (saccades).
  - Stable motion and smooth road conditions support prolonged fixations.
- Environmental Structure (Road Type, Terrain, and Scene Objects) –
  - Predictable environments (straight roads, structured paths) promote long fixations.
  - Unstructured, high-traffic environments (intersections, moving objects) lead to frequent gaze shifts.

Behavioral Interpretation of ID_Glance Classes

- **Class 0 (Saccades - No Fixation):**
  - Occur in highly dynamic, unpredictable environments requiring constant scanning.
  - Frequent in complex road structures, heavy traffic zones, and unstable movement conditions.
- **Class 1 (Fixation - Brief Visual Attention):**
  - Represent momentary attentional focus on relevant objects before shifting attention.
  - Found in moderate complexity environments where objects hold temporary visual relevance.
- **Class 2 (Long Fixation - Sustained Attention):**
  - Associated with structured, low-complexity environments that allow steady gaze.
  - More common on straight roads, traffic-controlled zones, and familiar pathways.

6.2.2 Final Summary for ID_Glance

SHAP analysis confirmed that environmental predictability, motion stability, and object placements are primary determinants of where and how long a cyclist looks at different elements in the scene.

6.2.3 Meditation (Mental Relaxation Level - Continuous Variable

The Meditation prediction model (**CatBoost**) demonstrated that speed, motion smoothness, and environmental conditions play a crucial role in defining a cyclist's mental relaxation state.

Key Influencing Factors for Meditation

- **Speed**: Higher speeds correlated with higher meditation scores, possibly due to predictable motion patterns and rhythmic movement.
- **Motion Smoothness (Acceleration & Angular Stability):**
  - Stable movement supports relaxation.
  - Sudden jerks or irregular acceleration changes introduce cognitive stress.
- **Environmental Features (Road Type, Traffic Elements, Terrain Complexity):**
  - Well-structured roads and cycling lanes promote relaxation.
  - Irregular terrain, road barriers, and high-traffic zones reduce meditation levels.

Behavioral Interpretation of Meditation Scores

- **High Meditation:** Observed in stable, structured environments with minimal distractions.
- **Low Meditation (Cognitive Strain):** Caused by environmental unpredictability, sudden acceleration changes, or external disruptions (e.g., traffic, intersections).

Final Summary for Meditation

- Sensor-based features (speed, acceleration) were dominant before PCA mapping.
- After mapping PCA components back to original features, road structure, object placements, and barriers emerged as significant contributors to meditation levels.

6.2.4 Attention (Cognitive Focus Level - Continuous Variable)

The Attention prediction model (Random Forest) highlighted that speed, yaw stability, and environmental predictability directly influence a cyclist's ability to maintain focus.

Key Influencing Factors for Attention

- **Speed & Motion Stability:** Faster speeds and structured environments (e.g., highways, dedicated cycling lanes) promote higher focus.
- **Yaw & Angular Motion (wz, ax, ay, az):** Large variations in yaw and angular velocity disrupt attentional stability.
- **Environmental Features (Road Type, Traffic Elements, Scene Objects):**
  - Well-defined infrastructure (barriers, cycling lanes, smooth roads) supports stable attention.

- Unstructured environments with unexpected road obstacles or frequent stops increase cognitive load.

Behavioral Interpretation of Attention Scores

- **Sustained Attention:** Observed in clear, structured navigation paths with minimal distractions.
- **Fluctuating Attention:** Linked to unstable motion, irregular terrain, and unpredictable external stimuli (traffic, pedestrians, roadblocks, etc.).

Final Summary for Attention

- Before mapping, PCA components (PC4, PC6, PC7, PC5, PC9) were dominant.
- After mapping, specific environmental features (road barriers, traffic elements, semantic object classifications) became interpretable.

6.3 Impact of Environmental and Physiological Features on Cognitive States

The integration of motion-based and environmental features provides valuable insights into how cyclists interact with urban landscapes:

- **Motion Stability:** Essential for both relaxation (meditation) and focus (attention).
- **Environmental Complexity:** Impacts gaze behavior (ID_Glance) and cognitive strain.
- **Predictable Infrastructure:** Helps maintain higher meditation and attention levels, supporting safer cycling navigation.

6.3.1 Limitations of the Study

While this study provides valuable insights into cognitive workload modeling, several limitations must be acknowledged:

- **Limited Dataset Size:** The dataset used for training and evaluation, although comprehensive, is relatively small. A larger dataset covering diverse environmental conditions, cycling behaviors, and rider demographics would enhance the generalizability of the models.
- **Real-time Adaptability**: The models were trained on pre-collected data, meaning they do not yet function in real-time scenarios. Implementing these models in real-time AI-assisted navigation systems would require further optimization and testing.
- **External Factors Not Considered**: This study focused on sensor and environmental data, but factors such as emotional state, fatigue, and weather conditions were not explicitly included. These elements could have an additional impact on cognitive workload and may need to be integrated in future studies.

Addressing these limitations would improve the **robustness, adaptability, and applicability** of AI-driven cognitive workload analysis in urban mobility settings.

6.3.2 Summary

This chapter analyzed model predictions, feature influences, and SHAP-based explainability for ID_Glance, Meditation, and Attention. The key findings demonstrate that:

1. Unstructured environments and motion instability increase gaze shifts (saccades) and cognitive strain.

2. Predictable infrastructure and smooth motion patterns promote mental relaxation and sustained focus.

3. SHAP analysis improves AI model interpretability, allowing urban planners to optimize cycling infrastructure for cognitive well-being.

These findings have direct implications for urban mobility, AI-driven navigation systems, and human-centered transportation safety. The next chapter will conclude the study and propose future research directions.

Chapter 7

Conclusion and Future Work

7.1 Summary of Contributions

This study explored the use of Explainable AI (XAI) techniques, specifically SHAP, to analyze cognitive workload in cyclists navigating urban environments. By integrating sensor data (EEG, GPS, motion-based features) and environmental mapping (road structure, traffic elements, terrain complexity), machine learning models were trained to predict three key cognitive states: ID_Glance, Meditation & Attention.

The research demonstrated how motion stability, environmental complexity, and object placement influence cognitive workload. The application of SHAP-based feature interpretability allowed for a transparent and explainable AI framework, providing insights that are critical for urban planning, AI-assisted cycling navigation, and human-centered transportation safety.

The key contributions of this study include:

- Developing an AI-driven cognitive workload analysis framework integrating EEG, GPS, and environmental mapping data.
- Applying Principal Component Analysis (PCA) for dimensionality reduction of geographic features, improving computational efficiency.
- Using SHAP to interpret model predictions, making AI-based cognitive analysis more transparent and understandable.
- Identifying key motion and environmental factors affecting cognitive workload, aiding in the design of safer cycling infrastructure.

7.2 Potential Applications (Urban Planning, AI-assisted Cycling)

The findings of this study have practical applications in transportation, smart mobility, and AI-assisted urban planning.

7.2.1 Urban Planning & Infrastructure Optimization

- Insights from SHAP-based cognitive workload analysis can be used to redesign cycling routes, prioritizing smoother, less cognitively demanding paths.
- Road safety measures can be optimized by identifying high cognitive load areas (e.g., intersections, high-traffic zones) where cyclist focus is reduced.

7.2.2 AI-Assisted Navigation for Cyclists

- AI-driven navigation systems can adaptively recommend optimal routes based on predicted cognitive workload, improving rider efficiency and safety.
- Integration of XAI-powered navigation aids can enhance real-time decision-making support, minimizing cognitive overload during cycling.

7.3 Future Research Directions

While this study provides important insights into cognitive workload modeling, several aspects require further exploration to enhance model generalization, real-time adaptability, and multimodal AI integration.

7.3.1 Expanding Dataset for Generalization

- A larger dataset incorporating diverse cyclist demographics, varying environmental conditions, and different cycling routes would improve the robustness of AI models.
- Including data from different geographical regions can help validate the generalizability of SHAP-based interpretability findings.

7.3.2 Real-time Explainability in Edge AI

- Current models rely on pre-collected data; transitioning to real-time AI inference on Edge devices would enable instant cognitive workload assessments during navigation.
- Implementing lightweight SHAP approximations for real-time model interpretation in embedded AI systems (e.g., smart helmets, AI-driven cycling assistants).

7.3.3 Multi-modal Fusion of Sensor Data

- Incorporating additional physiological and environmental data sources (e.g., heart rate, stress indicators, weather conditions) can enhance cognitive workload predictions.
- Multi-modal AI architectures combining sensor data, vision-based input, and cyclist feedback can improve adaptive AI-assisted navigation systems.

7.4 Final Remarks

This study contributes to the growing field of Explainable AI in cognitive workload modeling, offering a data-driven approach to understanding cyclist behavior in urban environments.

By applying SHAP-based explainability, this research bridges the gap between black-box AI models and real-world interpretability, ensuring that AI-powered cognitive workload assessments can be used for safer, smarter, and more efficient urban mobility solutions.

Future research should focus on enhancing dataset diversity, implementing real-time edge AI solutions, and integrating multimodal cognitive workload modeling techniques to further advance human-centered AI in transportation and mobility analytics.

Appendix A

Hyperparameter Configurations

A.1 Best Model Hyperparameters

The table below lists the hyperparameter configurations used for the best-performing models.

Model	**Hyperparameters**
XGBoost Classifier	learning_rate=0.1, max_depth=6, n_estimators=500
CatBoost Classifier	iterations=1000, depth=6, learning_rate=0.05
Random Forest Regressor	n_estimators=200, max_depth=10
CatBoost Regressor	iterations=1000, learning_rate=0.05, depth=6

TABLE A.1: Hyperparameter Configuration of the Best Model

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Acknowledgements

I sincerely thank my advisor, Professor Giovanni Gallo, for his invaluable guidance, continuous support, and encouragement throughout this research. I am also grateful to my co-supervisors, Professor Salvatore Cafiso and Professor Giuseppina Pappalardo, for their mentorship and insightful feedback, which significantly contributed to this work.

A special appreciation goes to Fatima and Zahra, whose collaboration and guidance during my research internship greatly enhanced my understanding and progress. I also extend my sincere thanks to my colleagues, Sameer Afzal and Asad Aslam, for their technical discussions, support, and motivation throughout the project.

I am also deeply thankful to my friend, Ali Ashar, who has been a constant source of support and encouragement throughout my master's journey. His help and guidance have been invaluable in navigating both academic and personal challenges.

Lastly, I am profoundly grateful to my parents, whose unwavering support and encouragement have been my greatest source of strength. Their belief in me has been instrumental in achieving this milestone.