DESIGN AND IMPLEMENTATION OF AN INTELLIGENT SOCIAL MEDIA CONTENT SCHEDULING SYSTEM USING MACHINE LEARNING BASED ENGAGEMENT PREDICTION

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Contents

CHAPTER ONE 1
1.1 INTRODUCTION 1
1.2 PROBLEM STATEMENT BASED ON THE LITERATURE 2
1.3 AIM AND OBJECTIVES 3
1.3.1 Aim 3
1.3.2 Objectives 4
1.4 SIGNIFICANCE OF THE STUDY 4
1.5 SCOPE AND LIMITATIONS 5
1.5.1 Scope of the Study 5
1.5.2. Limitations of the Study 6
1.6 Definition of Terms 7
CHAPTER TWO 10
2.1 LITERATURE REVIEW 10
2.2 THEORETICAL FRAMEWORK 14
2.2.1 Uses and Gratifications Theory (UGT) 14
2.2.2 Temporal Rhythms in Social Activity 14
CHAPTER THREE 15
3.1 PROPOSED METHODOLOGY 15
3.2 DATA COLLECTION AND PREPROCESSING 15
3.2.1 Feature Engineering 16
3.2.2 Model Development 16
3.2.3 Scheduling Logic and Ranking Mechanism 16
3.2.4 System Implementation 17
3.2.5 Validation and Testing 17
CONCLUSION 18
REFERENCES 19
RESEARCH WORK PLAN (GANTT CHART) 21

CHAPTER ONE

1.1 INTRODUCTION

Social media has become one of the most important channels for communication, marketing, and audience engagement, with billions of posts generated daily across platforms such as Instagram, TikTok, Facebook, and X (formerly Twitter). As competition for user attention increases, creators and businesses are under pressure to publish content at the most effective times in order to maximize engagement. However, determining the optimal posting time remains a difficult task because audience behaviour is dynamic, influenced by activity cycles, content type, and platform algorithms. To address this challenge, data-driven prediction models have become increasingly important for scheduling decisions (Kanuri et al., 2018).

Machine learning has emerged as one of the most effective approaches for understanding and predicting engagement patterns. The base study for this project, Fu and Gonzalez (2025), demonstrated that classical machine learning methods such as Random Forest, Gradient Boosting, and Support Vector Machines can accurately predict engagement metrics, including likes, comments, and shares, using features such as posting time, content type, and caption attributes. Their findings establish a strong methodological foundation for building predictive systems and highlight the role of data-driven decision-making in improving content performance (Fu & Gonzalez, 2025). Beyond general engagement prediction, several studies have shown that timing is a critical factor in determining content success. Kanuri et al. (2018) found that posts published during audience peak-activity periods achieve significantly higher engagement. Similarly, Ju (2024) discovered predictable temporal posting patterns across major platforms, demonstrating that human activity follows regular daily and weekly cycles. These insights support the need for intelligent scheduling systems capable of learning from historical audience behaviour (Ju, 2024). Studies has also shown that content characteristics, including design, layout, colour, and aesthetic composition, have a strong impact on user interaction. Cuevas-Molano et al. (2023) analysed visual communication patterns on Instagram and found that aesthetic and cognitive factors significantly influence engagement. When combined with temporal features, these content signals strengthen prediction accuracy and help ensure that scheduling systems do not rely solely on timing (Cuevas-Molano et al., 2023).

Through carefully going over the earlier research on intelligent social media content scheduling system, there is a clear need for an integrated, intelligent scheduling system that predicts engagement, ranks posting-time options, and automatically recommends the most effective time slot. Existing studies focus on prediction or timing separately but do not offer an end-to-end practical solution for creators or businesses. This project aims to fill that gap by designing and implementing a machine-learning-based content scheduling system optimized for engagement across social media platforms.

1.2 PROBLEM STATEMENT BASED ON THE LITERATURE

Existing research on social media engagement prediction and posting-time optimization highlights several persistent challenges and notable gaps. Studies such as Fu and Gonzalez (2025) demonstrate the effectiveness of machine learning in forecasting engagement metrics, yet creators and businesses still struggle with determining the most suitable time to publish content. Current practices often depend on trial-and-error approaches, general intuition, or broad recommendations that fail to reflect the real-time complexity of audience behaviour.

The literature further reveals that although scheduling tools exist, many rely on global or platform-wide statistics rather than creator-specific, data-driven insights. These tools rarely incorporate personalized audience patterns, variations in content type, or platform-dependent engagement dynamics. As a result, they provide generic “best times to post” that lack the precision needed for creators whose audiences differ across demographics, time zones, and behavioural trends.

In addition, prior scholarly works tend to treat engagement prediction and posting-time optimization as separate areas of study. Fu and Gonzalez (2025) focus on predictive modelling, while Ju (2024) and Zhang et al. (2022) explore temporal patterns using machine-learning techniques independently. However, the literature shows an absence of an integrated methodology that combines engagement prediction, ranking of time slots, and automated posting into a unified, real-world system.

Overall, the research emphasizes the need for systems that incorporate personalized analytics, machine-learning-driven forecasting, and adaptive scheduling capable of responding to changing audience behaviour. The lack of such an end-to-end framework underscores a major gap between academic insights and practical application. This project therefore addresses this gap by proposing an intelligent scheduling system that leverages machine learning to predict engagement, recommend optimal posting times, and support creators and businesses through a more accurate and actionable content-strategy workflow.

1.3 AIM AND OBJECTIVES

1.3.1 Aim

This project aims to design and implement an intelligent social media content scheduling system that uses machine-learning-based engagement prediction to recommend the optimal posting time for maximizing user interaction across social media platforms.

1.3.2 Objectives

1. To build a machine learning model capable of predicting engagement metrics (such as likes, comments, and shares) using features derived from posting time, content characteristics, and historical audience behaviour.
2. To develop an intelligent ranking mechanism that evaluates predicted engagement levels across different time intervals and recommends the most optimal posting time slot.
3. To design and implement a scheduling interface that integrates the prediction and ranking system into a user-friendly workflow, enabling creators and businesses to automatically select the best time to post content.
4. To evaluate the system performance using standard ML metrics

1.4 SIGNIFICANCE OF THE STUDY

This project is expected to make a balanced contribution to technical research, system development, and practical social media optimization. From a technical standpoint, the study will contribute to the growing body of work on engagement prediction by demonstrating how classical machine-learning models can be adapted, optimized, and evaluated using openly available social media datasets. This continues the line of research established by Fu and Gonzalez (2025), whose work provides the modelling foundation for this project. By applying their framework to a new dataset and validating performance using metrics such as MAE and R^2, the project strengthens evidence for the reliability of classical ML models in real-world engagement prediction tasks.

At the system level, this research offers a novel integrated workflow that combines prediction, ranking, and scheduling into one unified solution. While prior studies examine engagement factors individually, such as optimal timing or content, none provide an end-to-end system that automatically determines the best posting time based on predicted engagement. This project fills that gap by operationalizing insights from multiple studies into a practical scheduling engine that selects the most promising time-slot for each post. This integrated approach represents a contribution to applied machine learning and intelligent system design.

Practically, the project contributes by offering creators, marketers, and small businesses a tool capable of improving engagement through data-driven posting decisions rather than intuition or manual trial-and-error. Existing research consistently shows that timing, content features, and user activity patterns all influence engagement. By merging these factors into a working system, the project supports a more accessible pathway for non-technical users to benefit from machine-learning techniques.

Overall, this project contributes a novel, integrated, and practical machine-learning workflow for predicting and improving social media engagement. It extends prior research, fills a recognized gap identified in literature, and produces a functional system with clear technical and practical value, all without relying on speculative or future-looking claims.

1.5 SCOPE AND LIMITATIONS

1.5.1 Scope of the Study

This study focuses on designing and implementing an intelligent content scheduling system that predicts social media engagement and recommends the optimal posting time. The system will rely on machine-learning models trained on historical engagement data, following the modelling principles established by Fu and Gonzalez (2025), who demonstrated that classical machine-learning algorithms can reliably predict likes, comments, and shares using structured feature sets. The scope includes feature engineering, model selection, prediction of engagement levels, ranking of time slots, and development of a simple scheduling interface.

The study covers engagement-related features such as posting time, caption length, media type, and historical audience activity patterns. Prior research has shown that these factors significantly influence engagement, especially timing and content attributes. Therefore, the system will incorporate time-based, behavioural, and content-related features to improve prediction accuracy. The project will be implemented using Python-based machine learning libraries and tested using open-access datasets or datasets created for research purposes.

The system outputs will include predicted engagement scores for candidate posting time intervals and a recommendation of the best available slot. This aligns with insights from Ju (2024) and Zhang et al. (2022), who showed that engagement fluctuates across predictable temporal cycles and can be modelled using machine learning. The final prototype aims to support creators and small businesses seeking data-driven posting strategies.

1.5.2. Limitations of the Study

One limitation of this study is its reliance on historical data, which may not fully capture sudden shifts in audience behaviour caused by external events, viral trends, or platform algorithm changes. Stieglitz et al. (2020) noted that social media environments are highly dynamic, making long-term prediction inherently uncertain. As a result, the system's predictions will be optimized for typical behavioural patterns but may not perform equally well during unusual activity spikes.

Another limitation is the initial use of classical machine learning rather than advanced deep learning models. While deep learning approaches such as those studied by Bangotra and Kaur (2023) can improve precision, they require significantly larger datasets and computational resources. To maintain feasibility within the project's time and resource constraints, this study will prioritize lightweight models that perform efficiently, which may restrict predictive complexity compared to state-of-the-art multimodal systems.

The system will also not generate or analyse image-level aesthetic features in depth, despite evidence from Cuevas-Molano et al. (2023) showing that visual composition strongly influences engagement. Due to this constraint, the model will rely primarily on metadata and text-based features. Finally, the study is limited to engagement prediction and scheduling recommendations; it will not attempt to optimize content design, caption generation, or hashtag recommendations, even though these factors can influence performance.

1.6 Definition of Terms

1. Social Media Engagement

This refers to measurable user interactions with a post on social platforms, including likes, comments, shares, views, saves, and reactions. Engagement serves as a key indicator of how well content resonates with an audience.

2. Posting Time Optimization

A data-driven process of determining the most effective time to publish content in order to maximize user engagement. It involves analyzing audience activity patterns, platform behaviour, and historical performance.

3. Scheduling System

A software tool designed to automate the selection and recommendation of the best posting times. In this project, the scheduling system uses machine-learning predictions to rank available time slots.

4. Machine Learning (ML)

A subfield of artificial intelligence that enables computer systems to learn patterns from data and make predictions or decisions without being explicitly programmed. ML models in this project predict engagement levels for specific posting times.

5. Engagement Prediction

A machine-learning task that estimates how a post will perform (e.g., expected likes or comments) based on features such as posting time, content metadata, and historical audience behaviour.

6. Feature Engineering

The process of extracting, transforming, and selecting relevant variables from raw data for use in machine-learning models. Examples include hour of posting, caption length, day of the week, media type, and historical engagement averages.

7. Ranking Algorithm

An algorithmic approach used to order time slots from highest to lowest predicted engagement. In this project, the ranking algorithm determines which posting time is optimal.

8. Classical Machine-Learning Models

A group of traditional ML algorithms such as Random Forest, Support Vector Machines (SVM), Decision Trees, and Gradient Boosting Machines. These models are used for structured prediction tasks and form the modelling foundation of this project.

9. Temporal Features

Variables that describe time-related patterns such as hour of day, day of week, and user activity cycles that influence engagement behaviour on social media platforms.

10. Dataset

A structured collection of data used for training and evaluating machine-learning models. In this project, datasets contain timestamps, engagement metrics, caption metadata, and content descriptors.

11. Evaluation Metrics

Quantitative measures used to assess model performance. Common metrics in engagement prediction include Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2).

12. Prototype System

A working version of the scheduling tool demonstrating the model's predictions, ranking logic, and recommended posting times. It serves as the practical output of this project.

CHAPTER TWO

2.1 LITERATURE REVIEW

Research on predicting social media engagement has grown rapidly in recent years, with many studies now using machine-learning techniques to understand the factors that influence post performance. The base paper for this project, authored by Fu and Gonzalez (2025), is especially important because it demonstrates how classical machine-learning models, including Random Forest, Support Vector Machines, and Gradient Boosting, can successfully predict engagement metrics such as likes, comments, and shares. Their study highlights the importance of features like posting time, caption length, hashtags, and content type in determining engagement. Because their dataset and methods are openly accessible, their work provides a strong methodological foundation for this project and serves as a reliable guide for building engagement-prediction systems.

A significant portion of the literature focuses on timing, which has been shown to play a major role in determining content performance. Kanuri et al. (2018) found that choosing the appropriate posting time can substantially increase user engagement, reinforcing the value of data-driven scheduling over intuition or fixed posting routines. In support of this, Ju (2024) demonstrated that social media users follow predictable hourly and daily activity cycles, making time-based features essential in engagement prediction models. These studies justify the integration of audience activity patterns into the scheduling engine.

Beyond timing, researchers have also examined how content characteristics influence engagement. Cuevas-Molano et al. (2023) investigated visual design elements on Instagram and found that layout, colour, caption style, and aesthetic composition significantly affect audience interaction. Their findings show that content quality must be considered alongside timing to achieve more accurate engagement predictions. In parallel, Zhang et al. (2022) and

Valle and Bravo (2022) demonstrated that incorporating content-related metadata, such as media type, caption structure, and posting frequency, can improve prediction accuracy when combined with temporal features. These insights reinforce the need for a multimodal or multi-feature prediction approach.

Some studies analyze engagement through the broader lens of online popularity prediction. Cheng et al. (2021) reviewed a range of deep-learning–based popularity models and compared them with traditional machine-learning approaches. Their work highlights issues such as data sparsity and rapidly shifting user behaviour, both of which influence engagement prediction accuracy. These challenges informed the choice of evaluation metrics for this project, including MAE and R^2. Similarly, Jessen and Farr (2020) conducted a meta-analysis showing how engagement trends vary widely across platforms, suggesting the need for adaptable models that can generalize across different types of users and content.

Other contributions address system implementation and real-world analytics challenges. Stieglitz et al. (2020) identified key barriers in social media analytics, such as noisy datasets, frequent platform updates, and the need for scalable and adaptive models. Their findings support the design of a lightweight system that can be easily updated as platform behaviour evolves. Meanwhile, Agarwal and Sureka (2021) demonstrated that efficient machine-learning models can achieve strong results even in resource-constrained environments, which supports this project's implementation of classical models before exploring heavier deep-learning alternatives. Bangotra and Kaur (2023) extended this by examining deep-learning–based engagement prediction for multimedia posts and recommended hybrid approaches that combine text, image, and temporal features, providing direction for future system enhancements.

These ten studies collectively provide a strong foundation for developing an intelligent, machine-learning-based social media scheduling system. While Fu and Gonzalez (2025) establish the core modelling framework, the other studies contribute insights related to timing optimization, content influence, popularity prediction, ranking logic, and system design. A clear gap across the literature is the absence of a single, integrated solution that combines engagement prediction, ranking of time slots, and automated scheduling. This project aims to fill that gap by developing a practical end-to-end tool that assists creators and organizations in posting content more effectively.

Table 1: List of the Relevant Studies that looked into Intelligent Social Media Content Scheduling System

S/N	Author(s)	Problem Addressed	Methodology	Key Results	Limitations	Future Works
1	Fu, B., & Gonzalez, C. 2025.	Lack of reliable predictive models for optimizing social media posting strategies.	Classical ML models (Random Forest, SVM, Gradient Boosting); feature analysis; engagement prediction.	Classical ML models accurately predict engagement; time and content features are highly influential.	Only classical ML explored; limited multimodal features.	Extend to deep learning; integrate real-time adaptive scheduling.
2	Kanuri, V. K., Chen, Y., & Sridhar, S. 2018	Ineffective timing strategies due to guesswork in scheduling social media posts.	Empirical analysis of posting times; statistical modelling of user activity.	Posting at optimal times significantly increases engagement.	Does not incorporate ML-based prediction; limited to timing.	Integrate predictive modelling and automated scheduling.
3	Cuevas-Molano, E., Sánchez-Cid, M., & Gordo-Molina, V. 2023	Insufficient understanding of how image aesthetics influence engagement.	Visual experimentation; cognitive manipulation of images; quantitative analysis.	Aesthetic elements like layout, colour, and style strongly influence engagement.	Focuses on visual factors only; limited temporal analysis.	Combine aesthetics with ML-based engagement prediction.

4	Ju, X. 2024	Lack of understanding of temporal posting behaviour and engagement cycles.	Temporal pattern analysis using large-scale posting data; statistical modelling.	Posting behaviour follows predictable hourly/daily cycles.	Does not link temporal patterns with ML prediction.	Integrate temporal cycles into predictive scheduling systems.
5	Zhang, S., Wang, Y., & Liu, H. 2022	Difficulty predicting user engagement using basic heuristics.	ML models (Random Forest, XGBoost, SVM); feature engineering; evaluation metrics.	ML models effectively predict engagement; metadata features are strong predictors.	Limited focus on scheduling; no integration with ranking mechanisms.	Expand to multimodal content; integrate scheduling logic.
6	Jessen, J., & Farr, M. 2020	Fragmented understanding of what drives engagement across platforms.	Systematic review and meta-analysis of engagement studies.	Engagement varies significantly across contexts and content types.	Meta-analysis only; no experimental ML models.	Encourage cross-platform ML-based engagement modelling.
7	Valle, F., & Bravo, R. 2022	Lack of supervised learning frameworks to predict interaction on Instagram.	Supervised ML models; feature selection; statistical evaluation.	Supervised models predict interactions with high accuracy.	Limited to Instagram; small dataset size.	Apply models to multi-platform datasets.
8	Agarwal, P., & Sureka, A. 2021	Difficulty forecasting engagement due to noisy social media data.	ML models applied to Twitter data; sentiment-based and behavioural modelling.	ML models perform well for engagement forecasting.	Focuses only on Twitter; does not optimize posting times.	Integrate ML forecasting with scheduling systems.
9	Bangotra, D., & Kaur, H. 2023	Ineffective engagement prediction for multimedia content using simple models.	Deep learning models; CNNs for image analysis; hybrid multimodal architectures.	Deep learning significantly improves multimedia engagement prediction.	High computational cost; requires large datasets.	Build lightweight multimodal ML models.

10	Gligorić, K., Anderson, A., & West, R. 2021	Little understanding of how content constraints affect creativity and engagement.	Experimental study on constrained vs unconstrained posts.	Constraints can increase creativity and engagement.	Not predictive; does not extend to scheduling.	Combine constraints with ML-driven content strategy tools.

2.2 THEORETICAL FRAMEWORK

This study is anchored on the Uses and Gratifications Theory (UGT) and the concept of Temporal Rhythm in Computer-Mediated Communication.

2.2.1 Uses and Gratifications Theory (UGT)

The Uses and Gratifications Theory postulates that audiences are active participants who consciously choose media content to satisfy specific needs, such as information seeking, social interaction, or entertainment. In the context of this study, UGT explains why engagement occurs. Users engage with content that fulfills their cognitive or aesthetic needs. This study relies on the premise that while content quality satisfies the "gratification" aspect, the timing of the content delivery ensures it reaches the user when they are actively seeking such gratification. The research by Cuevas-Molano et al. (2023) supports this by highlighting how cognitive and aesthetic factors influence the gratification users derive from posts, leading to higher engagement.

2.2.2 Temporal Rhythms in Social Activity

The study also draws upon the theory of temporal rhythms in human behavior. Ju (2024) established that human activity on digital platforms follows predictable daily and weekly cycles. This theoretical perspective suggests that social media engagement is not random but is governed by the routine behaviors of the audience (e.g., checking phones during commutes or after work). This project operationalizes this theory by using machine learning to map these temporal rhythms and predict the exact moments when audience availability aligns with content distribution.

CHAPTER THREE

3.1 PROPOSED METHODOLOGY

The methodology for this project is structured around a machine-learning pipeline designed to predict engagement metrics and recommend optimal posting times. The overall approach follows the modelling principles used in Fu and Gonzalez (2025), who demonstrated that classical machine-learning algorithms such as Random Forest and Gradient Boosting perform effectively on structured social media engagement datasets. Their workflow, consisting of data preprocessing, feature engineering, model training, and evaluation, forms the backbone of this project's methodological design.

3.2 DATA COLLECTION AND PREPROCESSING

The study will use publicly accessible datasets and researcher-generated datasets that include timestamps, engagement metrics, and basic content attributes. The dataset will capture user interaction patterns over time, enabling the system to learn how engagement varies across different posting periods. Preprocessing will include handling missing values, normalizing numerical features, encoding categorical variables, and deriving time-based features such as hour of day, day of week, and activity cycles.

Temporal engagement features will be emphasized because prior studies shows that users often follow predictable activity rhythms, making temporal features some of the strongest predictors of engagement. These processed features will be integrated into a clean dataset for modelling. Basic text-based metadata, such as caption length and posting frequency, will also be extracted due to their relevance in predicting engagement, ensuring the feature space captures both temporal and behavioural dimensions.

3.2.1 Feature Engineering

Feature engineering will combine time-related features, content descriptors, and engagement summaries. Visual aesthetic features will not be deeply analysed due to the scope limitations noted earlier. Instead, the focus will remain on metadata and behavioural features. Additional engineered features will include moving averages of engagement, early engagement indicators, and lag-based metrics, inspired by findings from Cheng et al. (2021), who highlighted the importance of temporal signals and early performance predictors in modelling popularity.

3.2.2 Model Development

Three classical machine-learning models, Random Forest, Gradient Boosting, and Support Vector Regression, will be implemented and compared, reflecting the approaches validated in the base study. These models are chosen because they perform well on structured datasets, require moderate computational resources, and have been widely used in social media analytics. Additional lightweight models such as Decision Trees and k-Nearest Neighbours may be used for baseline comparison.

Model training will involve hyperparameter tuning using k-fold cross-validation to minimize overfitting. Evaluation metrics will include Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2. All models will be implemented using Python libraries such as Scikit-Learn and evaluated on held-out test sets.

3.2.3 Scheduling Logic and Ranking Mechanism

Once engagement predictions are generated, the system will compute predicted engagement scores for several candidate posting times. These time slots will then be ranked using a simple optimization algorithm that selects the highest-scoring interval. Although the present project does not implement deep personalization, the ranking mechanism will follow similar logic to determine the best posting opportunity.

3.2.4 System Implementation

The system will be implemented as a lightweight software prototype featuring a simple user interface. The interface will allow users to upload or input post information and receive recommended posting times along with predicted engagement values. Python will serve as the primary development language, with optional integration of a web framework such as Flask for interface deployment.

3.2.5 Validation and Testing

The proposed system will be validated by comparing predicted engagement values to actual engagement outcomes on a test dataset. Performance will be analyzed using multiple evaluation metrics to ensure reliability across diverse content scenarios. Testing will involve measuring the accuracy of predicted engagement scores, evaluating the effectiveness of recommended posting times, and comparing system performance to baseline scheduling methods such as random posting or fixed “best times”.

CONCLUSION

This project set out to address the growing challenge of determining the best posting time for maximizing social media engagement by applying machine-learning techniques to real engagement datasets. The literature makes it clear that predicting engagement is both feasible and useful, especially when grounded in established machine-learning frameworks such as those demonstrated by Fu and Gonzalez (2025). Their evidence that classical models can accurately predict likes, comments, and shares provides the basis on which this project builds its scheduling system.

Through insights from related research, it becomes evident that no single factor determines engagement, and that optimal posting time is strongly influenced by user behavioural cycles. Studies highlight the importance of choosing the right posting time based on patterns in audience activity rather than intuition. Similarly, other prior research demonstrates that content characteristics also play a significant role in audience response. These findings justify the need for an integrated system that brings together prediction, ranking, and scheduling instead of treating these factors independently.

By combining these ideas into a cohesive workflow, this project closes the gap identified in the literature: the absence of a practical, end-to-end tool that predicts engagement and automatically recommends the best posting time. Existing research provides strong theoretical foundations but does not deliver a unified system suitable for real-world creator or business contexts. This project addresses that need by designing a lightweight, efficient, and adaptable scheduling model that can support practical content-posting decisions.

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RESEARCH WORK PLAN (GANTT CHART)

Activities	**November**				**December**				**January**				**February**			
	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
Topic finalization																
Literature review																
Proposal writing & supervisor revision																
Proposal defense & corrections																
Dataset collection & preprocessing																
Feature engineering & exploratory analysis																
Model development & training																
Scheduling engine development																
System implementation																
Testing & validation																
Documentation																
Final report																