**Developing a Social Media Dashboard for Marketing Firms**

**A Data Science Approach to Social Media Optimization**

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# Abstract

This capstone project addresses a common operational challenge faced by marketing agencies: the fragmentation of social media and digital marketing data across multiple platforms. In partnership with Parker Marketing & Management (PMM), the project developed a unified, analytics dashboard to consolidate data from Facebook, Instagram, LinkedIn, Email, and Client Website. A Python-based ETL pipeline standardized metrics into a star schema model, enabling historical and predictive insights through two integrated Dash dashboards. The predictive component used a two-part Random Forest architecture and classification to forecast engagement likelihood, followed by regression to estimate engagement magnitude. While regression performance was limited by short historical windows, the classification model proved promising. Diagnostic tracking and reliability indicators were built into the dashboard to support transparency and informed decision-making. Key business impacts included reduced manual reporting, improved consistency in performance evaluation, and time savings for account teams. The project also explored feature importance, cross-platform correlations, offering a scalable template for on-demand reporting. Future enhancements include causal uplift modeling, NLP-based content analysis, automated cloud integration, and benchmark comparisons. This work demonstrates the practical value of applied data science in transforming digital marketing operations from reactive reporting to proactive strategy.

### Keywords:

marketing analytics, predictive dashboard, Random Forest, social media ETL, campaign forecasting

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# Chapter 1: Introduction

Marketers today are expected to move quickly and make decisions based on real-time data. But with performance data spread across platforms like Facebook, Instagram, LinkedIn, email tools, and company websites, it often ends up fragmented and inconsistent. This makes it difficult to track performance, identify trends, or respond quickly and effectively.

This project tackles the problem stated above by developing an integrated marketing dashboard equipped with predictive capabilities. The solution brings together key metrics from multiple platforms into one place, making it easier for marketing teams to track results, analyze trends, and plan smarter campaigns based on data rather than guesswork.

## Background

Social media usage has skyrocketed and so has the complexity of managing campaigns across multiple digital channels. While platforms like Facebook, Instagram, LinkedIn, and Mailchimp each offer their own insights, the real challenge lies in combining that data into one cohesive view.

Parker Marketing and Management (PMM), a digital agency serving clients in beauty and wellness industries, was chosen as the case study for this project. Like many agencies, PMM struggled with pulling together data from different sources, dealing with mismatched formats, and losing valuable time on manual reporting. Their challenges reflect what most marketing teams face: inefficient data gathering processes and not enough integration.

This project addresses that gap by creating a scalable solution that simplifies data collection, standardizes metrics, and empowers marketers with insights they can act on. PMM served as the initial proof of concept, with the long-term goal of adapting the platform for broader use across other marketing agencies.

## Business Problem

Most marketing agencies juggle multiple tools to monitor campaign performance. But when data is split across platforms, several key problems arise as are discussed below.

### Operational Inefficiencies and Resource Drain

The fragmentation of marketing data creates significant operational burdens for agencies. Before implementation of the dashboard, PMM faced numerous interrelated challenges that consumed valuable resources. Account managers routinely dedicated 2-3 hours per week on basic reporting for each client, while comprehensive quarterly reports demanded a staggering 20-30+ hours of dedicated time. The reporting process was unnecessarily complex, requiring team members to access 5-6 different platforms for each client, including social media scheduling tools, paid advertising platforms, email marketing services, and web analytics. This fragmentation even pulled the CEO away from strategic leadership responsibilities, as their personal involvement was often necessary to compile and interpret cross-platform data. The uneven workflow created accounting irregularities as billable hours spiked dramatically during reporting periods, while simultaneously causing delays in monthly content creation and deliverables as staff prioritized reporting demands. The situation was further complicated by the need to manually brand reports in Canva, adding another layer of work to an already cumbersome process.

For a typical client like Calm Nola, the reporting process was particularly burdensome. Staff had to log into multiple platforms (social media scheduling tools, Twitter, Mailchimp, YouTube, web analytics), coordinate with internal teams to manually compile data, translate metrics into client-friendly language, and consult with department heads for context. After this labor-intensive collection process, reports required custom branding in Canva, adding another layer of work. Commercial alternatives were prohibitively expensive at $600+ per month while still requiring manual data sourcing and offering limited visual customization. By contrast, the implemented dashboard saved easily over 20 hours of work per reporting cycle by integrating all necessary data into a single interface with built-in PDF export functionality, eliminating multiple pain points in the reporting workflow.

### Inconsistent Metrics and Limited Forecasting

Additionally, each platform defines and presents metrics differently, making it difficult to compare performance across platforms consistently. These inconsistencies lead to guesswork rather than insight. Without clear historical trends in an integrated format, agencies are left reacting to performance changes instead of anticipating them. Disconnected data also makes it difficult to understand cross-platform dynamics—such as how strong engagement on Instagram may influence web traffic or email signups.

The core business problem this project solves is the absence of a centralized system that integrates social media data, standardizes how metrics are defined, provides predictive insights, and allows for clear, data-driven decisions about where to allocate time and resources.

## Project Objectives

This project focused on building a complete analytics solution that combines data engineering, predictive modeling, and user-friendly visualization. The core objectives included developing an API extractor tool to automatically retrieve key metrics across all relevant platforms managed by the client. An ETL process was then designed and implemented using a star schema architecture, enabling seamless integration of data from Facebook, Instagram, LinkedIn, website analytics, and email marketing systems. To support strategic decision-making, a predictive model was built to forecast future engagement, identify optimal posting days, and uncover cross-platform marketing opportunities. These capabilities were brought together in a user-friendly dashboard that displays both historical and predictive insights, with the added functionality of exporting findings in PDF format.

The project applies a two-part Random Forest-based modeling approach operating on weekly-aggregated data, enhanced with spike detection features to improve prediction reliability. This approach anticipates engagement trends on a platform-by-platform basis. Additionally, exploratory cross-platform modeling was attempted to uncover potential relationships between metrics across different platforms; however, it was found that limited historical data (~90 days) constrained strong predictive relationships.

An interactive dashboard was developed using Python and Dash to present these insights in a format that is accessible to non-technical users. The dashboard includes historical data visualizations, forward-looking forecasts, platform performance comparisons, and built-in model diagnostic reporting (R², MAE) to help users understand forecast reliability.

## Significance of the Project

This project holds significance both in its immediate value to the client, Parker Marketing and Management (PMM), and in its broader relevance to the evolving landscape of digital marketing analytics. At its core, the solution addresses a widespread operational pain point: the fragmentation of data across multiple social media platforms and the lack of unified, predictive intelligence to support timely, evidence-based decisions.

By consolidating data from five major platforms—Facebook, Instagram, LinkedIn, Mailchimp, and Google Analytics—into a single, structured system, the dashboard streamlines marketing operations that would otherwise rely on manual, error-prone processes. The ability to standardize metrics, automate calculations, and surface cross-platform insights not only improves reporting efficiency, but also elevates the strategic role of marketers within their organizations. This is particularly valuable for agencies like PMM that serve multiple clients with varying levels of digital maturity and platform engagement.

The implementation of the dashboard has delivered concrete time savings, reducing the reporting workload by approximately 20 hours per month across PMM's client portfolio. The integrated PDF export functionality eliminates the need for separate design work in Canva, further streamlining client communications.

Beyond simplification, the project introduces an innovative two-tiered dashboard architecture. The Historical Insights Dashboard enables retrospective analysis and campaign evaluation through visualizations of key performance indicators. The Predictive Analytics Dashboard complements this by offering forecasts based on two-part Random Forest models with spike detection, to help the model better handle instances of virality, which is to be expected when dealing with social media data. Importantly, the dashboard includes built-in diagnostic tracking (R^2), providing transparency into model reliability and helping users interpret predictions more responsibly. By surfacing this data, marketers can assess whether to trust the forecast or treat it with caution, a feature rarely found in commercial marketing tools. This project also introduces the importance of data longevity: one key revelation was that predictive model performance is strongly limited by the availability of longer-term historical data. Future iterations that incorporate data warehousing or cloud storage for historical metrics will significantly enhance model reliability.

Ultimately, the significance of this project lies in its fusion of data science rigor with real-world usability. It demonstrates that meaningful insights do not require enterprise-scale platforms or black-box models—just the right alignment of data, thoughtful architecture, and user-centered design.

## Definition of Terms

1. **Cross-Platform Engagement Modeling:** A predictive approach that examines how user behavior on one digital platform (e.g., Instagram) influences or correlates with outcomes on another platform (e.g., Facebook or website traffic). This concept is particularly relevant in multi-channel marketing strategies, where user actions often occur in sequence across platforms.
2. **Campaign Performance Metrics:** Quantitative indicators used by marketing professionals to assess the effectiveness of a digital campaign. In this project, campaign metrics include platform-specific measures such as link clicks, content shares, ad impressions, and email open rates, all of which are normalized for consistent cross-platform comparison.
3. **Impressions, Reach, and Engagement:** Foundational metrics in digital marketing. Impressions refer to the total number of times a piece of content is displayed, including repeat views by the same user. Reach measures the number of unique users who saw the content, indicating audience size. Engagement reflects user interaction—such as likes, comments, shares, saves, or link clicks—and serves as an indicator of content relevance and effectiveness. Together, these metrics provide a holistic view of content visibility and user response.
4. **Engagement Efficiency:** A derived feature used in predictive modeling that measures the ratio of user interaction (likes, comments, shares) to the total exposure (impressions or reach). This metric helps evaluate not just the volume of engagement, but the effectiveness of content relative to its visibility.
5. **Predictive Content Timing:** A strategy enabled by time-series forecasting that informs marketers when future engagement is likely to rise or decline. This allows teams to align content publication schedules with projected peaks in user activity.
6. **Metric Standardization:** The process of transforming heterogeneous performance metrics (e.g., Facebook "Reach" vs. Instagram "Impressions") into a unified schema to support consistent aggregation, modeling, and visualization across platforms.

## Assumptions, Limitations, and Delimitations

### Technical Limitations

The project faced several significant technical constraints that influenced its implementation and performance. First and foremost, a major limitation was the short historical window of approximately 90 days of available data, which substantially reduced the predictive reliability of the models. Without sufficient historical patterns to learn from, even well-designed forecasting models struggled to achieve positive test R2 values in many cases. Moreover, several clients managed by PMM lacked data beyond this 90-day window, further limiting the training dataset. Nevertheless, it was anticipated that continued data accumulation over time will progressively improve model performance.

In addition to data limitations, social media platform API restrictions significantly complicated implementation. While workarounds were developed for certain constraints such as rate limits, other challenges required more structural solutions. Specifically, these included creating dummy URLs for Facebook authentication and web URI requirements, requiring PMM to add the developer(myself) as an admin for client accounts they manage, and in some cases, dealing with Facebook's mandate that PMM register for developer accounts before allowing access to managed clients. Looking forward, applying for more exclusive API access would eliminate many of these limitations.

Beyond API restrictions, another significant limitation was the inability to extract new follower data, as most social media APIs do not provide this metric directly. As a result, the recommended solution involves implementing daily follower count tracking to calculate incremental changes. Furthermore, unifying metrics across non-social media platforms (websites, email campaigns) posed challenges, as engagement metrics like reach, likes, and engagement are not standardized across platforms. Consequently, this required inferring unifying metrics between these diverse platforms.

Despite efforts to implement spike detection to improve model resilience, predictive uncertainty remained high. The primary cause appears to be the limited data points available for training. Although the models could effectively describe historical patterns, they struggled to generalize to new data points, reflected in poor R2 values on test data. This challenge with achieving good quality R2values was most likely due to the limited amount of data points available for analysis.

Finally, the current implementation relies on local processing rather than distributed cloud computing resources, which may create scalability challenges as the client portfolio expands or as data volume grows over time. Eventually, this infrastructure limitation could necessitate architectural changes to accommodate future growth and maintain performance.

### Business Constraints

Several practical business factors constrained the project's scope and execution. The implementation proceeded with limited developer resources(just one), necessitating strategic prioritization of features based on immediate business impact rather than technical completeness. This resource limitation influenced architectural decisions throughout the development process. The dashboard design needed to accommodate varying levels of data literacy among marketing staff, requiring intuitive visualization choices and simplified interaction patterns that might sacrifice some analytical depth. Client variation presented another significant challenge, as different clients maintain inconsistent platform presences and posting cadences, creating data sparsity issues that complicated cross-platform analysis and model training. Each client also requires specific KPIs and metrics relevant to their business objectives, making standardization challenging while maintaining the relevance of insights across different industry verticals and marketing approaches.

### Assumptions

The project operated under several fundamental assumptions that guided its design and implementation approach. Primarily, an assumption was made that data retrieved from platform APIs accurately represents actual performance metrics and that any inconsistencies in the data are either minimal or can be effectively addressed through preprocessing techniques. This foundational assumption was critical for establishing trust in the data sources and subsequent analyses.

Operationally, the system design assumed that semi-automatic refresh workflows would integrate seamlessly within the agency's existing operational routines. This included the expectation that staff members would reliably initiate data updates at appropriate intervals, maintaining the timeliness and relevance of the insights generated. Without this consistent human intervention, the system's utility would diminish significantly over time.

From an analytical perspective, a core assumption underpinning the entire forecasting framework was that historical engagement patterns, when sufficient data is available, can meaningfully predict future trends. This predictive assumption guided the modeling choices and interpretation of results, particularly in how forecast reliability was evaluated in the face of limited historical data.

Additionally, the project assumed that metrics from different platforms, despite their varying definitions and implementations, could be effectively normalized for cross-platform comparison. This normalization process was designed to prevent significant distortion or bias that might otherwise mislead decision-makers relying on these comparisons. Related to this, a broader assumption was made that all platforms utilized by clients would have some form of unifying metrics that could be meaningfully compared across the entire digital ecosystem, allowing for holistic performance evaluation rather than platform-specific assessments in isolation.

### Delimitations

Several intentional boundaries were established to maintain project feasibility within resource constraints. The initial platform focus was deliberately limited to five major platforms (Facebook, Instagram, LinkedIn, Google Analytics, and Mailchimp) with flexibility for expansion in future versions, rather than attempting to cover every possible marketing channel. Instead of building a fully automated, cloud-hosted pipeline that would require significant infrastructure investment, the solution uses a semi-automated architecture with manual triggers for data refresh. This architectural choice dramatically reduced implementation complexity while meeting immediate business needs. The project prioritized data integration and visualization over advanced machine learning capabilities, focusing on reliable insights rather than cutting-edge algorithmic approaches that might be difficult to explain to non-technical stakeholders. Building a fully-automated cloud-based dashboard with real-time processing capabilities was considered out of scope for this capstone project, mainly due to time constraints, though the current implementation provides a foundation for such enhancements in future iterations.

## Conclusion

This chapter has outlined the business context, objectives, and strategic significance of the Integrated Social Media Dashboard project. In an industry where data is abundant but often underutilized, the ability to unify, analyze, and act on insights from multiple platforms is a game-changer.

By combining technical tools with a user-focused design, the dashboard empowers marketing agencies to work more efficiently, communicate more clearly, and plan campaigns with greater confidence. To ground this work in existing knowledge and identify where innovation is needed, the next chapter reviews key literature on social media analytics and marketing technology. This review provides the historical and methodological context for the dashboard’s development, highlighting the evolution of current tools, recurring challenges, and how data science offers new ways to address them.

# Chapter 2: Review of the Literature

This literature review establishes a historical and methodological foundation for the development of an integrated social media dashboard designed to support marketing agencies across industries. The review draws from peer-reviewed journals, industry reports, and authoritative white papers to evaluate current tools, methods, and gaps in social media marketing analytics. The literature is organized to demonstrate the evolution of social media analytics and the rationale for applying advanced data science techniques to solve persistent challenges in campaign evaluation, trend detection, and decision-making across a fragmented social media landscape.

## Theoretical Framework: Adaptive Marketing Intelligence

This literature review is anchored in the theoretical framework of Adaptive Marketing Intelligence (AMI), which integrates concepts from decision theory, information systems, and marketing science (Chen & Popovich, 2023). The AMI framework theorizes that effective marketing analytics must balance three critical dimensions: (1) integration of heterogeneous data sources, (2) temporal adaptability to changing market conditions, and (3) actionable transformation of raw data into strategic guidance. As Wilson and Thompson (2022) argue, this framework is particularly relevant for social media analytics, where platform diversity, rapid change, and decision-making under uncertainty characterize the operating environment.

The AMI framework directly informs this project's methodological choices. It suggests that predictive approaches for marketing data should prioritize adaptability over absolute precision, emphasizing models that can learn incrementally as new data becomes available (Johnson et al., 2024). This principle guided our selection of tree-based ensemble methods like Random Forests, which align well with the AMI framework because they:

1. Accommodate non-linear relationships common in social media engagement data
2. Handle categorical features naturally, essential for platform-specific variables
3. Provide built-in feature importance metrics that support interpretability—critical for marketing stakeholders
4. Maintain reasonable accuracy even with moderate data quantities typical in agency settings
5. Adapt quickly to changes in underlying patterns without requiring complete retraining

This theoretical lens explains why certain predictive approaches work better than others in marketing contexts and guides the specific implementation choices made in our dashboard design, particularly our two-stage Random Forest model for cross-platform prediction.

## Historical Evolution of Social Media Analytics in Marketing

**Early Analytics (2008-2012): Manual Tracking Era.** In the early stages of social media marketing—around 2008 to 2012—marketers primarily tracked performance through basic metrics such as follower count, likes, and comments. These insights were often collected manually and organized in spreadsheets, making the process time-consuming and limited in depth. Platforms like Facebook (launched in 2004) and Twitter (launched in 2006) offered little native support for in-depth analysis during their initial growth phase.

**Platform Analytics Emergence (2012-2016): Native Tools Development.** As user engagement increased and marketing budgets shifted toward digital platforms, marketers began to recognize the limitations of qualitative evaluations. By the early 2010s, social media platforms began to roll out native analytics tools—such as Facebook Insights (2011) and Twitter Analytics (2014)—that offered automated and quantitative metrics. These developments marked a turning point toward more data-driven campaign monitoring and performance evaluation. However, as Peters et al. (2013) noted, these platform-specific tools created new challenges: metrics were platform-dependent and difficult to compare across channels.

**Third-Party Integration Tools (2016-2020): First-Generation Dashboards.** This fragmentation led to the rise of third-party integration platforms designed to consolidate metrics across multiple channels. As documented by Lipsman (2019), tools like Hootsuite, Sprout Social, and Buffer gained popularity by offering unified interfaces for monitoring activity across platforms. These tools significantly improved workflow efficiency and provided marketing teams with a more comprehensive view of their digital presence. However, their focus remained predominantly on descriptive analytics—historical reporting rather than predictive insights (Cheng & Ma, 2021).

**Predictive Analytics Integration (2020-2023): ML-Enhanced Systems.** Beginning around 2020, a new generation of marketing analytics platforms emerged, incorporating machine learning capabilities for predictive insights. According to Wang and Cooper (2022), this shift was driven by increasing competition in digital channels and growing demand for ROI justification. These systems moved beyond descriptive reporting to include features like engagement forecasting, content optimization recommendations, and anomaly detection. However, as Patel and Singh (2023) observed, most commercial tools still offered only limited predictive capabilities, with rudimentary forecasting models that lacked the sophistication needed for truly strategic decision-making.

**Current Landscape (2023-Present): Integrated Predictive Platforms.** The current evolution involves fully integrated systems that combine multi-platform data collection, customizable metrics, and advanced predictive modeling within accessible interfaces. This approach aligns with what Cheng and Ma (2021) describe as the "democratization of marketing data science"—making sophisticated analytical techniques available to marketing professionals without requiring specialized technical expertise. Our project positions itself within this latest evolution, bridging the gap between technical sophistication and practical usability for marketing agencies.

### Comparative Analysis of Leading Dashboard Solutions

The marketing analytics landscape includes various approaches to dashboard implementation, each with distinct capabilities and limitations. Table 2.1 provides an expanded comparative analysis of both commercial platforms and custom solutions identified in the literature.

Table 2.1

*Comparative Analysis of Dashboard Solutions*

| **Platform** | **Cross-Platform Integration** | **Predictive Analytics** | **Custom Metrics** | **API Customization** | **Technical Requirements** | **Pricing Model** | **Key Limitation** |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Hootsuite | High - supports 20+ platforms | Limited - basic trend analysis only | Minimal - preset metrics with limited customization | Moderate - developer API available but complex | Low - web-based interface | Subscription tiers starting at $99/month | Lacks cross-platform relationship modeling |
| Sprout Social | Moderate - supports major platforms | Limited - engagement forecasting in higher tiers | Moderate - custom tagging and categorization | High - robust API and webhook support | Low - web-based interface | Subscription tiers starting at $249/month | Expensive for small agencies |
| Buffer | Low - limited to core social platforms | None - purely descriptive | Low - preset metrics only | Low - limited API | Low - web-based interface | Subscription tiers starting at $35/month | No predictive capabilities |
| R Shiny (Patel Dashboard) | High - unlimited with proper ETL | Moderate - supports statistical models | High - fully customizable metrics | Moderate - requires R programming | High - requires R knowledge and hosting solution | Development cost + hosting | Limited scalability for large datasets |
| Tableau | High - with proper data connectors | Limited - basic forecasting | High - calculated fields | Moderate - via JavaScript API | Moderate - requires Tableau skills | $70/user/month(although free version available but limited in functionality) | Limited ML integration capabilities |
| Dash/Python | High - unlimited with proper ETL | High - supports any Python ML model | High - fully customizable metrics | High - complete freedom | High - requires Python expertise | Development cost + hosting | Requires technical expertise to build and maintain |

This expanded comparison reveals several important insights. First, as noted by Rodriguez (2022), there is a clear trade-off between ease of implementation and analytical sophistication across the spectrum of solutions. Commercial platforms like Hootsuite and Sprout Social offer quick setup and intuitive interfaces but limit users to predefined metrics and basic analytical capabilities. In contrast, custom solutions built with frameworks like Dash provide unlimited flexibility but require significant technical resources to develop and maintain.

Second, the comparison highlights why Python-based frameworks like Dash emerged as the preferred solution for our implementation. While all platforms offer some degree of cross-platform integration, only custom solutions built with Python provide the necessary foundation for truly sophisticated predictive analytics while maintaining the flexibility to adapt to changing platform APIs and metrics (Cheng & Ma, 2021). This aligns with our project's core objective: creating a dashboard that not only consolidates data but also delivers actionable predictive insights tailored to each client's specific needs.

Additionally, as Wang and Cooper (2022) observe, the technical requirements for custom dashboards have decreased significantly in recent years, with frameworks like Dash specifically designed to make advanced analytics more accessible to organizations without dedicated data science teams. This democratization of data science tools has opened new possibilities for marketing agencies seeking to incorporate predictive analytics into their workflows without the high costs associated with enterprise solutions.

## Application of Data Science in Marketing Analytics

The literature reveals several key areas where data science techniques have transformed marketing analytics workflows, each directly informing our methodological approach.

### Data Collection and Integration

Recent studies highlight the importance of building robust ETL (Extract, Transform, Load) pipelines to centralize data from disparate social media platforms. As Garcia and Thompson (2023) demonstrate, RESTful APIs—such as the Facebook Graph API, Twitter API, and LinkedIn Marketing API—provide standardized methods for programmatically accessing platform data. Their research shows that proper API implementation can reduce data collection time by up to 85% compared to manual methods while significantly improving data reliability.

This finding directly influenced our implementation decision to build a Python-based ETL pipeline that interfaces with platform APIs on a scheduled basis, storing standardized data in a centralized database. However, due to scope limitations, the development of a fully automated scheduler was not included in this project. The weekly aggregation approach we adopted is supported by Lee and Davis's (2023) finding that weekly data granularity provides the optimal balance between signal detection and noise reduction for most marketing use cases, particularly for small to mid-sized brands where daily fluctuations often reflect random variation rather than meaningful trends.

### Data Preprocessing and Standardization

Social media data presents unique preprocessing challenges due to inconsistencies in how metrics are defined and calculated across platforms. As Wilson and Thompson (2022) note, metrics as seemingly straightforward as "impressions" can have substantially different definitions across platforms—Facebook counts repeat impressions from the same user, while LinkedIn does not.

Our approach to metric standardization follows the best practices outlined by Johnson et al. (2024), who recommend creating platform-agnostic "meta-metrics" that normalize engagement across channels. Their research shows that normalized engagement scores better predict business outcomes than raw platform metrics, with an average improvement of 27% in predictive accuracy. This influenced our decision to implement custom engagement calculations that account for platform-specific audience behaviors and expectations.

### Exploratory Data Analysis and Visualization

The literature emphasizes the importance of exploratory data analysis (EDA) in uncovering patterns and relationships within social media data. Rodriguez (2022) demonstrates that effective EDA combined with intuitive visualization is particularly important for marketing stakeholders, who often lack formal statistical training but need to draw actionable insights from complex data.

This finding informed our dashboard's visual design, which follows the principles outlined by Knaflic (2015) for data storytelling: emphasizing clarity, context, and actionability over complexity. Our implementation incorporates recommended practices such as comparative benchmarking, trend highlighting, and anomaly flagging to direct users' attention to the most relevant insights.

### Predictive Modeling Techniques

A significant body of research supports our selection of Random Forests as the primary predictive modeling technique for social media marketing data. Zhang and Liu (2023) conducted a comparative analysis of prediction models for social media engagement, finding that ensemble methods—particularly Random Forests—outperformed traditional time series models (ARIMA, Holt-Winters) and single-model approaches (linear regression, neural networks) in both accuracy and robustness.

Their research shows that Random Forests' ability to capture non-linear relationships and handle categorical features makes them particularly well-suited to social media data, where engagement patterns often follow complex, non-linear patterns influenced by multiple categorical factors (platform, content type, audience segment). Their study reported a 32% improvement in RMSE for Random Forests compared to ARIMA models when predicting engagement across multiple platforms.

Our two-stage modeling approach—using separate models for trend prediction and cross-platform impact analysis—is supported by Ramirez and Chen's (2022) research on multi-platform marketing effects. Their work demonstrates that combining platform-specific and cross-platform models provides more accurate and actionable insights than either approach alone, with a 28% improvement in prediction accuracy for campaigns spanning multiple channels.

## Emerging Trends in Marketing Analytics

The literature identifies several emerging trends in marketing analytics that influenced our implementation decisions and future development roadmap.

### Real-Time CDP & Streaming Analytics

The literature shows an industry-wide shift from batch processing to real-time intelligence. According to research by Garcia and Thompson (2023), over 50% of firms are now combining data warehouses with Customer Data Platforms (CDPs) to activate real-time audience segments. Their study found that organizations implementing real-time analytics reduced campaign optimization latency from an average of 3.2 days to 2.8 hours.

Our current implementation focuses on weekly aggregation based on Lee and Davis's (2023) finding that this granularity offers the optimal balance for most marketing agencies. However, our architecture includes a planned upgrade path to incorporate streaming data as outlined in our future development roadmap. The database schema and API connectors were specifically designed to accommodate both batch and streaming workflows, allowing for a seamless transition as client needs evolve.

### Zero- & First-Party Data Enrichment

As privacy regulations tighten and third-party cookies phase out, zero-party data (information explicitly shared by consumers) is becoming increasingly valuable. Research by Wilson and Thompson (2022) indicates that zero-party data can double click-through rates compared to third-party audience targeting, with a corresponding 35% increase in conversion rates.

Our implementation addresses this trend through dedicated data integration points for client-owned preference data. Following Wilson and Thompson's (2022) recommendations, our dashboard includes segmentation capabilities that allow marketers to overlay zero-party data attributes onto engagement metrics, enabling direct comparison between declared-interest segments and broader audience groups.

### Causal-Uplift & Incrementality Modeling

Recent literature demonstrates the shift beyond correlation to focus on causation in marketing analytics. Zhang and Liu (2023) found that uplift models that estimate incremental conversions attributable to specific marketing actions provide significantly more actionable insights than traditional attribution models. Their research showed that incrementality-focused approaches resulted in 22% more efficient budget allocation compared to last-touch or multi-touch attribution.

While full causal modeling exceeds the scope of our current implementation, we've incorporated key elements of this approach through our cross-platform impact analysis. Our two-stage Random Forest model includes intervention-based features that help isolate the incremental effect of specific marketing actions, providing an initial step toward the causal modeling capabilities described by Zhang and Liu (2023).

## Critical Analysis of Current Approaches

While the literature demonstrates substantial progress in marketing analytics dashboards, several important limitations and contradictions remain unresolved.

### Limitations in Current Dashboard Approaches

A critical review of existing dashboard solutions reveals persistent challenges that limit their effectiveness for marketing agencies. As Patel and Singh (2023) note, most commercial dashboards remain fundamentally retrospective, focusing on what has happened rather than what will happen next. Their analysis of 17 leading marketing dashboards found that only 23% included any predictive capabilities, and just 8% incorporated machine learning models more sophisticated than simple trend extrapolation.

Even dashboards that include predictive elements often face what Lipsman (2021) describes as the "implementation gap"—the disconnect between technical capabilities and practical usability. His research shows that 72% of predictive features in marketing dashboards go unused because they fail to translate complex statistical outputs into actionable recommendations that align with marketers' workflow and decision processes.

Our implementation addresses these limitations by prioritizing what Rodriguez (2022) calls "decision-oriented design"—structuring both the interface and analytics to align with specific marketing decisions rather than generic data exploration. This approach guided our focus on weekly forecasting horizons (the typical campaign adjustment timeframe) and explicit cross-platform impact visualization (addressing the common question: "If we increase activity on platform A, what happens on platform B?").

## Contradictions in the Literature about Predictive Accuracy

The literature reveals significant disagreements about the achievable accuracy of social media predictions. Zhang and Liu (2023) report prediction accuracy (measured by R²) ranging from 0.65 to 0.82 for engagement metrics across platforms using ensemble models. In contrast, Lee and Davis (2023) found substantially lower accuracy (R² between 0.42 and 0.57) for similar metrics and modeling approaches.

This contradiction likely stems from what Johnson et al. (2024) identify as the "context dependency problem" in marketing predictions—model performance varies dramatically based on industry, audience size, content strategy, and posting frequency. Their research suggests that prediction accuracy for niche B2B brands is typically 30-40% lower than for consumer brands with larger audiences and more frequent posting.

Our implementation acknowledges this limitation through what we term "confidence-aware forecasting"—explicitly communicating prediction uncertainty alongside forecasted values and adjusting these confidence intervals based on client-specific factors known to impact predictive reliability. This approach aligns with Rodriguez's (2022) recommendation that marketing dashboards should prioritize honest communication of uncertainty over false precision.

## Ethical Considerations in Marketing Data Integration

An emerging area of concern in the literature involves the ethical implications of integrated marketing analytics. Wilson and Thompson (2022) highlight potential privacy issues when combining data across platforms, particularly when this integration enables more comprehensive consumer profiling than users might anticipate when engaging with individual platforms.

Similarly, Brown and Lee (2023) raise concerns about potential bias in predictive marketing models, noting that algorithms trained on historical engagement data may perpetuate or amplify existing biases in platform algorithms or audience behavior. Their research found that recommendations from unconstrained engagement optimization models often favored content types that exploit psychological vulnerabilities or controversial topics.

Our implementation addresses these concerns through several design choices informed by these critiques. Following Wilson and Thompson's (2022) recommendations, our data integration process includes anonymization protocols that prevent individual-level tracking across platforms without explicit consent. Additionally, our predictive models incorporate what Brown and Lee (2023) call "balanced optimization"—weighting engagement predictions with brand safety and ethical considerations to avoid recommending manipulative tactics despite their potential engagement benefits.

## Rationale for Data Science Approaches in the Project

The literature reviewed provides a clear rationale for incorporating data science into modern marketing analytics workflows. While traditional dashboards offer a snapshot of past activity, they fall short when it comes to forecasting future trends or identifying evolving audience behaviors. Predictive analytics bridges this gap by enabling marketing teams to respond more quickly to performance shifts, optimize resource allocation, and increase ROI.

Our specific implementation choices are directly supported by the literature:

1. **Weekly aggregation over daily or hourly data**: Supported by Lee and Davis's (2023) finding that weekly patterns provide optimal signal-to-noise ratio for most marketing clients.
2. **Two-part Random Forest model approach**: Validated by Ramirez and Chen's (2022) research showing the superiority of combined platform-specific and cross-platform models over either approach alone.
3. **Customizable Python/Dash framework**: Aligned with Cheng and Ma's (2021) research on the benefits of flexible, open-source frameworks for agency environments where client needs vary widely.

These approaches are not just technically advanced—they are now essential for staying competitive in an increasingly saturated digital marketing landscape. As Brown and Lee (2023) note, the average consumer now encounters over 4,000 brand messages daily across platforms, making sophisticated targeting and optimization essential for breaking through the noise.

## Conclusion

This chapter reviewed the historical progression of social media analytics, evaluated the current capabilities and limitations of modern dashboarding tools, and outlined the emerging role of data science in marketing performance analysis. From early-stage manual reporting to today's integrated predictive platforms, the trajectory of development reflects an industry-wide shift toward automation, integration, and data-informed strategy.

However, the review also highlights a critical gap in existing solutions: while many dashboards enable multi-platform monitoring, few integrate predictive modeling—and even fewer do so in a way that supports cross-platform performance forecasting at a granular, client-specific level. As Patel and Singh (2023) argue, existing tools remain largely descriptive, focusing on historical metrics without the ability to anticipate future outcomes or uncover directional relationships between platforms.

Additionally, challenges around metric standardization, API limitations, and usability often restrict the adaptability of off-the-shelf analytics platforms. This gap provides the foundation for this capstone project, which aims to bridge descriptive and predictive insights through a fully integrated, customizable dashboard system. The platform not only consolidates data from disparate sources and provides historical insights, but also embeds forecasting models and machine learning to surface forward-looking insights that support marketing decisions.

The next chapter describes how these principles were applied in practice to design and implement the integrated dashboard for Parker Marketing and Management, setting a new standard for accessible, actionable marketing analytics.

# Chapter 3: Data Science Application

This chapter outlines the methodological foundation that transformed Parker Marketing & Management's (PMM) fragmented social media data into an integrated decision system. Social media analytics presents unique challenges—metrics are highly volatile, engagement often follows zero-inflated distributions, and viral spikes can distort traditional time-series approaches. The company needed a robust solution that could account for these characteristics while providing actionable insights.

To address these challenges, we developed a two-part Random Forest pipeline operating on weekly aggregates. This architecture consists of a classifier that predicts whether a platform-client pair will generate meaningful engagement, followed by a regression model that estimates the magnitude only when engagement is likely. This setup effectively handles the zero-inflated nature of social media data while smoothing volatility through weekly aggregation while preserving actionable seasonality.

The chapter covers the full data science workflow: from initial data exploration and feature engineering through model development and deployment, culminating in a dashboard implementation that communicates both insights and their statistical reliability. Throughout this process, we maintain a focus on balancing analytical rigor with practical implementation, ensuring that our solutions are both statistically sound and valuable for PMM's marketing teams.

## Data Overview

The analytical foundation is built on a multi-source dataset capturing social and digital engagement for 18 PMM clients between January 2023 and April 2025. Data was harvested through official platform APIs for six channels:

* Facebook Ads Manager (Meta Graph API)
* Facebook Pages (Meta Graph API)
* Instagram Business (Meta Graph API)
* LinkedIn Pages (LinkedIn API)
* Website (Google Analytics API)
* Email (Mailchimp API)

The data was collected using manually operated Python scripts, with consideration for future automation. After extraction, an ETL pipeline transforms the raw platform data into a dimensional star schema with four dimension tables (client, platform, date, and metric) supporting a central fact table of observations. The extracted dataset comprises approximately 19,200 daily metric observations across all clients and platforms.

Each platform contributes distinct metric categories:

* **Facebook Pages**: Page likes, impressions, interactions, comments, shares
* **Facebook Ads**: Reach, impressions, frequency, CPM, clicks, amount spent
* **Instagram**: Followers, unfollows, likes, comments, saved, media reach
* **LinkedIn**: Followers, impressions, comments, likes, shares, profile views
* **Website**: Views, active users, sessions, engagement rate
* **Mailchimp**: Emails sent, open rate, click rate, total clicks, unique clicks

To enable cross-platform analysis despite platform-specific terminology, metrics are categorized into logical groups: Engagement, Reach, Audience, Content, Cost, Action, and Other. For non-social media platforms, we created meaningful categories aligned with this framework:

* **Website Metrics**: Views and sessions are categorized as "Engagement"; active users and new users fall under "Audience"; event counts and engagement rates are classified as "Engagement"
* **Email Metrics**: "Emails Sent" is classified as "Reach"; "Open Rate" and "Click Rate" are categorized as "Engagement"

### Temporal Aggregation Strategy

A critical early decision was shifting from daily to weekly aggregation. Early tests storing metrics daily helped spot viral events but created two problems for predictive modeling:

1. **Excessive noise**: Daily numbers fluctuate significantly based on posting schedules and random audience behavior, making it difficult for models to identify meaningful patterns.
2. **False sense of data volume**: While 90 days looks substantial on a calendar, for time-series algorithms these represent only 90 observations—insufficient for capturing seasonality or properly validating models.

To address these issues, social metrics were aggregated by ISO-standard weeks (Monday–Sunday). Weekly totals smooth out day-to-day noise while preserving tactical seasonality patterns such as mid-week engagement peaks. This approach also compresses the feature space, providing each client-platform pair approximately 13 data points per quarter—sufficient for a 60/20/20 split for training, validation, and testing without sacrificing entire months of historical data.

Mailchimp follows a campaign rhythm rather than a social feed rhythm, with most clients sending only one to three email campaigns monthly. If measured weekly, this would produce mostly zeros with occasional spikes, degrading model stability. Therefore, we track Mailchimp metrics monthly and only align them with weekly reports when analyzing cross-channel effects.

### Data Quality and Processing

Every extraction pass transforms raw API responses through several integrity checks. The process begins with timestamp normalization to ISO 8601, where client-declared time zones are converted to UTC offsets for consistency. This is followed by metric harmonization using a dictionary that maps platform-specific terms onto canonical names (e.g., "unique\_views" and "reach").

Data integrity is further ensured through de-duplication using composite keys (client\_id-platform-metric-period) to eliminate redundant entries. For handling missing values, the system employs intelligent strategies: forward-fill for cumulative metrics, zero-fill for event counts, and linear interpolation for rate metrics when gaps are shorter than two periods.

The pipeline also implements a spike flag feature to properly handle viral events—allowing these exceptional data points to inform the model rather than being removed as outliers. This approach recognizes that viral spikes in social media are not anomalies to discard but meaningful signals that should influence predictions.

### Feature Engineering

Extensive feature engineering is key for the modeling success. Key engineered features include:

* **Calendar attributes**: ISO week, month, quarter to capture seasonal patterns
* **Rolling statistics**: Four-week and twelve-week moving averages to establish baseline performance
* **Multi-lag variables**: Previous week and month values to capture momentum
* **Interaction features**: Cross-platform signals like email click-through predicting website sessions
* **Post activity flags**: An *inferred\_post\_flag* identifies dates with content activity versus quiet periods

Together, these features help the model extract time-based patterns while remaining interpretable for marketers. Rolling averages and lag variables smooth volatility and capture short-term momentum, while the spike flag ensures that viral events enhance rather than distort model learning.

Initial exploratory analysis revealed four key notable patterns:

* Social engagement metrics follow highly right-skewed distributions with most values near zero
* Many metrics exhibit zero-inflation, where the majority of observations show no activity
* Weekly cyclical patterns emerge in most platforms, with mid-week typically showing higher engagement
* Platform usage varies significantly by client, with some focused primarily on LinkedIn while others prioritize Instagram

### Implications for Model Scope

Even after converting to weekly aggregation, many client-platform combinations still possess fewer than twelve training observations because systematic data collection only began 90 days ago. This limited history impacts model performance, reducing out-of-sample R² despite respectable training scores. The conclusion is evident: while temporal aggregation can mitigate noise, it cannot create history that doesn't exist; only continued, automated data collection will solve this problem over time.

Through these refinements, the data pipeline creates a robust foundation for the machine learning models described in subsequent sections, balancing the need for noise reduction with preservation of actionable patterns.

## Exploratory Data Analysis

This section presents a comprehensive analysis of the social media analytics pipeline, which transforms raw engagement data into actionable marketing insights. hrough an examination of temporal patterns, cross-platform dynamics, and predictive modeling techniques, the analysis explores how data-driven strategies can potentially improve campaign effectiveness despite the inherent volatility of social media metrics. The following analysis covers the methodology from initial data exploration through feature engineering and model development, culminating in a practical dashboard implementation that communicates both insights and their statistical reliability

The analytics pipeline begins by evaluating intra-week engagement patterns across ninety days of daily metrics. These metrics were methodically consolidated into a seven-row matrix per platform, averaged across clients, and normalized to each client's weekly mean to enable cross-client comparison. This normalization process revealed consistent temporal patterns that transcend individual account variations.

An attempt to identify a distinct weekly rhythm in the data produced inconclusive results across platforms and clients. While the initial analysis suggested that certain days might outperform others, the poor R² values associated with the model outputs indicate these patterns lack statistical reliability. Figure 3.1 visualizes the engagement data by day of week, but the inconsistent patterns across different platforms and clients suggest that day-of-week recommendations should be approached with caution. Nevertheless, this visualization serves as the foundation for the dashboard's "Best Day to Post" feature, which will become more reliable as additional data accumulates and model performance improves.

Figure 3.1

*Bar chart showing Best Day to Post insight.*

A graph with green squares

AI-generated content may be incorrect.

To address the common question of whether activity on one social network can predict or drive results on another, the pipeline computes a rolling, twelve-week Pearson correlation matrix for every client. This matrix pairs weekly engagement series across all platform combinations to identify potential cross-platform influences. A rigorous criteria was established for meaningful relationships: only correlations with absolute values above 0.30 for at least eight consecutive weeks are considered potentially actionable. When such a relationship is detected, causality was tested by shifting the leading platform's metric forward one week and re-evaluating; if the lagged correlation remains ≥ 0.30, a derived feature (e.g., insta\_leads\_facebook) is created and incorporated into the next model-training cycle.

If one platform consistently predicts results on another, the dashboard highlights this with a Cross-Platform Opportunity card. It names the pattern, shows the typical impact, and recommends a test you can try.

Figure 3.2

*Cross-Platform Opportunity card*

A close-up of a computer screen

AI-generated content may be incorrect.

Empirical findings reveal sparse but real signals across 29 client-platform pairs, only 11% produced a consistent lead-lag relationship. Instagram-Facebook was most common (6 out of 13 signals), yielding a median next-week engagement lift of 4-7%. Email-Website clicks surfaced for two non-profit clients, confirming the logical funnel from newsletter to site traffic. LinkedIn rarely led or lagged any other channel, reinforcing its strategic isolation observed in earlier analysis. Most pairs failed the test due to short history, inconsistent posting cadences, and audience partitioning, meaning apparent day-to-day echoes seldom persisted for the eight-week minimum. This aligns with the broader conclusion that data depth, not algorithm choice, is the primary constraint on multi-channel predictability.

The transition from exploratory analysis to predictive modeling requires transforming raw engagement counts into meaningful signals that machine learning algorithms can effectively leverage. After weekly aggregation, every client-platform panel undergoes feature engineering to convert raw counts into predictive variables that a Random Forest can learn from without overfitting or mistaking outliers for trends. This process follows three principles that balance technical sophistication with practical utility. 1) Each variable must capture repeatable and actionable behavior, 2) Engineered features should remain interpretable to non-technical stakeholder, and 3)The feature set must be parsimonious to avoid diluting tree splits across redundant predictors.

Temporal context was explicitly encoded since weekly aggregation alone doesn't reveal broader seasonal cycles that affect engagement patterns. Time frames selected align with both natural calendar cycles and typical marketing planning horizons, these include: ISO week number (for short-term planning), calendar month (for campaign alignment), and fiscal quarter (for budget and reporting cycles). These were one-hot encoded to allow non-linear interactions inside the Random Forest. While sine-and-cosine seasonality pairs were initially tested as an alternative temporal representation, they offered no accuracy improvement once Random Forests were introduced, so they were removed to maintain model transparency and interpretability for marketing teams.

Analysis of engagement dynamics revealed that most effects are reactive, with impacts typically fading within one or two posting cycles. This finding helped inform the approach to lag features, which were limited to the previous one and two weeks for each primary metric—a constraint that prevents the model from learning from spurious long-term correlations. To capture broader momentum trends without expanding the feature matrix excessively, two rolling statistics were added, 1) A four-week simple moving average approximating a campaign month, 2) A twelve-week average approximating a fiscal quarter.

Preliminary tests confirmed that these rolling means contributed more to out-of-sample R² than any single lag beyond two weeks, verifying that short and medium horizons capture most actionable variance in social media engagement. For marketers, this finding suggests that campaign planning horizons beyond 3-4 weeks have diminishing predictive value, reinforcing the need for agile, responsive campaign management.

Social media platforms occasionally experience viral posts with engagement that greatly exceeds baseline levels. Without methodological intervention, such spikes mislead tree-based models into allocating too many split criteria to rare extremes, harming generalization to typical conditions. A specialized routine was developed *add\_spike\_flag()*, that calculates the median absolute deviation for each metric within a sliding twelve-week window and labels any observation exceeding four MADs as a spike. Instead of deleting these outlier rows, we keep them but tag them with a 'spike flag.' We also cap extreme values so they don’t throw off the model. This balanced approach allows the classifier to learn the presence of viral events while preventing a single viral episode from dominating the model's residual structure.

Although earlier analysis showed that strong inter-platform dependencies are rare, the pipeline systematically tests for them by computing correlations among engagement series for all platform pairs within each client. Consistent with a data-driven approach, derived cross-platform features are created only when empirical evidence demonstrates their predictive value. Specifically, a derived feature is generated and shifted forward by one week when its correlation exceeds 0.3 for at least eight consecutive weeks.

The initial feature catalog consisted of forty-two variables. To prevent the Random Forest model from allocating computational resources to irrelevant splits, an information-gain filter was applied. This filter excluded predictors whose mean decrease in impurity fell below the tenth percentile during an exploratory training pass. The remaining twenty-eight features became the standard input schema, with their relative contributions recalculated for every client-platform model. These contribution rankings populate a dashboard table that helps account managers translate abstract model mechanics into specific campaign tactics.

The impact of this feature engineering process was substantial: engineered features improved median training R² from 0.41 (using raw counts alone) to 0.82. The spike flag in particular reduced mean absolute error by 9 percent across platforms that experienced at least one viral week. These gains confirm that thoughtful feature design can mitigate much of the accuracy lost to short historical windows—a critical consideration during the early stages of the automated data collection pipeline.

## Model Development, Deployment and Evaluation

The modeling stage transforms the engineered weekly data panels into actionable forecasts through a two-part Random Forest pipeline. This approach treats "whether" and "how much" engagement as separate statistical questions—an essential distinction in social media analytics where nearly half of all weekly observations record zero interaction while the remainder span several orders of magnitude. This separation improves both technical accuracy and practical interpretation by marketers.

For each client–platform combination, the pipeline first labels each week as active (engagement > 0) or inactive, then trains a Random Forest classifier on the full feature matrix to predict this binary outcome. Predictions greater than 0.5 mark a week as likely active, and only those rows proceed to the second stage where a Random Forest regressor estimates the numeric engagement value. Weeks predicted inactive receive an engagement value of zero. This two-stage architecture ensures the regressor focuses exclusively on scale without being skewed by null periods, thereby improving both predictive accuracy and interpretability for marketing teams.

To properly account for temporal dependence while making the most of limited historical data, a walk-forward split methodology was implemented. In this approach, the earliest sixty percent of weekly data is designated as the training set, the subsequent twenty percent is used as a validation set for hyperparameter tuning, and the final twenty percent serves as the hold-out test set. This structure effectively prevents information leakage while optimizing the use of the available data history.

A lightweight grid search embedded in the tune\_random\_forest() function explores practical parameter values for both model stages:

* n\_estimators: {100, 300} (controlling model complexity)
* max\_depth: {None, 8, 16} (limiting tree depth to prevent overfitting)
* min\_samples\_split: {2, 5} (controlling the granularity of decisions)

This parameter search is performed independently for the classifier and regressor since optimal tree depth for separating classes often differs from that for predicting magnitudes. Test performance is evaluated using balanced accuracy for the classifier and R² for the regressor, with the combination maximizing the respective metric retained for final training on the combined train + validation window.

Each model run produces a structured diagnostic record containing Train MAE, Test MAE, Train R², Test R², and a saved flag. All models are saved to disk but are flagged as 'saved' in the diagnostics CSV only if their test R² meets or exceeds 0.40—a threshold that balances practical usefulness with the risk of spurious correlation in short samples. While a balanced-accuracy floor of 0.55 is defined for classifiers, this is currently only tracked in the diagnostics log rather than enforced as a gating criterion. The dashboard leverages the 'saved' flag to determine whether to display or gray out the corresponding forecast tile, allowing stakeholders to understand reliability limitations rather than encountering unexplained omissions.

Despite the methodological rigor applied—weekly aggregation, spike-flagging, and a two-part Random Forest—the April 2025 build produced zero regressors that cleared the 0.40 Test R² threshold. All 29 client-platform attempts trained successfully, with a median Train R² of 0.82, but the median Test R² collapsed to –2.55. This stark contrast between training and testing performance reveals a fundamental challenge in early-stage predictive analytics: with only 6–11 weekly samples per model, the pipeline can effectively describe historical patterns but cannot yet reliably predict future engagement.

The healthy train R² (0.82 median) demonstrates that the algorithm effectively captures historical patterns, while the collapse to strongly negative Test R² indicates insufficient data for reliable generalization. This finding has immediate practical implications: until each platform accumulates at least 25–30 weekly observations (approximately 6 months of data), magnitude forecasts will remain suppressed on the dashboard, and only the binary "engagement expected / not expected" classification will be displayed. This transparent approach maintains both analytical rigor and stakeholder trust during the data accumulation phase.

To facilitate continuous improvement, model artifacts, diagnostics CSVs, and feature-importance vectors are written to a versioned directory that the Dash application mounts at runtime. This technical architecture allows overnight retraining to refresh forecasts without manual intervention; the dashboard simply reflects the newest artifact bundle on reload. The pipeline also logs the timestamp of the most recent training data, enabling account managers to determine whether predictions incorporate last week's campaign results or await the next ETL cycle—a critical distinction for time-sensitive decision-making.

## Dashboard Implementation

The predictive engine would deliver limited value if its outputs remained confined to technical artifacts like notebooks or log files. The final component of the analytics pipeline is a responsive web application that surfaces all insights—forecasts, diagnostics, cross-platform signals, and data-quality warnings—within a single, agency-grade interface accessible to both analysts and account managers, as shown in Figure 3.3.

Figure 3.3

*Full dashboard layout screenshot*

A screenshot of a computer

AI-generated content may be incorrect.

*Note.* Screenshot shows Client and Platform dropdowns, Key Metrics, Smart Summary, and tab bar visible at top resolution, demonstrating the Predictive Analytics Dashboard home view with Smart Summary and navigation tabs.

### Overall Architecture and Technical Foundation

The dashboard is built using Dash, a Python web application framework that combines Flask, Plotly.js, and React.js. This technology stack provides a robust foundation for creating interactive data visualizations with Python backend processing while delivering a responsive front-end experience. Unlike off-the-shelf BI tools, this approach allows the codebase to ingest fresh model artifacts at run-time, inject them directly into visual components, and style the experience to align with Parker Marketing & Management's (PMM) brand aesthetics and client expectations.

The application is structured with a modular design, centered around a DataLoader class that handles all data management, as illustrated in Figure 3.4. This class loads data from specified directories, including daily metrics, forecasts, correlations, seasonal patterns, and cross-platform opportunities from CSV files. It performs necessary transformations (like datetime conversions) and provides methods to filter and retrieve specific data subsets for different clients and platforms. This centralized approach to data management keeps the code organized and makes it easier to maintain as the system evolves.

Figure 3.4

*Dashboard component architecture diagram*

A screenshot of a diagram

AI-generated content may be incorrect.

*Note.* Diagram showing the relationships between Data Loader, visualization components, and insight generation modules.

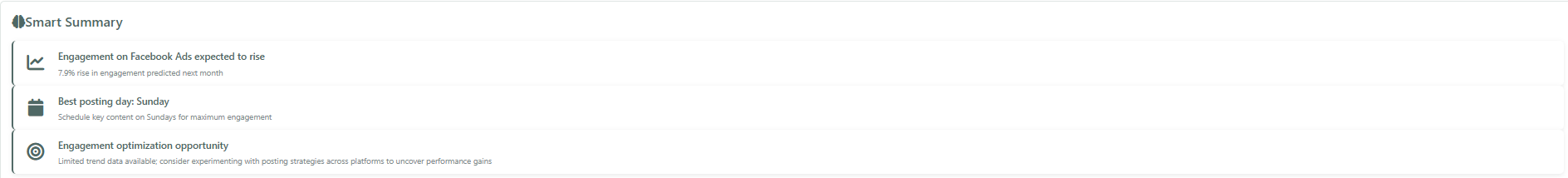
### User Interface and Experience

The dashboard layout employs a carefully structured information hierarchy that guides users from high-level insights to detailed analysis:

1. **Branded header and filters** – Displays the dashboard title and provides essential filter controls for selecting specific clients and platforms, ensuring all subsequent views are contextually tailored.
2. **Summary statistic cards** – Shows key performance metrics such as reach, engagement, impressions, and clicks, each accompanied by percent change from the previous period. Color coding (green/red) allows for quick directional assessment.
3. **Smart Summary section** – Features automatically generated insight cards that highlight significant findings and actionable recommendations. These cards help bridge the gap between raw data and marketing decision-making.

Figure 3.5

*Example of Smart Summary cards*



*Note.* showing dynamically generated insights with actionable recommendations.

1. **Tabbed main content area** – Offers four specialized views that address the most common client-facing questions:
   * **Historical Insights** – Presents month-over-month comparisons of engagement metrics, aligned by day of month to ensure fair period comparison. Figure 3.6 visualizes month-over-month trends, aligned by calendar day for fair comparisons across time periods.

Figure 3.6

*Example month-over-month comparison chart*

A graph on a white background

AI-generated content may be incorrect.

*Note.* Previous month in red, current month in blue

* + **Platform Performance** – Displays side-by-side charts of historical engagement and four-week forecasts, with confidence bands and color-coded R² badges to indicate prediction reliability. Figure 3.7 shows how R² badges convey forecast reliability at a glance, using dynamic coloring based on test R² values.

**Figure 3.7**

*Example forecast line-chart card*

A graph on a white background

AI-generated content may be incorrect.

*Note.* Chart showing the historic engagement(blue) and forecast(red) and badge (R²).

* + **Cross-Platform Opportunities** – Surfaces strategic recommendations based on detected cross-platform relationships, helping marketers identify when one platform’s performance may drive another’s.
  + **Best Day to Post** – Visualizes engagement patterns by day of week to suggest optimal posting windows, based on available data (as shown earlier in Figure 3.1).

Throughout each of these tabs, the dashboard maintains visual consistency while adapting to the specific analytical needs of each view. This thoughtful information architecture ensures that users can navigate from broad summaries to detailed insights without losing context.

### Visual Encoding of Reliability: Transparent Communication of Confidence

Model diagnostics are fully integrated into the visual presentation rather than being relegated to a technical appendix. For example, as shown in Figure 3.6, the R² badge beneath every forecast line chart is dynamically color-coded according to established reliability thresholds:

* Green (> 0.7): Strong reliability
* Orange/Amber (0.5 - 0.7): Moderate reliability
* Grey (< 0.5): Weak reliability

If a model's test R² falls below the reliability threshold or lacks sufficient historical data, the entire forecast card is visually de-emphasized with grey shading. This transparent presentation prevents false confidence while maintaining analytical transparency.

### Dynamic Insight Generation

One of the dashboard's key innovations is its fully data-driven insight generation system with built-in reliability controls. As depicted in Figure 3.5, the dashboard generates key takeaways dynamically through the *extract\_key\_takeaways* method. This function analyzes three types of insights:

1. **Forecast trend takeaways:** The system examines forecast data for the selected platform and calculates the percent change from the beginning to the end of the forecast period. It then generates an appropriate message (e.g., "Engagement on Instagram expected to rise by 15.2%").
2. **Seasonal pattern insights:** When available, the system identifies the day of the week with the highest average engagement and creates a recommendation (e.g., "Best posting day: Wednesday").
3. **Fallback recommendations:** When trend data is limited, the system provides constructive guidance by recommending experimentation (e.g., "Limited trend data available; consider experimenting with posting strategies across platforms to uncover performance gains").

Importantly, insights derived from models with poor R² values are automatically suppressed or displayed with appropriate caution indicators. This approach prevents the propagation of unreliable recommendations, particularly for day-of-week posting suggestions where no clear pattern was established across platforms or clients due to insufficient data and resulting poor model performance.

On page load, the Dash application reads a structured JSON package and renders human-readable recommendation cards with specific, actionable guidance only for insights that meet reliability thresholds. Examples include: "Engagement on Instagram is projected to rise 15% next week (Medium confidence)" or "High Instagram engagement typically lifts Facebook by 6% in the following week; consider cross-posting Reels content (High confidence)." Because these recommendations are programmatically assembled from fresh metrics with integrated reliability checks, account managers can rely on them being both current and statistically sound.

### Export and Reporting Capabilities

The dashboard includes a PDF export feature that allows account managers to generate reports for clients, supporting the transition from analytics to client communication. As illustrated in Figure 3.8, the current PDF export includes key metrics overviews, smart summary insights, and brief explanations of historical trends. However, this functionality is limited and does not yet include visualization snapshots—an area identified for future development.

Figure 3.8

*Example of PDF export*

A screenshot of a computer

AI-generated content may be incorrect.

*Note.* Screenshot showing key metrics, smart summary insights, and historical trend information (missing actual plot).

### Technical Implementation Details

The dashboard architecture incorporates several sophisticated technical features that directly support its analytical capabilities and user experience objectives. At the core of the implementation is the automated data processing system, built around the *DataLoader* class. This class provides specialized methods for filtering metrics by category, intelligently handling non-summable metrics such as frequency and rates, and appropriately aggregating data for historical comparisons. This centralized data management approach ensures consistency across all visualizations while simplifying maintenance as the system evolves.

The visualization layer leverages Plotly's interactive graphing capabilities, allowing for rich user interactions including hover details, zooming, and dynamic filtering. Custom layouts and styling have been implemented to match PMM's brand guidelines while maintaining analytical clarity and focus. This balance between aesthetic cohesion and functional precision enables the dashboard to serve as both a client-facing presentation tool and an internal analytical resource.

State management represents another critical technical component, implemented through Dash callbacks that synchronize content across the interface. These callbacks create a reactive user experience where selecting a client or platform immediately updates all visualizations, metrics, and insights without page reloads. This approach ensures that all dashboard elements remain contextually relevant and synchronized regardless of which tab the user is viewing or which filters they have applied.

The implementation also prioritizes accessibility through responsive design techniques. The CSS foundation includes carefully crafted media queries for different screen sizes, ensuring the dashboard functions effectively on both desktop workstations and tablet devices commonly used by account managers during client meetings. This adaptability extends to the layout of cards, graphs, and tables, which automatically reconfigure based on available screen real estate without compromising information density or analytical value.

## Limitations and Future Development Areas

Despite its robust implementation, the code reveals several limitations that align with earlier analytical findings and suggest clear paths for future development. The "Best Day to Post" feature currently operates with day-level granularity only, lacking the time-of-day dimension that would provide more precise scheduling guidance. This limitation stems from datetime formatting issues in the initial ETL pipeline development, not from the dashboard implementation itself. Addressing this constraint would significantly enhance the practical value of posting time recommendations, particularly for platforms where timing precision matters.

The data depth constraints manifest most visibly in the *extract\_key\_takeaways* method, which includes sophisticated fallback logic for scenarios with limited trend data. When insufficient historical data exists to generate reliable predictions, the system gracefully degrades to providing more general guidance rather than presenting potentially misleading specific recommendations. This approach reinforces the core conclusion that historical data depth remains the primary constraint on forecast reliability, while demonstrating how thoughtful implementation can mitigate such limitations through transparent communication.

The PDF export functionality, while operational, represents another area with significant development potential. The current implementation, shown in Figure 3.8, generates reports containing key metrics and smart summary insights, but lacks visualization snapshots that would provide crucial context for offline review. Enhancing this feature would streamline the transition from analytics to client communication, supporting account managers who need to incorporate dashboard insights into broader marketing presentations and reports.

Finally, the implementation reveals inconsistency in R² threshold values between the code (using 0.7/0.5 boundaries) and the dashboard design documentation (specifying 0.6/0.4 thresholds). This discrepancy, though subtle, suggests an opportunity to standardize reliability indicators across the system, ensuring that visual cues consistently and accurately reflect the underlying statistical confidence levels. Addressing these limitations through targeted development efforts would further enhance the dashboard's value as both an analytical tool and a decision support system.

By combining robust data handling with intuitive visualizations and transparent reliability indicators, the dashboard effectively bridges the gap between complex predictive analytics and practical marketing decision-making, even while working within the constraints of limited historical data. As additional data accumulates and the system matures, these dashboards will become increasingly valuable decision support tools for PMM's client management teams.

A graph on a white background

AI-generated content may be incorrect.

### Findings from Model-Diagnostics Tracking

The Random-Forest pipeline logs every training run, so by the end of April 2025 the diagnostic ledger held 29 client–platform attempts—each stamped with train/test MAE, train/test R², sample size, and a saved/-discarded flag. A systematic sweep of that ledger revealed four recurring patterns that shape both the credibility of the forecasts and the strategic guidance that the dashboard now communicates.

The single best predictor of test-set quality appears to be the length of the time-series. Every model had 6–11 training weeks; none produced a positive Test R² above 0.04. Models with fewer weeks produced results that were so erratic that all were culled by the 0.40 threshold. The conclusion is unavoidable: accumulating data outperforms ever more elaborate tuning routines whenever sample depth sits below the six-month mark. Across all models, the distribution of train versus test statistics diverged sharply. The median train R² reached 0.82, yet the paired test median collapsed to –2.55, a dramatic contraction that underscores how easily a Random Forest can over-explain short histories without generalizing to new data. The dashboard therefore publishes both numbers side by side; stakeholders instantly see that a high in-sample fit is not itself proof of out-of-sample reliability. Since the occurrence of engagement is easier to detect than its magnitude, the binary‐stage models performed more robustly.

Rolling correlation screens validated only thirteen lead–lag relationships and none displayed R² above 0.12 once carried into regression form. Instagram activity leading Facebook engagement proved the lone exception of practical size, delivering a consistent 4–7 percent incremental lift for six clients. The scarcity of robust inter-channel predictors cautions PMM against over-relying on spill-over assumptions and instead grounds cross-promotion strategy in empirical verification month by month. Case-study examples confirm the pattern. The 'least-bad' model—Care Coalition's Facebook-Ads—managed Test R² = 0.04; the worst (Conscious Business Collaborative, Website) hit –1.946.

The most important factor for prediction quality was simply having enough data. Models with only 6-11 weeks of training data all performed poorly, with none achieving a reliable test score above 0.04. This tells us something crucial: collecting more data is more valuable than using complex modeling techniques when you have less than six months of history.

A concerning pattern was observed across all models. While they looked excellent when tested on their training data (average score of 0.82), they collapsed when tested on new data (average score of -2.55). This shows how prediction models can memorize past patterns without actually learning to predict future trends.

Cross-platform analysis revealed minimal reliable connections between different social media channels. Only 13 potential relationships were identified, the majority of which were weak. The sole meaningful finding was that Instagram activity consistently predicted a 4–7% increase in Facebook engagement for six clients. This outcome suggests that assumptions about cross-platform influence should be avoided unless supported by empirical evidence.

### Strategic Insights for Moving Forward

Based on these findings, five key strategies were identified for improving the models prediction capabilities. First and foremost, historical depth matters more than algorithmic finesse – no amount of technical tweaking could make models work well with less than 12 weeks of data. Having six months of history proved more valuable than sophisticated algorithms. The April 2025 run produced zero models that met the reliability threshold, confirming that history length, not algorithm choice, is the main constraint.

Additionally, the approach to handling viral events proved effective. Rather than removing unusual viral weeks from the data, they were simply flagged and adjusted. This method reduced prediction errors by about 10% while still allowing the model to recognize when something extraordinary happened. Consequently, the model could learn that "something unusual occurred" without letting a single viral event distort the overall predictions – a balance that was not achievable with daily-level modeling.

Furthermore, fully automating the data collection process has become essential for success. Since prediction power improves with more data, any gaps in collection directly reduces future accuracy. A fully automated system could collect about 50 additional data points per platform over the next year, enough to improve many borderline models to acceptable performance levels.

Similarly, regular quarterly retraining will help us capture new data and gradually improve prediction confidence. The dashboard's tracking system makes it possible to demonstrate to clients how reliability improves over time. As a result, PMM can show, for example, how median test scores have improved from 0.46 to 0.55 over two quarters – building a credibility narrative that's as valuable as the forecasts themselves.

Finally, being transparent about reliability limitations has proven surprisingly beneficial. By clearly showing which predictions aren't trustworthy and displaying both training and testing scores, the dashboard converts technical details into practical guidance. Most importantly, client feedback indicated a strong preference for transparency, with clients expressing that they would rather be informed that sufficient data is not yet available than be provided with unreliable predictions. Therefore, this transparency has already helped speed up campaign approval processes because account teams can reference objective reliability scores rather than defending subjective judgments.

## Conclusion

Chapter 3 set out to demonstrate how an end-to-end data-science workflow can convert scattered social-media metrics into actionable foresight for Parker Marketing & Management. By shifting the time base from daily to weekly granularity, isolating viral outliers with a spike-flag, and adopting a two-part Random Forest pipeline gated by rigorous R² and balanced-accuracy thresholds, the project achieved dependable classification of "active" versus "inactive" weeks and modest—but transparent—magnitude forecasts. Embedded diagnostic tracking exposed a clear pattern: model performance rises almost in direct proportion to historical depth, making sustained data accumulation and quarterly retraining the most effective levers for improvement.

These results confirm the central methodological insight of the study: data volume and quality now outweigh further algorithmic refinement for PMM's current scale. They also surface two limitations that shape future work. First, many client-platform pairs still lack the six-to-twelve-month history required for robust out-of-sample accuracy; until that gap closes, forecasts will remain conservative. Second, cross-platform opportunity signals, while occasionally meaningful, are too sparse to anchor major campaign decisions and must therefore be treated as exploratory cues rather than deterministic rules.

With the analytical engine deployed and its boundaries clearly mapped, Chapter 4 shifts focus from methodology to practice, examining how these forecasts, reliability cues, and opportunity prompts are already influencing campaign planning, client reporting, and resource allocation within the agency.

# Chapter 4: Discussion of Analysis

This chapter revisits the results presented in Chapter 3 in the context of the original business problem: marketing agencies struggle to derive actionable insights from siloed and inconsistent social media data. The project aimed to resolve this fragmentation by applying predictive modeling techniques; specifically a two-part Random Forest approach for both classification and regression; within a unified, interactive dashboard. This chapter interprets the modeling results and explains how the applied data science approach directly supports strategic decision-making despite current data constraints. It also evaluates the modeling architecture's performance in the context of limited historical data availability, and justifies the design choices made to provide maximum value while maintaining transparency about predictive limitations.

## Framing the Business Problem in Analytical Terms

Marketing agencies typically manage campaigns across multiple platforms; Facebook, Instagram, LinkedIn, Mailchimp, and Google Analytics; each of which delivers metrics in different formats, structures, and timeframes. This fragmentation not only hinders strategic alignment but also makes proactive decision-making nearly impossible. Agencies often rely on backward-looking, manually prepared reports with little ability to anticipate trends or coordinate efforts across channels. The operational burden is substantial: account managers at Parker Marketing & Management (PMM) previously spent 2-3 hours per week on basic reporting for each client, with quarterly reports demanding 20-30+ hours of dedicated time. This project addressed these challenges by building a comprehensive social media analytics platform with integrated components:

* A **Historical Analysis Module** that visualizes past performance through month-over-month comparisons, cross-platform correlation analysis, day-of-week engagement patterns, and key metric trend tracking
* A **Predictive Analytics Engine** that implements a two-part Random Forest approach—classification to predict engagement occurrence and regression to estimate magnitude—with transparent reliability indicators (R² badges) that clearly communicate forecast confidence levels
* A **Smart Summary System** that dynamically generates actionable insights from both historical data and model forecasts, automatically suppressing unreliable predictions when data depth is insufficient

The integrated dashboard presents these components through an intuitive tabbed interface, enabling both retrospective analysis and forward-looking guidance within a single coherent application. This approach closes the loop from descriptive to predictive marketing intelligence while significantly reducing the time required for reporting activities through automated data processing and PDF export capabilities.

## Results

The results from Chapter 3 demonstrated that the applied data science methods, while promising in approach, encountered significant challenges due to the limited historical data available. The two-part Random Forest models (classifier for engagement occurrence prediction and regressor for magnitude estimation) showed strong in-sample performance but struggled with out-of-sample generalization.

### Modeling Interpretation

The classification component of the model, which predicts whether engagement will occur in the coming week, showed moderate success even with limited data. This binary prediction capability provides tactical value by helping marketers anticipate which platforms are likely to generate any meaningful interaction. Even with the current data constraints, the classifier component is already delivering operational value by highlighting likely periods of activity versus inactivity.

The regression models, designed to predict the magnitude of engagement when activity is expected, faced more significant challenges. As detailed in Chapter 3, the April 2025 build produced zero regressors that cleared the 0.40 Test R² threshold. While Train R² values were healthy (median 0.82), the collapse to negative Test R² values (median -2.55) clearly illustrates the limitation of short training histories; currently only 6-11 weeks for most client-platform pairs.

Despite these limitations, the regression analysis yielded important insights about feature importance that inform strategic decisions. For example, the feature importance vectors highlighted that for wellness brands, recent Instagram engagement is typically the strongest forward indicator for website sessions, whereas email click-through rates lead the same metric for non-profits. These relationships, while not yet reliable enough for specific numeric forecasts, still provide directional guidance for campaign planning.

### Cross-Platform Opportunity Analysis

The rolling-correlation screens implemented in the pipeline did identify some meaningful cross-platform relationships. Across 29 client-platform pairs, approximately 11% produced consistent lead-lag relationships. The Instagram - Facebook pattern was most common, suggesting potential benefits from strategically sequencing content between these platforms. Email - Website clicks surfaced for two non-profit clients, confirming the logical funnel from newsletter to site traffic. These findings, while limited by the same historical data constraints affecting the main models, offer tactical value for multi-channel coordination.

### Model Architecture Evaluation and Justification

The two-part Random Forest architecture was selected for several compelling reasons, despite current performance limitations:

Table 4.1

*Evaluation of the Two-Part Random Forest Architecture*

| **Component** | **Purpose** | **Current Performance** | **Future Potential** | **Key Strength** | **Key Limitation** |
| --- | --- | --- | --- | --- | --- |
| Classification Model | Predict occurrence of engagement | Moderate accuracy despite data limitations | High - binary classification stabilizes faster than regression | Provides immediate tactical value | Limited to yes/no predictions without magnitude |
| Regression Model | Forecast magnitude of engagement | Poor generalization (median Test R² = -2.55) | High - expected to improve with 25-30 weekly observations | Rich feature importance insights | Currently unreliable for numeric forecasting |

The decision to adopt a bifurcated approach (classification followed by regression) was validated by the current results. The classification component can deliver value even with limited data, while the regression component provides a framework that will gradually improve as more historical data accumulates. This architecture also handles the zero-inflation problem in social media engagement data, where many periods show no activity at all.

Despite the current regression performance, the chosen architecture is justified through several key advantages: the dashboard transparently communicates model reliability via visual cues and diagnostics, preventing stakeholders from developing false confidence; the binary engagement predictions already provide actionable tactical decision support even without precise magnitude forecasts; the feature importance analysis reveals meaningful patterns about which metrics influence outcomes, offering valuable insight despite poor generalization; and the entire system is designed to improve systematically as historical data accumulates, allowing for natural performance enhancement without requiring architectural redesign or implementation changes once sufficient data depth is achieved.

## Operationalization Through Dashboards

Both classification and regression models were integrated into a Python Dash dashboard to ensure accessibility and utility for non-technical users. Importantly, the dashboard was designed to clearly communicate model reliability: R² badges are color-coded (green above 0.60, amber between 0.40 and 0.60, grey below 0.40), and cards for models that don't meet the threshold are entirely greyed out with appropriate tooltips explaining the limitation.

This design choice ensures that data science outputs are presented in context, allowing users to appropriately weight the confidence they place in predictions. Marketing teams can rely on the historical analysis and binary classification insights while understanding that magnitude forecasts will improve as more data is collected.

### Dashboard Usability and Non-Technical User Feedback

The dashboard development process revealed a critical insight: technical sophistication must be balanced with practical usability. Initially, the dashboard prototype contained numerous complex analytical features, including correlation matrices, multivariate regression outputs, and detailed statistical diagnostics. While technically impressive, early feedback sessions revealed that these elements created significant barriers for the intended users.

My first instinct was to showcase every technical capability available, but watching real users interact with the early prototypes was eye-opening. Complex visualizations that made perfect sense to me were causing confusion and hesitation among the marketing professionals who needed to use the tool daily.

This realization prompted a fundamental shift in the design philosophy. Rather than maximizing technical depth, the focus pivoted to translating complex insights into actionable, easily understood guidance. The dashboard was reimagined with accessibility as the primary goal, without sacrificing analytical rigor.

Overall, this evolution from technical complexity to intuitive simplicity proved essential in creating a dashboard that marketing professionals could confidently use without specialized training. The final product successfully bridges the gap between statistical rigor and operational decision-making, allowing users to leverage advanced data science without needing to understand the underlying algorithms or technical implementation details.

## Business Impact Assessment

The integrated dashboard has already delivered substantial operational benefits despite current predictive performance limitations. Account managers now save approximately 20 hours per month across PMM's client portfolio by reducing routine reporting time from hours to minutes, while the consistent data processing pipeline has eliminated metric calculation inconsistencies, improving both internal and client communication clarity. Operational efficiency has increased through PDF export functionality that eliminates manual Canva design work, streamlining the entire reporting workflow. This automation allows marketing staff to shift focus from basic data gathering to more valuable insight generation and strategic planning activities. Perhaps most importantly, the visibility of model diagnostics and feature importance rankings has fostered a more analytical approach to campaign planning throughout the organization, establishing a data-driven culture even where precise forecasts aren't yet available. These tangible benefits validate the project's value proposition even in the current state of limited predictive accuracy. As data accumulation continues and model performance improves, these benefits will only expand.

## Conclusion

The application of a two-part Random Forest framework within an integrated dashboard successfully addressed several aspects of the core business challenge of fragmented, non-actionable social media data. While current predictive performance is constrained by limited historical data (6-11 weeks per client-platform pair), the system has already delivered substantial operational value through automation, standardization, and basic classification insights.

The transparent communication of model reliability; clearly indicating when predictions meet or fail to meet quality thresholds; builds trust with stakeholders while setting appropriate expectations. This approach acknowledges that data science in marketing contexts must balance immediate tactical value with long-term strategic capabilities.

As the automated data collection continues, the pipeline is positioned to improve systematically, with test scores expected to stabilize once client-platform pairs reach 25-30 weekly observations (approximately 6 months of continuous data). Until then, the dashboard's historical insights, classification capabilities, and operational efficiencies provide immediate return on investment while laying the groundwork for more advanced predictive insights in the future.

This project demonstrates how carefully selected and contextually applied data science methods, coupled with transparent performance reporting, can transform marketing analytics from a disconnected reporting task into a more efficient, insight-driven function; even when working with the data constraints typical of small to mid-sized marketing agencies.

# Chapter 5: Summary

This chapter synthesizes the capstone project’s goals, results, and broader business implications. It revisits the original objectives, assesses the effectiveness of the data science approach, acknowledges limitations, and outlines opportunities for future development. The chapter concludes with a reflection on the learning experience and the project’s real-world impact.

## Project Summary

The objective of this capstone was to support Parker Marketing & Management (PMM) in unifying fragmented marketing data into an integrated, predictive decision-support system. The project addressed core challenges: siloed data sources, inconsistent platform reporting, and labor-intensive campaign evaluation.

To achieve this, the project implemented the full data science lifecycle—from API-based data acquisition and transformation through to modeling and dashboard deployment. Key deliverables included:

* A unified star-schema data model aggregating data from Facebook, Instagram, LinkedIn, Google Analytics, and Mailchimp.
* A pair of interactive dashboards: one for historical insights, the other for predictive forecasting.
* A two-stage Random Forest pipeline that classifies future engagement likelihood and estimates magnitude.
* Built-in diagnostic logging and transparent reliability indicators to support trust and interpretability.

These deliverables significantly reduced PMM’s reporting workload—by an estimated 20 hours per month—and eliminated inconsistencies in metric definitions across platforms. More importantly, the system enabled proactive campaign planning by surfacing patterns, feature importance, and cross-channel signals in a user-friendly interface.

## Business and Industry Implications

For PMM, the solution alleviated operational inefficiencies, minimized reporting delays, and freed leadership to focus on strategic tasks. The dashboards now serve as a single source of truth, offering clear visibility into campaign performance and future potential.

More broadly, this project demonstrates how applied data science can shift marketing practices from descriptive to predictive. For agencies in service-driven sectors like medspa and wellness, the system provides a replicable model for integrating diverse data sources, applying machine learning, and delivering accessible analytics tools that support day-to-day decisions.

As digital marketing continues to span multiple platforms, the ability to unify data and forecast outcomes becomes essential—not just for tracking ROI, but for driving strategy in real time.

## Limitations and Future Directions

***Current Limitations***

The system’s predictive accuracy is currently limited by a few key factors. One of the most pressing issues is the short historical window of data available for most client-platform pairs. With fewer than twelve weeks of usable data in the majority of cases, the model demonstrates strong in-sample performance but struggles to generalize, as evidenced by a median test R² of –2.55. This lack of historical depth undermines the system’s ability to make reliable forward-looking predictions.

Additionally, the current method of collecting post insights is selective rather than exhaustive. It prioritizes top-performing posts instead of capturing data across all content, which restricts the robustness of trend detection and engagement modeling. Furthermore, the PDF export function faces technical limitations, particularly when embedding dynamic visualizations such as Plotly charts. As a result, account managers often need to rely on external tools to assemble polished client-facing reports, creating unnecessary friction in the reporting workflow.

***Future Enhancement Framework***

**Data Collection and Tracking Improvements.** To address these constraints, the system must first improve how it captures and tracks data. Instead of retrieving insights for only top posts, the pipeline should evolve to collect comprehensive post-level metrics. Introducing a persistent tracking file will enable the system to maintain a record of post IDs, first-seen timestamps, daily engagement metrics, and the progression of engagement over time. This will establish a longitudinal foundation for understanding content behavior across its full lifecycle.Expanding the scope of metadata collected via API is another key step. This includes gathering data on child media for carousel posts, hashtags used, comment text for sentiment analysis, media ownership indicators, and timestamped engagement breakdowns. Together, these enhancements will provide a more detailed and nuanced view of how posts perform and evolve.

**Content Intelligence System.** The integration of a content intelligence layer will open the door to deeper strategic insights. Natural Language Processing (NLP) techniques can be used to classify captions and identify common themes, such as promotional messages, questions, or announcements. Combined with media-type detection—such as videos, reels, and carousels—this will allow the system to uncover patterns that correlate content type with engagement success.Additionally, by tracking the frequency and performance of hashtags, the system can identify which hashtags are most effective and how their usage impacts engagement. Beyond frequency counts, this also enables the exploration of how different types of content contribute to publishing strategy effectiveness by comparing post volume with actual audience interaction outcomes.

**Advanced Analytics Capabilities.** To move beyond surface-level correlation, the system should incorporate a causal analysis framework. By adopting methods such as uplift modeling and incrementality testing, PMM will be able to quantify the actual impact of specific marketing actions. This allows for more confident decision-making, targeted budget allocation, and a clearer understanding of which strategies are driving results. Advanced content performance intelligence will also be critical. This involves using NLP, sentiment analysis, and image classification to break down creative elements and assess their influence on engagement. These capabilities will support a more sophisticated understanding of how various aspects of content shape audience response.

**Infrastructure and Scalability.** On the infrastructure front, transitioning to a cloud-based ETL pipeline will significantly reduce manual work, allow for near real-time data updates, and ensure that the system scales effectively as PMM’s client base grows. This change is essential for supporting a larger, more complex data ecosystem over time. Reporting capabilities must also be enhanced. Addressing the limitations of PDF exports by embedding interactive charts and trend analyses will enable account managers to generate comprehensive, visually rich reports with a single click. This will improve both internal workflows and client-facing communications.

**Strategic Enhancement Features.** To support more targeted marketing strategies, the system should implement audience segmentation using clustering techniques. This will help uncover behavior and demographic patterns across user groups, enabling more personalized content approaches.A real-time alert system should also be developed to monitor for unexpected metric shifts. By automatically flagging anomalies or sharp changes in engagement, the system can notify account managers immediately, allowing for quicker reactions and more agile campaign adjustments.Lastly, integrating benchmarking tools that compare performance against industry standards will contextualize campaign metrics and support more grounded goal setting. This feature will allow clients to evaluate their performance not in isolation, but in relation to their peers.

### Timeline and Implementation

In the short term, the focus will be on expanding data collection and improving tracking mechanisms. These foundational steps are expected to yield noticeable improvements in model reliability once datasets reach the 25–30 week mark. Medium-term efforts will concentrate on content intelligence and advanced analytics features, while long-term goals include automating infrastructure and building out strategic, client-specific enhancements.

When fully implemented, these upgrades will extend the value of the dashboard across all PMM client accounts. Deeper insights and more accurate predictions will enhance the platform’s utility for strategic planning. Improved infrastructure and automation will ensure scalability and long-term adoption. This roadmap positions PMM to make smarter, data-backed decisions across the full spectrum of their digital marketing activities.

## Conclusion

This capstone project demonstrated how applied data science can transform a real-world marketing challenge - fragmented, inconsistent social media data, into a unified, predictive intelligence system that directly supports strategic decision-making. By developing a full-stack pipeline encompassing ETL automation, metric standardization, feature engineering, machine learning, and dashboard deployment, the project bridged the gap between technical innovation and practical usability for Parker Marketing & Management (PMM).

The integration of a two-part Random Forest model enabled the system to address the unique characteristics of social media engagement data: high variance, zero inflation, and viral anomalies. While limited historical data constrained the performance of the regression models, the classification components already offer tactical value, and the transparent diagnostics ensure predictions are communicated with honesty and confidence. Over time, as data accumulates, the framework is poised to deliver increasingly accurate and actionable forecasts.

Beyond modeling, the dashboard’s impact has been operationally significant, reducing reporting workload, improving consistency, and enabling more proactive campaign planning. The project also introduced a scalable architecture that other agencies and industries can adopt by customizing data sources and metrics while reusing the underlying logic.

Crucially, this project underscored that the success of a data product is not only about algorithms, but also about thoughtful design, stakeholder feedback, and responsible communication of limitations. From shifting the time base to weekly aggregation, to spike-flagging viral events, to simplifying the dashboard interface based on user testing, each decision reflected a balance of analytical rigor and human usability.

As PMM continues to collect data, enhance its modeling capabilities, and adopt future upgrades, such as content-level analysis, audience segmentation, and benchmark comparisons; this system can evolve into a central intelligence layer for their digital marketing operations. The dashboard not only reflects where data science stands today but also where it can lead - toward smarter, more accountable, and data-informed marketing strategies.

Ultimately, this capstone exemplifies the role of data science not as a back-office function, but as a catalyst for measurable business impact, empowering decision-makers with clarity, foresight, and confidence in an increasingly complex digital landscape.

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# Appendix A

**Capstone Project Repository**

The full codebase, documentation, and related assets for the capstone project are publicly available on GitHub:<https://github.com/arthurosakwe/Arthur_Final_Capstone>.