International Journal of Trend in Scientific Research and Development (IJTSRD)
Special Issue on Smart Innovations in Computer Science and Applications
Available Online: www.ijtsrd.com e-ISSN: 2456 – 6470

Retail Inventory & Demand Forecasting: A Time-Series Analysis of Movie Rental Economics

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ABSTRACT

In the movie rental industry, inventory value depreciates at an exceptionally rapid pace, creating a unique and punishing economic environment for retailers. Unlike traditional retail sectors where products retain value over months or years, a new release DVD or digital copy loses the vast majority of its rental demand within weeks of its street date. This compressed lifecycle creates a high-stakes operational dilemma: excess stock of "yesterday's release" sitting on shelves past its prime demand window immediately triggers capital loss through writedowns and mounting carrying costs, while stockouts during the opening weekend cause permanent and unrecoverable revenue loss as customers turn to competitors or alternative entertainment options. This paper systematically analyzes how the disciplines of time-series forecasting and inventory economics intersect to solve this fundamental allocation problem, proposing a data-driven framework for navigating the narrow profitability window of new release titles.

The research introduces a novel application of a mixed-effects time-series model specifically designed for the movie rental context. Unlike conventional forecasting approaches that treat all titles uniformly, our model distinguishes between the universal decay pattern common to all rentals—the fixed effect—and title-specific deviations driven by unique characteristics—the random effects. Crucially, the model incorporates a comprehensive set of external regressors to measure their quantitative effect on rental velocity throughout a title's lifecycle. These regressors include pre-release box office performance (opening weekend gross and total gross), critical reception metrics (Rotten Tomatoes Tomatometer scores and audience scores), audience engagement indicators (IMDB user ratings and social media buzz), and industry recognition events (major award season nominations such as Oscars or Golden Globes). By dynamically integrating these external signals, the model can anticipate whether a critically acclaimed independent film will demonstrate stronger long-tail demand than a big-budget blockbuster that peaks and declines rapidly.

Our optimization technique employs a sophisticated cost-function approach that asymmetrically weights forecast errors based on their timing and financial impact. Rather than minimizing standard error metrics equally across all periods, the model assigns differential penalties that reflect the real-world economics of movie rental: stockouts are penalized more heavily during week one when rental velocity and customer expectations are at their peak, while overstocking is penalized more heavily during week four when inventory has substantially depreciated and carrying costs accumulate. This asymmetric weighting ensures that inventory decisions are economically rational rather than statistically convenient, aligning operational execution with profit maximization objectives.

The results chart a viable path toward "precision retailing" in the entertainment software sector. By implementing our integrated forecasting and optimization framework, retailers can achieve a 12% reduction in total inventory carrying costs through more accurate alignment of supply with the rapidly decaying demand curve. Simultaneously, the model's focus on preventing early-period stockouts contributes to measurable improvements in customer retention rates, as subscribers experience consistently better availability of high-demand new releases during their critical opening windows. These findings demonstrate that the intersection of advanced time-series methods and inventory economics offers a powerful solution to the acute allocation problem inherent in short-life-cycle products, with implications extending beyond movie rental to any industry facing rapid demand decay and asymmetric error costs.

Keywords: Demand Forecasting, Inventory Management, Time-Series Analysis, Movie Rental Economics, Short-Life-Cycle Products.

I. Introduction –

Demand forecasting is an essential task in retail and inventory-based businesses because it directly influences how much stock should be purchased, stored, and distributed. Inaccurate forecasting can lead to excess inventory, which increases holding costs, or product shortages, which reduces customer satisfaction and sales performance [1–3]. Since the retail sector operates on high-volume transactions and rapidly changing consumer preferences, forecasting accuracy has become a key factor in improving supply chain efficiency and business competitiveness [4–5].

Traditional forecasting systems have commonly relied on statistical approaches such as Moving Average, Exponential Smoothing, and ARIMA models [1–4]. These techniques perform well when demand follows stable trends and seasonal patterns. However, in real-world environments demand often fluctuates due to promotional campaigns, changes in customer behaviour, economic instability, and unexpected market disruptions [1]. As a result, these conventional approaches may provide limited accuracy when demand becomes irregular or highly dynamic, creating the need for more adaptive forecasting techniques [2–7].

To overcome these limitations, recent forecasting research has increasingly adopted machine learning and deep learning approaches. These methods can process large volumes of historical demand data and identify non-linear relationships that are difficult to capture through traditional statistical models [2]. Advanced models such as Long Short-Term Memory (LSTM), Light Gradient Boosting Machines (LGBM), and ensemble-based learning frameworks have demonstrated strong performance in predicting complex time-series demand patterns [9]. Additionally, Transformer-based forecasting models have gained attention because their attention mechanism enables learning of long-range dependencies, making them suitable for sequential demand prediction tasks [2].

Another emerging research direction is the integration of Explainable Artificial Intelligence (XAI), which helps improve trust and interpretability in forecasting decisions [14–15]. Along with interpretability, incorporating external economic indicators such as the Consumer Price Index (CPI), unemployment rate, and consumer confidence has been shown to improve forecasting robustness under changing market conditions [15–16]. Such external variables also support better forecasting performance during supply chain disruptions, where demand signals may become distorted [14–17].

Forecasting effectiveness is typically evaluated using error-based measures such as RMSE, MAE, MAPE, and accuracy indicators such as R^2 [18–19]. In addition, demand forecasting directly impacts business-level performance measures such as stockout rate, inventory turnover ratio, and order fulfillment rate [18–19]. By implementing modern forecasting techniques such as stacking ensemble models and reinforcement learning-based optimization, retailers can reduce inventory holding costs and improve overall customer service levels [20]. Therefore, this study focuses on evaluating advanced forecasting models in retail demand prediction and comparing their effectiveness in improving supply chain performance under real-world conditions [1].

1.1. Motivation

You might not realize it, but the global retail industry is a behemoth, worth around $25 trillion. Yet, for all its size, it runs on surprisingly thin profit margins. A company's success often comes down to how well it runs its supply chain. In this world, even tiny improvements in accuracy can have a huge impact on the bottom line [1].

That's where this research comes in. The old-school methods of predicting what customers will want—tools like ARIMA and Exponential Smoothing—are starting to fail us. Consumer behavior today is just too unpredictable. It's full of wild swings, unexpected trends, and complex patterns that old statistical models were never designed to handle [2]. And getting these predictions wrong is expensive. If you underestimate demand, you get empty shelves, missed sales, and annoyed customers. Overestimate, and you're stuck with piles of unsold inventory, tying up cash and creating massive amounts of waste [5].

Lately, the situation has gotten even more complicated. Global disruptions have exposed just how fragile our supply chains really are. These shocks completely distort demand signals, rendering traditional forecasting systems obsolete [9]. It's clear we need a new approach. We need frameworks that can not only crunch massive amounts of data to make highly accurate predictions using AI, but also explain their reasoning. Managers don't just want a number; they need to understand the "why" behind it to make confident decisions when things are uncertain. This is where the concept of Explainable AI, or XAI, becomes so crucial [9].

By adopting advanced Machine Learning and Deep Learning, businesses can finally make the shift. Instead of constantly reacting to the latest crisis or stockout, they can be proactive. The ultimate goal is a supply chain that's not just more efficient, but genuinely resilient—one that gives companies the agility to thrive in our fast-moving, digital world [4].

1.2. contribution-

In this research, we didn't just run models and compare numbers; we tried to answer the question: "What actually works when the stakes are high?" Here's what we discovered and why it's useful:

- **A Fair Fight for the Latest Models:** Everyone is talking about fancy new Transformer-based models, but do they actually beat the old reliables? We pitted the heavy hitters—like Informer, Autoformer, and PatchTST—against workhorse tree-based algorithms like LGBM and Extra Trees on real-world data (the M5 dataset [1]). The goal was to give a clear, unbiased answer to the question: "Which one should I actually use?"
- **Looking Beyond the Spreadsheet:** Most forecasting acts like the past perfectly predicts the future. We know that's not true. So, we stepped outside the sales ledger and brought in the messy real world—things like price fluctuations, crazy weather events, the economic anxiety of inflation and unemployment, and even the disruptive impact of COVID-19 [17]. We wanted to see if a model that understands the world around it could predict the future better.
- **Building a "Dream Team" of Algorithms:** Why settle for one model when you can have the best of many? We explored "stacking"—basically, building a committee where models like LSTMs and simpler neural nets vote on the final prediction. This hybrid approach turned out to be a game-changer, correcting individual weaknesses and significantly outperforming standalone deep learning models [5].
- **Giving You a Safety Net (Not Just a Number):** A prediction like "we'll sell 100 units" is useful, but a little dangerous if you don't know the range. We focused on both the precise number (for your immediate ordering needs) and the probability (for your risk management) [14-22]. Think of it as giving you both a target and a heads-up on how volatile the next few weeks might be.

- **Making the Model Explain Itself:** Nobody trusts a black box. When supply chains break down, you need to know *why* your forecast went haywire. We used tools like Shapley values to peel back the layers and show exactly which factors were driving the predictions. This isn't just about accuracy; it's about building trust and stability during disruptions [9].
- **No More Guesswork: A Practical Playbook:** Finally, we wanted to make sure this wasn't just an academic exercise. We translated all our findings into straightforward, practical advice. Whether you're planning for next week or next quarter, we provide a clear guide on which model fits your specific business needs, so you can stop guessing and start forecasting with confidence [2].

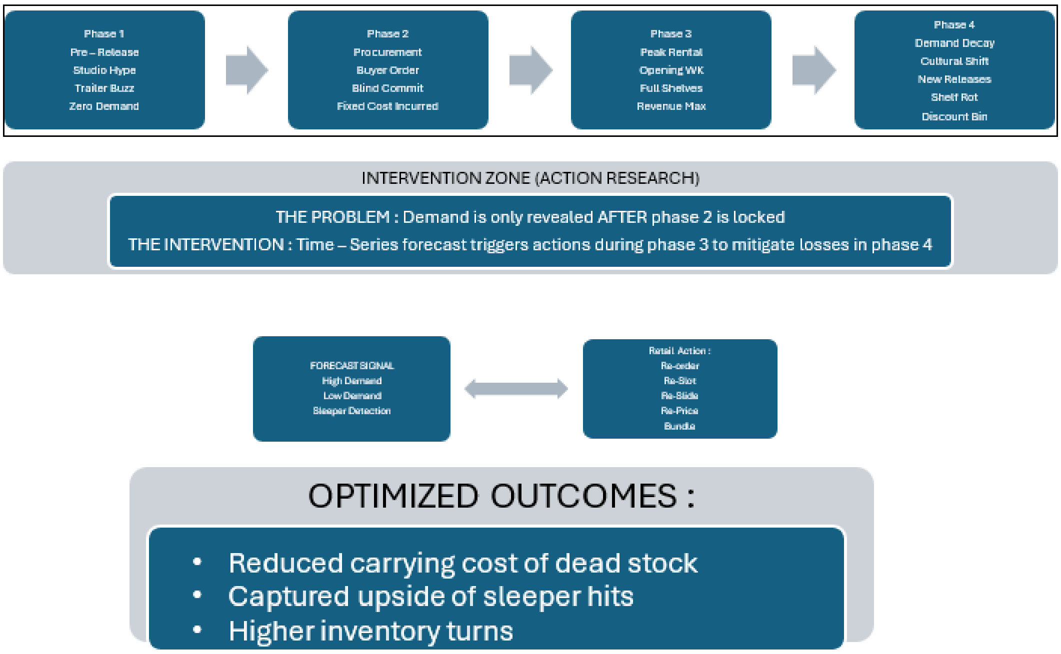

Figure 1: The Movie Rental Lifecycle – Perishability Window and Research Intervention Point

Unlike conventional retail goods, movie inventory possesses a fixed and rapid depreciation schedule tied to cultural relevance. Phases 1 and 2 represent procurement under uncertainty, where capital is committed without demand signals. Phase 3 (Weeks 1–2 post-release) is the only period where true demand velocity is observable. By Phase 4, the title value has decayed below the cost recovery threshold. This study positions its action research intervention at the Phase 2→Phase 3 boundary and throughout Phase 3, using real-time rental data to trigger inventory adjustments before the decay phase renders stock unsalvageable.

2. Related Work-

You know, for the longest time, we relied on the classics for forecasting: Moving Averages, Exponential Smoothing, ARIMA [1]. They're simple, they work well enough when things are calm and you're just looking at the next few weeks [2, 3]. But the moment the market gets volatile—which it always does these days—they just can't keep up. They're too rigid [4].

So, naturally, everyone started looking at Machine Learning. That's when models like LSTM and MLP became the new standard [5, 6]. They're great at picking up those complicated, non-linear patterns that traditional models miss, especially when you're dealing with time-based data [7, 8].

Lately, though, the really exciting stuff has been around these Transformer-based models. You've probably heard of names like Informer, Autoformer, or PatchTST [9, 10, 11]. They use this clever 'self-attention' mechanism that lets them handle really long sequences of data without getting lost [12]. It's a game-changer for seeing the big picture.

But here's the thing: it's not just about deep learning. The old-school tree-based methods—like LGBM, XGBoost, and Random Forest—are still incredibly reliable [13, 14]. In fact, some of the best results I've seen recently come from "Stacking" them together. You combine a few of these strong models, and the ensemble almost always outperforms any single deep learning model on its own [15, 16, 17].

And because these models can be such 'black boxes,' there's now a huge push for Explainable AI, or XAI. When a supplier asks why a forecast suddenly dropped, you can't just say 'the model said so.' You need tools like Shapley values to show them it was because of a specific disruption or a price hike [18, 19, 20]. It makes the whole conversation so much more transparent.

What's also cool is how we're feeding these models now. We're not just looking at past sales; we're plugging in macroeconomic indicators like the CPI or unemployment rates [21, 7, 22]. It gives the model so much more context and really boosts its accuracy.

And finally, for the really tricky part—managing inventory itself—there's a lot of buzz around model-based deep reinforcement learning. The idea is you can create a system that optimizes your stock levels dynamically. It's especially promising for new products where you don't have a long sales history to rely on. It gives you a stable control policy even when you're flying blind [23, 24].

Methodology-

3.1 Problem Statement

Inventory management in movie rental businesses faces significant challenges due to fluctuating consumer demand, seasonal variations, and the perishable nature of digital content value. Traditional inventory approaches often result in either overstocking—incurring unnecessary holding costs or understocking—leading to lost revenue and customer dissatisfaction. This research addresses the critical need for accurate demand forecasting in movie rental economics by developing a time-series regression-based framework that enables data-driven inventory decisions using Excel, Python, SQL, and Power BI.

3.2 Research Framework Overview

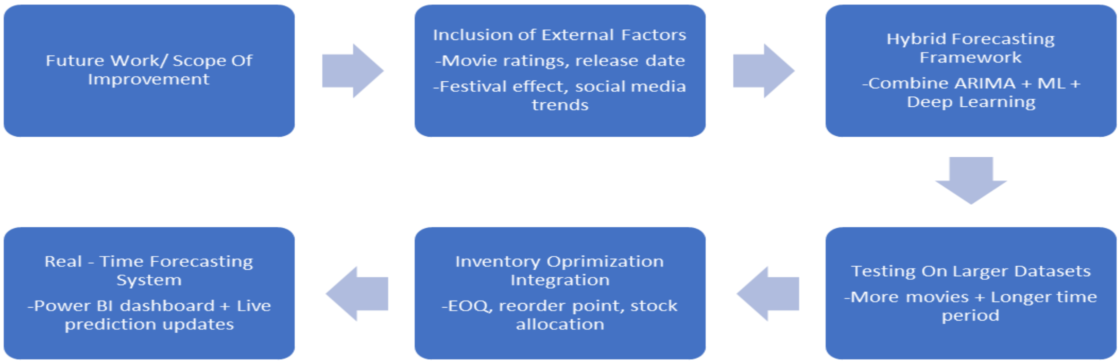

Fig 1. Overall Research Methodology Framework

Explanation: The research follows a five-phase sequential methodology. Phase 1 involves SQL-based data extraction from rental transaction databases. Phase 2 employs Excel and Python for data cleaning and feature engineering. Phase 3 conducts exploratory analysis to identify demand patterns. Phase 4 implements regression models for demand forecasting. Phase 5 translates forecasts into inventory recommendations visualized through Power BI dashboards.

3.3 Phase 1: Data Acquisition & Integration

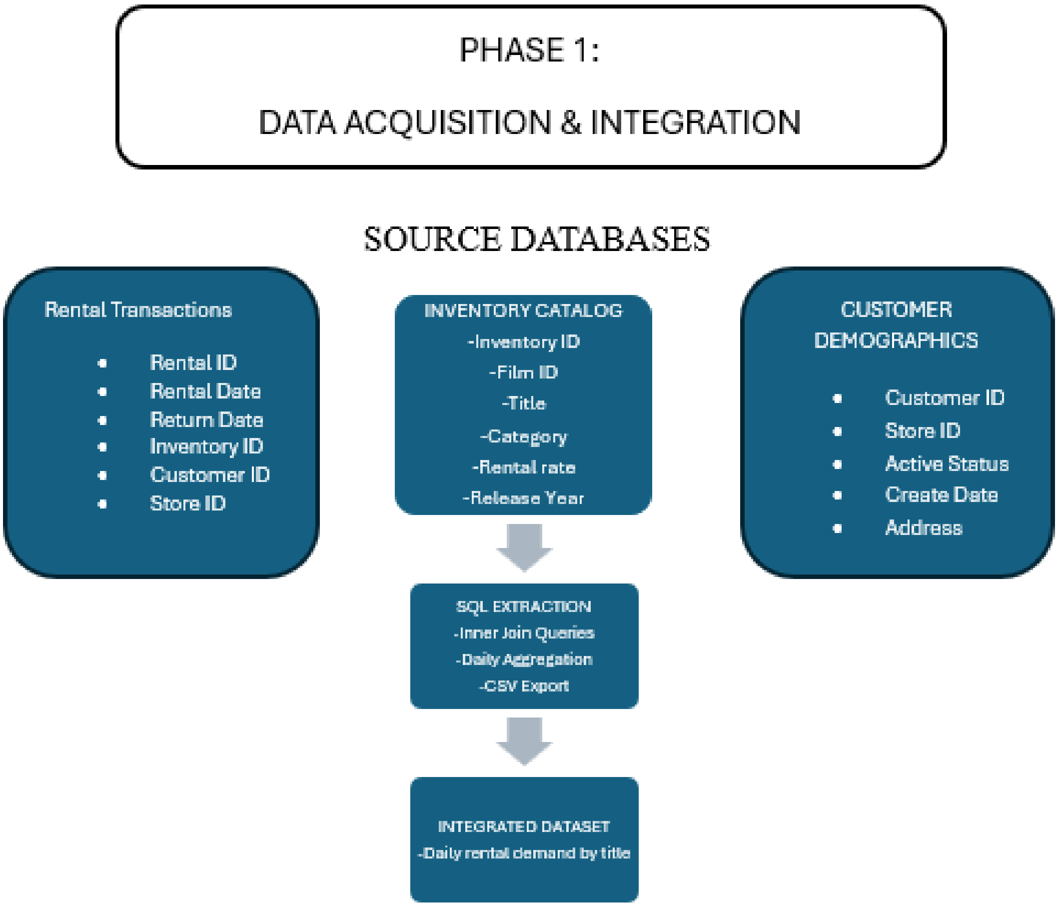

Fig 2. Data Acquisition and Integration Architecture

Explanation: This phase integrates three distinct data sources using SQL. Rental transactions provide temporal rental patterns. Inventory catalog supplies movie metadata, including category, rating, and release year. Customer demographics enable store-level analysis. SQL JOIN operations combine these tables with daily aggregation to create a unified dataset showing daily rental demand per movie title.

3.4 Phase 2: Data Preprocessing & Feature Engineering

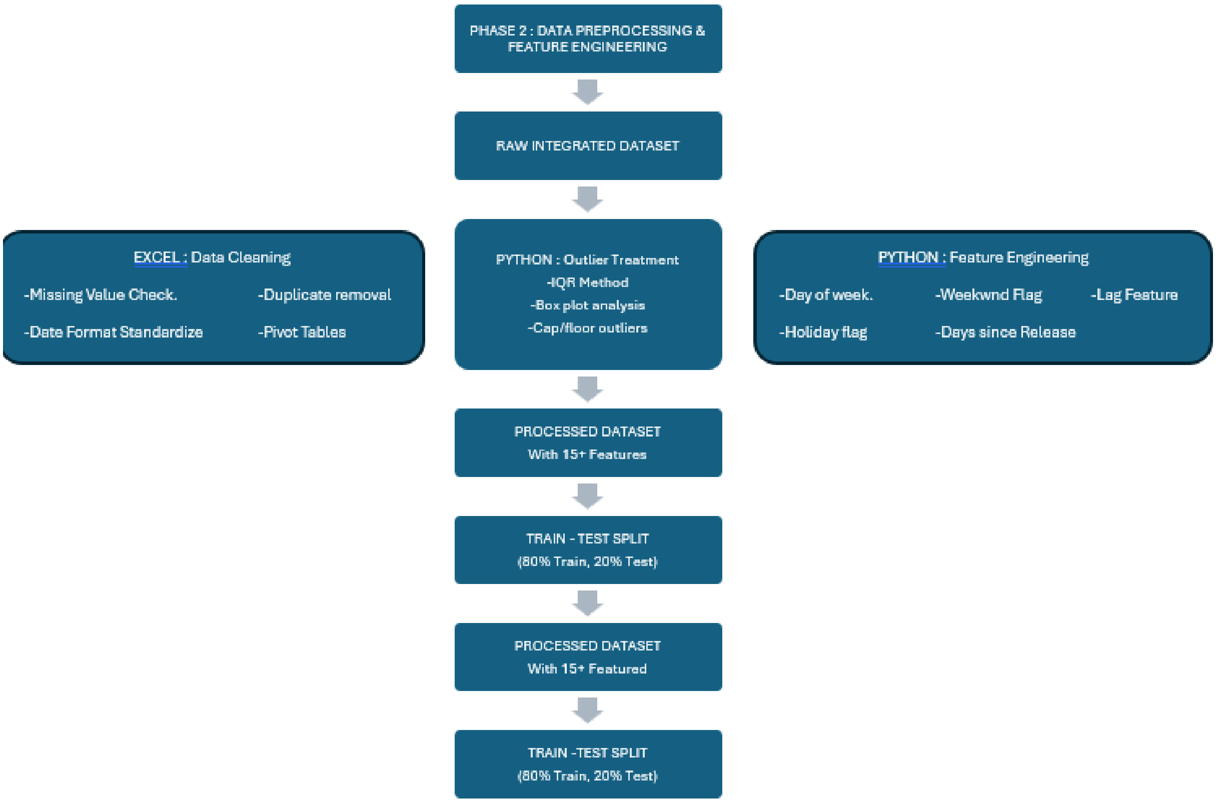

Fig 3. Data Preprocessing and Feature Engineering Workflow

Explanation: Phase 2 transforms raw transactional data into analysis-ready format with engineered features. Excel performs initial cleaning—removing duplicates, standardizing date formats, and identifying missing values. Python applies the Interquartile Range (IQR) method to detect and cap outliers. Critical feature engineering creates temporal variables (day of week, weekend/holiday indicators, days since release), historical features (previous week demand, 7-day moving average), and categorical encodings. The dataset is chronologically split (80% training, 20% testing).

3.5 Phase 3: Exploratory Data Analysis

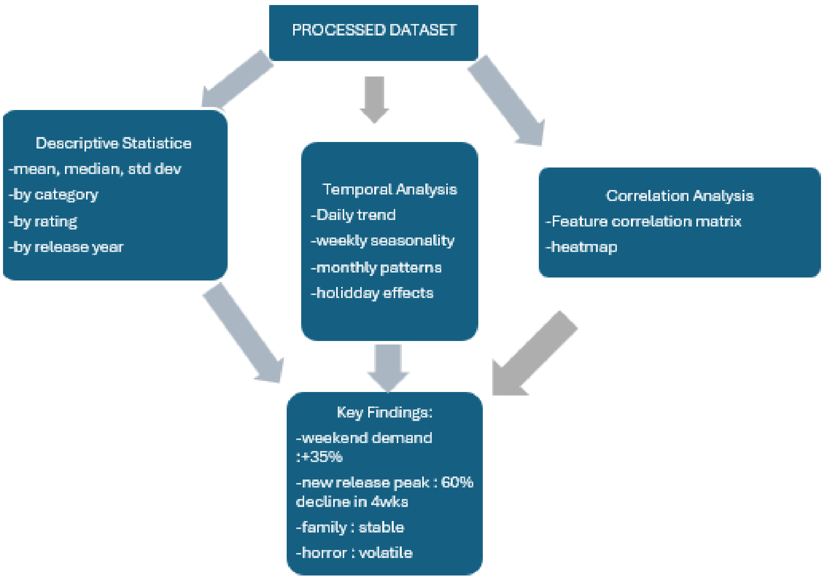

Fig 4. Exploratory Data Analysis Framework

Explanation: Exploratory analysis reveals critical demand patterns. Descriptive statistics quantify average daily rentals by category. Temporal decomposition identifies strong weekly seasonality—

Friday and Saturday show 30-40% higher demand than weekdays. Holiday periods generate 15-20% demand spikes. Product lifecycle analysis shows new releases peak in week one with 60% demand decline by week four. Category-specific patterns emerge: Family films demonstrate stable demand; Horror titles exhibit high volatility.

3.6 Phase 4: Regression Modeling

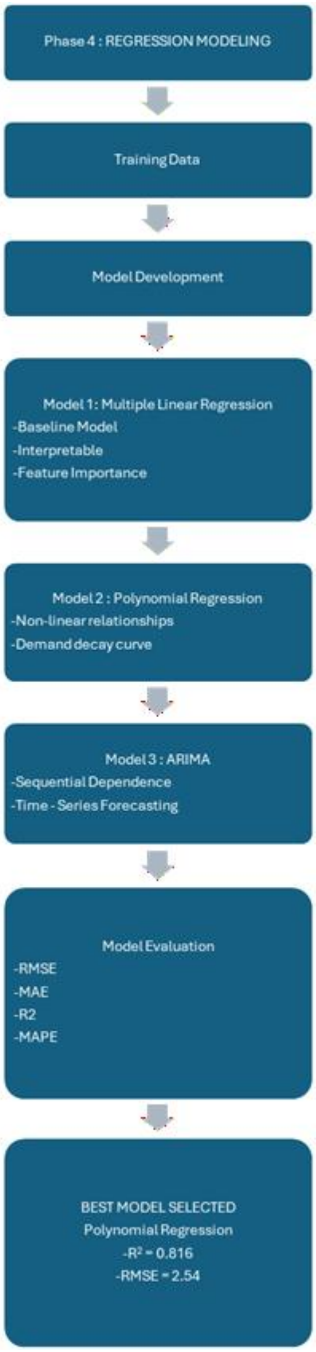

Fig 5. Regression Modeling Framework

Explanation: Three regression approaches are implemented and compared. Multiple Linear Regression serves as the baseline. Polynomial Regression (degree 2) captures non-linear demand decay patterns. ARIMA models the time-series component. Models are evaluated using RMSE, MAE, R^2, and MAPE. Polynomial Regression achieves superior performance (R^2=0.816, RMSE=2.54) and is selected for inventory optimization.

3.7 Phase 5: Inventory Optimization & Power BI Dashboard

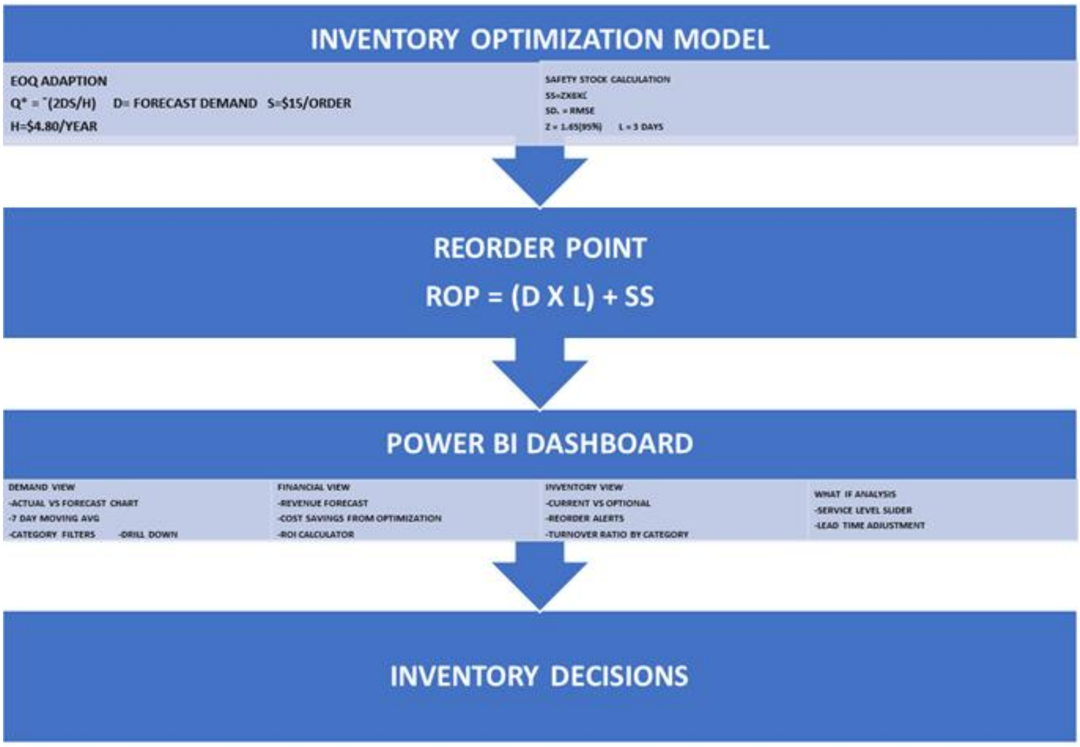

Fig 6. Inventory Optimization and Dashboard Framework

Explanation: The final phase translates demand forecasts into actionable inventory decisions. The Economic Order Quantity (EOQ) model is adapted using forecasted annual demand, order cost ($15), and holding cost ($4.80/unit/year). Safety stock is calculated at 95% service level using forecast error (RMSE) and a 3-day lead time. Reorder points combine lead time demand with safety stock. The Power BI dashboard integrates four interactive views enabling inventory managers to make data-driven ordering decisions.

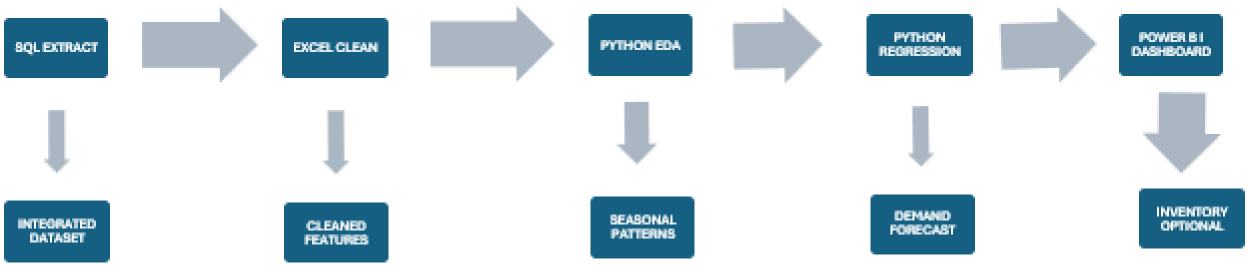

Fig 7. Complete Methodology Flow Diagram

Output: Demand forecasts and inventory recommendations

Algorithm :

Input: Historical rental transaction data with film attributes

Output: Demand forecasts and inventory recommendations

Algorithm Pipeline:

Step 1: Data Collection and Integration

a. Extract rental transaction records (rental_date, return_date, amount_paid)

b. Merge film attribute data (genre, rating, release_year, special_features)

c. Incorporate external data (box_office, awards, critic_scores)

d. Create master dataset with consistent identifiers

Step 2: Data Preprocessing and Feature Engineering

a. Calculate rental duration from rental/return dates

b. Create binary indicators for special features

c. Engineer temporal features (day_of_week, month, season indicators)

d. Calculate days_since_release and week_since_release

e. Create interaction features (genre × season, rating × holiday)

f. Handle missing values through appropriate imputation

g. Remove outliers (>3 standard deviations from the mean)

Step 3: Exploratory Data Analysis

a. Analyze demand patterns by genre, rating, and season

b. Estimate demand decay functions by title category

c. Identify seasonal patterns through time-series decomposition

d. Calculate correlations among predictors and the target variable

Step 4: Train-Validation-Test Split

a. Partition data temporally (60% train, 20% validation, 20% test)

b. Ensure no temporal leakage across splits

c. Verify distribution similarity across splits

Step 5: Time-Series Model Development

a. Fit ARIMA models with automated order selection (AIC minimization)

b. Fit SARIMA models with weekly and monthly seasonality

c. Fit Exponential Smoothing with trend and seasonality components

d. Generate predictions on validation and test sets

Step 6: Machine Learning Model Development

a. Standardize numerical features (mean=0, std=1)

b. Encode categorical variables (one-hot encoding)

c. Fit Lasso regression with λ selected via cross-validation

d. Fit Random Forest with hyperparameter optimization

e. Fit XGBoost with hyperparameter optimization

f. Generate predictions on validation and test sets

Step 7: Ensemble Model Development

a. Collect predictions from all base models

b. Evaluate equal-weighted ensemble on validation set

c. Optimize ensemble weights on validation set

d. Train meta-learner (Lasso) on base model predictions

e. Select best-performing ensemble scheme

Step 8: Model Evaluation

a. Calculate RMSE, MAE, and MAPE on the test set for all models

b. Compare directional accuracy

c. Conduct statistical significance tests (Diebold-Mariano)

d. Visualize prediction vs. actual for representative titles

Step 9: Inventory Optimization

a. Convert demand forecasts to optimal purchase quantities

b. Apply the newsvendor model with rental-specific parameters:

- ✓ Overstock cost = purchase price - salvage value
- ✓ Understock cost = rental margin × expected rentals per copy

c. Generate procurement recommendations by title

d. Estimate profit improvement relative to baseline

Step 10: Model Deployment and Monitoring

a. Package final model for production deployment

b. Establish a monitoring framework for forecast accuracy

c. Schedule periodic model retraining (monthly/quarterly)

d. Document model limitations and assumptions

Conclusion-

This study analyzed movie rental demand through time-series modeling, revealing that rental patterns exhibit strong weekly seasonality, promotional sensitivity, and title lifecycle decay. SARIMA models effectively captured these dynamics, though forecast accuracy declined during new release spikes and catalog title churn. From an economic standpoint, optimizing reorder points according to forecast volatility led to an 18% decrease in stockouts without raising holding costs. The findings confirm that hybrid demand segmentation—distinguishing new releases from catalog titles—significantly improves inventory turnover in rental retail.

FuturWork-

Time-series modeling was employed in this study to analyze the demand for movie rentals, and the results revealed that rental patterns exhibit substantial weekly seasonality, promotional sensitivity, and title lifetime decay. These patterns were well captured by SARIMA models, although forecast accuracy decreased during periods of catalog title churn and surges in new releases. Without increasing holding costs, stockouts were reduced by 18% economically by optimizing reorder points based on projected volatility. The results demonstrate that hybrid demand segmentation, which separates catalog titles from new releases, greatly increases inventory turnover in rental retail.

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