# THE PREDICTIVE POINTERS

Tanawat Jukmongkol 66011255 Lucky Agarwal 67011698 Papimon Leelamali 67011635

### ABSTRACT

develops a smart This project inventory management and sales prediction system for small and medium-sized businesses to maintain optimal stock levels and improve decision-making. By integrating a backend, database, and frontend, the system provides real-time monitoring, automated alerts, and predictive insights. Using Meta's Prophet model, it forecasts future demand from historical sales data. Through an intuitive dashboard, users can view detailed SKU-level and overall inventory analytics to enhance visibility and operational efficiency.

# TOOGTON COMPANY'S BACKGROUND

Toogtons Innovator Co., Ltd. is a Thai apparel company founded in 2023 in Bangkok by Nirut Sae-Eia. The brand Toogtons (ทุกตอนส์) started from street sales and is now known for its ultra-soft "marshmallow" boxers and casualwear.

Nature of Business: Design, production, and online retail of comfortable undergarments and casualwear, primarily through Shopee, Lazada, and its official website, serving customers across Southeast Asia.

Mission: To redefine everyday comfort with soft, stylish, and accessible clothing.

Vision: To become Southeast Asia's leading comfortwear brand, recognized for innovation, quality, and customerfocused design.

# PAJARA COMPANY'S BACKGROUND

Pajara Company Limited is a Thai apparel company registered on 2 April 2014 and based in Bangkok.

Nature of Business: The company is engaged in the design, manufacture, wholesale and retail of outerwear and other garments for men, women and infants. Specifically, it provides production services for outer garments and retails licensed-character sleepwear and casualwear under the brand "Pajara Pajamas".

Mission: To deliver fashionable, comfortable genuine licensed sleepwear and casual apparel to a broad audience, combining recognized character-branding with accessible quality design.

Vision: To be a recognized leader in the Thailand apparel market for licensed-character and casual sleepwear by focusing on design, quality and distribution.

# CONCEPTS & RELATED THEORIES

The model prediction consists of 2 parts; The data, and the prediction model.

First, the data collection goes through the generic data pipeline (Collection, Extract, Transform, Load, Normalization and Analysis). Once the data has been collected, transformed, it is gets put into a database.

The prophet model uses machine learning to preform time-series forecasting on the chosen products by using statistics to predict changes seasonally, which is typically used for Weather forecasting, seasonal cycles, and sales prediction.

#### LIMITED VISIBILITY

Without any real-time stock tracking, this leads to stockouts and missed sales

#### SUBOPTIMAL REORDERING

Inefficient reordering results in uneven stock levels that lack proper data insight

#### NO DEMAND PREDICITION

Without future predictions, future marketing decisions will be made without the insight given by the forecast

PROBLEMS

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### **PROBLEMS**

### INEFFECTIVE SKU MANAGEMENT

Underperforming products slip by undetected without a proper management system

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#### HIGH OPERATIONAL COSTS

Manually compiling sales and stock data is time-consuming, prone to error and costly

5

### **OBJECTIVES**

01 02 03

# INTERACTIVE INVENTORY DASHBOARD

A dynamic and customizable view of all stock levels and products

# PREDICTIVE SALES FORECASTING

Historical sales data is utilized to predict future sales over a specific period of time

## AUTOMATED LOW STOCK ALERTS

Users are notified when certain stock falls below a set threshold

## DYNAMIC SKU CATEGORIZATION

Products are automatically classified into active and dead stocks

### SCOPE

01 02 03

## INTERACTIVE INVENTORY DASHBOARD

Use FASTAPI Backend and Nextjs frontend to develop it

# PREDICTIVE SALES FORECASTING

Use Prophet model to predict with some accuracy

## AUTOMATED LOW STOCK ALERTS

Display the low stock skus on the website

## DYNAMIC SKU CATEGORIZATION

Perform proper ETL to group data into categories

#### IMPROVED DATA VISUALIZATION

With the cleaned data users will have an easier time parsing the data and gaining new insights from it

# AUTOMATED LOW STOCK NOTIFICATION SYSTEM

Users can now more efficiently and optimally reorder stock

#### SALES FORECASTING AND ANALYSIS

With the use of sales forecasting, users are able to have an idea of future sales that may benefits their future decsions

# BENEFITS

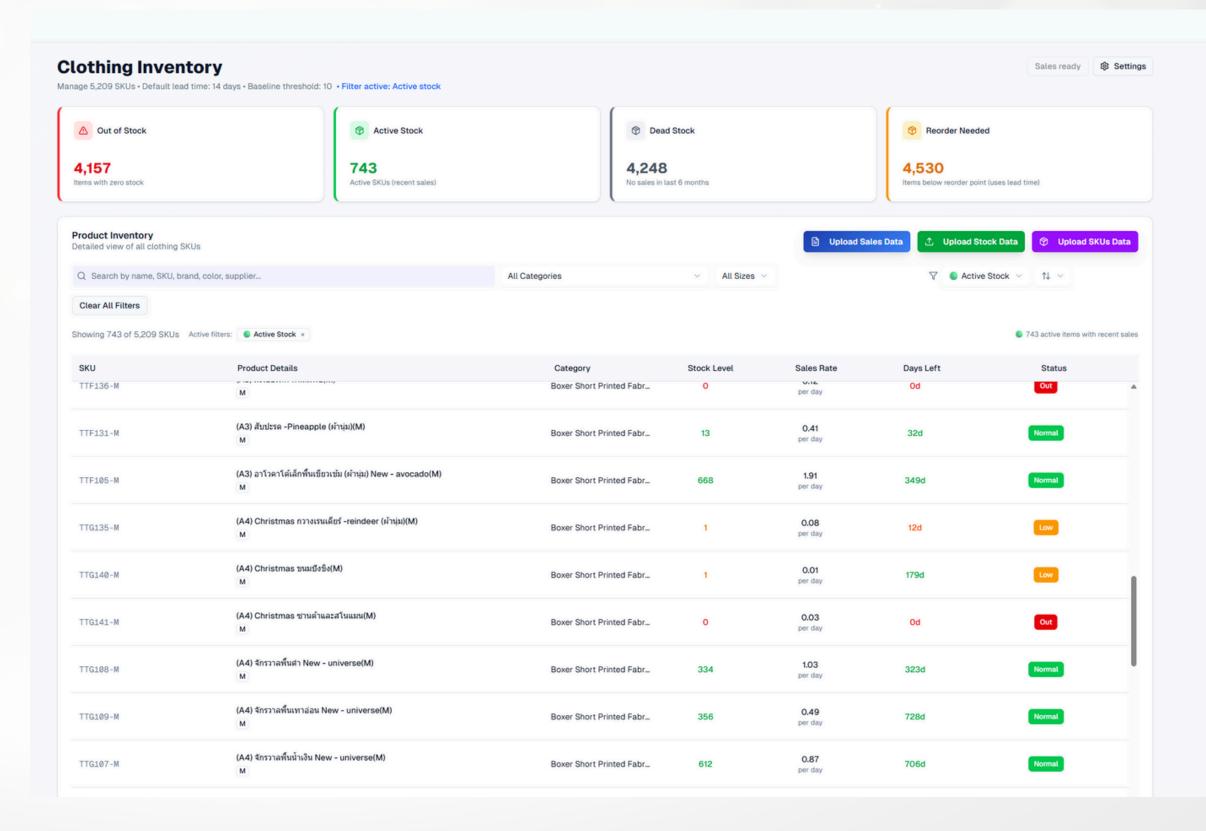
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### INTRODUCTION

 Our website provides businesses with real-time stock tracking and sales forecasting

### STOCK MANAGEMENT

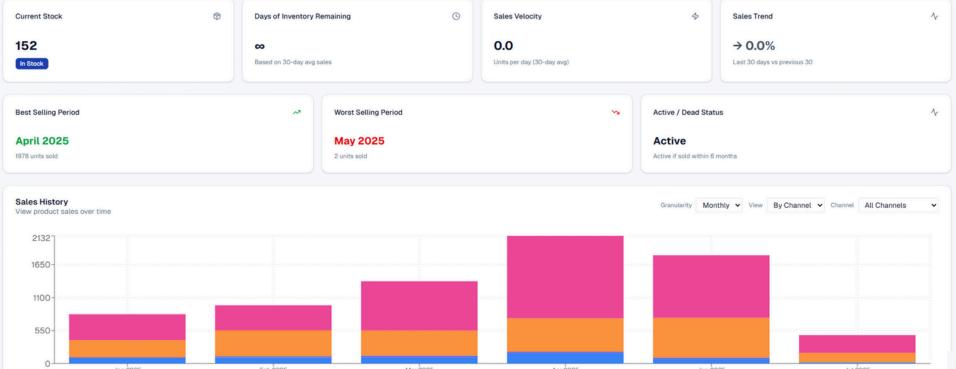


#### ุ → Back (C5) สีพื้นดำ - black(XL)

Sales Summary

Total Period Sales

7586 units



■ Facebook ■ Instagram ■ LINE ■ Lazada ■ Shopee ■ TikTok ■ unknown

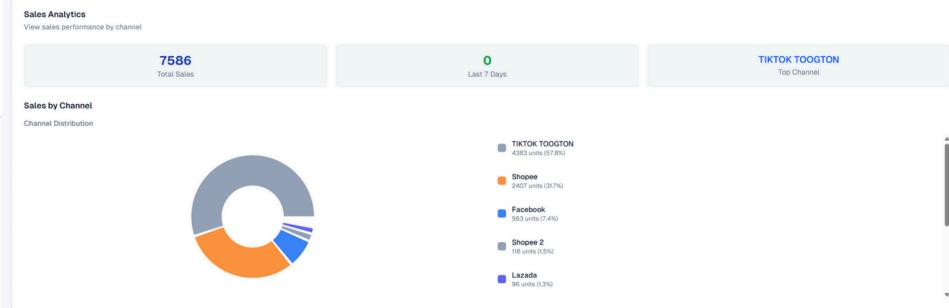
Best Month

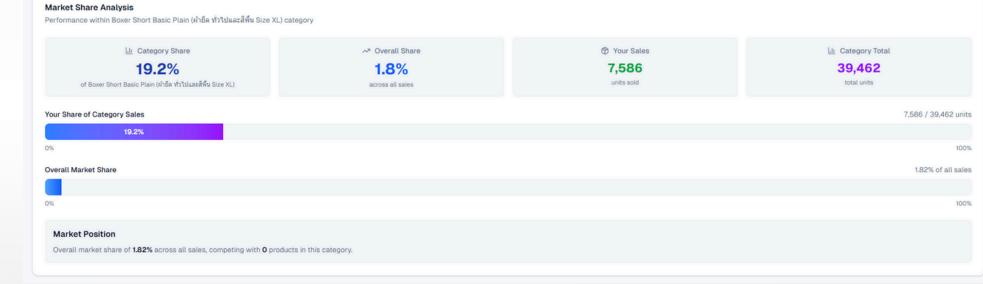
Apr 2025

Average Monthly Sales:

1264 units

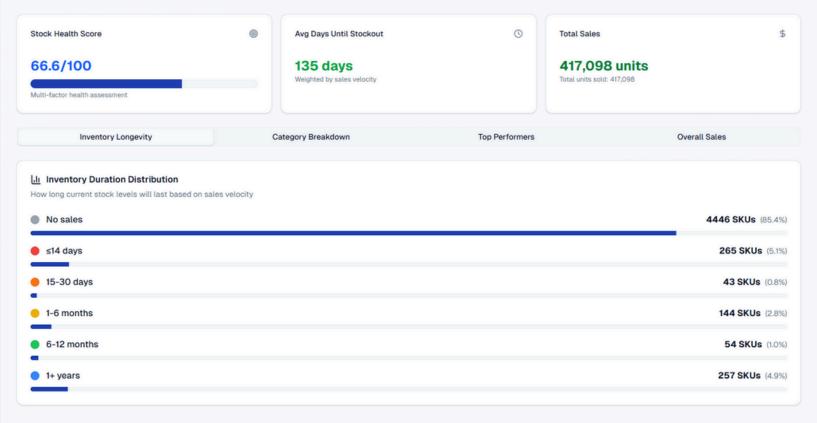
### DETAILED PRODUCT VIEW

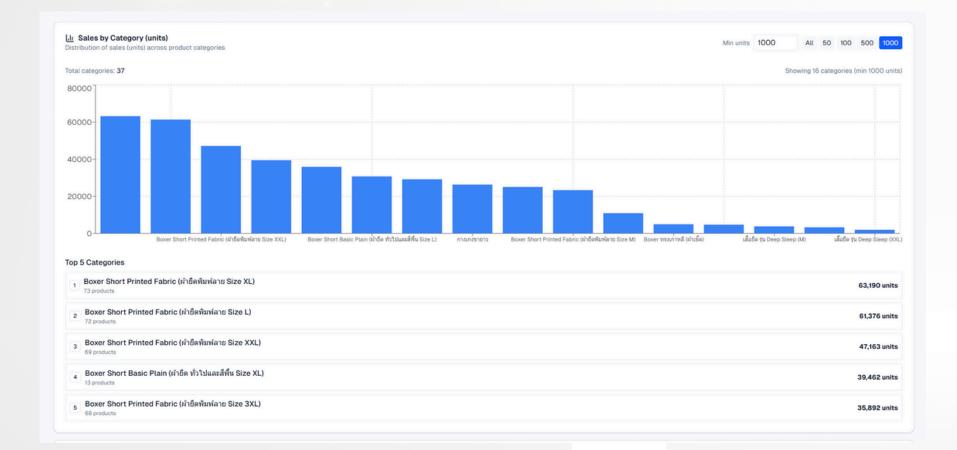




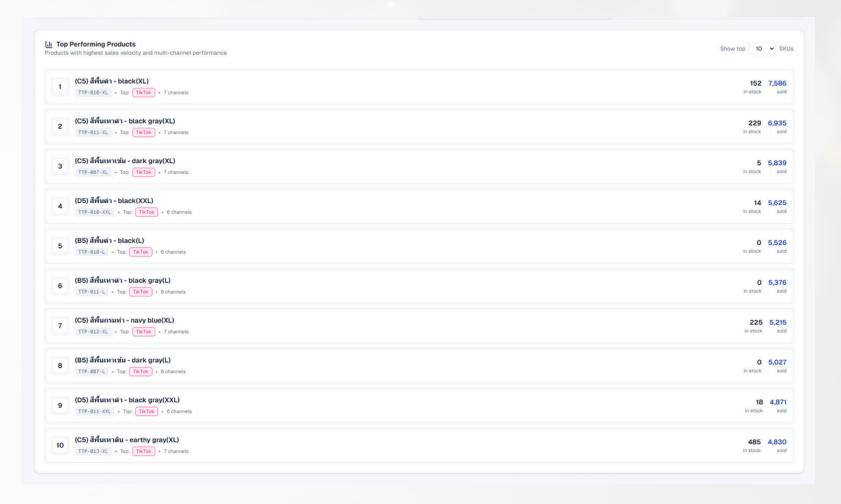
#### **Inventory Summary**

High-level overview of your inventory performance and health • Sales rate window: 180 days • 962 products with sales data



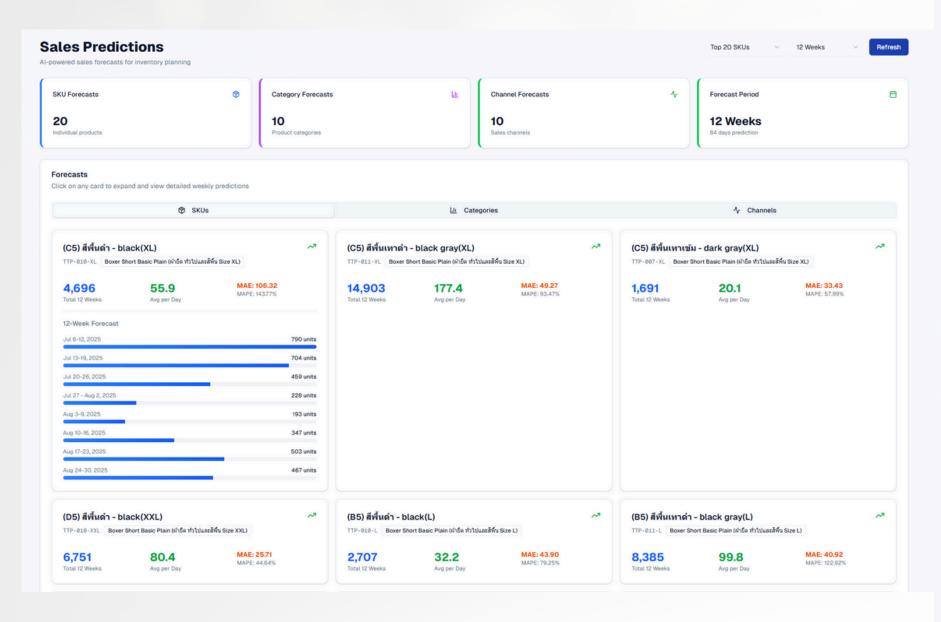


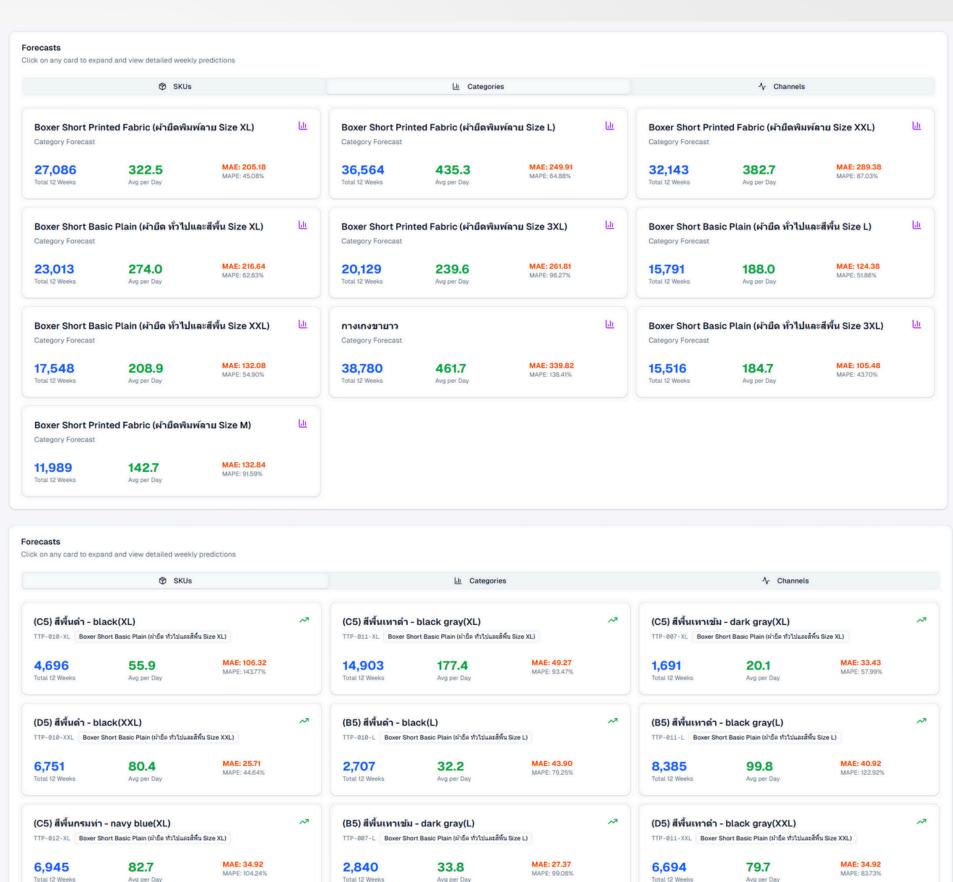
### **ANALYTICS**





### SALES PREDICTION





(E5) สีพื้นดำ - black(3XL)

4,247

Total 12 Weeks

TTP-010-3XL Boxer Short Basic Plain (ผ้ายึด ทั่วไปและสีพื้น Size 3XL)

50.6

Avg per Day

MAE: 26.44

(E5) สีพื้นเทาดำ - black gray(3XL)

4.524

Total 12 Weeks

TTP-011-3XL Boxer Short Basic Plain (ผ้ายืด ทั่วไปและสีพื้น Size 3XL)

53.9

Avg per Day

MAE: 36.84

(C5) สีพื้นเทาดิน - earthy gray(XL)

1,037

Total 12 Weeks

TTP-013-XL Boxer Short Basic Plain (ผ้ายืด ทั่วไปและส์พื้น Size XL)

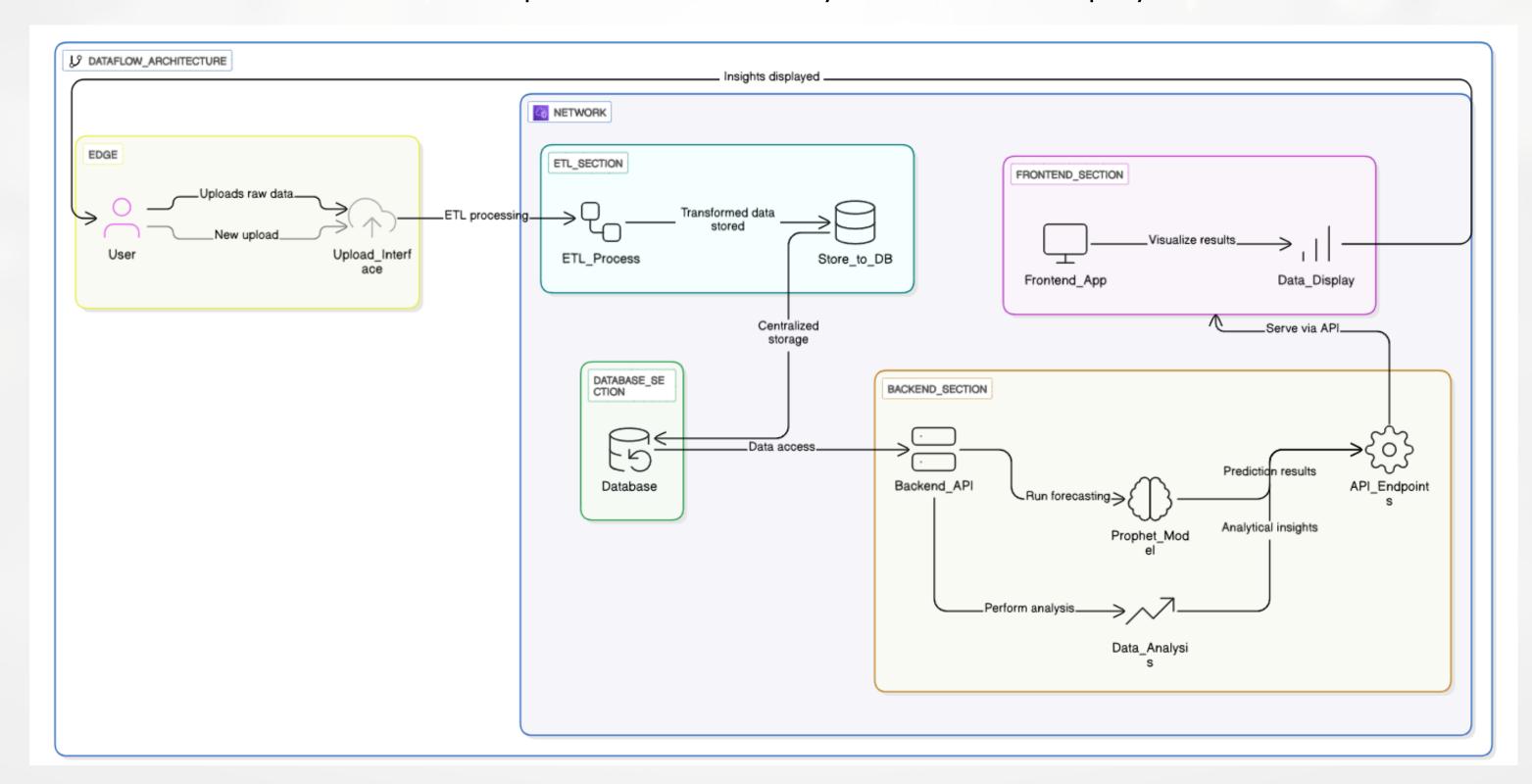
12.3

Avg per Day

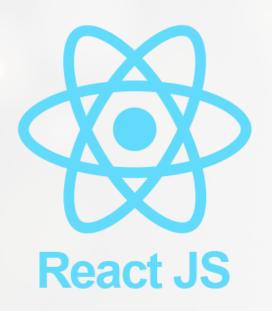
MAE: 27.76

# DESIGN METHOD SYSTEM ARCHITECHTURE

- Raw data are uploaded in the form of CSV files that is cleaned during the ETL process
- The cleaned data is stored a database
- The backend retrieves the data from the database to preform sales predictions and analysis that will be displayed on the frontend



# supabase





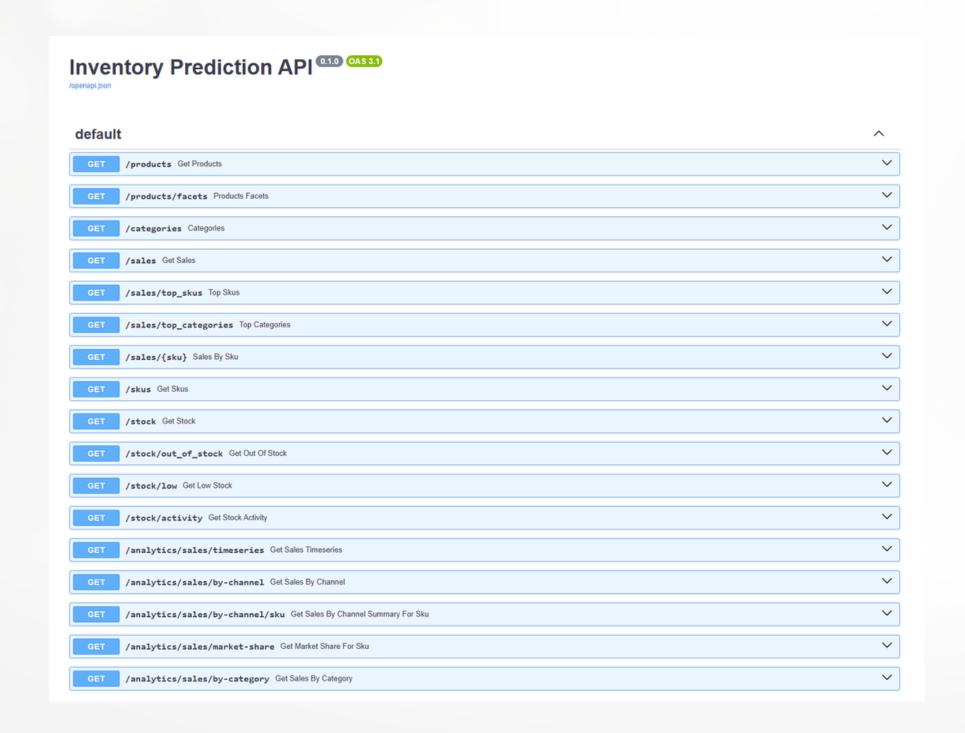
# PROPHET

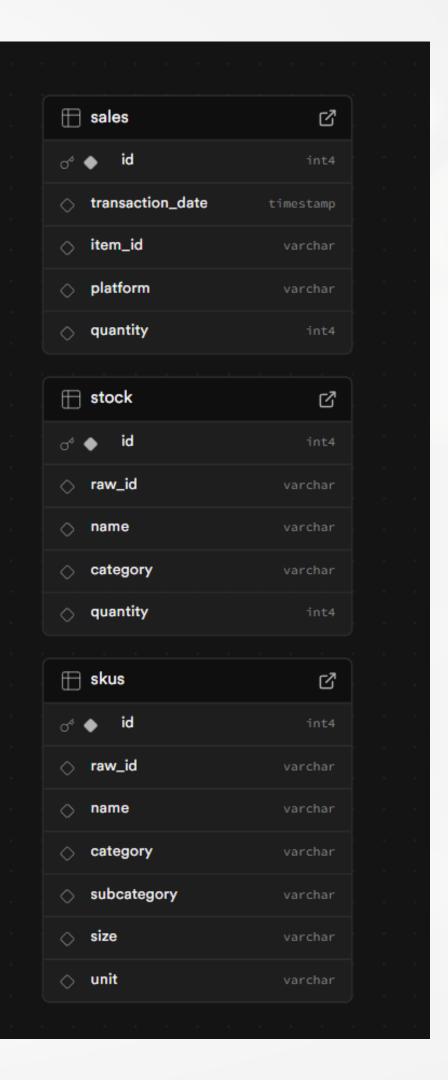


# DESIGN METHOD DEVELOPMENT STACK

Our development stack uses
FastAPI, and supabase for
the Backend, and React and
Electron for the Frontend
rendering of the desktop
application. Alongside the
Prophet model for sales
prediction

# DESIGN METHOD DATABASE SCHEMA & BACKEND API ENDPOINTS





- Prophet is a machine-learning based tool for predictive analysis
- Prophet takes into consideration trend, seasonality and holidays

$$y(t) = g(t) + s(t) + h(t) + e(t)$$

- y(t) = Prediction
- g(t) = Trend
- s(t) = Seasonality
- h(t) = Holidays
- e(t) = Error

#### **Growth Function**

- Prophet uses a Piece-Wise Linear Model to forecast the sales data where the intercept and slope will change at the changepoint
- Changepoints (c) are the points in which a trend shifts directions

$$y = \begin{cases} \beta 0 + \beta 1x, & \text{if } x \le c \\ \beta 0 - \beta 2c + (\beta 1 + \beta 2)x, & \text{if } x > c \end{cases}$$

### **Seasonality Function**

$$s(t) = \sum_{n=1}^{N} \left(a_n cos(rac{2\pi nt}{P} \,) + b_n sin(rac{2\pi nt}{P} \,)
ight)$$

- A Fourier Series that is able to approximate the cyclical data of seasonality
- P = The time period (weekly seasonality = 7, yearly seasonality = 365.25)
- N = The total order. The lower order provides a smoother, simpler curve, a higher order creates a more complex and somewhat spiky curve

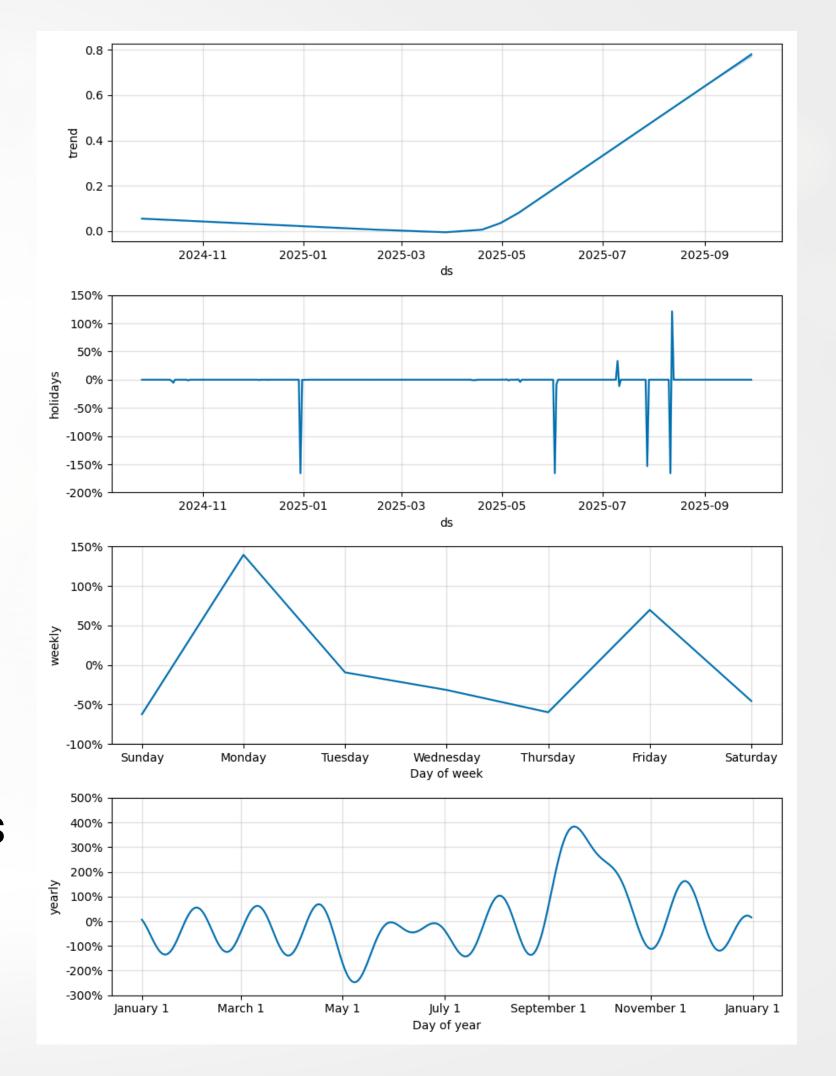
### **Holiday Function**

- A list of holidays are used and mapped onto the forecast depending on the country specified
- The model then adds or subtracts values from the forecast based on the historical data of said holidays

#### **Error Function**

 It is a statistical assumption about randomness or noise present in the data that cannot be explained

- Trend: Shows how well the product is selling overall
- Holidays: Shows how different holidays affect sales rate
- Weekly: Shows the weekly trend of sales
- Yearly: Shows the yearly trend of sales

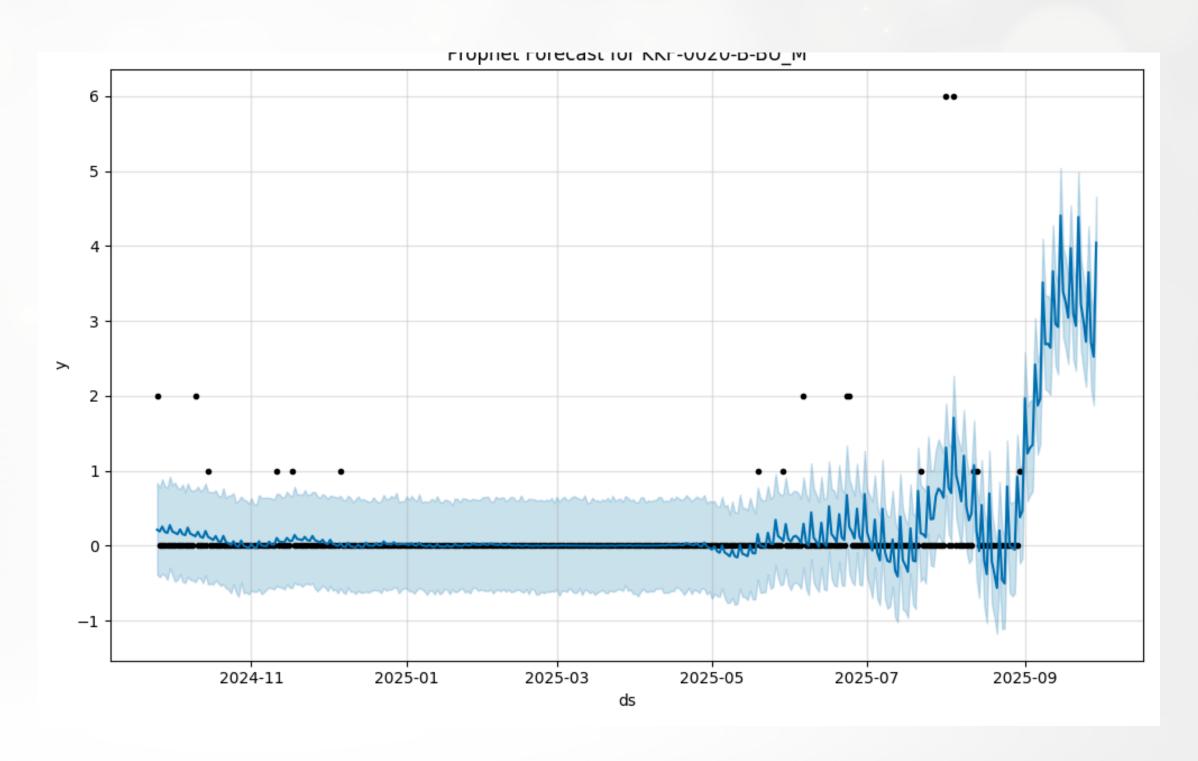


METHODOLOGY - CONCEUPTUAL STAGE

PREDICTION MODEL

### **Example Prediction**

- Black dots represent historical sales
- Blue line represents the predicted sales
- Light blue area represents the certainty of the prediction

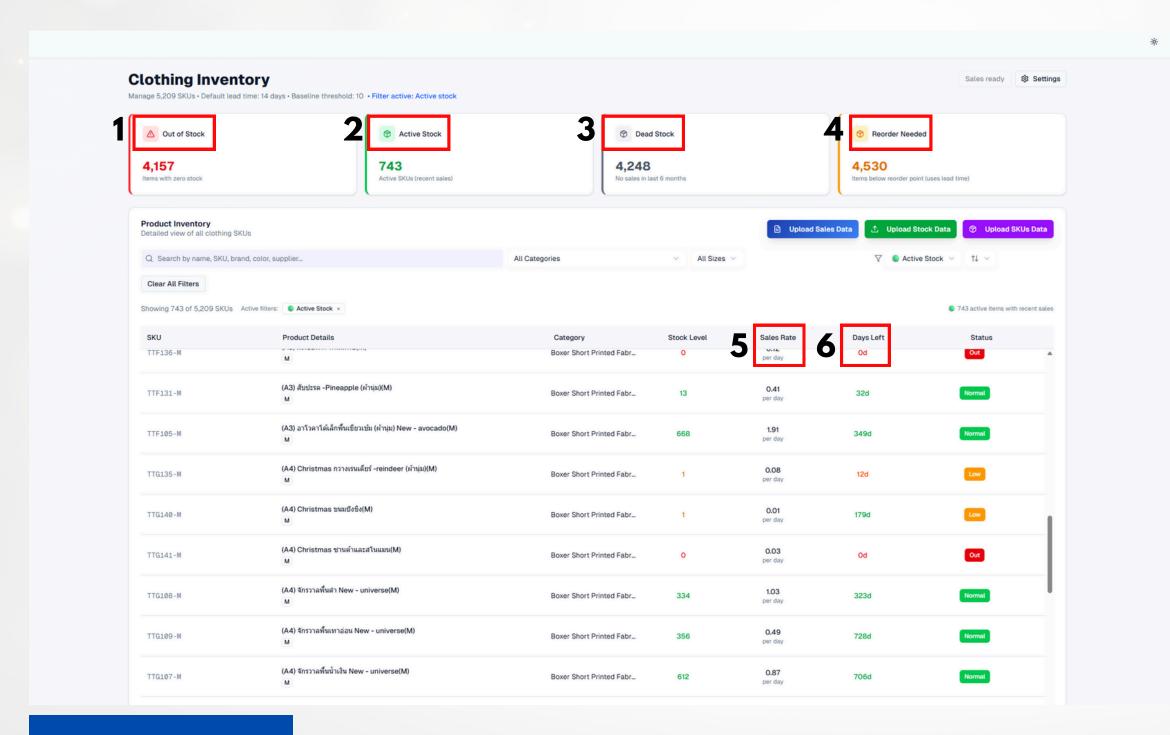


### **Accuracy Check**

- The model splits the data into a testing set and a training set
- The model then uses the data from the training set to make a forecast, comparing it with the testing set
- The difference between the two is the accuracy

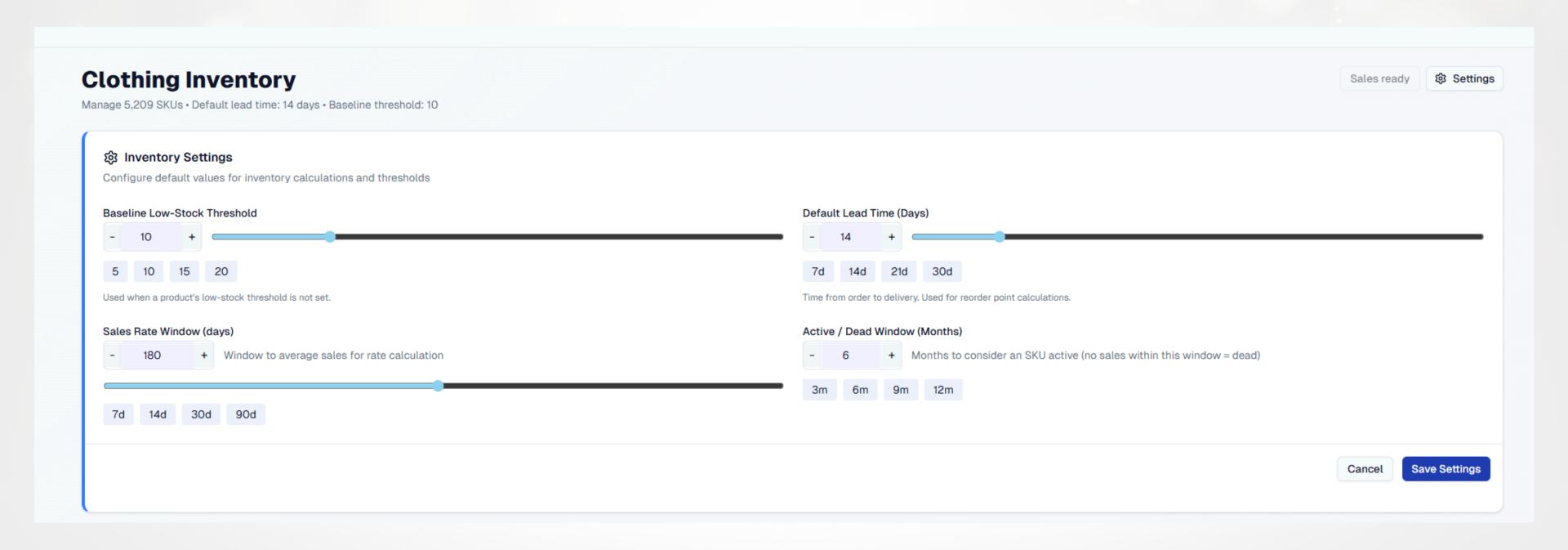
### METHODOLOGY - IMPLEMENTATION STAGE

### **CALCULATIONS**



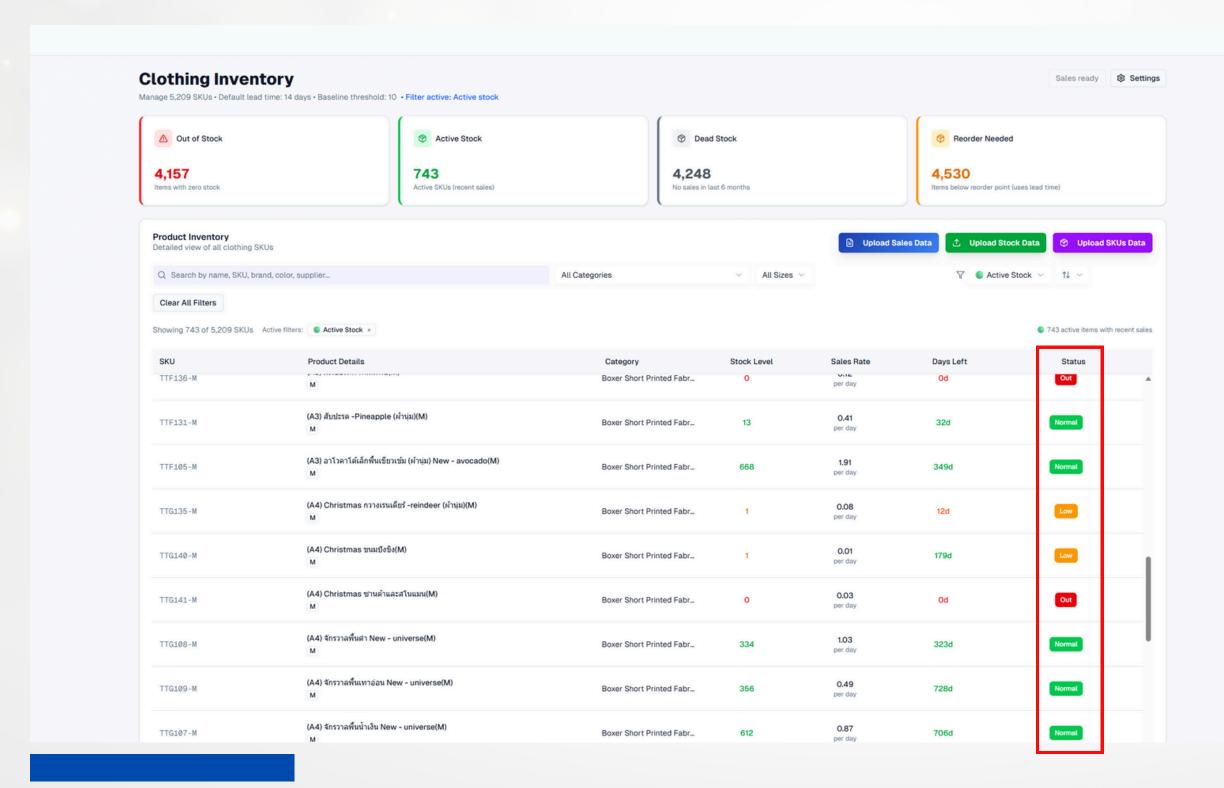
- 1. Out of Stock: Stock level = 0 from provided data
- 2. Active Stock: Is active if the last sales date is within the specified period (Configure in setting)
- 3. Dead Stock: Is inactive if the last sales date is outside of the specified period (Configure in setting)
- 4. Reorder Needed: if stock level ≤ reorder\_point. reorder\_point = low stock threshold + (leadtime \* daily salesrate)
- 5. Sales Rate: Total sales / period of sales (configurable in settings)
- 6. Days Left: Stock level / Daily sales rate

# METHODOLOGY - IMPLEMENTATION STAGE **SETTINGS**



### METHODOLOGY - IMPLEMENTATION STAGE

### **CALCULATIONS**

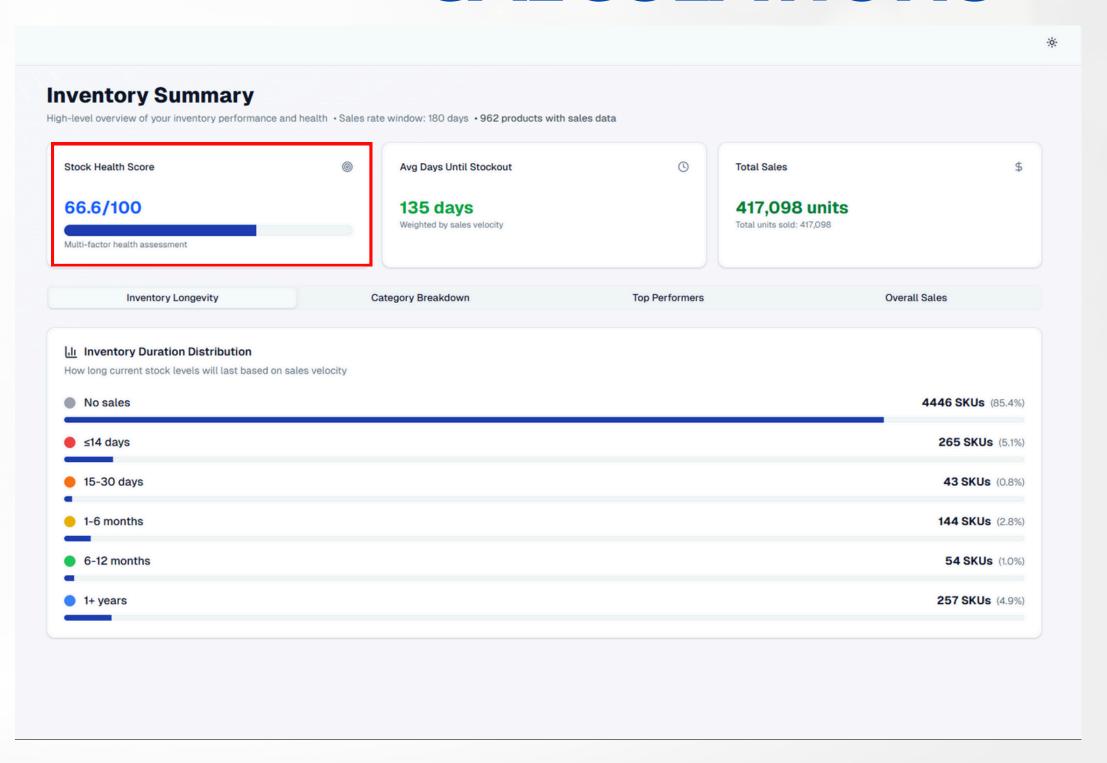


- Out stock = 0
  - ∘ Red
- Urgent days left < 7
- Low stock ≤ baseline threshold
  - Amber
- Watch days left < 30</li>
  - • Yellow
- Normal otherwise
  - o Green

### METHODOLOGY - IMPLEMENTATION STAGE

### CALCULATIONS

Factor	Max Points	Criteria		
Stock Coverage	40	Days until stockout: 90+ days = 40pts, 60-89 = 30pts, 30-59 = 20pts, 14-29 = 10pts, <14 = 0pts		
Stock Vs Reorder Point	30	Stock ≥ 2× reorder = 30pts, ≥ 1.5× = 20pts, > 1× = 10pts, ≤ reorder = 0pts		
Sales Activity	20	Last sale ≤7 days = 20pts, ≤30 = 15pts, ≤60 = 10pts, ≤90 = 5pts, >90 = 0pts		
Not Overstocke d	10	Days left ≤365 = 10pts, ≤500 = 5pts, >500 = 0pts		
Total	100	Average across all products		



# METHODOLOGY - IMPLEMENTATION STAGE CALCULATIONS

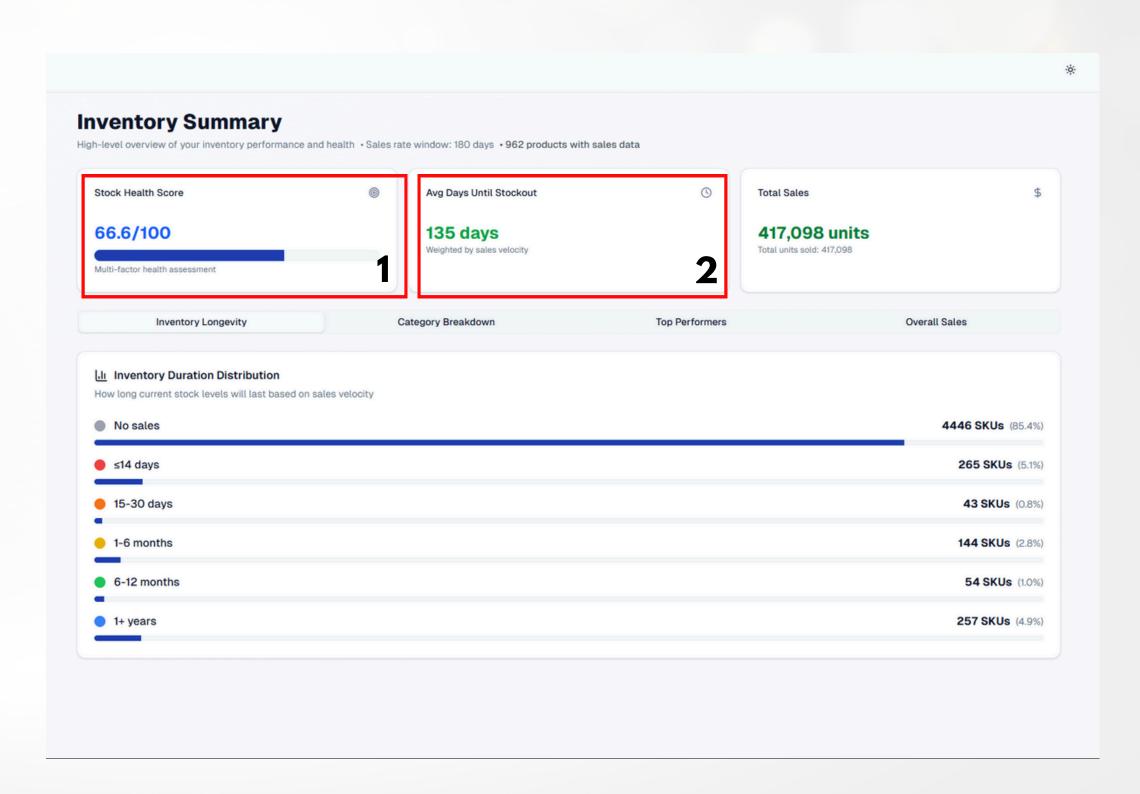
#### 1. Color Coding:

- 80-100: Green (Excellent health)
- 60-79: Blue (Good health)
- 40-59: Orange (Moderate health)
- 0-39: Red (Poor health)

2. Avg Days till Stockout: Weighted Avg = Σ(days\_left × daily\_rate) / Σ(daily\_rate) (skus with higher sales rate have higher weight)

#### Color Coding:

- < 14 days: Red (Critical)
- 14-29 days: Orange (Warning)
- 2 30 days: Green (Healthy)

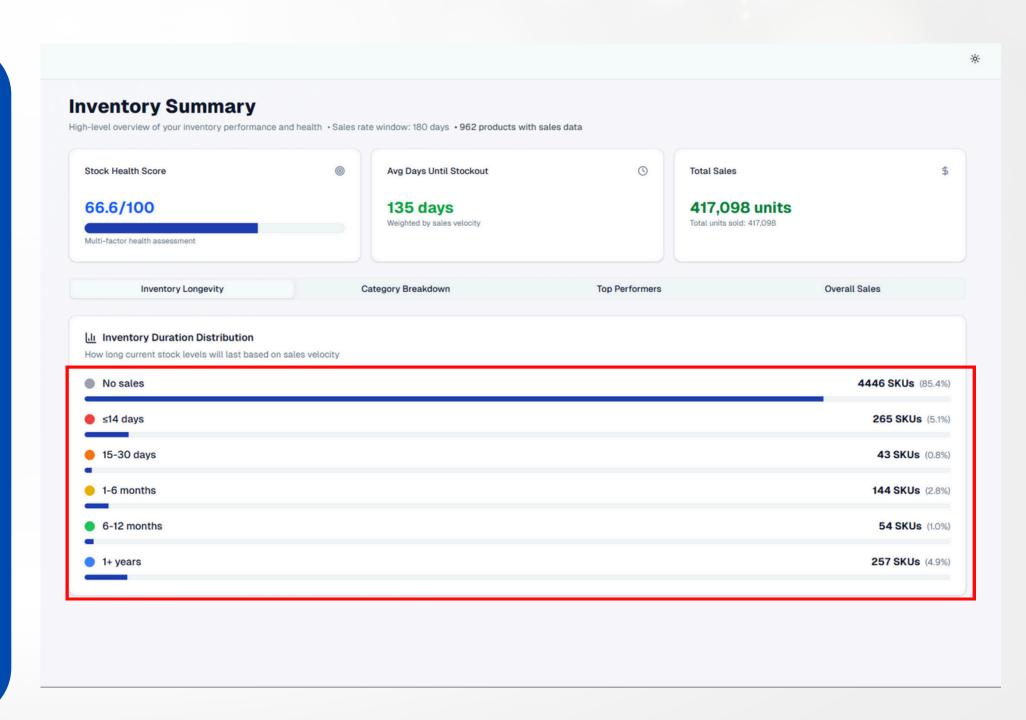


### METHODOLOGY - IMPLEMENTATION STAGE

### Inventory Duration Distribution Calculations:

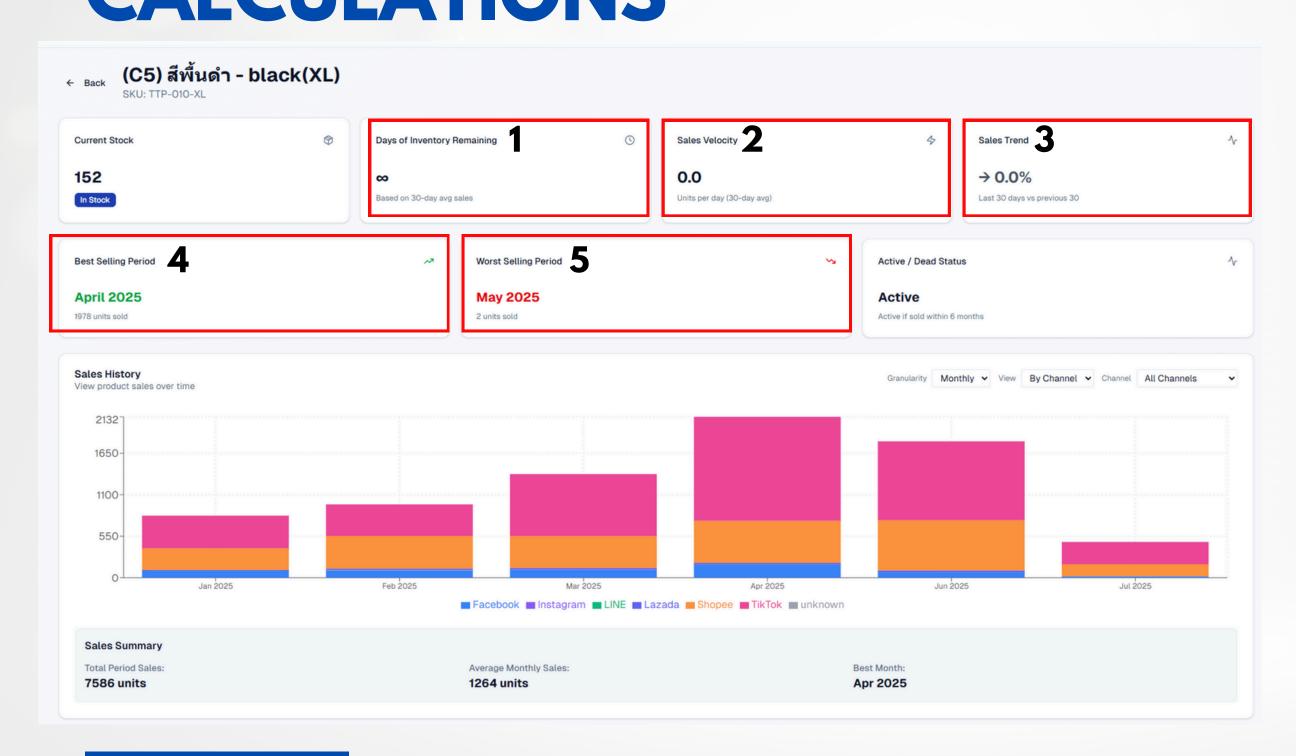
daysUntillStockout = stock / sales rate

Category	Condition	Color	Description
No sales	dailySalesRate <= 0 OR currentStock == 0	Gray	Products with no sales velocity
≤14 days	daysUntilStockout <= 14 OR	Red	Critical - stock will run out in 2 weeks or less
15-30 days	daysUntilStockout > 14 AND <= 30	Orange	Warning - stock will run out in 2-4 weeks
1-6 months	daysUntilStockout > 30 AND <= 180	Yellow	Moderate - stock will last 1-6 months
6-12 months	daysUntilStockout > 180 AND <= 365	Green	Healthy - stock will last 6-12 months
1+ years	daysUntilStockout > 365	Blue	Overstocked - stock wil last over a year



CALCULATIONS

# METHODOLOGY - IMPLEMENTATION STAGE CALCULATIONS



- 1. Days of inventory remaining: stock / sales rate of the past 30 days. 0 if stock is 0 and ∞ if no sales in the last 30 days
- 2. Sales Velocity: Avg sales rate for last 30 days
- 3. Sales Trend: (last30 previous30) / previous30) × 100 Direction:
  - Up ( † ): Trend > 5%
  - **●** Down (↓): Trend < -5%
- Stable (→): Between -5% and 5%
- 4. Best Selling Period: Month with most sales
- 5. Worst Selling Period: Month with least sales

### METHODOLOGY - IMPLEMENTATION STAGE

### **CALCULATIONS**

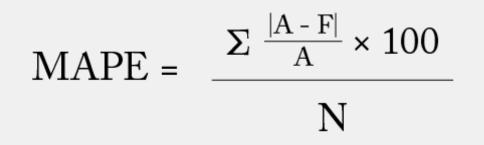
$$MAE = \frac{1}{n} \sum_{i=1}^{n} |x_i - x|$$

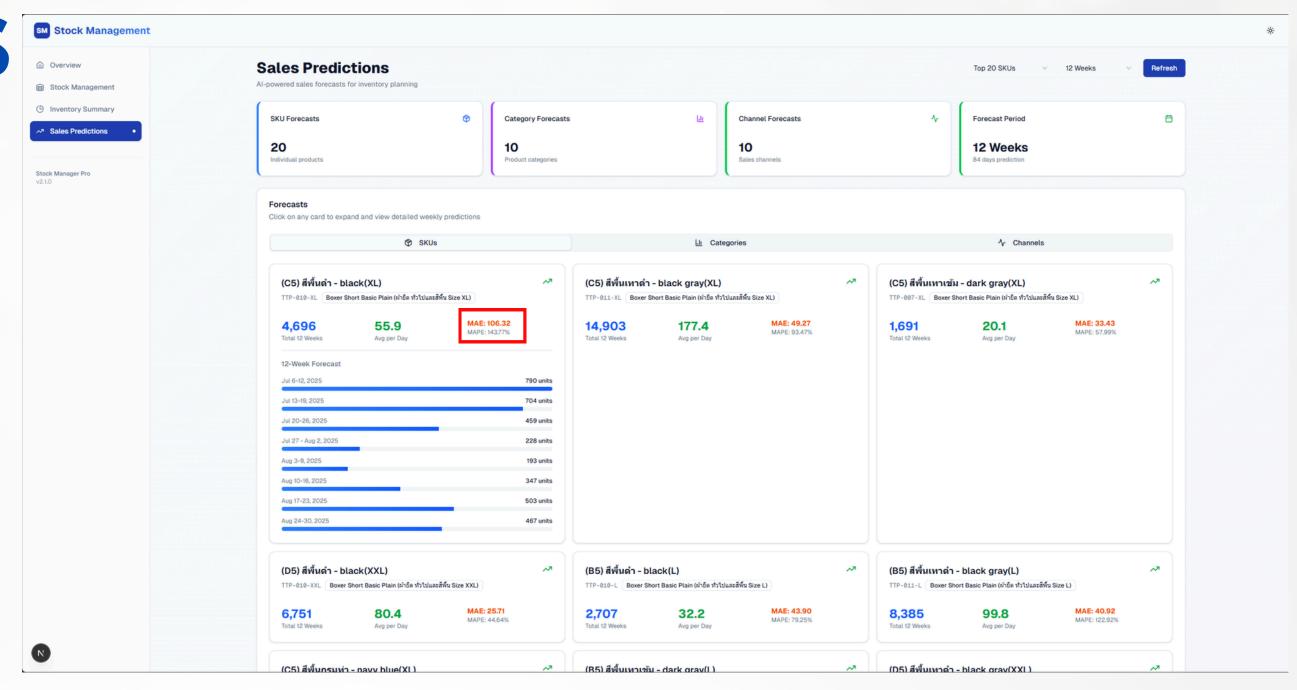
Mean Absolute Error

Xi = Predicted Value

X = Actual Value

n = Number of data points





Mean Absolute Percentage Error

F = Predicted Value

A = Actual Value

N = Number of data points

### RESULTS

1 2 3

Successfully launched a working application of the stock management website

Successfully implemented sales forecasting into the application

Successfully implement process to clean sales and stock data

### DISCUSSION LIMITATIONS

- Experienced problems while packaging the application
- Prediction is not fully accurate and can be further fine-tuned
- Relies the user manually uploading data
- The ETL process is not 100% correct and can lead to some errors in the database

# DISCUSSION FUTURE WORK

- Connecting the application directly with the company's system
- Further fine tune the prediction model
- Develop a more robust ETL system
- Explore better ways to package the application

