I2.02 - TEL Forecasting Tool

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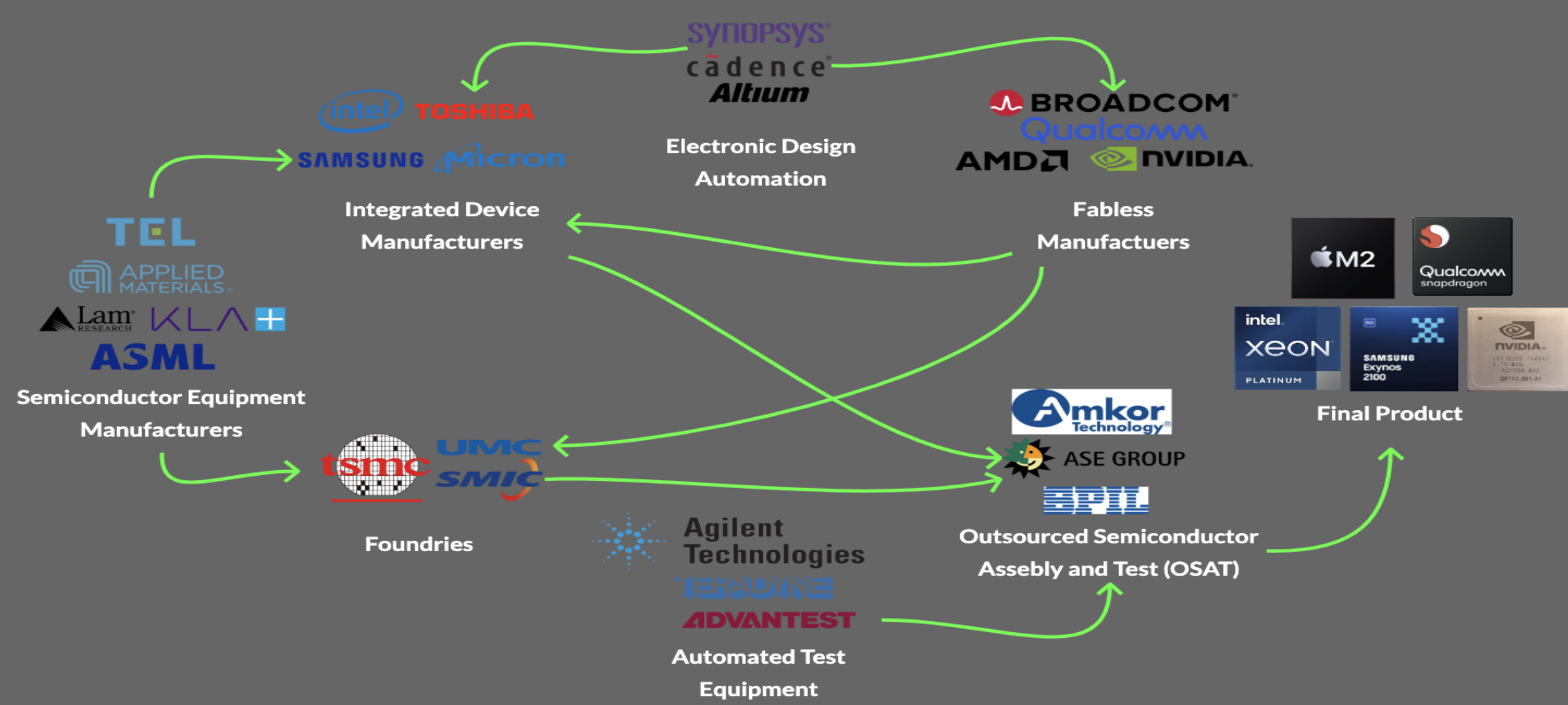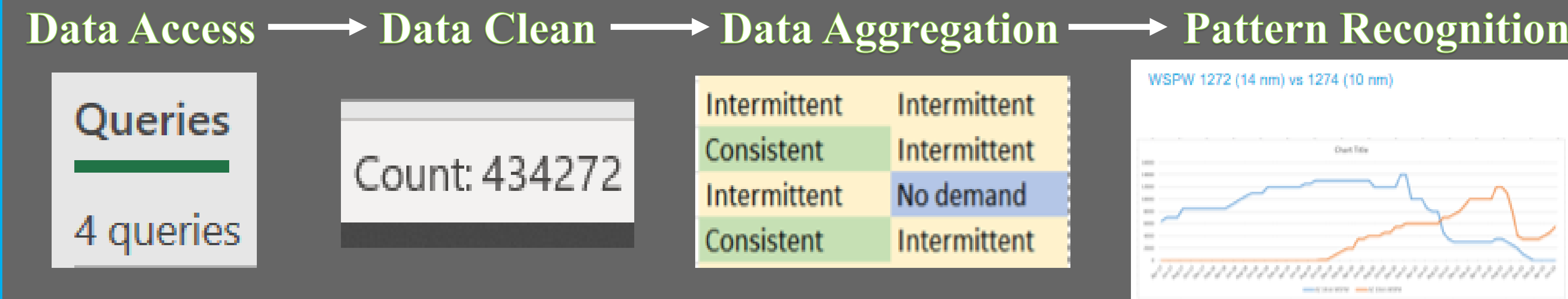
TEL — TOKYO ELECTRON

Problem Statement

TEL's absence of a dynamic method for processing raw spares data hinders demand prediction and burdens the planning team, reducing agility in responding to fluctuations in demand.
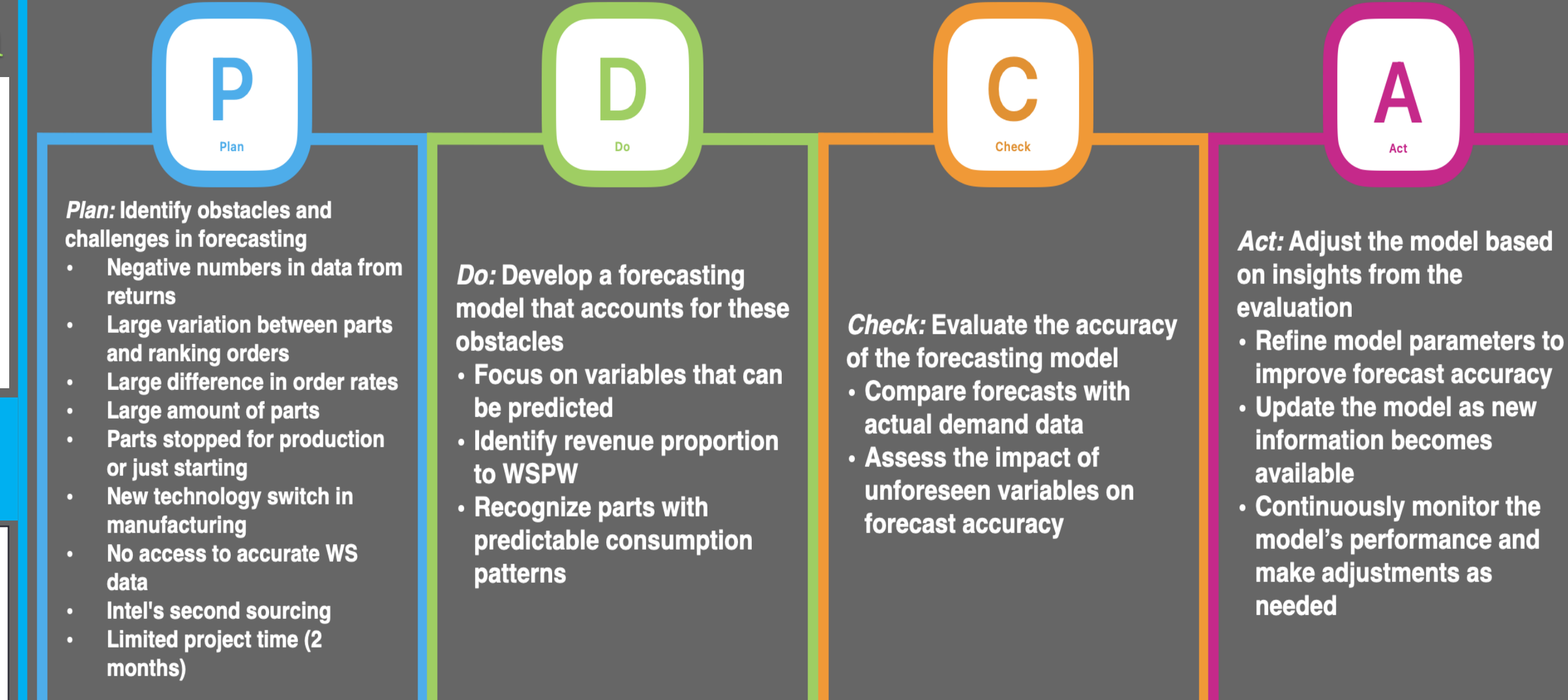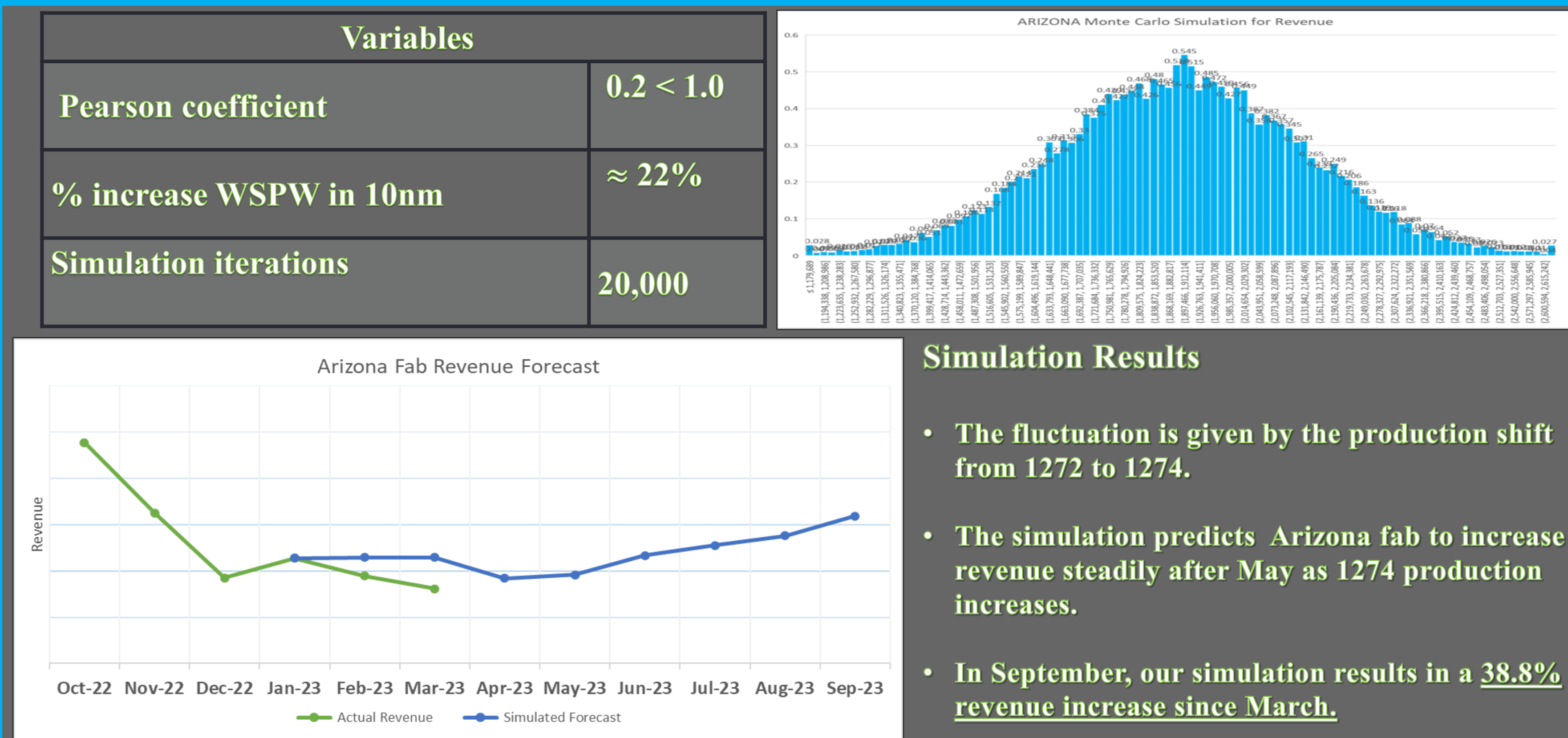
Background Information

INTERMITTENT · LUMPY · SMOOTH · ERRATIC
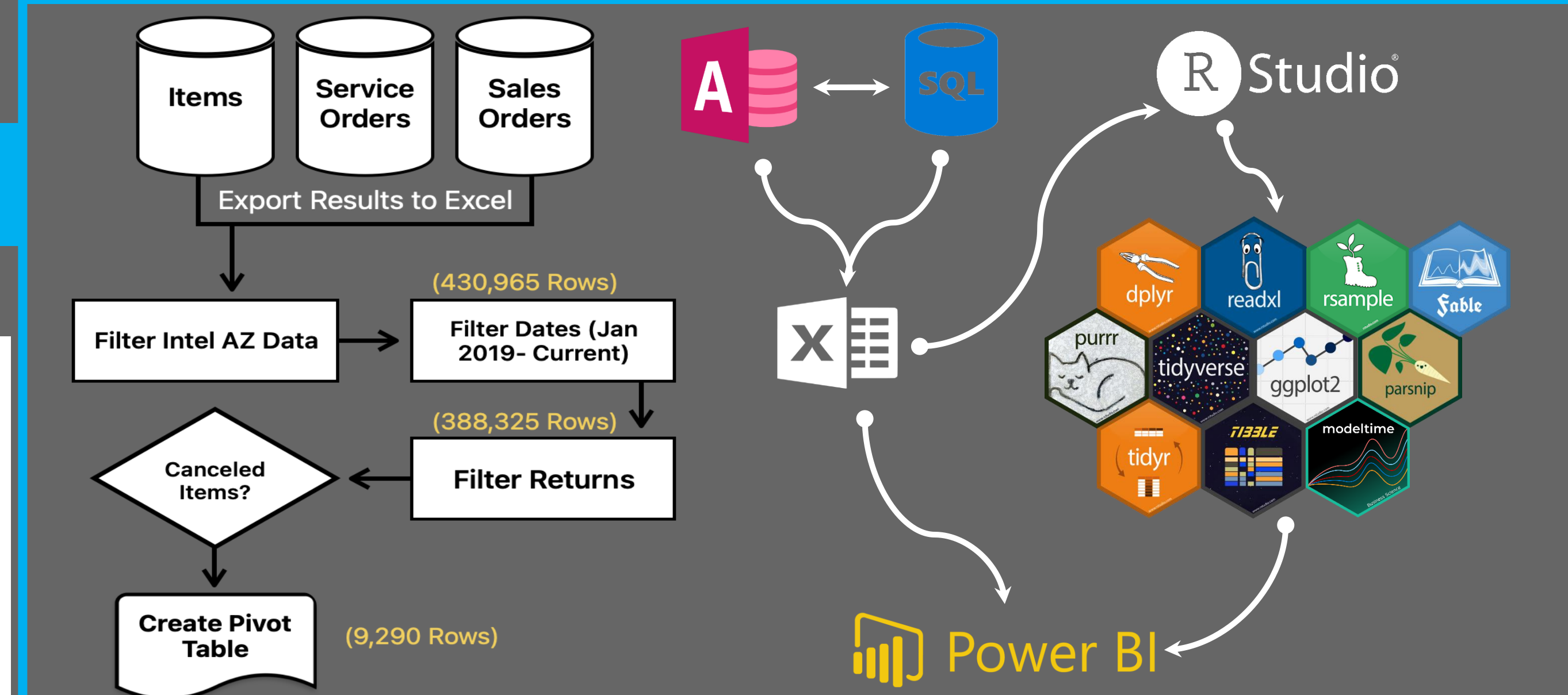
Variability in demand timing — HIGH / LOW

Variability in demand quantity — LOW / HIGH

Project Challenges

- Demand prediction
- 9500 parts, variable identification, WSPW
- Data quality issues
- Negative numbers for returns
- Data variation
- Technology switch
- Limited data access
- Intel's second sourcing
- Time constraints

Project Objectives

- Enhance spare parts demand prediction with accurate planning
- Identify and assess forecasted pattern usage
- Simulate pattern changes by adjusting forecasting factors
- Develop flexible system for managing evolving process nodes
- Plan to create Power BI dashboard for future improvements

Project Process

Data Access → Data Clean → Data Aggregation → Pattern Recognition

Queries — 4 queries

Count: 434272

Intermittent	Intermittent
Consistent	Intermittent
Intermittent	No demand
Consistent	Intermittent

WSPW 1272 (14 nm) vs 1274 (10 nm)

Multivariate Monte Carlo Simulation

Variables	
Pearson coefficient	0.2 < 1.0
% increase WSPW in 10nm	≈ 22%
Simulation iterations	20,000

ARIZONA Monte Carlo Simulation for Revenue

Arizona Fab Revenue Forecast

Simulation Results

- The fluctuation is given by the production shift from 1272 to 1274.
- The simulation predicts Arizona fab to increase revenue steadily after May as 1274 production increases.
- In September, our simulation results in a **38.8% revenue increase since March.**

Single Part Demand Forecasts in R-Studio

Test/Train Forecast:

Future Forecast: (h = 12 months)

Result Analysis

Model Type	MAE	MAPE	MASE	SMAPE	RMSE	RSQ
ARIMA	8.63	4.37%	0.43	1.09%	9.26	0.38
ARIMA W/ XGBOOST	7.75	3.94%	0.38	0.98%	8.29	0.53
ETS	16.16	7.84%	0.80	2.06%	18.45	0.58
PROPHET	6.08	3.03%	0.30	0.76%	6.58	0.88
LM	4.92	2.58%	0.24	0.63%	6.67	0.91
EARTH	8.69	4.32%	0.43	1.09%	10.08	0.52
NAIVE	20.25	9.80%	N/A	2.62%	23.31	NA

Design Approach

P — Plan: Identify obstacles and challenges in forecasting
- Negative numbers in data from returns
- Large variation between parts and ranking orders
- Large difference in order rates
- Large amount of parts
- Parts stopped for production or just starting
- New technology switch in manufacturing
- No access to accurate WS data
- Intel's second sourcing
- Limited project time (2 months)

D — Do: Develop a forecasting model that accounts for these obstacles
- Focus on variables that can be predicted
- Identify revenue proportion to WSPW
- Recognize parts with predictable consumption patterns

C — Check: Evaluate the accuracy of the forecasting model
- Compare forecasts with actual demand data
- Assess the impact of unforeseen variables on forecast accuracy

A — Act: Adjust the model based on insights from the evaluation
- Refine model parameters to improve forecast accuracy
- Update the model as new information becomes available
- Continuously monitor the model's performance and make adjustments as needed

Human Factors

- Eliminate manual calculations and reduce employee workload.
- High visibility for easy data interpretation.
- Enhanced customer satisfaction and timely supply orders.
- Ergonomic and human factors principles.
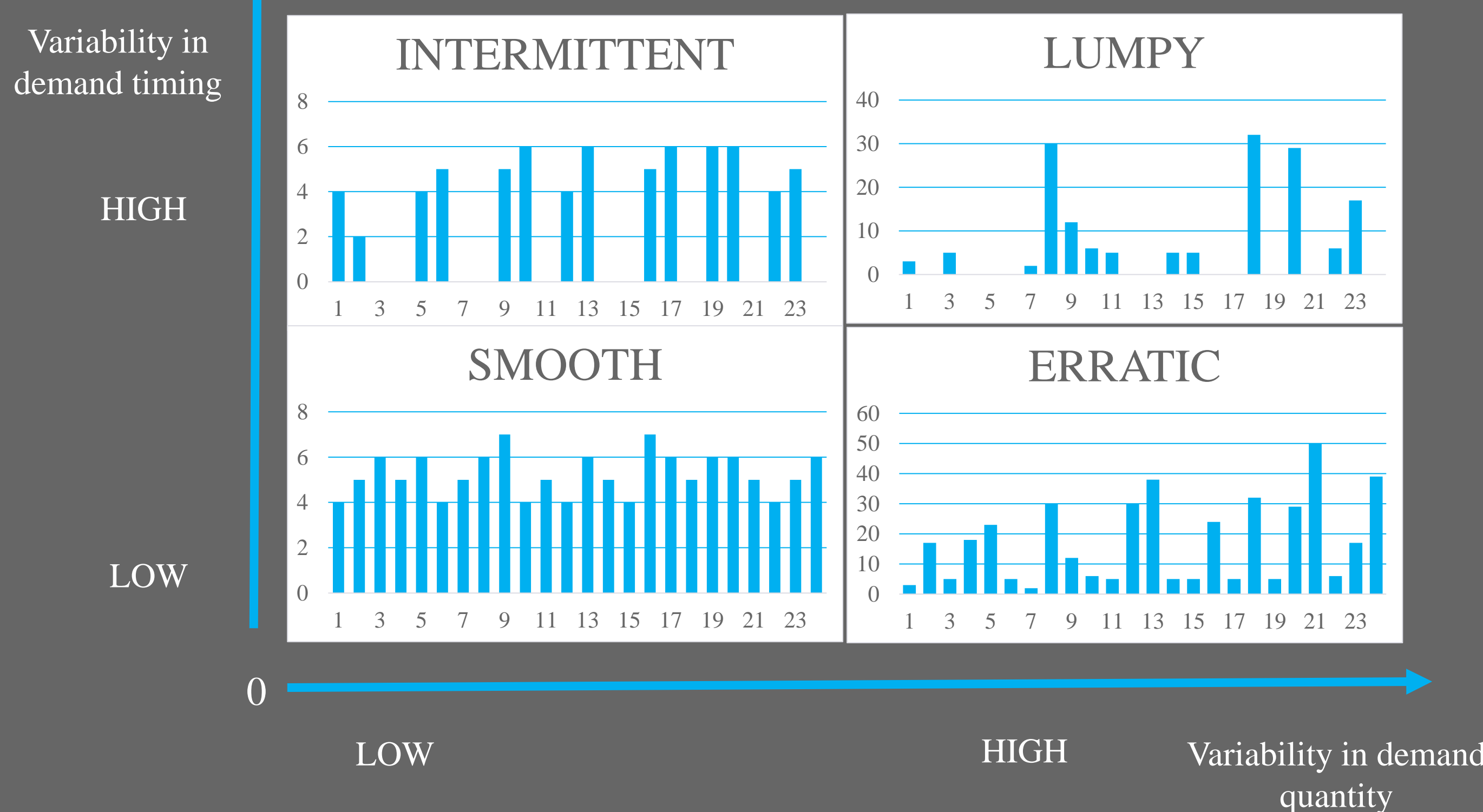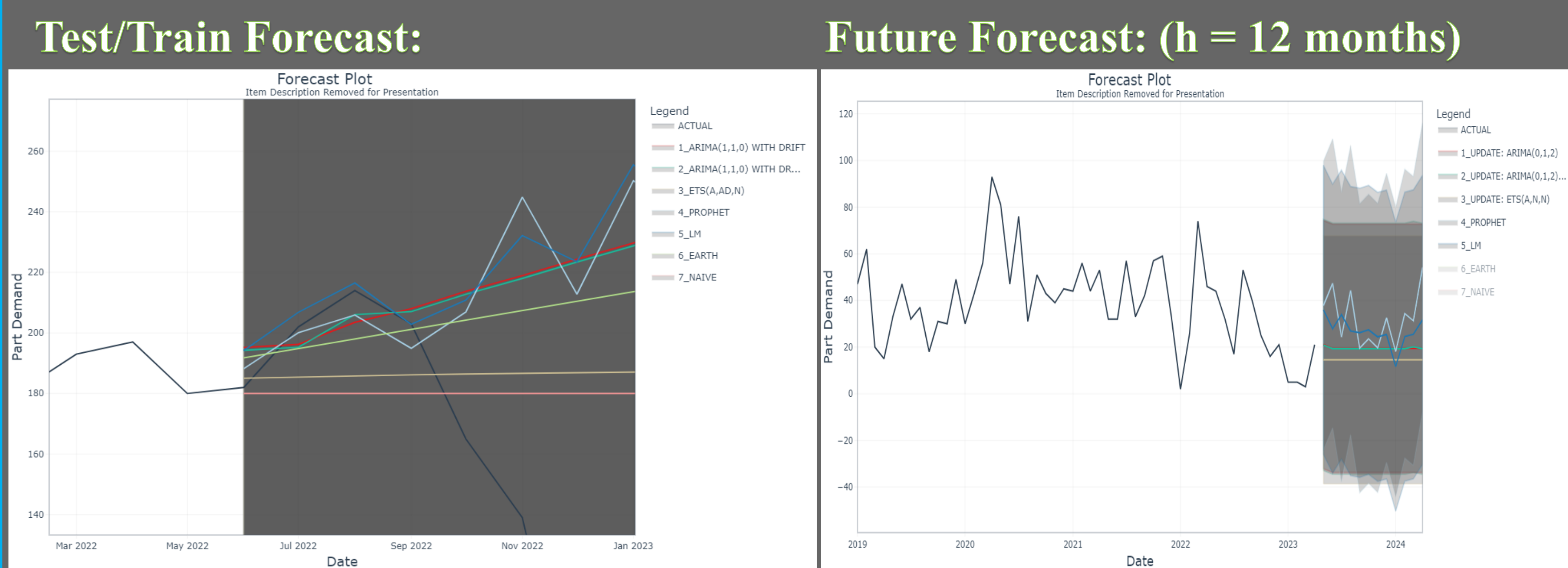
Software Applications

Items · Service Orders · Sales Orders

Export Results to Excel

Filter Intel AZ Data → (430,965 Rows) → Filter Dates (Jan 2019– Current) → (388,325 Rows) → Filter Returns → Canceled Items? → Create Pivot Table (9,290 Rows)

R Studio — dplyr, readxl, rsample, fable, purrr, tidyverse, ggplot2, parsnip, tidyr, TIBBLE, modeltime

Power BI

Team Members