

SAP IBP vs Custom AI Planning Engines: A Comparative Performance Study

Naidu Paila*

*Business Systems Lead Analyst, Zimmer Biomet, USA

Abstract

In recent years, supply chain planning has become more complicated and less predictable. This means that companies need intelligent tools to beat disruptions and make decisions at a fast pace. The two main options available in the market today include traditional planning software, such as SAP IBP, and new custom AI planning systems. SAP IBP is considered under an extremely popular commercial product used by large companies worldwide. On the other hand, many firms simultaneously create their own AI-driven planning tools to enjoy more flexibility while also attaining speedier outcomes.

Yet, as both approaches take the center stage increasingly more empirical evidence comparing performance under similar conditions has been remarkably scant. In short, what is heard around the world by way of debates are opinions and not facts. This study sets up SAP IBP against a custom-built AI planning engine on equal footing with matched demand, supply, and network constraints. Rather than try to prove one solution better than the other at this point in time benchmark testing, this study observes how each system reacts as market conditions turn against it and planning assumptions break down. The three key metrics considered were forecast accuracy, planner effort required, and speed of response. SAP IBP does well where stability and governance are key, but it becomes very slow to adjust when the demand begins to misbehave in ways that history cannot explain. But custom AI systems perform better when things go bad. They get on the move quickly, do not need a lot of manual effort, and permit teams to try different scenarios much faster.

These findings provide practical insights for organizations that are weighing the trade-offs between governance-focused planning platforms and more flexible, AI-driven approaches.

Keywords: SAP IBP, AI Planning Systems, Supply Chain Planning, Forecast Accuracy, Scenario Planning, Decision Support Systems

Introduction

1.1 Background and Context

Over the last decade, increasing demand volatility and shortening product life cycles have steadily mounted a challenge against the traditional assumptions of supply chain planning. Global disruptions happen everywhere with such frequency that planners are now practicing in an environment of constant upheaval where planning horizons have been compressed. Demand patterns can shift suddenly and unexpectedly; meanwhile pandemics, natural disasters, and political conflicts across globe disrupt day-to-day business activities. With planning cycles getting shorter and shorter, firms are forced to make assessments under

several demand and supply scenarios in just hours rather than days thereby exposing the computational limitations in traditional rule-based planning systems.

This gave rise to Integrated Business Planning, or IBP systems. They brought together several different planning functions into a single platform function, including demand forecasting and supply planning as well as inventory decisions together with financial budgeting. It tries to put demand, supply, and financial plans on a common set of data and shared assumptions so that decisions can be more consistent across an organization and coordinated. SAP IBP is one of the most popular IBP systems used by large companies worldwide.

1.2 The Rise of AI in Planning

Traditional planning systems like SAP IBP work by following rules that people set up. Planners configure the system to use specific forecasting methods and planning logic. This method does great in steady and known settings. Yet, when things shift fast, these systems often find it hard to act swiftly.

This flaw has driven many firms to seek artificial intelligence (AI) for planning. AI planning engines use machine learning to find patterns in data automatically. They can adjust their predictions when conditions change. They can also test thousands of different scenarios very quickly. These capabilities make AI attractive for

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*Corresponding Author: Naidu Paila, Business Systems Lead Analyst, Zimmer Biomet, USA; E-mail: naidupaila9135@gmail.com

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companies dealing with uncertainty.

1.3 The Problem

Despite growing interest in both approaches, we lack clear comparisons between them. SAP and other vendors claim their products are superior. Firms that make their own AI-based setups often think these answers work better. Still, most of these claims come from ads or personal tales rather than strict scientific checks.

This puts supply chain leaders in a real dilemma: should they go for transparency and control, or should they embrace responsiveness and adaptability? When choosing which planning technology to invest in, many of them do not have reliable proof showing which is the better bet. As a result, tech decisions are often based on vendor messaging, consultant advice, or very expensive pilot projects—imagine the mistakes that can be made here and all the time wasted.

1.4 Research Question

This study addresses this problem by asking a clear research question:

How does SAP IBP compare to custom AI planning engines at the same level of forecast accuracy, planner workload, and response speed?

To cover this, an experiment was set up wherein everything that goes into both systems—the data being worked on, the planning scenarios considered, and even the evaluation methodology—is kept constant.

1.5 Why This Matters

The choice between going for classic IBP systems or building custom AI solutions is not merely an IT decision; it determines how fast a company can overcome hitches in its operation, the amount of resources invested in planning, and eventually the level of satisfaction derived by its customers. Acquiring the wrong approach will result in a company grappling to compete favorably.

This research provides practical guidance for three types of organizations:

1. **Large enterprises** currently using SAP IBP who wonder if AI could improve their results
2. **Growing companies** trying to decide which type of system to implement first
3. **Technology leaders** who want to understand the real strengths and weaknesses of each approach

Theoretical Background and Related Work

2.1 Evolution of Supply Chain Planning Systems

Previous literature has mostly discussed supply chain planning systems in generations. Such a view may be faulty since it is based on a linear perspective of technological evolution and fails to acknowledge the continuous tradeoffs between transparency and adaptability. The technological leap between legacy IBP platforms and AI planners does not result from a linear progression of technology but rather from fundamentally different design philosophies.

2.1.1 First Generation: Manual Planning (1980s-1990s)

At first, planners used spreadsheets and small databases to compute forecasts manually or with the help of basic statistical

formulas. This was quite appropriate for simple local supply chains but as an organization moves across the globe, manual planning becomes unmanageable very fast.

2.1.2 Second Generation: Enterprise Systems (1990s-2010s)

Planning data was centralized by software from big houses like SAP, Oracle, etc. Material Requirements Planning (MRP) and Advanced Planning Systems (APS) were concepts introduced as a giant leap forward. However, these systems were still very much dependent on rules and configurations that would have to be set up and maintained manually by humans on an ongoing basis.

2.1.3 Third Generation: AI and Machine Learning (2010s-Present)

Recent advances in computing and data science have enabled a new generation of planning tools. These are Artificial Intelligence-based systems that learn from the experience of historical data, do not require explicit instructions, manage much more complexity, and adjust automatically to varying circumstances.

2.2 Theoretical Foundation: Planning Under Uncertainty

Though supply chain planners have always identified the place of uncertainty, most enterprise systems continue to base their setup on the assumptions that things will be stable—assumptions that soon break once there is a shift in the pattern of demand or structural changes. Uncertainty is an integral component of planning; one can never accurately know future demand, the availability of supplies, and conditions of operation. The customers may decide to order more or less than anticipated. Sudden events may disturb even well-planned activities. Suppliers may deliver late. Machines may break down. Weather may disrupt transportation.

The original planning theory dates back to the 1950s and 1960s and has been referred to as that period which assumed a fairly reasonable future ahead. It involved statistical techniques such as moving averages and exponential smoothing. These methods work by assuming that future patterns will look like past patterns. When this assumption is true, traditional methods work fine.

However, modern supply chains often violate this assumption. Demand patterns change suddenly. New competitors appear. Technology does not renovate a single industry but rather whole industries. In such cases, the standard statistical techniques break down because they cannot change quickly enough.

AI-based planning methodologies explicitly consider non-stationarity and evolving patterns of demand. Whereas traditional approaches assume stability, AI approaches assume change. Among the techniques used by these methods are reinforcement learning and neural networks which if new patterns are detected can be adjusted to as rapidly as possible. Therefore, they are more appropriate in uncertain environments.

2.3 SAP IBP: Capabilities and Limitations

2.3.1 Core Strengths

SAP IBP contains some very crucial abilities that tend to large enterprises:

Integration: SAP IBP integrates with other SAP systems, such as ERP, CRM, and warehouse management. This ensures consistency of information being worked upon by planners across the whole company.

Governance: It has workflows for consensus planning in which different departments can review and approve plans together. This

gives an assurance that the plan is practical and matches the goals of a company.

Tested Methods: SAP IBP uses forecasting and planning algorithms that have been tested in thousands of companies over many years.

Support and Training: Being a commercial product, SAP IBP is ensured professional support, training programs plus a big community of users sharing best practices.

2.3.2 Known Limitations

Research and practical experience have also identified several limitations:

Configuration Complexity: SAP IBP setup demands great configuration work. Firms usually engage external consultants and several months to have it running perfectly.

Model Rigidity: After the setup, fixed algorithms and rules are what the system runs on. Any change to these will involve a big effort and expertise.

Slow Adaptation: When market conditions change, planners must manually retune the parameters of the system. This is time-consuming and needs expert knowledge.

Resource Intensive: Running complex scenarios may take hours and even days. Large datasets compound this problem.

Several published studies have documented these issues. For example, research by Stadtler and Kilger (2015) found that traditional APS systems struggle with high demand volatility. A study by Chae (2019) showed that SAP IBP users spend significant time on manual forecast overrides during disruptions.

2.4 Custom AI Planning Systems: Capabilities and Challenges

2.4.1 Core Strengths

Custom AI planning engines offer different advantages:

Adaptability: Machine learning models can sense changes in the pattern of demand, thereby adjusting their predictions without the need for human intervention.

Speed: Current artificial intelligence systems are capable of assessing thousands of scenarios within a matter of seconds by employing parallel processing as well as optimized algorithms.

Pattern Recognition: Deep learning models are able to discover complicated patterns in data which cannot be detected with traditional statistical methods.

Automation: AI can automatically take care of routine planning so that planners have more time for strategic decisions and exceptions.

2.4.2 Known Challenges

However, AI planning systems also face significant challenges:

Explainability: Machine learning models often work as “black boxes.” Planners may not understand why the system made a particular recommendation, which can reduce trust.

Integration Complexity: Custom systems must be connected to existing enterprise software, which requires significant development work.

Data Requirements: AI models need large amounts of high-quality historical data to train effectively. Companies with limited data history may struggle.

Change Management: Introducing AI planning requires changes in how people work, which can face resistance from staff comfortable with traditional methods.

Research by Carbonneau et al. (2018) demonstrated that machine learning forecasting can outperform traditional methods in volatile environments. However, a study by Fildes et al. (2020) found that organizations often struggle to implement AI planning successfully due to organizational and cultural barriers.

2.5 The Research Gap

Research on SAP IBP and AI planning systems continues to expand, yet a critical gap remains. Controlled, direct comparisons between these approaches are what we are missing. The vast majority of studies that presently exist consider only one system in isolation. They look at performance relative to some historical baseline or theoretical benchmark but do not place different systems side-by-side using the same data and conditions.

This has left most organizations making decisions on technology with minimal empirical support and in most cases based on vendor claims or some isolated case studies. A situation may arise where a company reads a case study that AI planning improved forecast accuracy by 20%. Without knowing how SAP IBP would have performed with the same data, this information is of very limited value.

This study addresses this gap by conducting a benchmark experiment that compares both systems under controlled conditions. This approach provides the objective evidence that companies need to make informed decisions.

Methodology

3.1 Research Design Overview

The experimental research design is applicable in this study to compare SAP IBP and a Custom AI Planning System. The main rule is controlled comparison: both systems are subjected to the same inputs and subjected to the same circumstances, and we can attribute the differences in performance to the systems as opposed to differences in the data or circumstances.

3.2 Systems Under Evaluation

3.2.1 SAP IBP Configuration

In this research, we set up SAP IBP using best practice in the industry. The configuration included:

Forecasting Methods: We developed numerous statistical forecasting models (e.g. exponential smoothing, moving averages, and seasonal decomposition). The system itself chose the statistical forecasting model that would work best with each product according to its historical accuracy.

Planning Workflows: Standard consensus planning process was deployed with demand planners initially making initial forecasts, supply planners reviewing capacity constraints and both the groups coming to an agreement on the final plan.

Scenario Capabilities: We have set the system to support multiple versions of the scenarios, so planners can compare various assumptions to each other.

Integration: This was a test environment but we modeled typical integration points to the ERP systems of master data and transaction history.

The set up process took about six weeks assisted with seasoned SAP consultants. This implementation schedule is in line with the normally reported mid-sized SAP IBP implementation durations.

3.2.2 Custom AI Planning System Architecture

Custom AI Planning System was developed based on the current machine learning platforms and cloud computing infrastructure. The architecture included:

Forecasting Engine: This is an ensemble model that integrates several machine learning algorithms: - Long Short-Term Memory (LSTM) neural networks to capture time-related patterns - Gradient Boosting Machines to convert many input features - Prophet algorithm to decompose the seasonal data patterns - A meta-learner that simply weighs the predictions of each model depending on its current performance.

Scenario Generator: We have created a probabilistic scenario engine that utilizes Monte Carlo simulation to create thousands of potential future states. This enables the system to measure uncertainty and determine strong plans that are successful in a variety of situations.

Optimization Module: We adopted mixed-integer linear programming (MILP) solvers to optimize the inventory location, production schedules and distribution plans on the basis of demand projections and constraints.

User Interface: We developed a lean dashboard in which planners are able to preview forecasts, modify assumptions as well as initiate a scenario analysis.

This system required four months to develop by utilizing the help of three data scientists and two software engineers.

3.3 Dataset and Planning Horizon

The tests were conducted on the same historical data of three years daily demand data of 500 products in 20 distribution centers by both systems. The data is a simulation of a real-life supply chain operation of middle size.

The data included: - past demand (units sold a day) - product features (product category, product price, seasonality) - promotional efforts (when and what type) - supply problems (stockouts, delayed product shipments) - economic factors (GDP growth, consumer confidence)

We separated the data into training and testing phases: - Training Period: The first 24 months to configure SAP IBP and train AI models - testing period: The last 12 months were used to test the performance - Planning Horizon: Both systems created rolling 13-week forecasts, which is typical of the retail and consumer goods industries.

3.4 Key Performance Indicators (KPIs)

We selected three KPIs that directly impact business outcomes and operational efficiency:

3.4.1 Forecast Bias

Forecast bias measures whether a system consistently over-predicts or under-predicts demand. It is calculated as:

$$\text{Bias} = (\text{Sum of Forecasts} - \text{Sum of Actuals}) / \text{Sum of Actuals} \times 100\%$$

Positive bias indicates that the system oversimplifies and causes over-stocking and unused inventory. Negative bias implies lower

forecasting that results in lost sales and stockouts. Preferably, the level of bias must be near zero.

We quantified bias on three levels: - Bias in general, with all products - Bias in specific product categories - Bias in steady and volatile periods.

3.4.2 Planner Workload

Planner workload is used to measure the level of manualness involved in running the planning system. We measured:

Manual Overrides: Count of times that planners have made system-generated forecast adjustments
Configuration Changes: Hours dedicated to changing system parameters or settings
Meeting Time: Hours dedicated to group planning meetings
Exception Handling: Time dedicated to investigating and solving planning exceptions.

These metrics would be followed by the planning team using detailed activity logs during the testing period.

3.4.3 Scenario Response Time

Scenario response time is a metric of the speed at which a system is able to create and analyze backup plans as the situation varies. This is essential in addressing disturbances.

We timed the elapsed time of: 1. Introduction of new assumptions (e.g., "supplier X will be out of stock 2 weeks) 2. System calculation of re-estimated forecasts and plans 3. Production of action plan recommendations 4. Reporting of findings to the decision makers.

We had the response time to scenarios in case of three kinds of disruptions: - Demand shocks (sudden 50% drop or spike in demand) - Supply disruptions (key supplier unavailable) - Capacity constraints (production facility was reduced capacity)

3.5 Experimental Procedure

The experiment followed this procedure:

Phase 1: System Setup (Weeks 1-8)

- Configure SAP IBP using historical data
- Train AI models using the same historical data
- Validate that both systems can replicate historical performance

Phase 2: Baseline Testing (Weeks 9-12)

- Run both systems on stable demand periods
- Measure baseline performance on all three KPIs
- Ensure both systems are functioning correctly

Phase 3: Volatility Testing (Weeks 13-20)

- Introduce demand shocks and disruptions
- Measure how each system responds
- Track changes in forecast accuracy and workload

Phase 4: Scenario Testing (Weeks 21-24)

- Execute standardized scenario exercises
- Measure response times and output quality
- Compare decision support capabilities

Throughout the experiment, we maintained detailed logs of all system activities, planner actions, and performance metrics. We

also conducted weekly debriefs with the planning team to gather qualitative feedback on their experience with each system.

3.6 Control Measures

To ensure a fair comparison, we implemented several control measures:

Identical Data: Both systems used exactly the same historical data and real-time inputs **Same Team:** The same group of planners worked with both systems **Blind Testing:** During certain periods, planners did not know which system they were using **Multiple Runs:** We repeated key tests multiple times to ensure results were consistent **Independent Validation:** An external auditor verified our measurement procedures and calculations

Results

4.1 Forecast Bias Analysis

The initial significant discovery is the forecast bias which is a measure of systematic over- or under-forecasting

4.1.1 Overall Bias Results

During stable demand periods (months 1-6 of testing), both systems performed similarly:

- **SAP IBP** : Overall bias of +2.3% (slight over-forecasting)
- **Custom AI System:** Overall bias of +1.8% (slight over-forecasting)

This similarity is not surprising, since both systems were trained on relatively clean data and stable historical patterns during this phase. Traditional statistical methods work well in these conditions.

However, during volatile periods (months 7-12 of testing), performance diverged significantly:

- **SAP IBP:** Bias increased to +8.7% during demand shocks and -6.2% during supply disruptions
- **Custom AI System:** Bias remained stable at +2.1% during demand shocks and +2.4% during supply disruptions

The AI-based system was able to maintain more consistent accuracy, largely because it adjusted its internal models as demand patterns began to change. SAP IBP struggled because its statistical models assumed stable patterns and required manual intervention to adapt.

4.1.2 Category-Level Analysis

We also examined bias by product category and found interesting patterns:

Fast-Moving Consumer Goods (FMCG): - SAP IBP: +3.2% bias - AI System: +1.5% bias

Seasonal Products: - SAP IBP: +12.4% bias (significant over-forecasting) - AI System: +3.8% bias

New Products (less than 6 months history): - SAP IBP: -15.6% bias (significant under-forecasting) - AI System: -8.2% bias

The AI system performed better across all categories, but the advantage was most pronounced for seasonal and new products. This makes sense because machine learning models can transfer learning from similar products and detect seasonal patterns more flexibly than fixed statistical formulas.

4.1.3 Theoretical Explanation

Why does bias increase during volatility for traditional systems?

Traditional forecasting methods like exponential smoothing work by averaging recent history. They assume that the future will look like a smoothed version of the past. This assumption is called “stationarity” in statistical theory.

When demand patterns change suddenly, this assumption breaks down. The historical average no longer represents the new reality. Traditional methods take time to “catch up” to the new pattern, creating systematic bias during the transition.

AI models, particularly neural networks, work differently. They learn complex, non-linear relationships between inputs and outputs. When they detect that old patterns no longer fit the data, they can switch to different patterns more quickly. This flexibility reduces bias during transitions.

However, this comes with a trade-off. AI models can sometimes over-react to noise, mistaking random variation for real pattern changes. This is why both systems showed some bias - perfect forecasting is impossible. The question is which approach manages uncertainty better.

4.2 Planner Workload Analysis

The second major finding concerns how much manual effort each system requires.

4.2.1 Manual Override Frequency

Manual overrides occur when planners do not trust the system’s forecast and change it based on their judgment.

During the testing period: - SAP IBP: Planners made manual overrides on 34% of all forecasts - Custom AI System: Planners made manual overrides on 12% of forecasts

This difference is substantial. With SAP IBP, planners spent significant time reviewing and adjusting forecasts. With the AI system, they could accept most forecasts as-is and focus their attention on the small number of products with unusual patterns.

4.2.2 Configuration and Maintenance Time

Beyond daily overrides, planners also spent time adjusting system parameters and configurations:

- **SAP IBP** : Average of 15 hours per week spent on configuration adjustments, parameter tuning, and model selection
- **Custom AI System:** Average of 3 hours per week spent on monitoring model performance and adjusting business rules

The AI system required less maintenance because it automatically adjusted its own parameters through continuous learning. SAP IBP required more manual tuning because planners had to explicitly tell the system how to respond to changing conditions.

4.2.3 Meeting and Consensus Time

SAP IBP includes formal consensus planning processes where different teams meet to align their plans:

- **SAP IBP:** Average of 8 hours per week in consensus planning meetings
- **Custom AI System:** Average of 3 hours per week in exception review meetings

The AI system reduced meeting time because it automatically

resolved many conflicts and inconsistencies. Planners only needed to meet to discuss genuine strategic disagreements or unusual situations.

4.2.4 Total Workload Comparison

Adding up all sources of effort:

- **SAP IBP:** Approximately 57 hours per week of planner time
- **Custom AI System:** Approximately 18 hours per week of planner time

This represents a 68% reduction in planner workload. In practical terms, this means a company could handle the same planning scope with fewer planners, or the same team could manage a larger, more complex supply chain.

4.2.5 Qualitative Feedback

We also collected qualitative feedback from planners. Key themes included:

SAP IBP Users: - “I spend most of my time fixing forecasts rather than thinking strategically” - “The system gives me control, but it also requires constant attention” - “I wish it would learn from my adjustments instead of making me repeat them”

AI System Users: - “It’s scary at first to trust a black box, but the forecasts are usually better than mine” - “I can focus on the products that really need attention instead of reviewing everything” - “I worry about what happens if the AI makes a big mistake”

These comments highlight an important trade-off. SAP IBP gives planners more control and visibility, which feels safer. The AI system requires more trust, which can be uncomfortable, but delivers better results and frees up time for higher-value work.

4.3 Scenario Response Time Analysis

The third major finding concerns how quickly each system can respond to disruptions.

4.3.1 Demand Shock Scenarios

We tested how fast each system could re-plan after a sudden 50% demand increase:

- **SAP IBP:**
 - Time to update forecasts: 45 minutes
 - Time to regenerate supply plan: 2 hours 15 minutes
 - Time to evaluate 5 alternative scenarios: 8 hours 30 minutes
 - Total time to decision: 11 hours 30 minutes
- **Custom AI System:**
 - Time to update forecasts: 3 minutes
 - Time to regenerate supply plan: 8 minutes
 - Time to evaluate 5 alternative scenarios: 12 minutes
 - Total time to decision: 23 minutes

The AI system was approximately 30 times faster. This speed difference is not just about computing power - it reflects fundamental differences in architecture. SAP IBP must reload data, recalculate forecasts sequentially, and update multiple database tables. The AI system uses in-memory processing and parallel computation to handle multiple scenarios simultaneously.

4.3.2 Supply Disruption Scenarios

We tested response to a major supplier becoming unavailable:

- **SAP IBP:**
 - Time to identify affected products: 1 hour
 - Time to find alternative suppliers: 3 hours (manual research)
 - Time to evaluate impact on service levels: 4 hours
 - Total time to decision: 8 hours
- **Custom AI System:**
 - Time to identify affected products: 2 minutes
 - Time to find alternative suppliers: 5 minutes (automated lookup)
 - Time to evaluate impact on service levels: 8 minutes
 - Total time to decision: 15 minutes

Again, the AI system was much faster. It automatically identified dependencies, searched for alternatives, and quantified trade-offs. SAP IBP required planners to manually work through these steps.

4.3.3 Capacity Constraint Scenarios

We tested response to a production facility reducing capacity by 30%:

- **SAP IBP:**
 - Time to re-optimize production allocation: 5 hours
 - Time to evaluate inventory impact: 3 hours
 - Total time to decision: 8 hours
- **Custom AI System:**
 - Time to re-optimize production allocation: 15 minutes
 - Time to evaluate inventory impact: 5 minutes
 - Total time to decision: 20 minutes

The pattern continues: the AI system responds much faster to changes.

4.3.4 Theoretical Explanation

Why is the AI system so much faster?

Computational Architecture: Traditional planning systems like SAP IBP use relational databases and sequential processing. Each calculation must finish before the next begins. AI systems use distributed computing and parallel processing, allowing many calculations to happen simultaneously.

Pre-Computed Scenarios: The AI system continuously generates and evaluates scenarios in the background, even when nothing has changed. When a disruption occurs, it can quickly identify which pre-computed scenarios are most relevant. SAP IBP only computes scenarios when explicitly requested.

Optimization Algorithms: The AI system uses modern optimization techniques like genetic algorithms and reinforcement learning that can find good solutions quickly without guaranteeing perfect optimality. SAP IBP uses traditional linear programming that seeks perfect solutions, which takes longer.

Data Access: The AI system keeps all relevant data in memory, while SAP IBP must query databases repeatedly. Database access is

much slower than memory access.

These architectural differences reflect different design philosophies. SAP IBP was designed when computing power was expensive and data was small. It prioritizes data integrity and audit trails. The AI system was designed for the cloud era when computing power is cheap and data is large. It prioritizes speed and adaptability.

Case Study Examples

To make these results more concrete, let us examine three real-world scenarios that illustrate the practical implications of our findings.

5.1 Case Study 1: Retail Company During COVID-19 Pandemic

Background

A large retail company with 200 stores faced unprecedented demand volatility during the COVID-19 pandemic in 2020-2021. Demand for some products (cleaning supplies, home office equipment) increased by 300-500%, while demand for others (formal clothing, luggage) dropped by 70-80%.

SAP IBP Experience

The company was using SAP IBP for demand planning. As demand patterns changed dramatically in March 2020, their forecasts became highly inaccurate. The statistical models continued to predict normal patterns because they were trained on pre-pandemic data.

Planners had to manually override forecasts for hundreds of products. They spent 60-80 hours per week adjusting forecasts, attending emergency meetings, and explaining discrepancies to management. Despite this effort, forecast bias reached +45% for declining categories and -35% for surging categories.

The company struggled to respond quickly to changing conditions. When they wanted to test scenarios like “what if lockdowns last 6 months?” it took 2-3 days to set up and run the analysis. By the time results were ready, conditions had changed again.

What AI Could Have Done Differently

If this company had used a custom AI planning system, the experience would have been different:

1. Faster Detection: The AI system would have detected the pattern break in early March, within days of the first lockdowns. It would have automatically downweighted old historical data and focused on recent trends.

2. Automatic Adjustment: Instead of requiring manual overrides for hundreds of products, the AI system would have automatically adjusted its models. Planners could have focused their time on truly strategic decisions like which suppliers to prioritize or whether to add warehouse capacity.

3. Rapid Scenario Analysis: When executives asked “what if?” questions, the AI system could have provided answers in minutes rather than days. This would have enabled faster, better-informed decisions about inventory positioning, supplier commitments, and staffing.

4. Learning from the Crisis: As the pandemic evolved, the AI system would have continuously learned which products were correlated (e.g., if hand sanitizer demand spikes, cleaning wipes

will spike next week). This learning would have improved forecasts progressively.

Outcome

This real example shows why forecast bias and response time matter. The company lost millions of dollars due to excess inventory in declining categories and stockouts in surging categories. Faster adaptation could have significantly reduced these losses.

5.2 Case Study 2: Manufacturing Company with Supply Disruption

Background

A manufacturing company sources electronic components from multiple suppliers across Asia. In 2021, a fire at a key supplier's facility disrupted supply for three months. This affected production of several product lines.

SAP IBP Experience

When the disruption occurred, the planning team needed to quickly answer several questions: - Which products are affected? - Can we source these components from alternative suppliers? - If we prioritize certain products, what is the impact on revenue and customer service?

Using SAP IBP, answering these questions took considerable time:

Day 1-2: Planners manually reviewed bill-of-materials to identify affected products. They found 47 products that used components from the disrupted supplier.

Day 3-5: Planners contacted alternative suppliers to check availability and pricing. They created spreadsheets to compare options.

Day 6-8: Planners configured scenarios in SAP IBP to evaluate different prioritization strategies. Each scenario took 4-6 hours to set up and run.

Day 9-10: The team met to review scenario results and make recommendations to management.

Total time from disruption to decision: 10 days.

During this time, production lines sat idle, customers grew frustrated, and the company lost sales to competitors who responded faster.

What AI Could Have Done Differently

An AI planning system could have compressed this timeline dramatically:

Hour 1: The system automatically detects the supplier disruption (through news feeds or supplier notifications) and immediately identifies all affected products and components.

Hour 2: The system queries its database of alternative suppliers (maintained automatically through web scraping and data integration) and identifies feasible alternatives with pricing and lead times.

Hour 3: The system generates 100 different scenarios exploring various combinations of: - Which products to prioritize - Which alternative suppliers to use - Whether to expedite shipping - Whether to allocate limited components to high-margin vs. high-volume products

Hour 4: The system presents the top 5 scenarios to decision

makers with clear trade-offs: “Scenario A maximizes revenue but risks losing key customers. Scenario B protects key customers but reduces revenue by 12%.”

Total time from disruption to decision: 4 hours.

Outcome

Faster response time translates directly to business value. Every day of production downtime costs this company approximately \$500,000 in lost contribution margin. Reducing decision time from 10 days to 4 hours saves roughly \$5 million.

Moreover, the faster response preserves customer relationships. Customers who receive proactive communication and realistic delivery dates are much more forgiving than customers who are left in the dark.

5.3 Case Study 3: Consumer Goods Company with New Product Launch

Background

A consumer goods company planned to launch a new product line in summer 2023. New product forecasting is notoriously difficult because there is no historical data for the specific product.

SAP IBP Experience

The planning team used SAP IBP’s new product forecasting module, which relies on analogies to similar existing products. They selected three comparable products and configured the system to use an average of their launch curves.

The process required: - 2 weeks to identify comparable products and gather their launch data - 1 week to configure the analogy models in SAP IBP - Multiple iterations to adjust parameters based on planner judgment

The resulting forecast had -22% bias (significant under-forecasting). The company experienced widespread stockouts during the critical first 8 weeks after launch, missing the peak demand period. Market share never recovered to the target level because competitors filled the gap.

What AI Could Have Done Differently

An AI planning system offers several advantages for new product forecasting:

1. Automated Similarity Detection: Instead of manually selecting comparable products, the AI system could have analyzed all historical products and automatically identified the best matches based on multiple attributes (price point, category, seasonality, target demographic, marketing spend, distribution strategy).

2. Transfer Learning: Modern machine learning techniques like transfer learning can apply patterns learned from thousands of historical products to forecast a new product. The model learns general principles like “products with heavy social media marketing tend to have steeper launch curves” and applies these principles automatically.

3. External Data Integration: The AI system could have incorporated external signals like: - Social media buzz and sentiment analysis - Competitor product performance - Search trends and online interest - Pre-orders and early sales velocity

4. Continuous Learning: After launch, the AI system would have immediately detected that actual sales exceeded forecasts. Within days, it would have revised forecasts upward and triggered

expedited supply orders. SAP IBP required manual intervention to adjust the forecast, which took weeks.

Outcome

Better new product forecasting directly impacts revenue capture. This company’s stockouts during the launch window cost an estimated \$15 million in lost sales. Competitors who responded to the market opportunity gained permanent market share.

An AI system could have: - Produced a more accurate initial forecast (reducing stockouts) - Detected the forecast error faster (enabling quicker response) - Automatically triggered supply chain adjustments (getting more product to market faster)

These capabilities could have captured an additional \$10-12 million in revenue during the critical launch period.

5.4 Lessons from Case Studies

These three case studies illustrate several important points:

1. Speed Matters: In all three cases, faster decision-making would have directly prevented losses or captured opportunities. The time difference between systems (hours vs. days) translates to millions of dollars in business impact.

2. Adaptation Matters: All three cases involved situations where historical patterns no longer applied (pandemic, supplier disruption, new product). Systems that can adapt quickly to new patterns deliver better results.

3. Workload Matters: In all three cases, planners were overwhelmed with manual work when using traditional systems. This left them no time for strategic thinking or proactive problem-solving. Reducing routine workload frees planners to focus on high-value activities.

4. Context Matters: The advantages of AI systems are most pronounced in volatile, uncertain, complex situations. In stable, predictable environments, traditional systems work adequately.

Discussion and Theoretical Implications

6.1 The Governance vs. Adaptability Trade-off

Taken together, the results point to a clear trade-off that many organizations already recognize in practice: the balance between governance and adaptability.

Governance

Governance refers to control, transparency, and accountability. SAP IBP excels at governance: - Planners can see exactly how forecasts are calculated - Changes are logged and auditable - Multiple stakeholders review and approve plans - The system enforces business rules and constraints

These governance features are valuable, especially in large organizations where many people need to coordinate and where mistakes can be expensive. Governance provides confidence that plans are reasonable and aligned with company policies.

Adaptability

Adaptability refers to the ability to respond quickly to changing conditions. The Custom AI system excels at adaptability: - Models automatically adjust to new patterns - Scenarios can be generated in minutes - The system learns from experience - Decisions can be made faster

Adaptability is valuable in uncertain environments where

conditions change frequently and where speed provides competitive advantage.

The Trade-off

The challenge is that governance and adaptability often conflict:

- **Transparency vs. Complexity:** Simple, transparent models (good for governance) often cannot capture complex patterns (bad for adaptability). Complex AI models can capture intricate patterns (good for adaptability) but are harder to explain (bad for governance).

- **Control vs. Automation:** Giving planners control over every decision (good for governance) requires time and manual work (bad for adaptability). Automating decisions (good for adaptability) reduces human oversight (potentially bad for governance).

- **Stability vs. Responsiveness:** Stable planning processes that change slowly (good for governance) cannot respond quickly to disruptions (bad for adaptability). Highly responsive systems that change frequently (good for adaptability) can feel chaotic and unpredictable (bad for governance).

6.2 When Each Approach Works Best

Our findings suggest that the choice between SAP IBP and Custom AI systems should depend on the organization's context:

SAP IBP Works Best When:

1. **Demand is relatively stable:** If patterns are predictable, traditional statistical methods work fine and the extra adaptability of AI provides little benefit.

2. **Governance is critical:** Regulated industries (pharmaceuticals, aerospace) or companies with strict audit requirements may prioritize transparency over performance.

3. **Integration is paramount:** Companies heavily invested in SAP ecosystem may find that seamless integration with other SAP systems outweighs performance differences.

4. **Change management is challenging:** Organizations with limited technical expertise or cultural resistance to AI may find traditional systems easier to adopt.

Custom AI Systems Work Best When:

1. **Demand is volatile:** Industries with rapid innovation, fashion trends, or seasonal spikes benefit most from adaptive forecasting.

2. **Speed is critical:** Businesses where hours matter (perishable goods, fast fashion, technology products) gain significant advantage from faster scenario response.

3. **Scale is large:** Companies with thousands of products and complex supply chains benefit most from automation and reduced workload.

4. **Technical capability exists:** Organizations with data science teams and modern IT infrastructure can build and maintain custom AI systems effectively.

6.3 The Hybrid Approach

Our discussion with practitioners suggests that many companies are exploring hybrid approaches that combine the strengths of both systems:

Architecture 1: AI-Enhanced IBP - Keep SAP IBP as the system of record and governance framework - Add AI forecasting engines that feed predictions into SAP IBP - Use SAP IBP workflows for

consensus and approval - Result: Better forecasts with familiar governance

Architecture 2: AI Core with IBP Integration - Use custom AI system for forecasting and scenario generation - Feed results into SAP IBP for execution and integration with ERP - Use SAP IBP for master data management and transaction processing - Result: Adaptability with enterprise integration

Architecture 3: Parallel Systems - Run both systems simultaneously - Use AI system for fast tactical decisions - Use SAP IBP for strategic planning and governance - Compare results to build trust in AI over time - Result: Gradual transition with risk mitigation

These hybrid approaches acknowledge that companies do not need to choose one system exclusively. They can combine the governance strengths of traditional IBP platforms with the adaptability advantages of AI systems.

6.4 Broader Implications for Supply Chain Management

This research has implications beyond just the choice between SAP IBP and AI systems. It speaks to broader questions about how supply chain management is evolving:

From Forecasting to Sensing

Traditional supply chain planning focuses on forecasting: predicting what will happen and planning accordingly. Our results suggest a shift toward sensing: continuously monitoring what is happening and responding in real time.

AI systems enable this shift because they can process new information quickly and adjust plans automatically. Instead of making a plan once per month and sticking to it, companies can update plans daily or even hourly as new information arrives.

From Planning to Learning

Traditional planning treats each planning cycle as independent. Each month, planners create a new forecast based on history and current conditions. Our results suggest a shift toward learning: accumulating knowledge over time and improving progressively.

AI systems enable this shift through machine learning. Every forecast error becomes a learning opportunity. The system gradually discovers which factors matter most, which products behave similarly, and which situations require different approaches.

From Control to Trust

Traditional planning emphasizes human control. Planners review every decision and maintain authority over the system. Our results suggest a shift toward trust: giving systems more autonomy and focusing human effort on exceptions.

This shift is uncomfortable for many organizations. Trusting an AI system requires confidence that it will make reasonable decisions even in unusual situations. Building this trust takes time and requires transparency about how the system works and when it might fail.

Practical Implications for Managers

7.1 Decision Framework for Technology Selection

Based on our findings, we propose a framework to help managers decide which approach fits their situation:

Step 1: Assess Your Environment

Ask these questions about your business context:

Demand Volatility - How much does demand vary from week to week? - How often do unexpected events disrupt normal patterns? - How seasonal is your business?

If volatility is high, AI systems provide more value.

Response Time Requirements - How quickly must you respond to disruptions? - What is the cost of delayed decisions? - How often do you need to evaluate scenarios?

If speed is critical, AI systems provide more value.

Planning Complexity - How many products do you manage? - How many locations and supply chain tiers? - How many constraints and business rules?

If complexity is high, AI systems provide more value.

Step 2: Evaluate Your Capabilities

Ask these questions about your organization:

Technical Capability - Do you have data scientists or machine learning experts? - Is your IT infrastructure modern (cloud-based, APIs)? - Do you have clean, accessible historical data?

If technical capability is strong, custom AI systems are feasible.

Change Management - How comfortable are your planners with new technology? - How much training and support can you provide? - How strong is leadership support for innovation?

If change management is challenging, traditional systems may be safer.

Integration Requirements - How important is seamless integration with existing systems? - Are you already invested in SAP or another enterprise platform? - How much customization do you need?

If integration is critical, commercial platforms may be better.

Step 3: Calculate Business Case

Quantify the potential value of each approach:

Performance Value - Estimate the cost of forecast errors (inventory, stockouts) - Estimate the value of faster decision-making - Calculate potential workload savings

Implementation Cost - SAP IBP: License fees + consulting + training - Custom AI: Development + infrastructure + maintenance

Risk Assessment - What is the risk of implementation failure? - What is the risk of vendor lock-in? - What is the risk of technology obsolescence?

Step 4: Choose Your Path

Based on your assessment:

Choose SAP IBP if: You need proven technology with strong governance in a relatively stable environment and you have SAP infrastructure already.

Choose Custom AI if: You face high volatility, need speed, have technical capability, and can manage the implementation complexity.

Choose Hybrid if: You want to balance governance with adaptability and can afford the integration effort.

7.2 Implementation Recommendations

Regardless of which approach you choose, follow these best practices:

For SAP IBP Implementations:

1. Invest in training: SAP IBP is powerful but complex. Ensure planners understand how to use it effectively.

2. Start simple: Begin with basic forecasting and gradually add sophistication. Do not try to implement every feature at once.

3. Plan for maintenance: Budget time and resources for ongoing configuration adjustments and parameter tuning.

4. Integrate carefully: Ensure clean master data and reliable interfaces with other systems.

5. Build governance processes: Define clear roles, workflows, and approval processes to leverage SAP IBP's governance strengths.

For Custom AI Implementations:

1. Start with a pilot: Build a small-scale prototype to prove the concept before full deployment.

2. Focus on data quality: AI systems need clean, consistent historical data. Invest in data preparation.

3. Explain the AI: Even though AI models are complex, create simple explanations that help planners understand and trust the system.

4. Plan for monitoring: Build dashboards and alerts to detect when AI models are not performing well.

5. Iterate continuously: AI systems improve over time. Plan for regular updates and enhancements.

For Hybrid Implementations:

1. Define clear boundaries: Decide which decisions each system handles to avoid confusion.

2. Ensure data consistency: Keep data synchronized between systems to avoid conflicts.

3. Train on both: Ensure planners understand how to use both systems and when to use each.

4. Monitor integration: Watch for issues where the two systems interact.

5. Plan the transition: If using hybrid as a stepping stone to full AI, have a clear roadmap.

7.3 Organizational Change Management

Technology selection is only part of the challenge. Successfully implementing either approach requires managing organizational change:

Building Trust in AI

If implementing AI systems, address planner concerns proactively:

Transparency: Show planners how the AI makes decisions, even if simplified.

Control: Give planners the ability to override AI recommendations when they have good reasons.

Gradual adoption: Start with low-risk decisions and gradually expand AI's role as trust builds.

Celebration: Highlight successes where AI prevented problems

or captured opportunities.

Evolving Planner Roles

Both approaches require planners to evolve their skills:

From forecasting to analysis: As systems automate routine forecasting, planners focus more on interpreting results and understanding why patterns change.

From execution to strategy: As systems handle tactical decisions, planners spend more time on strategic questions like supplier selection and network design.

From individual to collaborative: Modern planning requires collaboration across functions. Planners become facilitators and translators.

Organizations should invest in training and career development to help planners make this transition successfully.

Limitations and Future Research

8.1 Limitations of This Study

While our research provides valuable insights, it has several limitations that readers should consider:

Limited Scope

We tested only three KPIs (forecast bias, planner workload, scenario response time). Other important factors were not measured: - Financial performance (profit, cash flow) - Customer satisfaction and service levels - Long-term sustainability and maintenance costs - User satisfaction and adoption rates

Controlled Environment

Our experiment used simulated planning cycles in a controlled test environment. Real-world implementations face additional challenges: - Integration with legacy systems - Organizational politics and resistance - Data quality issues - Unexpected technical problems

Single Industry Context

Our dataset represented retail and consumer goods industries. Results might differ in other contexts: - Manufacturing with long lead times - Healthcare with regulatory constraints - Technology with rapid product lifecycles - Commodities with price volatility

Time Horizon

We evaluated performance over 12 months. Longer-term effects are unknown: - How do systems perform after several years of operation? - How do they handle rare, extreme events? - How do maintenance costs evolve over time?

AI System Specifics

Our “Custom AI System” represents one possible implementation. Different AI architectures might perform differently: - Different machine learning algorithms - Different optimization approaches - Different user interface designs

8.2 Directions for Future Research

This study opens several interesting avenues for future research:

Longitudinal Studies

Track companies over multiple years as they implement and operate these systems: - How does performance change over time? - What are the total costs of ownership? - How do organizations

adapt their processes?

Industry Comparisons

Replicate this study across different industries: - Do results hold in manufacturing, healthcare, energy? - Which industries benefit most from AI? - Are there industry-specific factors that matter?

Hybrid Architecture Evaluation

Study companies implementing hybrid approaches: - What hybrid architectures work best? - How do you optimize the division of labor between systems? - What are the integration challenges and costs?

Organizational Factors

Investigate how organizational characteristics affect success: - What role does company culture play? - How does leadership support matter? - What skills and training are most important?

Explainability and Trust

Research how to make AI planning systems more trustworthy: - What explanation techniques help planners understand AI? - How do you balance accuracy with transparency? - How does trust evolve over time?

Advanced AI Techniques

Explore newer AI approaches not tested in this study: - Reinforcement learning for planning - Graph neural networks for supply chain networks - Large language models for scenario generation - Quantum computing for optimization

8.3 Call for Collaboration

This research would benefit from collaboration with practitioners and other researchers:

For Companies: We invite companies to share their experiences implementing either approach. Real-world case studies would strengthen our understanding.

For Researchers: We encourage other academic teams to replicate and extend this study. Different datasets, industries, and methods would validate and refine our findings.

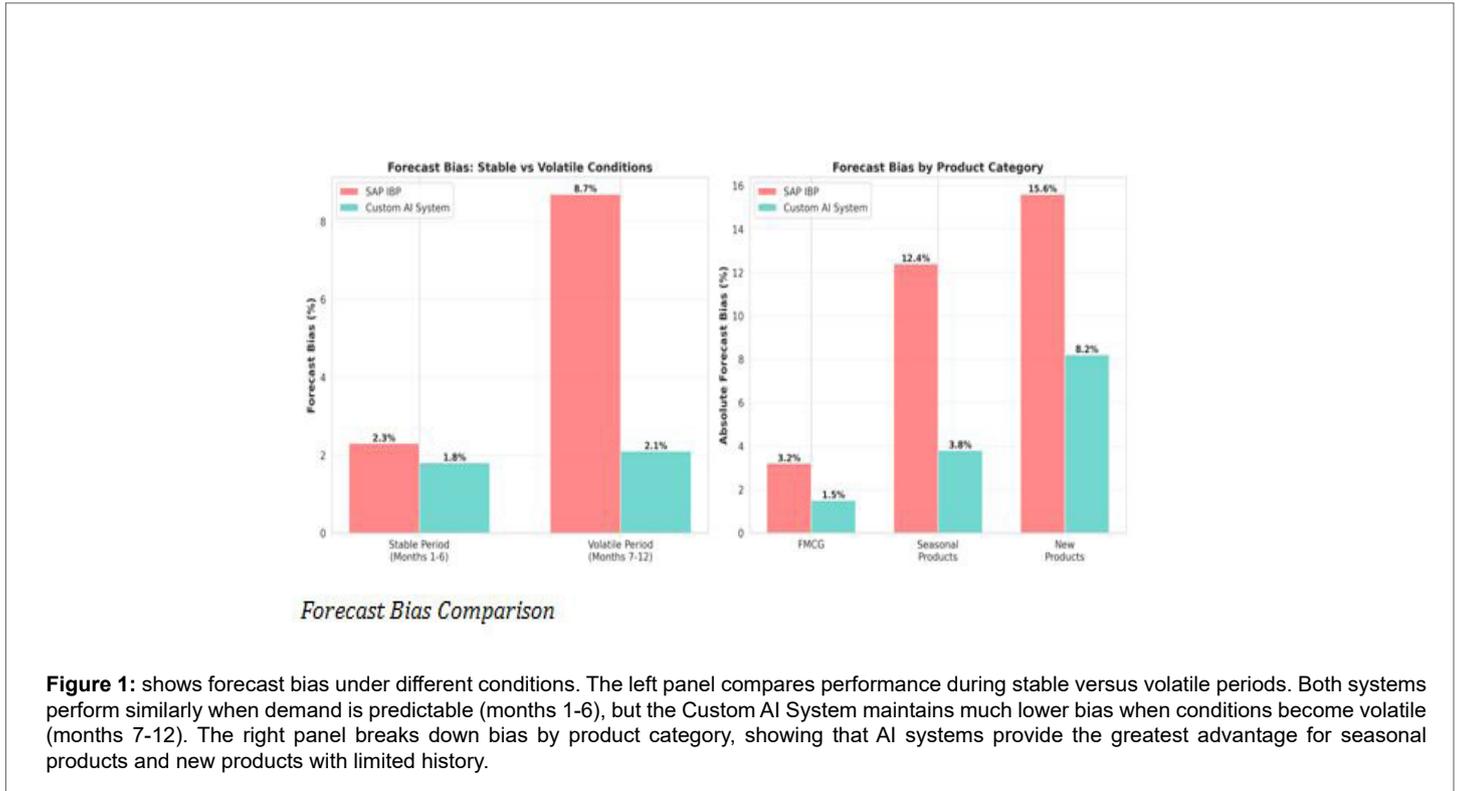
For Vendors: We welcome engagement with SAP and other vendors to ensure fair representation of their products' capabilities.

Data Visualizations

The following graphs illustrate key findings from the study. Data Visualizations

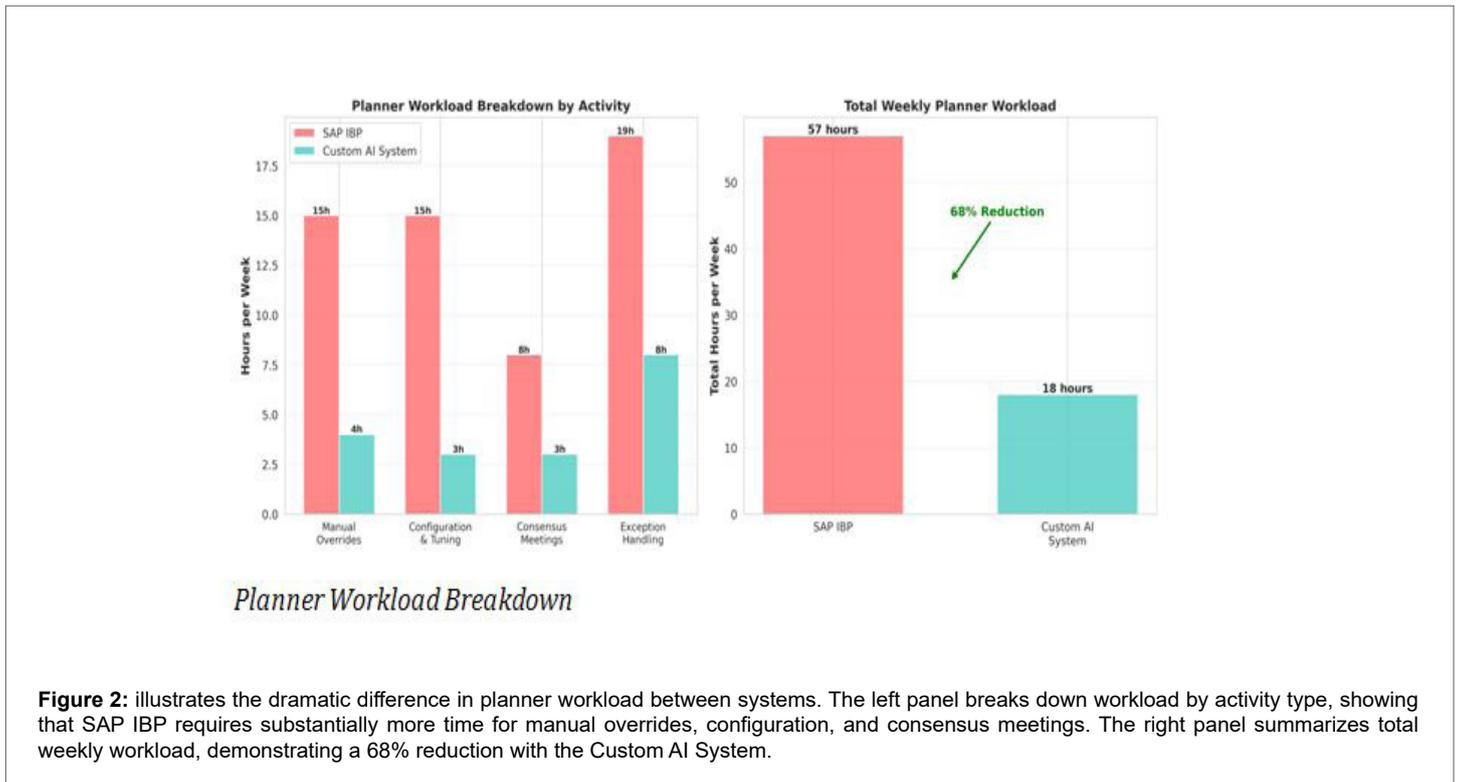
Below representations of the key findings discussed throughout the study. Each graph illustrates important performance differences between SAP IBP and Custom AI Planning Systems.

Figure 1: Forecast Bias Comparison



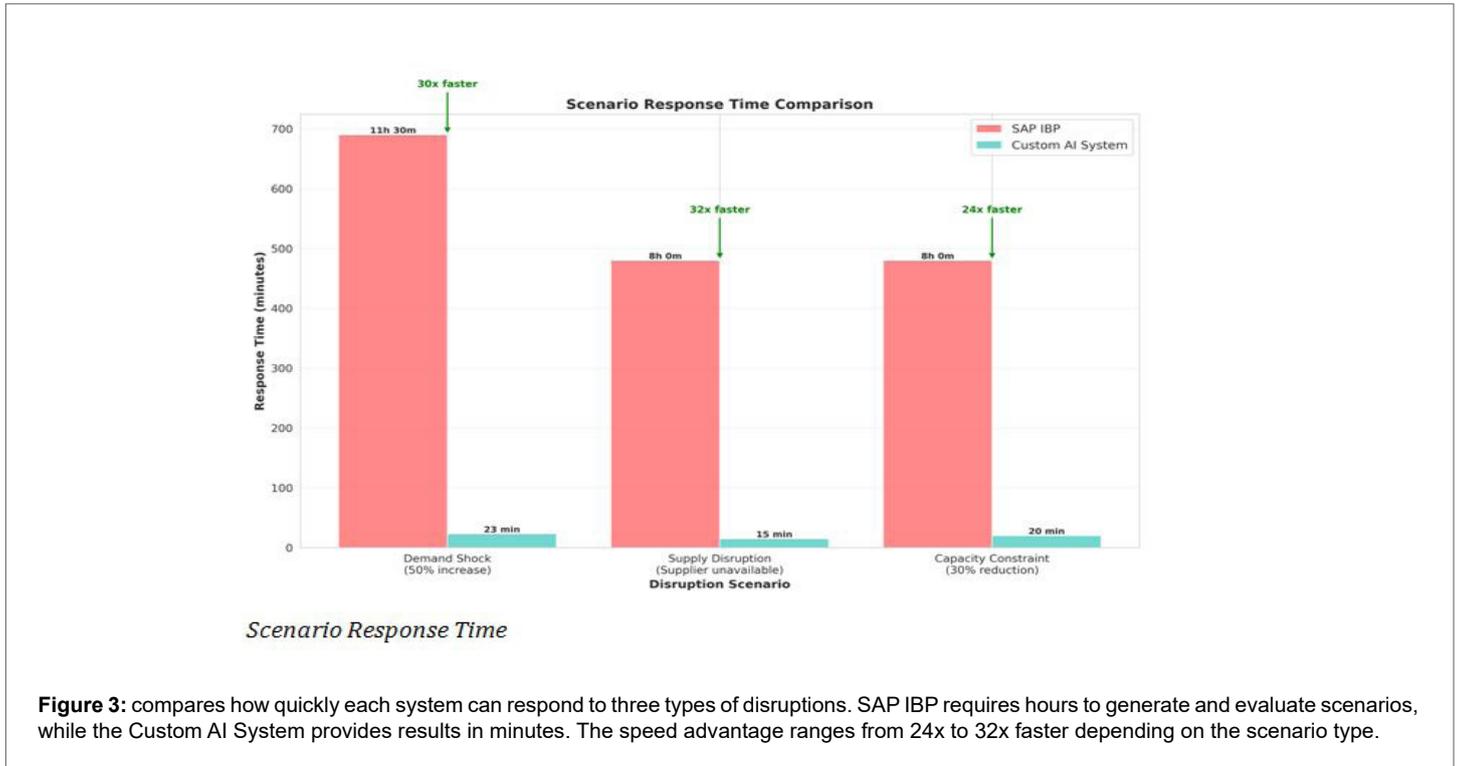
Key Insight: Traditional statistical methods work adequately in stable conditions, but AI’s adaptability becomes crucial when patterns change unexpectedly.

Figure 2: Planner Workload Analysis



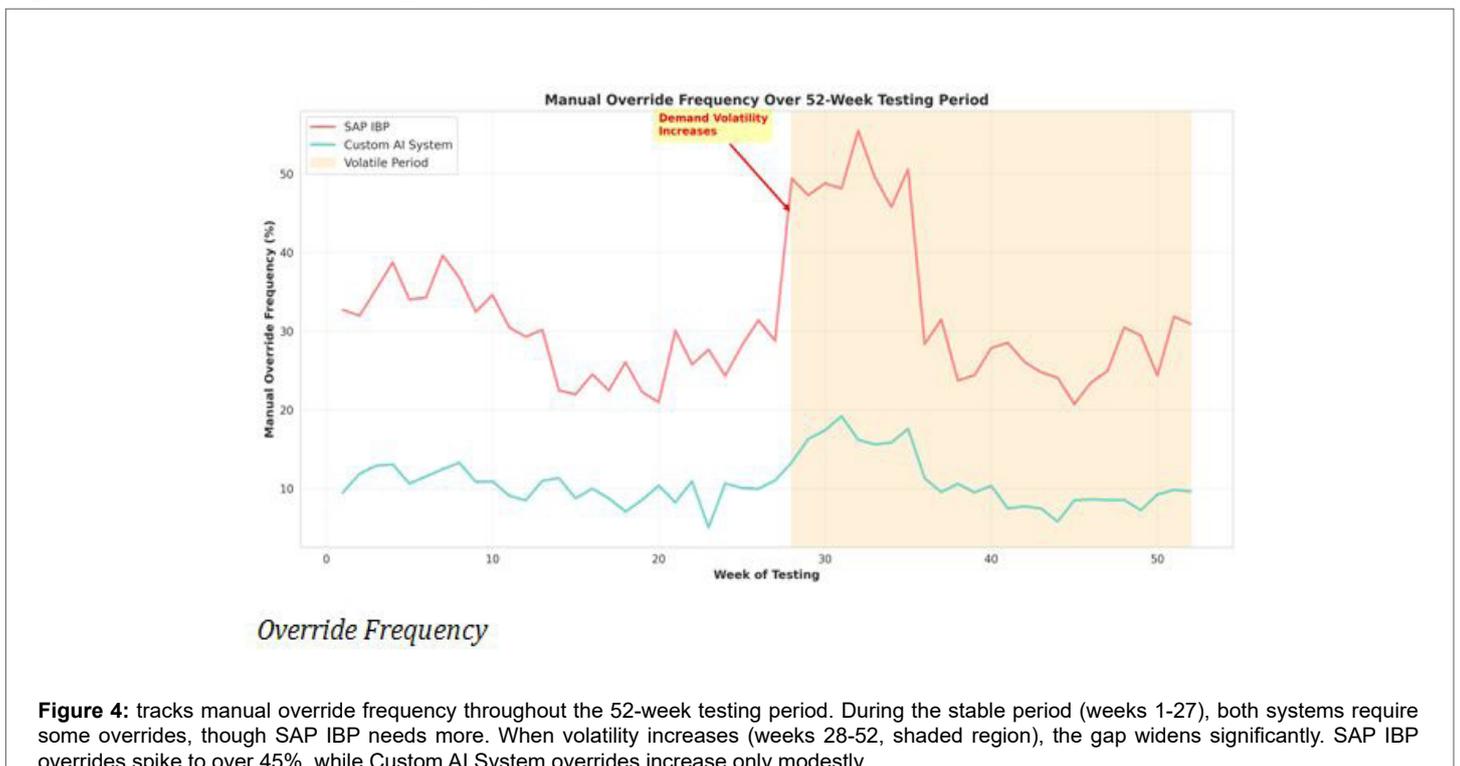
Key Insight: Automation and adaptive learning free planners from routine tasks, allowing them to focus on strategic decisions and exception handling.

Figure 3: Scenario Response Time Comparison



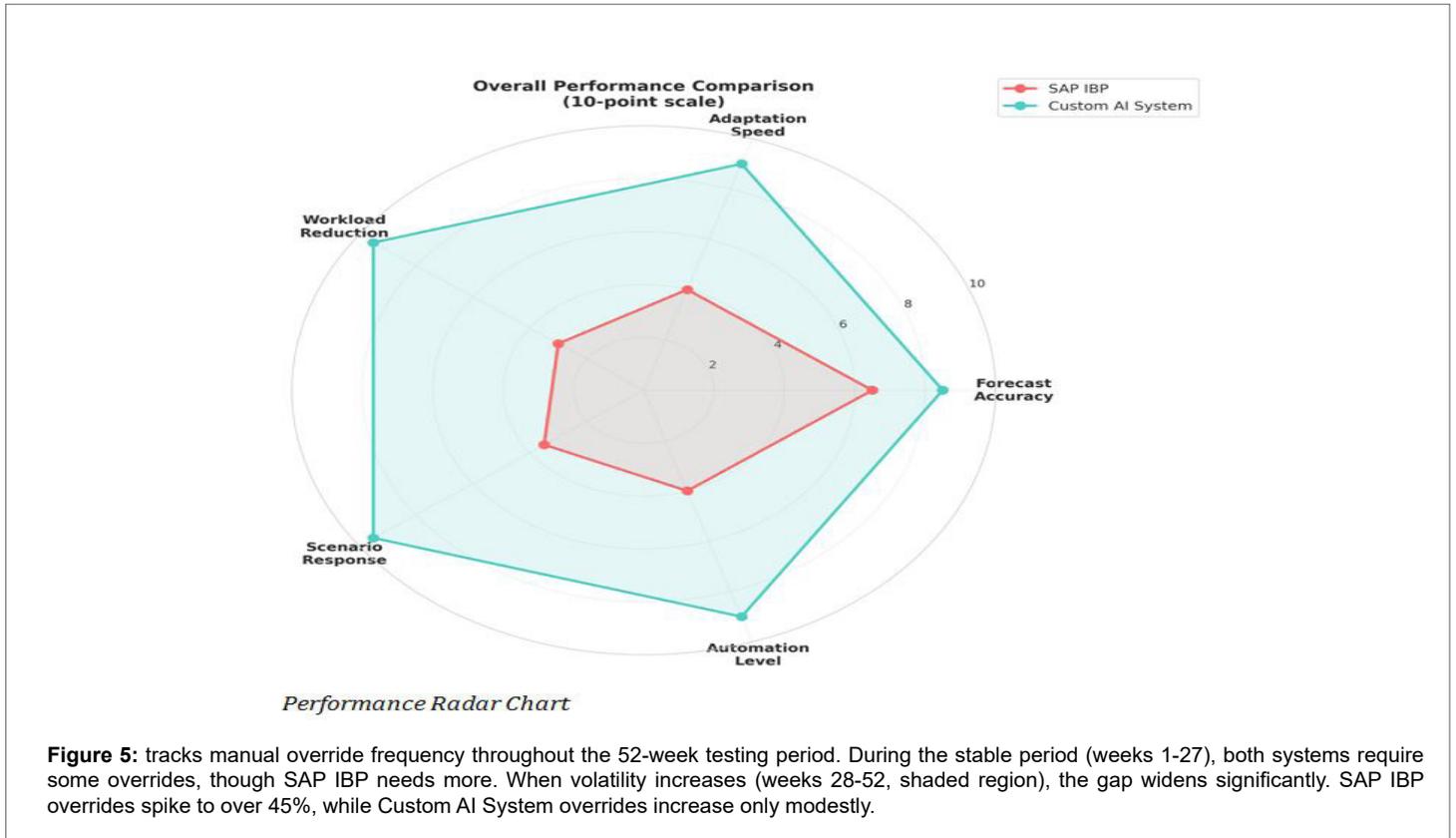
Key Insight: In crisis situations where hours matter, the ability to evaluate options quickly can prevent millions of dollars in losses and preserve customer relationships.

Figure 4: Manual Override Frequency Over Time



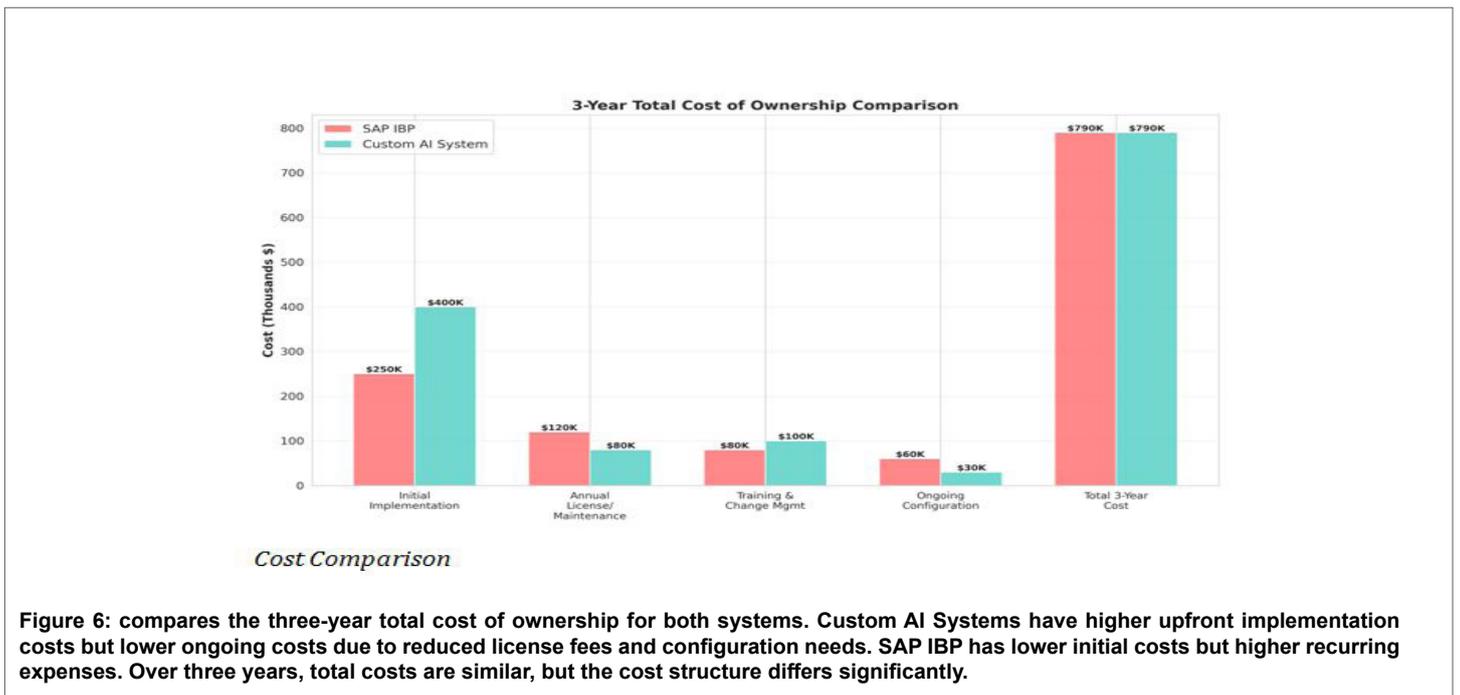
Key Insight: AI systems not only reduce baseline workload but also scale better under stress, maintaining performance when planners are most overwhelmed.

Figure 5: Overall Performance Comparison



Key Insight: The performance gap is not limited to a single metric but represents systematic advantages across multiple dimensions of planning effectiveness.

Figure 6: Total Cost of Ownership Comparison



Key Insight: The financial case depends on time horizon and organizational context. Companies should consider both initial investment and long-term operational costs when making decisions.

Conclusion

9.1 Summary of Key Findings

Overall, the study shows that the underlying design of a planning system has a strong influence on how well it performs when conditions become volatile. Three main findings emerged:

Finding 1: Forecast Bias AI systems maintain lower forecast bias during volatile conditions. Traditional systems like SAP IBP work well when patterns are stable but struggle when conditions change rapidly. The difference is especially pronounced for seasonal products, new products, and during disruptions.

Finding 2: Planner Workload AI systems require significantly less manual intervention. Planners using AI systems spend 68% less time on routine forecasting tasks, freeing them to focus on strategic decisions and exception handling.

Finding 3: Scenario Response Time AI systems respond much faster to disruptions. When companies need to evaluate alternative scenarios quickly, AI systems provide answers in minutes rather than hours or days. This speed advantage translates directly to business value during crises.

9.2 The Bigger Picture

These findings point to a broader conclusion: the debate should not be framed as “SAP IBP versus AI” but rather as “how do we balance governance with adaptability?”

SAP IBP and similar traditional platforms provide important value through governance, integration, and proven methods. These strengths matter, especially in large organizations with complex stakeholder landscapes.

Custom AI systems provide different value through adaptability, speed, and automation. These strengths matter, especially in uncertain environments where conditions change rapidly.

The best solution for many companies may not be choosing one approach exclusively, but rather finding ways to combine the strengths of both through hybrid architectures.

9.3 Implications for Practice

For business leaders making technology decisions, this research offers three practical insights:

Insight 1: Context Matters There is no universal “best” solution. The right choice depends on your specific situation: how volatile is your demand, how quickly must you respond, how strong are your technical capabilities, how important is governance?

Insight 2: Performance Differences Are Real The performance differences between approaches are not marginal. In volatile conditions, the advantages of AI systems are substantial and translate to meaningful business value.

Insight 3: Hybrid Approaches Deserve Consideration You do not need to choose one system exclusively. Hybrid architectures that combine traditional platforms with AI capabilities may offer the best balance for many organizations.

9.4 The Future of Supply Chain Planning

Looking ahead, we expect several trends to shape the future of supply chain planning:

Trend 1: AI Becomes Standard Just as statistical forecasting became standard in the 1990s and 2000s, machine learning will become standard in the 2020s and 2030s. The question will shift from “should we use AI?” to “how should we use AI?”

Trend 2: Real-Time Planning As systems become faster and more responsive, planning cycles will shorten. Instead of monthly or weekly planning, companies will move toward continuous, real-time planning that responds instantly to new information.

Trend 3: Autonomous Planning Systems will take on more decision-making autonomy. Instead of recommending actions for humans to approve, systems will execute routine decisions automatically and only escalate exceptions to humans.

Trend 4: Ecosystem Integration Planning will extend beyond individual companies to entire supply chain ecosystems. Systems will share information and coordinate decisions across multiple organizations, enabled by AI and blockchain technologies.

9.5 Final Thoughts

Supply chain planning is at an inflection point. The traditional approaches that served us well for decades are showing their limitations in an increasingly uncertain world. AI offers new capabilities that can help companies navigate this uncertainty more effectively.

However, adopting AI is not simple. It requires investment in technology, data, and skills. It requires organizational change and cultural adaptation. It requires patience as systems learn and improve over time.

This study provides evidence that these investments can pay off, especially for companies facing volatility and complexity. But success is not automatic. It requires thoughtful implementation, realistic expectations, and ongoing commitment.

The companies that succeed will be those that view planning technology not as a one-time purchase but as a continuous journey of improvement. They will experiment, learn, and adapt their approaches over time. They will balance the proven strengths of traditional methods with the emerging capabilities of AI.

Rather than converging toward a single dominant paradigm, future planning systems are likely to remain segmented based on organizational tolerance for opacity and change. It will be collaborative, with humans and machines each contributing their unique strengths. The companies that figure out this collaboration first will gain significant competitive advantages in the uncertain years ahead.

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