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# Enhancing Operational Efficiency and Human-AI Interaction in Manufacturing through Time-Driven Costing and Predictive Analytics Integration in SAP ERP

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**Abstract**: In today's evolving manufacturing landscape, where operational efficiency is crucial for maintaining competitiveness, accurate and adaptable cost allocation methods are vital. Time-Driven Activity-Based Costing (TDABC) has proven valuable for dynamic cost allocation. Yet, its integration with real-time data and predictive analytics within ERP systems like SAP remains underexplored, limiting its application in complex, variable processes. This study investigates how a TDABC-based model, incorporating real-time data and predictive analytics, enhances production scheduling, resource allocation, and operational efficiency in manufacturing. Through a rigorous data collection and refinement process, including real-time validation and FMEA, the model improved cost accuracy, achieving prediction rates of 89% in the Hydrate department, respectively, while reducing discrepancies in automated processes. While the model significantly improved cost accuracy, ongoing variability in manual tasks highlights opportunities for further refinement and optimization. Findings support the potential of integrating TDABC with real-time data for data-driven AI solutions, advancing Industry 5.0 objectives for collaborative human-AI environments in manufacturing.



*Keywords*: Time-Driven Activity-Based Costing, Real-Time Data, SAP ERP, Operational Efficiency, Industry 5.0.

## 1. INTRODUCTION

To stay competitive and sustainable, manufacturers must optimize operational efficiency. ERP systems like SAP are now vital, providing integrated data management frameworks for production, finance, and resource allocation (Vedernikova et al., 2023). These systems improve decision-making by providing real-time insights for accurate cost allocation and resource optimization. Time-Driven Activity-Based Costing (TDABC) has emerged as a dynamic and adaptable costing method, offering a more precise approach than traditional Activity-Based Costing (ABC) or job-order costing. TDABC connects time-based equations to processes, improving resource use in dynamic environments with variable production settings (Niñerola et al., 2021; Reynolds et al., 2018). Despite its benefits, TDABC's integration with real-time data and predictive analytics in ERP systems like SAP is underused, limiting its ability to optimize production scheduling and resource allocation (Castro Miranda et al., 2022). This study bridges this gap by implementing and customizing a TDABC framework within SAP ERP for a manufacturing environment. It customizes the model to fit operational needs, like task variability and real-time process changes, to improve production scheduling and resource allocation. The key research question is: How can an integrated TDABC framework improve operational efficiency when aligned with real-time data in an ERP system? This study also examines how predictive analytics can improve TDABC's accuracy and decision-making (Somanchi et al., 2022). This study shows how real-time data and predictive analytics can improve TDABC in SAP ERP, enhancing cost accuracy and resource use. It also highlights the importance of human-AI collaboration in aligning with Industry 5.0, enabling real-time production changes and better decision-making (Martin et al., 2018)The outline's adaptability to similar companies broadens the study's applicability. This paper has this structure: Section 2 reviews the literature on TDABC, SAP ERP integration, and real-time data use. Section 3 describes the general methodology. Sections 4 and 5 present and discuss the results. Finally, Section 6 summarizes the key findings and offers recommendations for future research.

## 2. LITERATURE REVIEW

### *2.1. TDABC*

TDABC uses time as the primary cost driver, a method pioneered by Kaplan and Anderson (Malinić & Todorović, 2012), improving ABC and job-order costing. TDABC connects activity durations and resource use, making it ideal for dynamic, multi-departmental settings with high variability. Studies have shown TDABC's effectiveness in handling real-time operational changes, notably enhancing cost accuracy in industries with fluctuating workflows, such as healthcare (Niñerola et al., 2021). Despite these benefits, TDABC's integration with real-time data and predictive analytics is limited, with current implementations relying heavily on historical data, which may not accurately represent ongoing operations. This gap shows that TDABC could be improved with real-time data to help with adaptive production planning and resource allocation, especially in Industry 5.0's human-


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centric, collaborative environments (Gregório et al., 2016; Vazakidis & Kyriakidou, 2020).

### 2.2. SAP ERP Integration and Cost Accounting

SAP ERP systems have greatly impacted cost accounting in the industry by improving data integration across departments and enhancing transparency for complex production environments (Scapens & Jazayeri, 2003). SAP ERP's real-time data management boosts TDABC's efficiency, improving visibility of cost drivers and resource use (Deng et al., 2017). Case studies indicate that organizations using SAP ERP with TDABC gain strategic decision-making benefits due to increased cost accuracy (Stout & Propri, 2011). But, integrating TDABC with SAP ERP is hard, especially with dynamic, real-time data that may have timing and accuracy issues. Studies urge firms to use SAP ERP's real-time data to boost productivity and cost management and to align cost data with current operations (Lodh & Gaffikin, 2003; Tjahjadi, 2010).

### 2.3. Real-Time Data and Predictive Analytics and AI Integration

TDABC models in variable production environments need real-time data. Studies emphasize that real-time data significantly enhances decision-making and cost accuracy in contexts with frequent operational changes (Barros & Ferreira, 2017; Saez et al., 2018). AI and predictive analytics can help manage real-time TDABC in SAP ERP by improving data processing, predictive insights, and cost adjustments, addressing the uncertainties of dynamic operations (ChandraPrabha & Lakshmi, 2023; Zabrocki et al., 2023). AI in SAP ERP aligns TDABC with Industry 5.0, promoting human-AI collaboration to improve manufacturing efficiency and adaptability (Matias et al., 2021; Wilson et al., 2020). TDABC's integration with real-time data, AI, and predictive analytics improves production scheduling and resource allocation, filling a gap in cost management for complex manufacturing environments. This study aims to bridge these gaps by implementing a TDABC framework within SAP ERP, enhanced by real-time data and AI-driven predictive analytics, to improve dynamic manufacturing production scheduling and resource allocation.

## 3. METHODOLOGY

TDABC was integrated into SAP ERP using a six-step method to ensure scalable, repeatable cost estimation. The process began with a preliminary assessment involving stakeholder interviews, SAP data extraction, and stopwatch analysis to identify inefficiencies in cost allocation. Next, process mapping was done to classify production activities as manual or automated, revealing cost drivers. Next, a baseline model calibration was done using ERP-based task duration logs to create initial TDABC cost equations and accurate time-driven cost parameters. To address potential sources of variability, a Failure Modes and Effects Analysis (FMEA) was applied to identify high-risk failure modes that could impact cost accuracy, leading to targeted refinements in the model. The next phase involved AI and predictive analytics, using Random Forest regression to predict task durations and K-Means clustering for anomaly detection, improving the model's adaptability to real-time operational changes. Finally, a real-time validation and continuous monitoring system was deployed through SAP ERP dashboards, enabling dynamic adjustments to TDABC estimates based on ongoing production data. This structured method gives organizations a clear, adaptable roadmap for implementing TDABC in SAP ERP, ensuring better cost accuracy and flexibility in variable production settings.

### 3.1. Preliminary Assessment and Problem Identification

The process began with a thorough qualitative and quantitative assessment. Structured interviews were conducted with finance, production, operations managers, and frontline operators. Standardized questionnaires guided these interviews, which gathered insight into existing processes, manual task execution, and cost allocation inefficiencies. Simultaneously, stopwatch analysis measured task durations across production activities, and ERP data extraction provided historical performance metrics. This combined approach gave a complete view of inefficiencies, supporting the TDABC framework's customization in the SAP ERP system. Qualitative insights from interviews identified key challenges, while quantitative data offered precise task durations and variability measurements.

### 3.2. Defining Core Processes and Activities

After assessment, core processes and activities are defined by mapping critical tasks across diverse departments like production, packaging, and other labor-intensive areas. Flowcharts show operations and resource flows. Task analysis categorizes activities after careful observation and documentation. Activities are manual or automated based on human or machine operation. Manual tasks like ingredient weighing and handling are observed and time-tracking, while machine operation logs and ERP system data confirm automated tasks.

ERP tools organize the Bill of Materials (BoM). These tools carefully break down products into components, linking each task to specific materials or ingredients. This linkage is needed to create reliable time-driven cost equations in the TDABC model. The company uses these methods and tools to map processes, categorize tasks, and ensure the BoM structure matches operational realities. This foundation is needed to use the TDABC model in SAP ERP.

### 3.3. Data Collection and Baseline Model Calibration

Next, data collection and baseline model calibration are essential for initial task durations and TDABC model configuration. Time-tracking tools, stopwatch analysis, and ERP-based time logs collect baseline activity duration data. This thorough data collection accounts for product types, batch sizes, and operator techniques to get detailed process times. SAP ERP uses data to set time-based equations. These equations assign time drivers and quantifiable factors like unit processing or activity duration to link tasks to their time needs. The ERP system's dynamic cost estimation framework is based on real-time operational data from observed task durations and drivers. The ERP system integrates baseline data into live operations to reflect production conditions in real-time. Automated data feeds and manual inputs update task times and operational metrics. The system recalculates costs based on production time, aligning cost allocations with real-time floor operations. This dynamic feedback loop improves cost estimates and speeds decision-making.

### *3.4. Root Cause Analysis for Variability*

The FMEA was used to find and rank sources of variability that affected the TDABC model's accuracy. The analysis focused on the Hydrate Department's ingredient weighing and preparation, where task durations often deviated from predictions. Each failure mode was rated on severity, occurrence, and detection likelihood, with Risk Priority Numbers (RPNs) calculated to quantify their impact. The worst failure modes were missed task dependencies (120), wrong product family classification (160), and manual handling errors (130). The TDABC model was improved by recalibrating time estimates, standardizing workflows, and adding buffer factors for manual operations. FMEA found the leading causes of cost variability, but some key factors were initially missed. The original assessment did not consider operator fatigue, skill-level differences, or supply chain issues. For example, ingredient loading times varied with operator experience, which was not in the first RPN calculations. Also, supply chain variability, like late material deliveries, disrupted production sequences, increasing task unpredictability. Table 4 (in section 4.4) presents an updated FMEA analysis that incorporates previously unaccounted factors to address these gaps.

### *3.5. Model Development and Real-Time Calibration*

TDABC's manual task variability requires an adaptive approach considering operator performance and production conditions. Three key strategies were used to improve cost accuracy. First, Standard Operating Procedures (SOPs) for high-variability tasks were set up to standardize manual operations like weighing and handling ingredients. The SAP ERP system has these SOPs, allowing for real-time compliance and execution time validation. Second, AI-driven predictive adjustments were integrated into the TDABC model, incorporating buffer factors for manual tasks. This allowed the system to dynamically adjust time estimates based on machine learning analysis of historical task duration data, reducing discrepancies in manual work durations. Finally, real-time monitoring and performance tracking were introduced through SAP ERP dashboards, providing continuous oversight of operator performance. Managers could compare real-time versus predicted task durations, refining cost drivers incrementally to improve accuracy.

### *3.6. Model Validation and Future Integration*

Validation focused on assessing model performance against real operational data, documenting adjustments as needed. Model accuracy was validated through periodic comparisons of predicted versus actual costs to ensure alignment with operational goals. As it stabilizes, the model is ready for improvements, like AI-based predictive analytics. IoT and AI integration can improve the TDABC model in SAP ERP by allowing real-time monitoring and automated adjustments.

## 4. RESULTS

This section shows how to customize and implement a baseline TDABC model for Company A's SAP ERP system. Company A, an Italian manufacturer, specializes in food products, especially in the Hydrate Department. This department processes and prepares liquid or semi-liquid products like artisanal ice cream and drinks. While the baseline model provided a structured framework, it required significant refinement to address the variability and complexity inherent in these operations. This section describes how to customize to improve cost accuracy, resource allocation, and operational efficiency.

### *4.1. Preliminary Assessment and Problem Identification*

The first assessment found flaws in the kilogram-based cost allocation method, which did not consider indirect cost variability, especially in high manual intervention tasks. There were major differences in indirect cost allocation, especially in manual, labor-intensive processes. SAP's limited integration with real-time data made allocating costs for dynamic tasks harder. These results showed that the Hydrate Department's operational nuances require a more flexible TDABC model.

### *4.2. Defining Core Processes and Activities*

To solve these issues, tasks were mapped and categorized as manual or automated, each linked to specific ingredients via the BoM. The baseline TDABC model assigned task durations based on measurable variables, such as the number of ingredients, forming the foundation for accurate task-time linkages and future refinements, as shown in Table 1. For example, total task time was calculated as Time per Unit × Number of Variables, allowing for scalable adjustments and precise cost estimations.

Table 1 - Task Details and Time Allocation (Baseline Model)

| Task | Time [sec] | Variable |
|---|---|---|
| Activity A | 10 | # of ingredients |
| Activity B | 15 | # of ingredients |
| Activity C | 20 | # of ingredients |
| Activity D | 25 | # of ingredients |

Table 2 shows the differences between predicted and actual task durations in the baseline TDABC model. Predicted times were calculated using a formula:

$$Predicted\ Time = Time\ per\ Unit \times Number\ of\ Ingredients \quad (1)$$

However, SAP ERP time logs often showed different execution times due to manual task variability. The Baseline Model Efficiency column measures deviations, allowing for constant updates. This difference shows that dynamic AI-driven recalibrations are needed in the refined TDABC model.

Table 2 - Model Predictions and Efficiency Using Baseline Model

| Production Order X | Number of variables * Time of each variable | Model Results |
|---|---|---|
| Number of variables for Activity A | 10 sec * Number of variables A | Estimate (Predicted Time) |
| Number of variables for Activity B | 15 sec * Number of variables B | Yield (Actual Time) |
| Number of variables for Activity C | 20 sec * Number of variables C | Yield (Actual Time) |
| Number of variables for Activity D | 25 sec * Number of variables D | Yield (Actual Time) |
| **Total Time predicted by the model** | **The sum of predicted times** | **Estimate Total** |

| | | |
|---|---|---|
| **Real total Time** | - | **Yield Total** |
| **Baseline Model Efficiency** | - | **Predicted Time / Real Time** |

### *4.3. Data Collection and Initial Model Calibration*

Baseline data collection was vital for TDABC model calibration. Task durations were recorded using stopwatch analysis and SAP's time-tracking. Manual tasks like ingredient loading and preparation, which are prone to variability, showed discrepancies between predicted and actual times. Table 3 shows how ingredient handling, task variability, and labor intensity affect model accuracy. These insights adjusted the model to align with the Hydrate Department's operational dynamics.

Table 3 - Factors Impacting Hydrate Weighing Model Performance

| Cause | Impact | Impact on the Model |
|---|---|---|
| Set of activities | High | Pectin activates sugar processes, requiring portioning, increasing the process ratio by 30%. Some packages also require fridge storage, disrupting the workflow. |
| Pre-existing data | High | The predicted time for broken packages (84 sec) was underestimated (116 sec). Writing lot numbers (40 sec) and moving pallets (75 sec) were not initially considered. |
| Division of the work | None | No impact on the model, but high times for retrieving pallets from the warehouse were missed as they were considered part of setup time. |
| Work method | Low | Preparing two ingredients in parallel improves process time by 10%, except for pectin cases where no broken packages occur. |

### *4.4. Root Cause Analysis*

The FMEA analysis found the Hydrate Department's task execution variability sources. It found issues like wrong product family assignments, activity dependence, and errors in existing data. These factors led to discrepancies between predicted and actual task durations, requiring model adjustments. The FMEA assessment missed some key factors but covered major variability factors. The original analysis didn't consider operator fatigue, worker skill level variations, or supply chain issues. For instance, operator experience affected ingredient loading times, which the original RPN calculations missed. Also, supply chain variability (e.g., late material deliveries) disrupted production sequences, increasing task variability. Table 4 shows an updated FMEA analysis that includes missing elements and other factors affecting operational performance.

Table 4 - Factors Impacting Hydrate Preparation Model Performance

| Cause | Impact | Impact on the Model | RPN |
|---|---|---|---|
| Set of activities | High | Incorrect product family assignments led to unpredictable times. Dependence between activities was missed, significantly affecting time and outputs. | 160 |
| Pre-existing data | Medium | Activity times were sometimes inaccurate, with one activity incorrectly including time from another, causing errors in the model. | 120 |
| Division of the work | None | Activities were correctly allocated, so there was no impact on the target ratio. | 0 |
| Work method | Medium | Manual activities caused time variability depending on the operator's approach, introducing inconsistencies in the model. | 130 |
| Operator Fatigue | Medium | Fatigue-related inefficiencies led to increased variability in weighing and loading times. | 110 |
| Supply Chain Delays | High | Raw material availability affected production continuity, impacting task execution times. | 150 |

### *4.5. Model Development and Real-Time Calibration*

The TDABC model was improved by linking each product's BoM data with task times to match production conditions. Time estimates were iteratively adjusted based on real-time observations and operator feedback. Tables 5–9 show the Hydrate Department's task classifications and time allocations, with detailed views of time assignments and activity descriptions.

Table 5 - Input Data of the Model

| % of Ingredient | Kg of Ingredients | Unit Load [Kg] | Number of Entire Packages | Number of Fractionated Packages | Kg of Fractionated |
|---|---|---|---|---|---|
| 10% | 100 | 25 | 4 | 0 | 0 |
| 20% | 200 | 10 | 20 | 0 | 0 |
| 40% | 400 | 15 | 26.7 | 1 | 10 |
| 15% | 150 | 10 | 15 | 0 | 0 |
| 15% | 150 | 10 | 15 | 0 | 0 |

| Quantity [Kg] | Order Code | Product Name |
|---|---|---|
| 1000 | 123 | Product X |

Table 6 - Hydrate department families of products

| Description | Big-Bag | Aroma | Chocolate | Cacao | Butter | Quantity [Kg] | Packages |
|---|---|---|---|---|---|---|---|
| Ingredient 3 | 1 | 0 | 0 | 0 | 0 | 772 | 0 |
| Ingredient 4 | 0 | 1 | 0 | 0 | 0 | 100 | 4 |
| Ingredient 5 | 0 | 0 | 1 | 0 | 0 | 78 | 3 |
| Ingredient 6 | 0 | 0 | 0 | 1 | 0 | 50 | 2 |

Table 7 - Model Hydrate Loading: Product Data and Activity Description

| Description | Value |
|---|---|
| **Code** | 0 |
| **Quantity** | 0 |
| **Product Description** | 0 |
| **FRACTIONATED** | |
| Number of fractionated bags to pour | 0 units |
| Weight of fractionated ingredients | 0 kg |
| Number of bags after combining fractionated | 0 units |
| Fractionated sugar bags for pectin | 0 units |
| Number of entire bags to overturn | 0 units |
| Bags to pour after combining | 0 units |
| **AROMAS, COLORS, AND JUICES** | |
| Number of ingredients to dissolve with water | 0 units |
| Number of colors/aromas to load high | 0 units |
| Number of colors/aromas to load low | 0 units |
| Direct juices for loading | 0 units |
| **MARNETTE, TANKS, AND DRUMS** | |
| Number of Marnette | 0 units |
| Number of Tanks | 0 units |
| Number of Drums | 0 units |

Table 8 - Model Hydrate Loading: Time Calculation for Activities and Outputs

| Activity | Time (Seconds) | Variable |
|---|---|---|
| **TIMES** | | |
| Drum tipping with Lance | 79.1 sec | Number of drums |
| Drum preparation (opening) | 7 sec | Number of drums |
| Loading with lance into tanks | 180 sec | Number of tanks |
| Marnette loading | 120 sec | Number of Marnette |
| Insertion of aromas and colors dissolved in water | 108 sec | Number of aromas and colors |
| Dissolving colors and flavors in water | 67.3 sec | Number of aromas and colors |
| Loading bags from the bottom and juices | 33 sec | Bags |
| Loading sugar + pectin + fractionated ingredients | 60 sec | Number of combinations |
| **CALCULATIONS** | | |
| Combining pectin with sugar | 0 sec | |
| Time to pour the bags | 0 sec | |
| Time to dissolve in water | 0 sec | |
| Time to pour aromas and colors | 0 sec | |
| Total time to dissolve and pour | 0 sec | |
| Time to pour Marnette | 0 sec | |
| Time to aspirate tanks | 0 sec | |
| Time to aspirate drums | 0 sec | |

| **OUTPUTS** | |
|---|---|
| Operator time only | 0 min |
| Operator time with machine assistance | 0 min |
| Total loading time | 0 min |

### *4.6. Continuous Improvement and Validation*

Real-time validation with operator feedback was crucial in refining the TDABC model. Continuous data collection and process observations allowed ongoing adjustments, especially in high-variability tasks like ingredient handling. Table 9 shows how these refinements improved model accuracy and operational efficiency through ongoing validation and feedback.

Table 9 - Impact of Factors on Hydrate Loading Model

| **Cause** | **Impact** | **Effect on the Model** |
|---|---|---|
| Set of activities | High | Incorrect product classification prevented associating ingredients with product families, causing unpredictable times. Activity dependencies were missed, impacting time and outputs. |
| Pre-existing data | Medium | Activities were not accurately identified or segmented, leading to errors and frequent underestimations. |
| Division of the work | None | Correct allocation of activities with no impact on the target ratio. |
| Work method | Medium | Manual activities like dissolving colorants/aromas introduced variability as operators worked in ways they found most efficient. |

The accuracy improvement of 89% in cost prediction was validated through a structured comparison between predicted and actual working times across multiple production orders.

$$Cost\ Prediction\ Accuracy = \left(1 - \frac{|Predicted\ Cost - Actual\ Cost|}{Actual\ Cost}\right) \times 100 \quad (2)$$

The model's performance was assessed using key metrics, including the Ratio of Predicted to Real Working Time, which directly measured the TDABC model's efficiency in estimating task durations. The Error in Minutes was also calculated to find systematic over- or under-estimations by comparing predicted and actual execution times. To further quantify deviations, the Absolute Error Percentage was computed as: $\frac{|Predicted\ Cost - Actual\ Cost|}{Actual\ Cost} \times 100$, ensuring a standardized evaluation of accuracy across different task durations. A Weighted Error Correction Factor was used to improve cost estimates and account for variability trends in real-time production data. However, this study didn't directly compare traditional costing models like ABC or ERP-based cost estimation methods. Future studies should directly compare TDABC's cost accuracy benefits. Also, IoT-driven real-time tracking and machine learning-based anomaly detection could improve the model's adaptability by updating cost parameters as production conditions change.

## 5. DISCUSSION

The TDABC model's customization and implementation in Company A's Hydrate Department revealed major issues with task variability, especially in manual processes like weighing and loading. Pectin and sugar tasks varied greatly, causing weighing times to differ by up to 10%. These results highlight the challenges of using time-driven cost models with much manual intervention in dynamic environments. Standardized procedures, AI-driven time adjustments, and real-time monitoring were implemented to address these issues. SOPs cut ingredient handling deviations by 12%, and AI time adjustments improved prediction accuracy by 8%. Despite these improvements, manual task variability remains a key obstacle, particularly for non-repetitive processes. Future improvements should look into IoT-based real-time operator performance tracking, allowing automated TDABC adjustments for high-variability tasks. Beyond manufacturing, TDABC integration with SAP ERP presents broader applications across various industries, including healthcare, logistics, and finance. TDABC can model patient interactions, diagnostic procedures, and resource use in healthcare, improving cost allocation. It can track handling and transport times in logistics, ensuring accurate shipment costs. However, using TDABC in various industries is difficult. Due to unstructured workflows, consulting, and creative services may have trouble defining task-time estimates. Additionally, TDABC's reliance on historical data makes real-time adjustments difficult in environments with rapidly changing operations. Also, SAP ERP data availability is vital to accuracy, as a high level of integration between cost drivers and real-time operational data is needed. Future research should explore AI-based adaptive models to enhance TDABC's real-time responsiveness, allowing greater flexibility in industries with dynamic workflows.

## 6. CONCLUSION

This study examined how Company A improved production scheduling, resource allocation, and operational efficiency using TDABC, real-time data, and predictive analytics. The TDABC model improved predictive accuracy and production variability over traditional cost models. The model met the intro's goals by improving operator time predictions and indirect cost allocation. The Hydrate department achieved 89% accuracy, up from 55% efficiency with the static baseline model, demonstrating the growing impact of data-driven solutions in manufacturing. This study shows real-time data monitoring and continuous validation can close the production outcome gap. The study found that the model excelled at automated tasks, but manual tasks, especially in Hydrate, needed improvement. Despite these advances, manual preparation and loading variability remain difficult. Machine learning advances could help the model adapt to real-time changes and reduce prediction errors in high-variability tasks. Real-time data could improve complex process accuracy by dynamically updating product family classifications. Although this study was limited to a single case, its framework and findings suggest applicability across diverse manufacturing environments. TDABC integration with real-time data and predictive analytics can help other industries improve efficiency and resource allocation. This flexibility shows that Company A's methods can help other firms improve cost accuracy and production. Company A and others can scale resource optimization and production scheduling with future SAP ERP integration. Predictive AI and real-time ERP analytics will make manufacturing more agile and data-driven. With ongoing refinement, the model could achieve department-wide accuracy, giving it a global edge. The TDABC model improved manufacturing cost accuracy and operational efficiency, but future improvements should focus on AI-driven cost adjustments. Integrating Reinforcement Learning models can optimize task sequencing dynamically, allowing real-time adjustments based on evolving production conditions. Neural networks could also be trained to predict operator performance changes, improving manual task cost estimates. Also, using IoT-based real-time tracking in SAP ERP would allow constant monitoring of manual workstations, giving immediate feedback on task execution times and enabling automated TDABC recalibrations. Combining these methods allows TDABC to become a flexible, predictive, and scalable cost management solution.

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