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Improving the Custom Color Ordering Process with Artificial Intelligence for a Manufacturing Firm

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Abstract.
Purpose: Practitioners who try to apply AI in Business Process Management (BPM) often face a gap between theory and real-world implementation, because most prior work stays at a high level and offers limited replicable implementation blueprints or measurable evidence of value. This study addresses that gap by reengineering a custom color ordering workflow, following the BPM lifecycle and integrating two AI components: machine learning for palette extraction and generative AI for reference image previews.
Methods: The as-is process was mapped in BPMN 2.0 and analyzed using root-cause and value-added analysis. A to-be process was then designed using BPM redesign levers (task elimination, resequencing, integration, and enabling technology). An integrated web platform prototype was built and tested to measure four Process Performance Indicators (PPI): Cycle Time, Response Time, administrative staff hours per order, and Automation Ratio.
Result: Prototype tests showed significant improvement. Response Time reduced from 8 days to 8 minutes (-99.4%). The overall Cycle Time reduced from 92 to 74 days (-19.5%). The administrative workload per order was reduced from 88 to 0.4 staff hours (-99.5%). The redesigned workflow automated 8 of 15 activities, increasing the Automation Ratio from 0% to 53.3%.
Novelty: This study delivers a practical, replicable roadmap for embedding AI capabilities into an operational workflow while staying aligned with BPM principles and tracking measurable PPI. The blueprint can help organizations respond faster to customers, improve throughput, and reduce administrative burden, so staff can focus on higher-value work.

Keywords: Business process management, Artificial intelligence, Machine learning, Generative AI
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INTRODUCTION

Digital transformation fundamentally changes how manufacturing and service companies interact with customers, driving expectations for a faster turnaround, tailored solutions, and seamless self-service experiences [1], [2]. Indonesia offers a particularly telling example of this shift, especially where the creative economy meets hospitality, sectors where interior design choices and material finish directly influence how customers perceive brand identity and quality [3], [4]. Government initiatives targeting priority tourism zones have only intensified the demand for consistently excellent interior environments [5], while the country's digital landscape, with roughly 212.9 million people online (around 77% of the population) and 167 million actives on social media, has made data-driven, instant decision-making the new norm [6]. Against this backdrop, choosing the right upholstery color becomes more than an aesthetic choice. It is a strategic tool for shaping the atmosphere, reinforcing brand consistency, and boosting customer satisfaction.

Existing research has made important strides but leaves significant gaps. Machine Learning techniques have proven effective at extracting dominant colors and visual patterns from images through clustering algorithms and computational analysis [7]. A common practical choice is K-Means clustering, an unsupervised method that groups similar pixels to support image segmentation and color-feature based analysis, as demonstrated in prior image-processing applications [8]. In applied image-processing work, explicit color features have also been used effectively as inputs for classification tasks, reinforcing the feasibility of feature-driven color analysis in operational pipelines [9]. In parallel, Generative AI has shown it can produce compelling, context-sensitive visualizations quickly, yet these tools rarely get woven into measured, end-to-end business processes [10]. Moreover, much of the current BPM literature treats AI as a structural component without measuring its impact on process metrics like Cycle Time, Response Time, or Automation Ratio, and without testing predicted improvements through simulation [11], [12], [13]. As a result, a critical gap remains: the field lacks a replicable blueprint that simultaneously applies BPM to the

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custom-color workflow, integrates ML-based palette extraction with GenAI-based previews within a BPM guided workflow and directly quantifies process effects using PPI and simulation.

To answer the problems, three research questions are formulated:

1. How can an end-to-end information system for custom-color ordering improve staff efficiency and the customer experience in a real manufacturing setting?
2. What do the as-is and to-be business process models look like when the workflow is redesigned and operationalized within the BPM lifecycle?
3. To what extent do AI-enabled changes shift key process performance indicators: Cycle Time, Response Time, administrative staff hours per order, and Automation Ratio under simulation?

Addressing these questions, this study makes three contributions. First, this study offer a BPM guided, end-to-end blueprint that pairs ML for color analysis with GenAI visualization to compress decision latency. Second, this study present a case-based system design covering process models, architecture, and prototype scope that comparable manufacturers can replicate. Third, this study provide a PPI driven simulation that quantifies anticipated process gains before production rollout. This study is limited to Manufacturing Firm custom-color ordering process. This study focus on process discovery, BPM oriented redesign, the system architecture with proof-of-concept validation, and a PPI based simulation. Field deployment and revenue outcomes are outside the present scope and are reserved for future work.

BPM provides both a proven lifecycle for discovery, analysis, redesign, and monitoring and a set of redesign levers for more radical, cross-functional change when incremental improvement stalls [13], [14]. Recent studies increasingly position artificial intelligence and machine learning (ML) as enablers of predictive monitoring and decision support within the BPM. However, much of the discussion remains conceptual rather than grounded in measurable process metrics [11], [12]. During execution, Business Process Management Suites (BPMS) can streamline coordination in digital-product environments, and pairing BPM with omnichannel design has demonstrably improved internal operations in retail settings [15]. System-oriented implementations that integrate data acquisition, remote visualization, and monitoring dashboards have also been reported in the Scientific Journal of Informatics, illustrating how integrated platforms can strengthen operational visibility and support faster decision-making in practice [16]. Within the BPM lifecycle, PPI, including Cycle Time, Response Time, and Automation Ratio, provide a common vocabulary for assessing redesigns, whereas value-added analysis classifies work as Value-Adding (VA), Business Value-Adding (BVA), or Non-Value-Adding (NVA) [13], [17]. Because full deployments can be costly or risky, simulations are widely used to estimate the operational effects prior to rollout [13]. Even so, a persistent limitation remains: AI-BPM integration is often treated at an architectural or managerial level, with too little reliance on PPI and simulations to substantiate credible, process-level claims [11], [12].

Machine learning has emerged as a go-to solution for image-driven color analysis across design and manufacturing domains. Standard pipelines extract color palettes through K-means clustering and normalize them into consistent color spaces, many implementations further incorporate histogram and feature-based heuristics to stabilize results under varying illumination [7], [18], [19]. Domain-specific prototypes then map the extracted palettes onto furniture and interior elements to reduce manual iteration and accelerate ideation [18], [20]. In addition, related work on image representation and metadata generation suggests that hybrid color-feature extraction (e.g., combining clustering-based color analysis with complementary color descriptors) can improve the consistency of color-based representations for downstream use [21]. In parallel, generative AI produces rapid, context-aware visualizations that allow users to preview alternatives and shorten decision cycles, with documented gains in immersion and personalization for creative tasks and interface concepts [20], [22], [23]. However, these technologies are often studied in isolation using ML as an algorithmic module and GenAI as a user experience layer. The combined end-to-end impact on operational processes is underexplored and rarely measured through PPI or validated through simulation.

Collectively, existing studies establish BPM as a robust framework for process transformation, identifies ML as an effective utility for automating color analysis, and recognizes GenAI's power for visualization [10], [13]. What remains absent is a reproducible playbook that fuses BPM with integrated ML-based palette extraction and GenAI-based visualization within a single operational workflow, and then quantifies process-level impact using PPI, specifically cycle time, response time, staff efficiency, and automation ratio estimated through simulation [11], [12]. Building on this foundation, this study casts BPM as the methodological spine and the engine of change, this study embed ML not as a stand-alone tool but as a unit operation inside a reengineered image to palette to preview pipeline whose marginal contribution can be measured [7] and this study integrate GenAI as a governed service that closes the decision loop with realistic previews, enabling instrumentation of decision latency and downstream handoffs [10], [22]. In line with BPM best practice, the evaluation defines the relevant PPI and uses simulations to estimate to-be effects before deployment, thereby tying redesign choices (BPM plus AI) to expected operational outcomes and translating architectural advances into measurable values [15], [17], [18]. Positioning BPM as a continuous enabler for digital innovation also reinforces the need to link redesign choices to measurable operational outcomes, rather than treating BPM as a one-off initiative [24]. These gaps motivated the design science case and simulation-based assessment presented in the next section.

METHODS

This study adopts an exploratory sequential mixed methods design within a BPM oriented, design science case at manufacturing firm [25], [26]. The qualitative phase elicits and analyses the manual custom-color process, and the quantitative phase evaluates the redesigned model via prototype performance testing to estimate process-level effects, consistent with the BPM lifecycle (discovery, analysis, redesign, realization, evaluation). Figure 1 visualizes the BPM aligned flow from data collection to simulation-based evaluation and maps activities to the research questions [13], [27], [28].

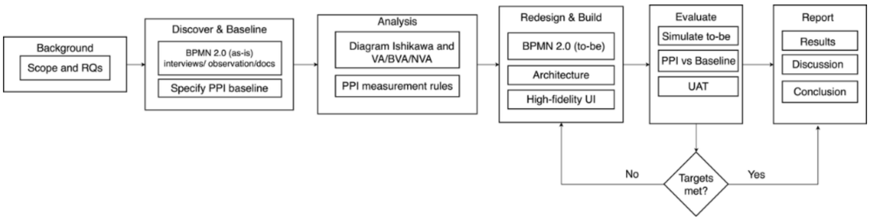

Figure 1. Research methodology for the custom color ordering process (BPM-aligned flow)

Data and participants

Primary data were collected through semi-structured interviews with purposively selected participants, namely a manager, a product specialist, and a customer [28]. A semi-structured interview guide was prepared to keep the question flow consistent across participants while still allowing follow-up probing when needed [29]. Interviews were complemented by non-participant observation and document analysis of SOPs, historical paper forms, and internal catalogs. The manager leads IT and operations with over 15 years overseeing information systems and cross-functional process coordination. The product specialist brings more than a decade of experience in synthetic-upholstery product development, including color formulation and production handoffs. The customer is a returning B2B client who has previously ordered from PT XYZ. The interview guide follows the BPM lifecycle to ensure coverage of discovery, analysis, and redesign needs.

Process discovery and baseline analysis (as-is)

The as-is workflow was modeled in BPMN 2.0 using interview transcripts and observational data. To structure causal factors, this study conducted a root cause analysis across process, technical, user, and organizational domains. Value-added analysis then classified each activity as VA, BVA, or NVA to pinpoint non-value-adding work [17]. Quantitative baselines drew from stakeholder estimates compiled into four PPI. Cycle Time spanned initial request to final delivery, response time covered initial request to first visualization, administrative staff hours aggregated per-order effort, and Automation Ratio calculated fully automated activities as a percentage of total activities. These baselines revealed that incremental fixes would fall short, justifying a BPM-guided redesign using established levers [30].

BPM oriented redesign (to-be)

Guided by the BPM literature on redesign levers, the target model specified task elimination, resequencing, enabling technology, and integration to remove paper-based handoffs, front-load decision support, consolidate stakeholder interactions, and shift routine manual work to system automation [13]. The to-be journey was structured so customers could upload a reference image, receive automated palette extraction and an immediate visualization, and complete a fully digital order, while product specialists were repositioned toward validation and exception handling with end-to-end status visibility.

System architecture and prototype scope

The target design was translated into a web-based information system that orchestrates three services: an ML service for image analysis and palette extraction, an external GenAI service accessed through REST APIs to generate interior previews, and a persistence and monitoring layer for orders and state tracking. Functional and nonfunctional requirements were derived directly from as-is pain points and stakeholder needs. To vet both usability and technical feasibility, this study built a high-fidelity user interface prototype and a proof-of-concept pipeline [31], [32].

ML pipeline for palette extraction

The ML proof-of-concept was implemented in Python. This study used OpenCV for preprocessing and color-space normalization and applied K-means clustering from scikit-learn to identify dominant colors in the uploaded image [7]. The sequence comprised image ingestion with resizing and normalization, pixel clustering into k groups, and computation of cluster centroids as palette colors returned in HEX codes, which then fed the downstream visualization and recommendation interface.

Generative AI module for instant previews

For instant previews, the set of dominant colors was formatted into a prompt template describing an interior scene rendered with the extracted palette and sent to a GenAI service to produce context-aware visualizations that support rapid decision making [10]. Integration was handled via REST APIs, and both outputs and metadata were stored with the corresponding order record. The intent was to compress decision latency rather than replace production grade rendering.

To-be evaluation design and prototype performance testing

Consistent with BPM practice, this study defined four PPI: Cycle Time, Response Time, administrative staff hours per order, and Automation Ratio. This section specifies their measurement rules and data sources. To obtain the quantitative to-be data, this study used a design science approach by conducting direct functional testing on the high-fidelity information system prototype developed for this research. This prototype fully integrates the ML pipeline for palette extraction and the GenAI service for visualization. The as-is data, in contrast, was derived from stakeholder estimates and process mapping.

This testing methodology adopted a black-box testing approach, where the system was evaluated based on its inputs (e.g., uploading a reference image) and outputs (e.g., the resulting color palette and visualization). This functional verification was complemented by API-level considerations commonly discussed in modern REST API testing literature [33], [34]. It also applied User Acceptance Testing (UAT) principles using scenario-based tests that follow the real customer workflow, to make sure the prototype meets the functional requirements of the to-be process [35], For evaluation after deployment, user adoption and information system success can be assessed using integrated acceptance and success frameworks such as UTAUT2 and HOT-fit, which can complement process performance indicators [27]. Table 1 summarizes the operational definitions and where each value was obtained for the as-is baseline and the simulated to-be.

Table 1. Process Performance Indicators (PPI): operational definitions and data source.

Indicator	Definition (unit)	As-is data source	To-be data source
Cycle Time	Sum of activity durations (days)	Stakeholder estimates, BPMN as-is mapping	Prototype performance testing (minutes for system tasks, fixed production/shipping
Response Time	Upload to first preview (minutes)	Stakeholder estimates (Interviews)	Empirical test outputs (ML+GenAI latency)
Administrative staff hours per order	Manual admin time per order (hours)	Activity-level estimates from as-is mapping	Residual manual tasks in to-be model
Automation Ratio	Automated / total activities (%)	0% in manual baseline	Automated-task count in to-be

Four main PPI were defined. Cycle Time (CT) follows the formula 1.

$$CT = \sum_{i \in \text{end-to-end path}} d_i \qquad (1)$$

To isolate digital effects, production and shipping durations remained constant at baseline values, while automated system tasks used measured prototype performance. Response Time (RT) follows the formula 2.

$$\mathrm{RT} = \mathrm{t}_{\mathrm{preview}} - \mathrm{t}_{\mathrm{upload}} \qquad (2)$$

Directly reflecting the integrated ML and GenAI pipeline's end-to-end performance as measured empirically during functional testing. Administrative Staff Hours per order (ASH) follows the formula 3.

$$\mathrm{ASH} = \sum_{a \in A_{admin}} d_a \tag{3}$$

Quantifying residual manual administration time in the redesigned process and enabling direct comparison of staff-hour efficiency. Automation Ratio (AR) is

$$AR = \left(\frac{N_{auto}}{N_{total}}\right) \times 100\% \tag{4}$$

Expressing the share of activities executed end-to-end by the system. These definitions enable consistent computation of absolute and percentage changes between as-is baseline and to-be prototype performance.

Validity considerations

Multiple validity considerations shape how far these findings extend. Internal validity hinges on the quality of two inputs, stakeholder estimates of baseline performance and empirical measurements from the prototype tests. Construct validity unfolded through iterative cycles. The research design (Figure 1) included a built-in validation loop: the redesigned process and UI aimed squarely at root causes identified during analysis, then faced evaluation against baseline performance metrics. Designs that fell short went back for another round of refinement, while those hitting targets moved forward. Presenting results to the manager and product specialist provided a practical check. Both confirmed the new system addressed their main concerns and delivered the expected improvements, validating that the redesign solved real problems rather than theoretical ones.

RESULT AND DISCUSSION

The design science approach produces four outputs with clear customer and business impact. First, discovery findings and a quantitative baseline documenting the manual (as-is) workflow and its main pain points, including long waiting times and heavy administration workload. Second, a BPM-guided redesign of the to-be process using standard levers such as task elimination, resequencing, integration, and enabling technology to remove non-value-adding work and reduce delays. Third, system realization artifacts including the architecture, a high-fidelity prototype, and a proof-of-concept implementation. Fourth, performance-testing estimates quantified through PPI, showing how the redesign improves customer response speed and reduces staff administrative burden while increasing process visibility and scalability.

As-is process discovery and baseline

Through semi-structured interviews, non-participant observation, and document analysis, this study developed a BPMN 2.0 model of the custom-color ordering process [17]. Two case types dominate: a standard catalog path and a special-request path that requires iterative formulation and validation. The root cause analysis surfaced root causes across four domains: process (paper forms, expert-dependent handoffs, unpredictable revision loops), technical (no integrated system and no automation for color extraction or illustration), user (on-site consultations and long waits), and organizational (fragmented records and limited end-to-end visibility). Based on stakeholder-elicited timings, the baseline PPI are as follows. The cycle time, measured from the initial customer request to final delivery, averages 92 days. The response time, measured from request initiation to the first visualization or sample, averages eight days. Administrative workload averages eighty-eight staff hours per order. The automation ratio is zero, indicating a fully manual process. Because these are interview-based estimates, they serve as order-of-magnitude baselines that motivate a redesign beyond incremental improvement. Figure 2 depicts the manual as-is workflow.

Figure 2. As-is custom-color workflow (BPMN 2.0). Paper-based handoffs and expert-dependent loops

BPM oriented redesign (to-be)

Guided by BPM, this study applied four redesign levers task elimination, resequencing, enabling technology, and integration to compress decision latency and remove non-value-adding work [15], [36]. In the to-be journey, customers upload a reference image, receive automated palette extraction followed by an immediate interior preview, and then complete a digital order. Product specialists shift from manual execution to validation and exception handling with full, end-to-end status visibility. In the redesigned model, 8 of 15 activities are automated, concentrated in intake, color analysis, preview generation, and order capture. Figure 3 illustrates the reengineered to-be workflow with automated steps indicated.

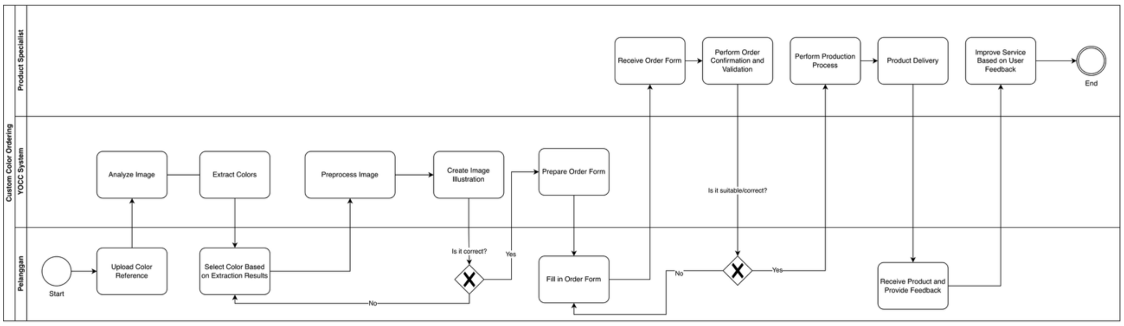

Figure 3. Automated steps shaded (8 of 15), covering intake, palette extraction, preview generation, and order capture

System realization: architecture, prototype, and PoC

The target process was translated into a web-based information system that coordinates three services. An ML pipeline handles image analysis and palette extraction, using OpenCV for preprocessing and scikit-learn K-means to derive dominant colors. An external generative AI service accessed through REST APIs with consistent endpoint conventions to improve integration clarity and maintainability [37]. API-level robustness and testing considerations follow modern REST API testing literature [38]. A persistence and monitoring layer records orders, system states, and audit trails. To validate usability and workflow coherence, a high-fidelity user interface prototype was developed covering account management, image upload, palette review, preview generation, order submission, and status tracking. A proof-of-concept implementation verified the end-to-end progression from image ingestion to palette extraction to preview generation. Pixels are clustered into k groups using K-means, and the resulting centroids are returned as HEX codes [9], [19]. These codes are then inserted into a prompt template, a preview is requested from the generative service, and both outputs and metadata are stored with the associated order record. Figure 4 depicts the end-to-end system architecture that operationalizes the target process, while Figure 5 illustrates the high-fidelity prototype workflow.

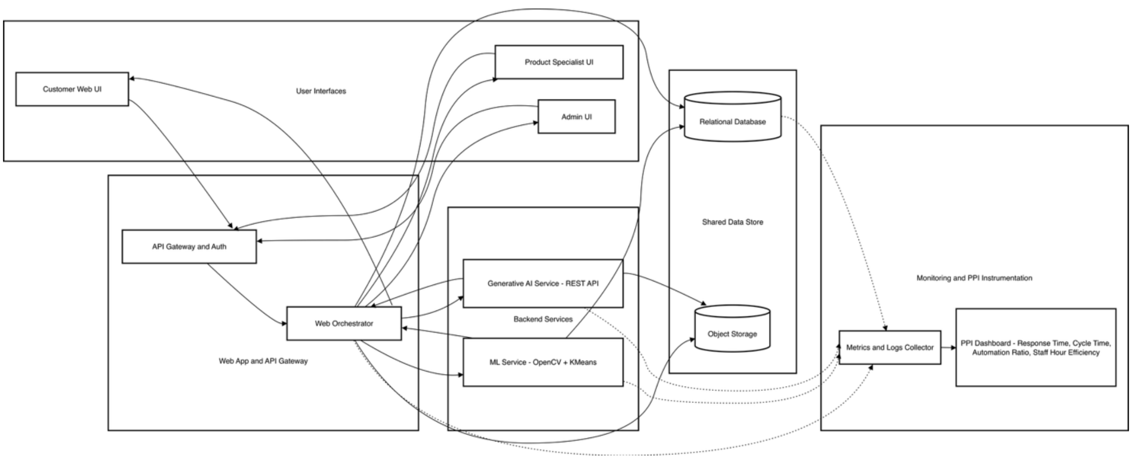

Figure 4. Web app orchestrator, ML palette extraction, GenAI preview via REST, data store & monitoring

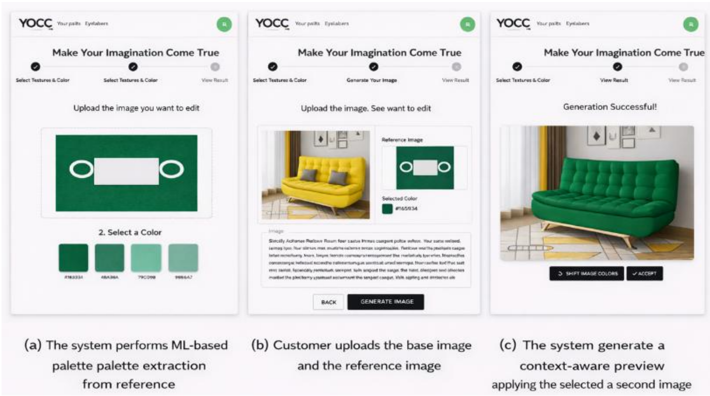

Figure 5. The high-fidelity workflow allows customers to upload a base (brand logo) and a reference image for the system to extract a color palette and generate a context-aware preview

Simulation-based estimates of process impact

Before deployment, the target design underwent prototype performance testing to estimate shifts in PPI using the operational definitions in Table 2 [39]. System tasks were modeled in minutes, while manual production and logistics durations remained constant.

Table 2. Process Performance Indicators (PPI): as-is vs. to-be (prototype)

Indicator	As-is	To-be	Relative
Cycle Time (days)	92.00	74.03	-19.5%
Response Time (to first preview)	8 days	8 minutes	-99.4%
Admin staff hours per order	88.0 h	0.4 h	-99.5%
Automation Ratio	0%	53.3%	-

Cycle Time decreases from 92.00 to 74.03 days, which represents a reduction of 19.5 percent. Response Time, measured from the initial request to delivery of the first preview, drops from 8 days to 8 minutes, which represents a reduction of 99.4 percent. Administrative staff hours per order fall from 88.0 to 0.4, which represents a reduction of 99.5 percent. The Automation Ratio rises from zero to 53.3 percent. These improvements concentrate in the early decision and documentation stages where automation and tighter integration were introduced. Section 5 discusses the quantitative effects in greater detail and relates them to qualitative trade-offs reported by stakeholders.

Synthesis of BPM redesign levers and AI impacts

As summarized in Table 2, the improvement patterns mirror the specific BPM levers applied and clarify why the PPI shifts occur. Task elimination and integration removed paper forms, duplicate entries and manual handoffs, which directly reduced administrative effort and increased the Automation Ratio. Resequencing moved decision support to the front of the workflow by presenting AI-generated previews before orders were finalized, reducing indecision loops and shortening Response Time. Enabling technology, machine learning-based palette extraction paired with generative AI visualization replaced expert-dependent checks with immediate, repeatable outputs, which contributed to a lower Cycle Time by shortening early-stage iterations. While the front-end stages improved substantially, production and shipping remained unchanged, explaining why they become the residual bottleneck in the overall Cycle Time. From a practical perspective, the synthesis highlights two direct benefits. For customers, the system reduces uncertainty by turning "waiting for the first preview" into a near-immediate step, which helps decisions happen faster. For staff, automation shifts effort from repetitive administration to validation and exception handling, supported by end-to-end status visibility that improves coordination and scalability as order volume grows.

Managerial implications

Bringing Response Time down from days to minutes tackles the chief customer pain point uncertainty and speeds decisions on custom requests. A roughly 19.5% decrease in Cycle Time improves throughput, overall responsiveness, and automating more than half of the activities enables capacity growth without a linear increase in headcount. Staff responsibilities shift toward validation and exception handling, aligning human effort with higher-value tasks. This aligns with modern BPM goals of improving consistency and transparency, allowing managers to prioritize automation for organizational efficiency [40], [41].

Technology trade-offs
Machine learning automates color extraction and reduces subjective handoffs. However, its performance depends on representative training data and careful tuning, and biased datasets can erode relevance. Generative AI provides immersive, context-aware previews that aid decision-making. However, outcomes depend on prompt quality and may not perfectly match physical color or texture [42]. Cloud API costs and web platforms (information systems) also require active management. Centralizing data and status tracking improves visibility across the process, but doing so demands investment in security, availability, onboarding, and maintenance [43]. An end-to-end stack delivers speed and personalization, although it introduces integration complexity and requires close coordination among disciplines during development and validation.

Threats to validity
Findings rest on simulation models parameterized with interview-elicited durations for the baseline, and actual latencies in production may diverge under real workloads or organizational shifts. Because the investigation focused on a single case, generalizability was constrained. This study did not quantify financial outcomes, such as return on investment, or examine long-horizon adoption, both of which require post-deployment studies. Model performance also depends on the availability and quality of training data for machine learning and the reliability of external generative AI services.

Contributions to research and practice
The research integrates BPM with machine learning and generative AI within a single instrumented workflow and quantifies expected process effects through PPI before implementation. The result is a replicable blueprint spanning discovery, redesign, architecture, prototyping, proof-of-concept, and simulation-based evaluation. Practitioners in comparable customer-facing, custom-order settings can adapt this framework directly. The case also serves as a learning model for organizations operating within similar scope. For researchers, the case provides process-level evidence of AI-enabled BPM that moves beyond architectural narratives and responds to calls for a complementary agenda between BPM and digital innovation, providing a measurable, BPM aligned evaluation.

CONCLUSION
This study shows how artificial intelligence can be operationalized within the BPM lifecycle to improve customer-facing custom color ordering processes. The BPM-guided redesign was realized as an end-to-end information system that integrates ML-based palette extraction and GenAI-based previews. Prototype-based estimates indicate major gains at the early decision stage: Response Time reduces from 8 days to about 8 minutes (-99.4%) and administrative effort reduces from 88.0 to 0.4 hours per order (-99.5%). The as-is and to-be models also demonstrate how standard BPM redesign levers (task elimination, resequencing, integration, and enabling technology) shift work from manual handling to automation, especially in intake, color analysis, preview generation, and order capture. Overall, the expected Cycle Time decreased from 92.00 to 74.03 days (-19.5%) and the Automation Ratio increased from 0% to 53.3%, while production and shipping remain the residual bottlenecks. This study is based on a single case and relies on prototype-based measurements combined with simulation estimates grounded in interview-derived baselines, so actual performance may differ once the solution runs in day-to-day operations under real workloads and change-management conditions. Future work will validate the PPI after deployment, track user adoption over time, assess financial outcomes such as ROI, and benchmark alternative ML/GenAI pipelines, including their cost–performance trade-offs. In practice, the proposed blueprint helps firms respond to customers in minutes, reduce administrative burden, and scale custom orders with better end-to-end visibility.

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