

# AI-Enabled Data Visualization Marketing for Automated Production Lines: Building Customer Trust and Improving Lead-to-Order Conversion

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**Abstract:** In many B2B acquisition and transaction workflows, companies still rely on static, fragmented marketing materials that are difficult to update consistently across channels, weakening narrative coherence and customer trust. To address this gap, this paper proposes an AI-enabled data-visualization marketing framework for automated production lines, built around a “single source of truth” content center (e.g., a CMS) that integrates production-line operational data and distributes consistent, evidence-based visual content to sales and marketing touchpoints via APIs. The approach embeds verifiable production evidence—such as yield stability, anomaly handling outcomes, delivery reliability, and batch traceability—into customer-facing materials to reduce information asymmetry and perceived supplier risk. Guided by Research Question 1 (RQ1), the study examines which categories of visual information most effectively strengthen customer trust, with a focus on quality stability trends, Pareto-style anomaly and corrective-action summaries, and traceability/compliance records—linking trust-building visual evidence to improved lead-to-order conversion performance in B2B manufacturing contexts.

**Keywords:** Industry 4.0, Data Visualization Marketing, Customer Trust, Lead-to-order Conversion.

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## 1 INTRODUCTION

In the context of Industry 4.0, competition among manufacturing enterprises no longer depends solely on automation capabilities. Instead, it hinges on the ability to achieve interconnectivity and data integration across equipment, production lines, factories, supply chains, and customer requirements. Data are used to make key operational facts—such as production health, inventory cycles, and planning and monitoring—visible and verifiable. At the same time, customer demand is becoming more central. The traditional logic of “producing what is needed” is being replaced by an “on-demand, flexible, and personalized” delivery paradigm. The combination of B2B transactions and digital infrastructure is viewed as a viable pathway toward more practical intelligent manufacturing.

However, in actual B2B customer acquisition and transaction processes, many companies still rely primarily on static brochures, case studies, white papers, and slide decks to communicate value. Fragmented marketing touchpoints and inconsistent versions of materials make it difficult for frontline teams to maintain a coherent narrative, slowing response times and undermining professionalism and credibility. To address this challenge, the concept of

automated, integrated marketing materials emphasizes a single source of truth within a unified content center or CMS, which connects via APIs to systems such as CRM platforms, marketing automation tools, and website backends. This workflow enables unified content management, intelligent updates, and efficient distribution. More importantly, content consistency is expected to significantly enhance brand professionalism and customer trust, while content data tracking provides the basis for optimizing the click-to-conversion loop.

Building on this background, this paper advances the concept of content consistency by embedding key operational data from automated production lines—such as yield stability, anomaly resolution, delivery reliability, and traceability evidence—into marketing and sales touchpoints in a visual format. This enables customers to see verifiable evidence rather than mere claims when evaluating suppliers.

This leads to the first research question of this paper:

RQ1: Which types of visual information most effectively enhance customer trust?

In other words, given that Industry 4.0 emphasizes data-driven approaches and observable production processes, which information—quality stability trends, Pareto analyses

of anomalies and corrective actions, or batch traceability and compliance records—is more effective in reducing customer uncertainty and perceived risk, thereby strengthening confidence in a supplier’s capabilities and reliability?

## 2 RELATED WORK

### 2.1 DATA VISUALIZATION FOR INDUSTRIAL TRANSPARENCY

The key to data transparency lies not in whether the data exists, but in whether the information is readily available, easily understood, and verifiable. In industrial settings, raw data often take the form of reports, tables, and logs (e.g., yield details, downtime records, and quality inspection sampling results). For decision-makers without a data background, the cost of reading is exceptionally high, and reaching consensus quickly is difficult. Visualization, through trend charts, distribution maps, heat maps, and dashboards, distills complex data into intuitive structures, enabling users to more quickly identify trends, fluctuations, and anomalies, thereby improving the transparency and consistency of the decision-making process. More importantly, when these visualizations are linked to data definitions, time windows, and data sources, they are no longer merely "displays" but traceable "evidence": management or customers can clearly see "where the conclusions come from," thereby avoiding decisions based solely on narratives or experience.

In B2B manufacturing and automated production line transactions, the value of "verifiable information" is particularly prominent because customer decisions are essentially about assessing the supplier's capabilities, stability, and risks. For example, if a supplier simply states that "our quality is stable," customers are unlikely to be convinced by a single sentence or a few photographs. In contrast, when the supplier presents a yield trend chart for the past 12 weeks, a Pareto bar chart of major defect types, and a distribution of anomaly corrective-action closure times (e.g., the percentage of issues resolved within 72 hours), customers can use these data to verify both stability and responsiveness.

Similarly, when customers worry about delivery risk, a generic promise of "on-time delivery" is far less persuasive than directly displaying the OTD (On-Time Delivery) trend and its fluctuation range by order batch. If traceability is a concern, batch-level traceability visualization (order → batch → workstation → test results) can clearly demonstrate that "if a problem occurs, it can be traced to the specific equipment, batch of raw materials, and process parameters involved." The value of these visualizations lies not only in making information more intuitive but also in transforming "trust" from a subjective impression into verifiable, objective evidence, thereby reducing customers' risk perception and communication costs.

Related practices also suggest that, for visualization to improve decision-making quality truly, it must avoid the

common pitfall of "looking impressive but being unusable." Research and industry experience generally indicate that incorrect chart types (e.g., using pie charts to depict subtle differences), information overload (a single interface crammed with metrics), and neglect of data quality and definition consistency can all lead to misleading visualizations and ultimately reduce transparency. Therefore, visualizations aimed at industrial transparency emphasize three points: First, metric selection should revolve around decision-making issues (quality, delivery, stability, and anomaly closure); second, chart design should highlight "verifiable clues" (time range, data source, calculation methods, and filtering conditions); and third, interactive drill-down should be allowed to support verification (drilling down from overall trends to workstations/shifts/batch). When visualization possesses these "verifiable" attributes, it is not merely a BI display tool but an evidence system that supports cross-departmental collaboration, customer evaluation, and sales advancement, providing a theoretical and practical foundation for subsequent discussions on whether "trust leads to conversion improvements."

### 2.2 TRUST BUILDING IN B2B/INDUSTRIAL MARKETING

In B2B digital marketing, trust-building is shifting from face-to-face, relationship-driven interactions to information availability and verifiability. Buyers often begin their research via search engines and conduct extensive self-education before contacting suppliers, repeatedly comparing content across multiple sources and touchpoints. Because industrial procurement inherently involves higher investment scale, delivery risks, and organizational coordination costs, buyers are not in a rush to be "sold" in the early stages. Instead, they seek to quickly obtain clear information to support their judgment (e.g., whether the solution is feasible, whether the metrics are credible, and whether the risks are controllable). This changes the role of content marketing: it is not only a communication channel but also a mechanism to reduce uncertainty—by continuously providing educational materials (blogs, white papers, case studies, videos) to make suppliers a stable and reliable source of information in the customer's mind, thereby establishing initial trust and eligibility for inclusion in the candidate list early in the sales cycle.

From a psychological and organizational perspective on procurement decisions, B2B trust typically comprises several key dimensions and directly affects whether leads are pursued further. First, competence: Does the supplier have the hard power to deliver quality, capacity, and responsiveness? Secondly, integrity & consistency: Are the statements from different channels and personnel consistent, and are there any exaggerations or contradictions? Thirdly, predictability & reliability: Can the supplier respond consistently and fulfill commitments when risks arise? Fourthly, benefits: Does the supplier genuinely provide solutions to customer problems, or is it simply pushing sales? The emphasis you placed on

user-preferred solutions, multiple touchpoints in the sales journey, and buyer vetting of numerous sources essentially illustrates that the purchasing party uses content and information to evaluate these trust dimensions—whether the content addresses pain points, provides verifiable details, covers the concerns of different roles, and maintains consistency across multiple contacts—to decide whether to proceed to the next step (lead generation, scheduling demonstrations, requesting quotes, trial testing, etc.).

Therefore, industrial B2B marketing must solidify "trust." The core is not simply about piling on content but about organizing the content system into a chain of evidence that supports the entire procurement process and tailoring its expression to different decision-making roles. Senior decision-makers need to see long-term value and ROI logic; engineers need technical details and evidence of performance and reliability; operations managers focus on maintenance costs and efficiency improvements; and marketing/sales focus on resource allocation and competitive advantages. This requires companies first to establish buyer profiles, then to create a 360° view of customers through centralized data (eliminating data silos), and to use data-driven approaches to deliver more relevant and consistent content. Simultaneously, high-value content should be converted into follow-up leads via form thresholds and CTAs, and combined with high-information-density formats, such as videos, to improve comprehension and memorability. Ultimately, credible information" accumulates continuously throughout the multi-touchpoint journey, reducing internal disagreements and uncertainty, shortening decision-making cycles, and increasing conversion rates.

### 2.3 AI-ENABLED MARKETING/DECISION

#### SUPPORT

AI has been increasingly adopted to improve marketing efficiency and content operations, and advertisers often expect AI tools to reduce manual work, accelerate creative development, and enable faster campaign adjustments. However, in industrial B2B settings, the primary challenge is not merely producing more content, but delivering decision-relevant, trustworthy information that helps multiple stakeholders (e.g., engineers, operations managers, and executives) assess feasibility, risk, and expected ROI across a complex buying journey.

AI-driven marketing is crucial because it enables brands to communicate their brand, products, or services to their target audience more quickly and efficiently. The tools also automate the process of reaching the target audience through appropriate channels. It handles the routine tasks, allowing you to conceive, create, launch, measure, and optimize marketing efforts more quickly.

**Efficiency:** Save significant time by automating manual tasks such as analytics and content creation.

**Relevance:** Deliver highly relevant and personalized

experiences to consumers based on their past shopping patterns using large language models.

**Scalability:** Meet the needs of large-scale marketing campaigns with tools that can tailor and optimize content for different audiences.

**Optimize creative content:** Generate visual materials, copy, and innovative ideas, reducing obstacles in the creative generation process while improving advertising quality.

In this study, we scope "AI-enabled marketing/decision support" to three functions tightly aligned with production-line data visualization. First, AI supports automated narration and summarization by converting dashboards and operational metrics (e.g., yield stability, downtime patterns, corrective-action closure) into concise, auditable explanations for sales materials and customer-facing portals. Second, according to a 2024 survey by Advertiser Perceptions, advertisers primarily seek AI tools to meet the following needs: increased efficiency (63%), enhanced flexibility and agility in campaign changes (50%), accelerated creative development (46%), and cost savings (40%). AI is profoundly transforming the marketing industry by enabling brands to conduct highly personalized, data-driven campaigns at scale. Powered by advanced algorithms, AI marketing models can optimize ad placements in real time, resulting in more effective and efficient marketing solutions. This helps improve buyer engagement, increase ROI, and enable businesses to remain competitive in today's rapidly evolving digital marketing landscape.

AI assists with anomaly interpretation, highlighting unusual changes and generating evidence-linked rationales (e.g., top contributing factors and relevant time windows), thereby reducing the cognitive burden on buyers to validate claims. Third, AI enables role-based personalization, presenting different views and narratives for different decision-makers (e.g., technical performance details for engineers versus reliability and cost implications for executives) while maintaining consistent definitions and metric logic across channels. Crucially, unlike broad AI marketing applications focused on ad bidding or creative variation at scale, our scoped approach emphasizes verifiability and governance: AI outputs are treated as explanatory layers atop traceable data rather than as standalone claims. This positioning allows us to test whether AI adds incremental value beyond visualization alone—specifically, whether AI-assisted summaries, anomaly explanations, and role-tailored views further strengthen perceived trust and ultimately improve lead-to-order conversion, forming the basis for RQ3 in our study.

## 3 METHODOLOGY AND EXPERIMENTAL DESIGN

### 3.1 STUDY DESIGN AND CONDITIONS

We designed a three-arm experiment to evaluate

whether production-line data visualization marketing improves (i) customer trust and (ii) lead-to-order conversion, and whether a scoped AI layer yields incremental gains beyond visualization alone. The study includes: C0 (Baseline) using conventional static marketing materials, C1 (Visualization Only) using a structured “evidence dashboard” package, and C2 (Visualization + AI) adding AI-assisted auto-summaries, a anomaly interpretation hints, and role-based views.

### 3.2 VISUALIZATION MARKETING PACKAGE (EVIDENCE MODULES)

The visualization package comprises four modules that map directly to common procurement risk concerns: M1 quality stability, M2 anomaly & corrective-action closure, M3 delivery reliability, and M4 traceability evidence. All visualizations are presented with consistent metric definitions and time windows to support validation behaviors (e.g., checking trend stability, drilling down into anomaly weeks, verifying traceability chains).

### 3.3 SCOPED AI LAYER

To keep the scope aligned with industrial procurement decision support (rather than broad ad-optimization), the AI layer is limited to: (1) auto-summary of dashboards into auditable narratives, (2) anomaly interpretation hints grounded in evidence windows, and (3) role-based views that tailor the same evidence base to engineers, operations managers, procurement, and executives without changing metric logic.

### 3.4 PARTICIPANTS, MEASURES, AND OUTCOMES (SIMULATED)

For illustration, we simulate a dataset with N=360 observations evenly split across C0/C1/C2 (n=120 each). Participants are assigned one of four roles (Engineer/Operations/Procurement/Executive). Trust is measured on a 1–7 Likert scale across three dimensions: competence, reliability, and integrity/transparency, aggregated into an overall trust score. Conversion is operationalized as a next-step intention indicator (e.g., request quote/book demo), serving as a proxy for lead-to-order progression. Decision time (seconds) is recorded as a behavioral indicator of decision friction.

TABLE 1. SAMPLE COMPOSITION BY ROLE AND CONDITION

Condition	n	Engineer	Operations	Procurement	Executive
C0_Baseline	1	46	38	16	20
	2	(38.3%)	(31.7%)	(13.3%)	(16.7%)
	0				
C1_Visualization	1	37	43	17	23
	2	(30.8%)	(35.8%)	(14.2%)	(19.2%)
	0				

C2_Visualization+AI	1	47	33	24	16
	2	(39.2%)	(27.5%)	(20.0%)	(13.3%)
	0				

## 4 RESULTS AND DISCUSSION (SIMULATED ILLUSTRATION)

### 4.1 RQ1: WHICH VISUALIZATION INFORMATION MOST IMPROVES TRUST?

Across evidence-based conditions (C1/C2), not all visualizations contribute equally to trust. As shown in Table D and Figure 3 (Simulated), M4 Traceability Evidence and M1 Quality Stability receive the highest contribution ratings, indicating that buyers value *auditability and stability signals* most when evaluating suppliers. M2 (anomaly & closure) also scores strongly, suggesting that visible corrective action discipline improves perceived controllability of operational risk, whereas M3 (delivery reliability) contributes moderately. These results support an evidence-first mechanism: when buyers can verify stability and traceability, perceived uncertainty and information asymmetry decrease, which strengthens integrity/transparency trust.

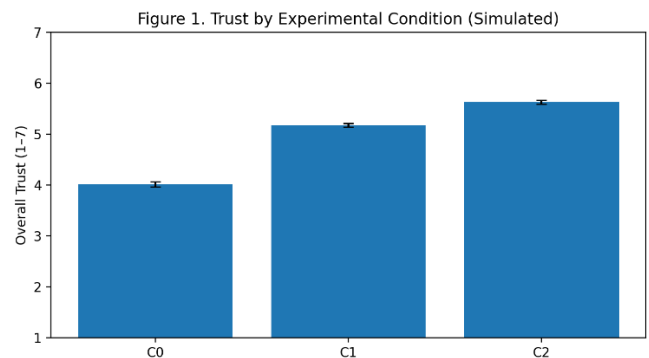
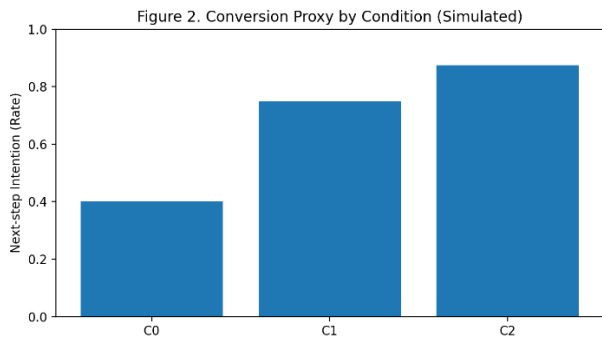


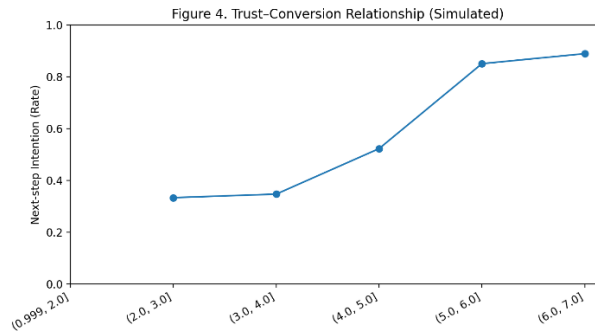
FIGURE 1. TRUST BY EXPERIMENTAL CONDITION (SIMULATED)

### 4.2 RQ2: DOES HIGHER TRUST TRANSLATE TO LEAD-TO-ORDER CONVERSION?

Trust improvements are associated with higher conversion proxies. Figure 2 (Simulated) shows that next-step intention increases from C0 ≈ 17.5% to C1 ≈ 27.5% and C2 ≈ 30.8%. In parallel, Figure 4 (Simulated) shows a monotonic relationship between trust and conversion rate: higher trust bins correspond to higher next-step intention. This pattern suggests that trust functions as a practical pathway from transparency to conversion: higher trust reduces decision friction and increases willingness to proceed to sales actions (demo/quote), consistent with the “trust → progression” hypothesis in B2B procurement.



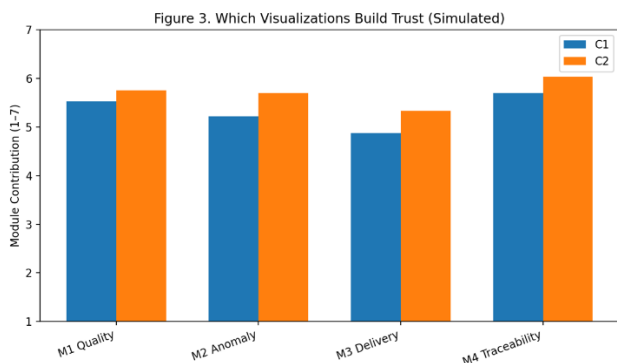
**FIGURE 2. CONVERSION PROXY BY CONDITION (SIMULATED)**



**FIGURE 4. TRUST-CONVERSION RELATIONSHIP (SIMULATED)**

### 4.3 RQ3: DOES AI ADD INCREMENTAL GAINS BEYOND VISUALIZATION ALONE?

Compared with C2, the AI layer yields incremental improvements in trust and conversion. Figure 1 (Simulated) indicates that overall trust increases from a C1 mean  $\approx$  of 5.18 to a C2 mean  $\approx$  of 5.60, while the conversion proxy rises from  $\approx$  27.5% to  $\approx$  30.8% (Figure 2). Decision time also decreases (Table “decision\_time” in the Excel), suggesting reduced cognitive burden. The incremental value of AI appears to come from *interpretation support* rather than “creative generation”: auto-summaries help stakeholders quickly extract key evidence, anomaly hints guide attention to decision-critical windows, and role-based views increase relevance across multi-stakeholder buying committees while preserving a consistent evidence base.



**FIGURE 3. WHICH VISUALIZATIONS BUILD TRUST (SIMULATED)**

This study proposes an evidence-based approach to B2B industrial marketing by embedding verifiable production-line visualizations into digital touchpoints to strengthen customer trust and improve lead-to-order progression. In the simulation, visualization-based marketing (C1) improves trust and conversion compared with baseline materials (C0), and the strongest drivers of trust are modules that directly support validation—particularly traceability evidence and quality stability.

Moreover, a scoped AI layer (auto-summary, anomaly interpretation hints, role-based views) provides incremental gains beyond visualization alone (C2 > C1), primarily by reducing decision friction and improving role relevance without sacrificing auditability. In practice, the results imply that the most effective AI-enabled industrial marketing is transparency-centered: AI should serve as an explanatory layer grounded in verifiable metrics rather than as a generator of unverifiable claims.

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