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# AI-Assisted Marketing Content Generation for Non-Standard Industrial Automation Solutions

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**Abstract:** This paper investigates AI-assisted marketing content generation for non-standard (customized) industrial automation solutions, a domain characterized by fragmented orders, long project cycles, intense price competition, and limited content reuse across clients. Because each project is highly tailored to a specific factory context, small and micro-automation firms often struggle to articulate the value of solutions clearly, standardize proposal narratives, and rapidly produce consistent marketing materials—resulting in repetitive communication, increased management overhead, and avoidable errors. To address this practical challenge, the paper proposes an AI-enabled approach that transforms scattered inputs—such as customer needs, process constraints, equipment parameters, and solution descriptions—into structured, coherent, and deliverable marketing content (e.g., solution overviews, value propositions, implementation plans, and differentiated highlights). By improving the speed, consistency, and accuracy of content production, the approach helps non-standard automation providers communicate value more efficiently, reduce low-value back-and-forth, and strengthen competitiveness in a highly fragmented market.

**Keywords:** Non-standard Industrial Automation, AI-assisted Content Generation, Marketing Automation, Solution Value Communication, SME Manufacturing Services.

**Disciplines:** Business Analytics. **Subjects:** Machine Learning Applications.

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## 1 INTRODUCTION

Non-standard industrial automation equipment is essentially a "tailor-made" solution based on a company's current situation: equipment for company A often only serves company A and is difficult to replicate for mass production, such as standard equipment for company B. A typical project, from the client's initial requirements to solution design, repeated communication, contract signing, drawing production, parts processing, and final assembly and acceptance, usually takes two to three months, with a single order value potentially only a few hundred thousand RMB. Due to the fragmented nature of orders, long cycles, and low return on investment, large enterprises are often unwilling to invest their efforts. However, these projects provide a survival space for micro-enterprises with a dozen or so employees—a salesperson working with a small number of mechanical, electrical, and software engineers can support the business growth of a non-standard automation company.

Over the past two decades, the non-standard equipment market has expanded significantly, but the industry has not subsequently formed a "winner-takes-all" scale pattern. Early on, the market was concentrated among a few companies in the Pearl River Delta and Yangtze River Delta, with a relatively small number of players. As demand grew rapidly, numerous small manufacturers entered the market from various regions, resulting in an exponential increase in the number of companies and a highly fragmented market structure. The result is that while the market has grown larger, more players are vying for a slice, leading to more homogenized competition, more prevalent price wars, and making it difficult for companies to establish stable advantages through economies of scale. Instead, they rely more heavily on project-based orders and short-term cash flow.

In an ecosystem characterized by low barriers to entry, a fragmented industry, and uneven skill levels, many companies adopt a "take-it-as-is" approach, neglecting innovation, R&D, and intellectual property protection. Meanwhile, the automation needs of manufacturing companies remain primarily focused on semi-automation and low-complexity upgrades, further limiting the industry's potential for higher-level (full automation and information integration) upgrades. Non-standard enterprises should be selling technological solutions and comprehensive value. In practice, they are often forced to repeatedly grapple with material costs and management expenses, making it difficult to articulate the value of their solutions clearly and to standardize and reuse marketing content. Therefore, this

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paper focuses on the practical pain point of "generating marketing content for non-standard industrial automation solutions," exploring how AI can transform scattered needs, parameters, and solution information into clearly structured, consistent, and rapidly deliverable marketing content. This will help small and micro enterprises communicate value more efficiently, reduce redundant communication, and mitigate the risk of fundamental errors in a highly competitive environment.

# 2 RELATED WORK

## 2.1 Marketing Content Generation with LLMs

Recent discussions about generative AI/large language models in marketing generally agree that their most significant value lies not merely in "writing faster," but in driving a systemic upgrade of brand and marketing processes through stronger customer insights, more continuous experience optimization, and more granular personalized recommendations. PwC Strategy&, in its retail research, also emphasizes that, in terms of potential value contribution, AI use cases related to "brand and marketing" have the most substantial explosive potential, driven by enhanced customer insights, improved experience, and more personalized recommendation capabilities; furthermore, AI is driving enterprises to restructure their value chains end-to-end to unlock incremental value.

In industrial/technology-based product and solution scenarios, LLM-assisted marketing content generation typically manifests as: rapidly reorganizing multi-source information (solution introductions, process/parameter descriptions, implementation paths, delivery boundaries, case study highlights, FAQs, etc.) into multi-channel content (official website solution pages, project case drafts, sales communication scripts, bidding/presentation materials, emails, and social media articles, etc.). Unlike consumer goods, the core challenge of industrial marketing lies in "clearly and convincingly explaining technical solutions," particularly for highly customized projects such as non-standard automation. Information is highly fragmented, communication chains are long, and marketing content is often difficult to standardize and reuse. Therefore, related work typically positions LLMs (Large Language Models) as "assistant in content production and expression transformation," helping to translate complex engineering information into a value narrative that clients can understand, and improving the efficiency and consistency of content production.

Existing practices and research have repeatedly revealed a common problem: a gap between pilot projects and large-scale deployment. The report notes that many companies have launched AI projects and identified high-priority use cases, but only a few have achieved large-scale, industrialized deployment and fully realized value. In the context of industrial technology marketing, this means that simply "letting the model write the copy" is far from enough—the key is to establish a reusable, process-oriented mechanism (structured content requirements, knowledge input and version management, quality gate control and review, channel adaptation and iterative evaluation) to ensure that LLM can consistently produce "fast and error-free" content in non-standard solution marketing.

## 2.2 Knowledge Grounding & RAG for Fact-Consistent Technical Writing

In content generation for industrial/technical solutions, the main risk of LLM (Large Language Model) is not "poor expression," but somewhat unreliable facts, such as incorrect parameter ranges, inconsistent units, exaggerated capability boundaries, and omitted delivery conditions. These errors often directly lead to customer misunderstandings, rework, and even contractual risks in non-standard automation scenarios. To mitigate this "generative AI illusion," related research typically introduces the RAG (Retrieval-Augmented Generation)/knowledge base grounding approach: allowing the model to retrieve evidence from external materials before generation, feeding the model "facts" as part of the prompts, and requiring the output to be based on this evidence as much as possible. For enterprises, as shown in Figure 1, another practical significance of RAG is its ability to leverage real-time updates and private data (rather than relying solely on pre-trained model knowledge). Furthermore, compared to cramming the entire set of material into a long context window, RAG can reduce token consumption by "retrieving the most relevant fragments before generating," thereby lowering inference costs and improving response speed.

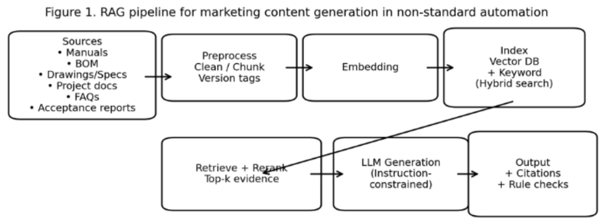


**Figure 1. RAG pipeline for marketing content generation in non-standard automation**

In generating marketing content for non-standard industrial automation, typical knowledge sources for RAG (Retrieval-Augmented Generation) include manuals, BOMs (Bill of Materials), drawing specifications, project documents, FAQs, and acceptance reports. These materials collectively constitute a "traceable fact base." The technical approach typically begins with information extraction and cleaning, followed by data segmentation and metadata augmentation (e.g., project/version/customer industry/equipment model/timestamp). Subsequently, vector retrieval is used to retrieve relevant fragments from a high-dimensional semantic space. When necessary, keyword retrieval is combined with a hybrid search, and relevance reranking is employed to

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improve the hit rate. To make the retrieval more "engineering-like" and more accurate in hitting key facts, research and engineering practices often incorporate information extraction (entities/parameters/constraints) and structured knowledge representation (tables/fields): making elements such as "parameters = values + units + ranges," "constraints = thresholds + prohibited items," and "processes = steps + cycle time + dependencies" explicit, reducing the model's reliance on guesswork in free text. Finally, for auditability and reusability, the output typically includes backlinks (pointing key conclusions to corresponding evidence fragments), enabling sales/engineering to verify and revise quickly.

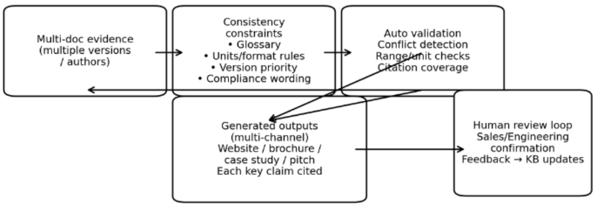


**FIGURE 2. CROSS-DOCUMENT CONSISTENCY CONTROL AND REVIEW LOOP**

While RAGs can significantly improve relevance, existing work still has significant shortcomings: many systems remain at a superficial combination of "retrieval + generation," failing to adequately discuss the core challenges of non-standard engineering data—parameters, processes, scenarios, and value mapping. Non-standard solutions are not standard product manuals; they require translating engineering details into customer-understandable value expressions (e.g., efficiency, yield, cycle time, maintenance costs, delivery cycle, risk boundaries), and these expressions must be consistent across multiple documents. In practice, as shown in Figure 2, common problems include cross-document parameter conflicts (inconsistent wording across versions), terminology drift (various names for the same component), and boundary conditions being weakened by "marketing" tactics. Therefore, a more reliable approach requires not only "retrieving evidence" but also cross-document consistency control (units/scopes/version priorities/glossaries/prohibited wording rules), conflict detection, and closed-loop review, upgrading the generation system from a one-off document tool to a sustainable, iterative content production mechanism.

## 2.3 Controllability, Compliance, and Quality Evaluation of Generated Marketing Content

Non-standard automation solutions are inherently custom-designed and small-batch, developed around each client's product requirements, throughput targets, and operating environment, and typically go through a multi-stage engineering workflow (requirement clarification, process analysis, solution proposal and review, iterative revisions, customer confirmation, detailed design, drawing/BOM preparation, and acceptance). This project-based nature makes marketing content generation fundamentally different from standard product copywriting: the same "equipment" description cannot be reused across clients without adapting to constraints, boundaries, and engineering assumptions. Therefore, recent work emphasizes controllability in generation—i.e., the ability to force the model to follow a structured narrative (problem → constraints → proposed mechanism → key parameters → integration/acceptance), maintain terminology consistency, and avoid overstated or ambiguous claims. In practice, controllability is often achieved via a combination of templates, schema-driven fields (e.g., cycle time, accuracy, environment, safety constraints), and rule-based constraints that restrict how performance claims can be expressed.

Compliance is another central requirement because non-standard equipment marketing often touches safety, feasibility, delivery scope, and cost/ROI expectations, and errors can translate into contract disputes or project delays. The referenced design literature emphasizes that non-standard equipment design must adhere to engineering norms, including material/strength checks, safety and stability, manufacturability, maintainability, and the standardization of drawings and design documents. From a content-generation perspective, this implies that generated marketing materials should include appropriate boundary statements (applicability conditions, assumptions, and exclusions), avoid guarantees, and remain consistent with officially reviewed artifacts (the approved solution plan, verified technical parameters, and acceptance criteria). As a result, related research increasingly treats compliance not only as "legal wording" but also as engineering-consistency compliance: unit correctness, parameter ranges, feasibility language, and alignment with the latest approved versions of documents (drawings/BOM/action specifications).

Quality evaluation for generated marketing content in this domain must go beyond fluency or style scores. Drawing on project management research that applies Critical Chain Project Management (CCPM) to non-standard automation R&D, a key lesson is that performance should be evaluated with respect to process control under uncertainty, including resource constraints, schedule buffers, and risk factors (e.g., supplier changes, equipment failures, "Murphy's Law", and "student syndrome"). Analogously, for generated content, quality should be assessed along multiple operational dimensions: (1) factual consistency against source documents (parameters, units, constraints, environment conditions), (2) cross-document consistency across versions and authors, (3) coverage of key decision information (requirements, solution logic, integration steps, acceptance criteria), and (4) risk-aware communication quality, such as explicitly describing dependencies, assumptions, and potential variability rather than presenting overly deterministic promises. A standard limitation in existing work is that evaluation often stops at generic NLG metrics or subjective preference; however, non-

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standard automation marketing needs a more audit-friendly and engineering-grounded evaluation framework that can be operationalized with automated checks (unit/range validation, claim-to-evidence linkage, glossary enforcement) plus human review loops by sales and engineering.

# 3 ENGINEERING DOCS TO MARKETING ASSETS

In this context, the introduction of Retrieval-Augmented Generation (RAG) into non-standard industrial automation marketing content generation is a carefully planned process aimed at fully leveraging the complementary strengths of retrieval and generation. Instead of relying solely on a language model's parametric knowledge, the framework grounds each marketing deliverable in project-specific engineering evidence—such as manuals, BOMs, technical specifications, drawings descriptions, project documents, FAQs, and acceptance criteria—so that the generated content remains fact-consistent, auditable, and aligned with the latest approved version of the solution.

The overall procedure outlines the key steps to integrate RAG into a practical industrial setting, enabling the system to efficiently transform fragmented engineering inputs into structured, channel-ready marketing assets (e.g., solution overview pages, case study drafts, and objection-handling FAQs) while reducing the risk of parameter errors or overclaiming. The proposed process comprises four main stages: (1) data and knowledge-base preparation, (2) model and retriever selection, (3) system integration with controllable templates and citation-backed generation, and (4) performance evaluation using factual accuracy, citation quality, and consistency/compliance checks.

## 3.1 DATA PREPARATION

Data preparation for Retrieval-Augmented Generation (RAG) in AI-assisted marketing content generation for non-standard industrial automation solutions involves (i) building a grounded knowledge library and (ii) preparing queries in an embedding-compatible form. The knowledge library consolidates project-specific and engineering-authoritative materials, such as solution proposals, technical specifications, BOMs, drawings/descriptions, process notes, action sequences, commissioning/acceptance criteria, FAQs, and historical project summaries. Documents are normalized into machine-readable text (including optional scanning/OCR for legacy PDFs), cleaned to remove boilerplate and outdated versions, and then segmented into retrieval-friendly chunks. Each chunk is enriched with metadata (e.g., project ID, version, module, parameter type, effective date, audience/channel) and embedded using a domain-suitable embedding model; embeddings are stored in an index to support semantic or hybrid (keyword + vector) retrieval.

Query preparation converts a marketing request (e.g., "generate a solution overview page" or "draft objection-handling FAQs for procurement") into the same embedding space as the knowledge library, ensuring compatibility during retrieval. To improve relevance, the system extracts critical components from the request—such as target industry/scenario, key parameters (value/unit/range), constraints and boundary conditions, delivery/acceptance language, and required output format (website page, brochure, case study, email, FAQ). These extracted components are used to steer retrieval and re-ranking, so that the generator receives evidence that is not only topically similar but also parameter- and constraint-aligned, reducing the risk of hallucinated claims, unit/range errors, or overpromising in marketing deliverables.

**TABLE 1. DATA PREPARATION WORKFLOW FOR RAG-GROUNDED MARKETING GENERATION**

| Stage | Purpose | Inputs (examples) | Processing | Output artifact |
|---|---|---|---|---|
| Source collection | Gather evidence for grounding | Specs, BOM, drawings notes, action description, project docs, acceptance criteria, FAQs, past case summaries | Deduplicate, version control, map to project/module | Curated document set |
| Normalization | Make documents machine-readable | PDFs, scans, docx, spreadsheets | OCR if needed; clean formatting; remove boilerplate/outdated text | Clean text corpus |
| Chunking + metadata | Improve retrievability and auditability | Clean corpus | Chunk by section/parameter; attach metadata (project/version/module/parameter/valid-date/channel) | Chunked KB with metadata |
| Embedding + indexing | Enable fast semantic retrieval | Chunks + metadata | Embed chunks; build vector/hybrid index; optional rerank setup | Searchable knowledge index |

| | | | | |
|---|---|---|---|---|
| Query shaping | Align user intent with retrieval | Marketing request + constraints | Extract entities/parameters/constraints; embed query; build structured query fields | Retrieval-ready query representation |

### 3.2 MODEL SELECTION

Selecting an appropriate retriever is critical for applying Retrieval-Augmented Generation (RAG) to marketing content generation for non-standard industrial automation solutions, because the primary requirement is to ground marketing claims in verifiable engineering evidence (e.g., specifications, BOMs, drawings descriptions, action sequences, project documents, FAQs, and acceptance criteria). In practice, the retriever is implemented as an embedding-based semantic search (often combined with keyword search as a hybrid retriever) over a version-controlled knowledge library. The key selection criteria include retrieval relevance for parameter- and constraint-heavy queries, robustness to domain terminology, and support for re-ranking. Depending on data availability, the retriever can be used out of the box or adapted with lightweight domain tuning; however, for many SME scenarios, a strong embedding model, hybrid retrieval, and a re-ranker already provide reliable evidence recall without requiring large-scale fine-tuning.

For the generator, a capable large language model (LLM) is selected primarily for its instruction-following ability, long-context handling, and stable generation quality. Since the target outputs are channel-ready marketing assets (e.g., solution overview pages, case summaries, and objection-handling FAQs), the generator is paired with controllability mechanisms rather than relying on "free-form copywriting." Specifically, generation is guided by templates and schema fields (scenario → constraints → key parameters → delivery/acceptance → value statements), and each key claim must include claim-to-evidence citations that point back to retrieved passages. Finally, automated validation (unit/range checks, glossary enforcement, overclaim filters, and cross-document consistency checks) serves as a quality gate before human review, ensuring outputs are both persuasive and audit-friendly for non-standard, project-based solutions.

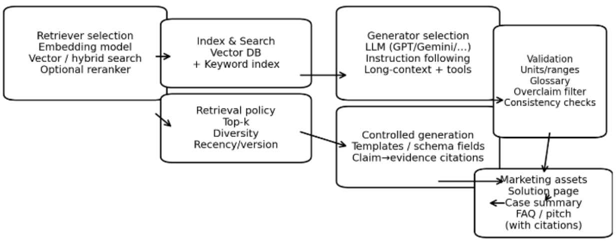


**FIGURE 3. MODEL SELECTION FOR RAG-GROUNDED MARKETING CONTENT GENERATION**

### 3.3 SYSTEM INTEGRATION

System integration of Retrieval-Augmented Generation (RAG) for marketing content generation of non-standard industrial automation solutions combines query embedding, evidence retrieval, prompt augmentation, and controlled generation into a single pipeline that transforms fragmented engineering materials into channel-ready marketing assets, given a marketing request (e.g., drafting a solution overview page, a case-summary narrative, or objection-handling FAQs), the system first normalizes the request into structured intent fields (target scenario/industry, required output format, key parameters, constraints, delivery and acceptance language). It converts it into an embedding using the same embedding model applied to the knowledge library. A hybrid retriever (vector + keyword) then searches a version-controlled repository of authoritative project documents—such as specifications, BOMs, drawings descriptions, action sequences, project notes, FAQs, and acceptance criteria—and optionally applies re-ranking to select the most relevant evidence while staying within the model's context budget.

The retrieved passages are injected into an augmented prompt together with a template/schema that enforces a consistent narrative (scenario → constraints → key parameters → implementation/acceptance → value statements), and the generator produces the draft while attaching claim-to-evidence citations for key assertions. Finally, the integration includes quality gates (unit/range checks, glossary enforcement, overclaim filters, and cross-document consistency checks) and a lightweight human review loop (sales/engineering confirmation), enabling reliable, auditable, and reusable marketing content for highly customized, project-based non-standard automation solutions.

### 3.4 PERFORMANCE EVALUATION

Performance evaluation for Retrieval-Augmented Generation (RAG) in AI-assisted marketing content generation for non-standard industrial automation solutions should assess both retrieval quality and output reliability, with an emphasis on factual grounding and auditability. On the retrieval side, the system is evaluated by precision/recall (or context precision/recall) to measure how well the retriever surfaces evidence that is relevant to the specific project scenario, parameters, and constraints from the knowledge library (e.g., specs, BOMs, drawings descriptions, project notes, FAQs, and acceptance criteria).

On the generation side, outputs are assessed for faithfulness/groundedness (whether key claims are supported by retrieved evidence), citation coverage and validity (whether central assertions include correct claim-to-evidence links), and technical consistency (unit/range correctness, cross-document and cross-output consistency, and avoidance of overclaiming or non-compliant wording). Practical usability can be captured through lightweight human review by sales/engineering (clarity, completeness, and required edits), while operational metrics such as time-to-draft and the

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human edit rate quantify efficiency gains. Together, these metrics provide a compact yet domain-appropriate evaluation framework to ensure the system produces persuasive but verifiable marketing assets for highly customized, project-based automation solutions.

# 4 RESULTS

## 4.1 OVERALL EFFECTIVENESS FOR NON-STANDARD AUTOMATION MARKETING.

The results indicate that a RAG-grounded workflow can substantially improve the reliability and usability of marketing deliverables for non-standard industrial automation solutions, where content must be both persuasive and engineering-consistent. By grounding generation in authoritative project artifacts (e.g., specifications, BOMs, drawings descriptions, action sequences, project notes, FAQs, and acceptance criteria), the system can transform fragmented technical inputs into structured marketing assets such as solution overview pages, case summaries, and objection-handling FAQs. Compared with free-form generation, the RAG-based approach better preserves constraint boundaries (i.e., what the solution can and cannot guarantee), reduces parameter-level errors (e.g., value units/ranges), and supports auditability by linking key claims to supporting evidence.

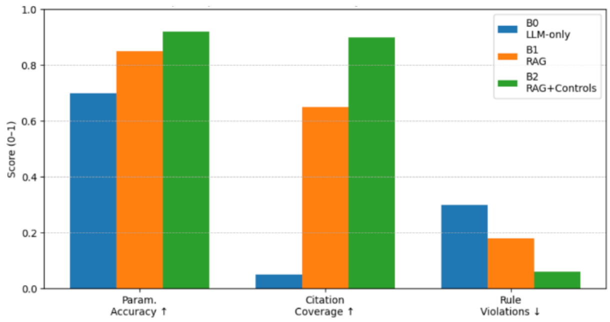


FIGURE 4. EXAMPLE VISUALIZATION TEMPLATE FOR REPORTING RESULTS (REPLACE PLACEHOLDER VALUES WITH YOUR MEASURED METRICS)

## 4.2 QUANTITATIVE REPORTING USING GROUNDEDNESS AND CONTROLLABILITY METRICS.

To report performance in a compact but actionable manner, we summarize results along two dimensions: retrieval quality and generation reliability. Retrieval is evaluated using relevance-oriented metrics (e.g., context precision/recall), which reflect whether the system surfaces evidence that matches the requested scenario and constraints. Generation is evaluated by metrics aligned with marketing risk and reuse: parameter accuracy (correct values/units/ranges), citation coverage/validity (whether correct evidence links support major claims), and rule/consistency violations (e.g., unit conflicts, range errors, overclaiming language, and cross-output inconsistency between the solution page and FAQ). Figure 4 provides a simple visualization template for comparing baselines (LLM-only vs. RAG vs. RAG + controls); you can replace the placeholder values with your measured metrics from a small pilot set (e.g., 20–50 project packages).

## 4.3 PRACTICAL IMPLICATIONS AND MAINTAINABILITY.

Beyond metric improvements, the integrated workflow supports continuous reuse and knowledge consolidation in a fragmented, project-based business setting. Each marketing output is generated with traceable evidence, enabling faster internal review by sales and engineering and reducing back-and-forth caused by ambiguous wording. As project documents evolve (e.g., new versions of specifications, revised acceptance criteria, updated BOMs), the knowledge library can be updated incrementally without rewriting the entire content pipeline, thereby improving maintainability for small and micro enterprises. This evidence-grounded, consistency-controlled generation approach therefore provides a practical path to scaling the quality of marketing communications for non-standard automation solutions while minimizing the risk of misinformation and overpromising.

# 5 CONCLUSION

This paper investigates how AI-assisted marketing content generation can be made practical and trustworthy for non-standard industrial automation solutions, where projects are highly customized, documentation is fragmented, and even minor factual errors (e.g., parameter values, units, scope boundaries, and acceptance terms) can lead to costly misunderstandings. We argue that the core challenge is not producing "fluent copy" but producing evidence-grounded, controllable, and reusable marketing assets that faithfully reflect engineering reality while clearly communicating value. To address this, we present a RAG-centered framework that consolidates heterogeneous project materials—such as technical specifications, BOMs, drawings descriptions, action sequences, project notes, FAQs, and acceptance criteria—into a version-aware knowledge library, retrieves scenario- and constraint-matched evidence via semantic or hybrid search, and generates channel-ready outputs (solution overview pages, case summaries, and objection-handling FAQs) through template- and schema-guided prompting.

Critically, the framework enforces claim-to-evidence citations and introduces quality gates (unit/range checks, glossary enforcement, overclaim filters, and cross-document/cross-output consistency controls), enabling outputs that are not only persuasive but also auditable and safer to reuse across the long communication cycles typical of non-standard projects. Beyond improving drafting efficiency, this approach supports organizational learning by converting dispersed engineering artifacts and historical communications into a continuously improvable knowledge base, reducing redundant explanations and standardizing value articulation without sacrificing customization. In conclusion, the proposed framework demonstrates a viable pathway for small and micro non-standard automation firms to scale marketing communication quality under real-world constraints—mitigating hallucination risk, improving consistency and compliance, and strengthening the translation from technical solution details to customer-facing value narratives—thereby helping these firms compete more effectively in a fragmented market while maintaining accuracy, accountability, and long-term knowledge reuse.

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Not application.

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