A Model-Driven and Explainable Framework for LLM-Powered Text Classification in Web Intelligence and Marketing Applications

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Abstract

This research introduces a conceptual and explainable framework that brings together Model-Driven Architecture (MDA), Model-View-Controller (MVC), Large Language Models (LLMs), and Human-in-the-Loop (HITL) methods to support intelligent web systems used in marketing. The framework was developed from recent studies on web intelligence, model-driven design, and explainable AI. It responds to three issues often discussed in this literature as system complexity, the need for transparency, and the role of stakeholder collaboration. Within the framework, business goals are organized through the MDA layers of CIM, PIM, and PSM, linked with MVC components, and paired with provenance tags (AI-only, AI + Human, Human-only) that strengthen accountability and interpretation. A small proof-of-concept exercise was carried out using real posts from the Thai-language Aizhongchina Facebook page, with ChatGPT-5 applied to explore how the framework could classify posts and assign confidence-based provenance labels for content-style classification in a content marketing context. The example helps show how structured modeling, explainable AI, and human review can work together while keeping brand tone and stakeholder oversight intact. The main contribution of the research is its combination of software-engineering logic with explainable and human-centered AI in one transparent framework. Although the work remains conceptual, it provides a practical model that can guide future implementation that future studies could test it on larger datasets, extend it to other marketing cases with real implementation, and include quantitative evaluation to confirm its performance.

Keywords: MDA, MVC, Web intelligence, AI marketing, LLM, XAI

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1. INTRODUCTION

The digital age has made the internet an essential tool for conducting most daily operations. The base of contemporary computing systems consists of web-based technologies which develop in parallel with user needs and online service operations. Web Intelligence (WI) emerged as a reality through the combination of artificial intelligence systems with web technologies and data mining techniques. The first research focused on rule-based reasoning and static content mining until the field shifted to create dynamic personalized and context-sensitive systems [1]. The modern AI era has brought back interest in WI because web applications now employ machine learning and user modeling and adaptive decision systems to process large data sets while maintaining operational transparency [2–5].

The combination of artificial intelligence with data science and software engineering has made WI the core research subject [6, 7]. Modern web systems that use machine learning technology perform essential marketing operations through automated customer engagement and sentiment analysis and recommendation services which need flexible and explainable systems [8]. The system faces major obstacles in achieving scalability and integrating AI technology and maintaining system transparency [9–11]. The maintainability of software systems becomes achievable through Model-Driven Architecture (MDA) which separates requirements and design from implementation according to [12, 13]. When combined with the Model–View–Controller (MVC) pattern, MDA ensures modularity between system logic, user interfaces, and control layers, supporting clear human–AI interaction in web systems [14]. The process receives enhancement through Large Language Models (LLMs) which include GPT-4 because they enable automated model-to-code transformations for Agile model driven development [14, 15]. The integration of these systems improves operational efficiency and traceability and human oversight which are essential for marketing systems that need to follow ethical and regulatory requirements.

The research presents a web intelligence framework which unites Human-in-the-Loop (HITL) design principles with LLM-based labeling systems. The framework uses MDA principles by applying Computation Independent Model (CIM), the Platform Independent Model (PIM) and the Platform Specific Model (PSM) to create systems and improve system transparency. The combination of automated and human-verified labeling produces datasets which contain detailed metadata and feedback from reviewers [16–19]. The framework unites MDA with WI and LLMs and HITL to build web systems that serve users while being sustainable and preserving human involvement in decision-making processes.

The research creates a conceptual framework for intelligent web applications through its analysis of web intelligence and model-driven development and explainable systems in current academic literature. The framework draws on MDA principles and incorporates LLMs together with HITL design. The framework enables development organization through its three MDA layers which include CIM and PIM and PSM to enhance project structure and team collaboration and model transparency. The Thai-language Aizhongchina Facebook page is used as an example to demonstrate how the framework performs text classification while preserving brand consistency and content style.

This study is presented as a conceptual framework paper rather than an empirical test. The framework unites MDA, MVC, LLMs and HITL into a single design structure while adding provenance tagging to track decision-making processes between AI-only, AI + Human and Human-only approaches for building explainable web-based marketing systems.

2. THEORIES AND RELATED WORKS

2.1 Web Intelligence

Web intelligence operates as a scientific field that unites artificial intelligence with data science and web technologies to develop adaptive systems which produce customized results for users. The system aims to convert unchanging web content into interactive systems which adapt to personal user preferences. Recommendation engines and adaptive interfaces and conversational agents and intelligent retrieval systems have become essential components in marketing and education and healthcare and e-commerce [20, 21].

Web intelligence functions through autonomous intelligent agents that work independently to achieve specific objectives [22], including chatbots, recommender systems, personalization tools, and dynamic web applications as examples of manifestations. LLMs such as GPT-4 [23], Claude [24], and LLaMA [25] have brought forth a new generation of agents that handle unstructured data to perform summarization, classification, and content generation. The models operate web applications through automated communication and tagging and feedback analysis but their black-box operation makes them difficult to understand [26–28] which creates problems in critical areas such as healthcare and justice [29]. Human operators work with AI systems through HITL methods which unite artificial intelligence operational efficiency with human oversight capabilities [30–32].

Web intelligence systems under current development focus on building trust-based systems which provide explainable results and enable collaborative work [33–36]. AI-based campaign optimization and personalization for marketing and business teams needs transparency and traceability to achieve usability and maintain ethical reliability [37, 38]. The research extends previous work by developing an explainable model-based system for intelligent web systems which suits marketing and content intelligence applications that need automated processes to maintain human oversight.

2.2 Model-Driven Architecture and Modular Design in Web Intelligence Systems

The development of intelligent web systems has become more complex because they now combine adaptive features with personalization and sophisticated AI functionality. The complexity of software development is managed by model driven development through abstract models which simplify and organize the development process in software engineering. The MDA framework provides a structured approach to managing the increasing complexity of intelligent web systems. It defines three abstraction layers as CIM, PIM PSM which together connect business requirements with technical implementation [39, 40].

Prior studies have refined the application of MDA at different stages of development. For example, [41] explored ontology integration at the CIM level to enhance semantic consistency, while [42] proposed generating a PSM model from a PIM model for NoSQL databases. Similarly, [43] developed a transformation approach from CIM to PIM for healthcare interoperability, and [44] illustrated PSM implementation through platform-specific coding in cross-platform environments. These works collectively demonstrate that MDA enables transparency, modularity, and maintainability across abstraction levels, ensuring traceability from conceptual design to system deployment.

When combined with MVC pattern, MDA enhances modularity and flexibility by separating data, interface, and control components within intelligent web systems [45, 46]. Recent model-driven studies, such as [47, 48], demonstrated how LLMs can interpret conceptual diagrams and automatically generate executable code in a model-driven environment. However, these approaches still lack explainability and human validation, both of which are addressed in the framework proposed in this study.

2.3 Large Language Models and Human-in-the-Loop Workflows

Intelligent web applications have received a boost in text-based functionality from LLMs which enable general-purpose usage through their natural language understanding, classification, and text generation capabilities. Marketing-driven systems effectively use LLMs to perform content tagging along with sentiment analysis and product description generation and customer support assistance. The development of intelligent agents has been revolutionized by LLMs which enhanced their ability to automate complex work and decision-making tasks. Researchers developed intelligent systems through combining LLMs with intelligent agent architectures which resulted in adaptive systems with context-aware automation capabilities [49, 50]. LLMs require proper supervision due to their obscure functioning. Human-in-the-Loop frameworks have become essential because they ensure intelligent systems operate reliably while maintaining ethical standards to address transparency and accountability issues [51–53]. The future of artificial intelligence development depends on uniting human expertise with code-based methods and Large Language Model capabilities to possibly create a bridge between modern AI and future Artificial General Intelligence (AGI) [54]. HITL workflows have become essential in marketing applications that utilize machine learning and LLMs because these systems need careful handling of tone and emotion as well as brand messaging in marketing and business fields [55]. Through collaborative interfaces non-technical users can authenticate AI labels and provide contextual information and modify training processes [56]. Such workflows improve accuracy while ensuring intelligent systems correctly display organizational knowledge and policies.

2.4 Explainability in AI-Driven Web Systems

Explainable Artificial Intelligence (XAI) has emerged as a fundamental research domain in both theoretical and practical fields because it enhances system efficiency and robustness and provides transparency and builds trust. Research studies show that this technology provides AI system transparency through model interpretability which leads users to trust the generated outputs [57]. Reinforcement learning systems need explainable robustness because they must prove both reliability and accountability [58]. The level of user trust in AI results depends on two factors which are causability and explainability because these elements determine how people understand and accept AI systems [59, 60]. The relationship between human understanding and machine logic that XAI establishes results in stakeholders developing greater trust for AI-based systems.

The development of trustworthy explanations faces multiple significant obstacles even though researchers have made recent advancements in this area [61–63]. Research today aims to study complete systems instead of analyzing individual models. Real-world applications need complete transparency between input and output stages to monitor all operations and record vital information and user responses. Web intelligence has evolved from ontology-based systems to LLM architectures which brought enhanced automation yet introduced new difficulties for marketing applications to handle explainability and collaboration and modularity. The present systems lack integration between AI functionality and traceability systems and human monitoring requirements.

The proposed framework addresses current limitations by integrating metadata recording with provenance tagging systems as AI-only, AI + Human and Human-only to enhance explainability through transparent data flow and traceable decision records. The Explainability Layer functions as the central component that logs provenance, confidence scores, and human feedback, enabling continuous learning through feedback loops and threshold adjustment. This mechanism aligns with the principles of human–AI collaboration [64] and HITL approach, establishing full traceability from conceptual objectives to system behavior through the integration of MDA and MVC pattern.

TABLE 1 summarizes key related works on LLM-based frameworks and contrasts them with this study. The current research on LLM integration within model-driven development and auditing and

HITL workflows lacks a single conceptual framework which unites MDA with MVC and LLMs and HITL and provenance tagging for marketing-oriented web intelligence.

Table 1: Comparison of related studies on LLM-based frameworks and the proposed research

Study	**Domain**	**Validation**	**Contribution**	**Why Different from Our Work**
Chen et al. (2025) [48]	LLM task control	Conceptual and prototype	Structured state-based control	Focuses on execution control, not stakeholder collaboration, provenance, or MDA/MVC integration
Niculescu et al. (2025) [47]	Model driven development	Prototype demo	Bridges models and code generation	Lacks HITL, explainability, or marketing focus
Dai et al. (2023) [52]	Text analysis	Applied study	Demonstrates HITL effectiveness in classification	Narrow application (qualitative coding); not a generalized architecture
Sadik et al. (2024) [65]	Agile model driven development	Prototype	Integrates LLM into model driven development	Missing explainability, stakeholder roles, provenance logging
Shah (2024) [32]	LLM methodol-ogy	Conceptual	Methodology for reliable prompting	Not a system framework; lacks MDA/MVC and marketing context
This Study	Marketing & Web Intelligence	Illustrative case (Aizhongchina)	Unified framework with explainability & provenance	First to combine MDA, MVC, LLM, HITL with provenance tagging for stakeholder collaboration

3. PROPOSED FRAMEWORK: A MODEL-DRIVEN AND EXPLAINABLE FRAMEWORK FOR LLM-POWERED WEB INTELLIGENCE SYSTEMS

3.1 Overview and Framework Scope

The conceptual framework combines MDA with MVC design patterns and LLMs and human-in-the-loop validation and system-level explainability. The primary objective of this integration work focuses on creating web systems that use intelligence to achieve robustness while maintaining transparency and business logic which stakeholders have defined. The framework developed from marketing needs to build automated intelligent systems which maintain human oversight and traceability functions. MDA functions as the fundamental methodology which divides system concerns into three distinct abstraction levels starting with CIM (business objectives defined by stakeholders) followed by PIM (logical workflows and rules) and ending with PSM (technical implementation details). MVC provides an exact implementation structure which divides these abstractions into separate software components that remain simple to maintain.

The conceptual integration system allows marketers and content strategists to collaborate successfully with technical developers who serve as stakeholders. The system becomes more scalable through automated LLM-based classifications yet human validation processes maintain business objective alignment and system accuracy and transparency.

The framework architecture consists of several subsections which describe its main components along with their operational workflows.

3.2 System Architecture and Components

The proposed conceptual architecture (FIGURE 1) integrates components that ensure transparency, robustness, and alignment with stakeholder objectives. The system operates through MDA which divides its structure into three abstraction levels. CIM enables business analysts and marketing teams to establish rules and requirements for content labeling standards which include matching and non-matching and unclear and mixed styles. The system uses these criteria to generate workflow logic and validation rules and confidence thresholds which function without dependence on specific technologies. The PSM process transforms workflows into actual implementations through the definition of algorithms and APIs and databases and user interfaces. The flow from CIM to PIM to PSM enables organizations to achieve their business objectives through measurable processes while maintaining deployment stability.

While MVC framework operationalizes these abstractions. The Model handles datasets that have been labeled from CIM and PIM stages and the Controller performs classification tasks by using machine-learning and LLM components and sends uncertain results to human evaluators for assessment. Stakeholders can use the View system to examine and adjust AI outputs by working through interfaces which allow them to provide direct feedback to improve data precision and model effectiveness.

The Explainability Layer maintains accountability through its function of documenting AI prediction results together with confidence levels and reviewer activities and system origin information (AI-only, AI + Human, Human-only). Stakeholders can monitor decision-making activities through the metadata system which results in increased trust levels. Visual modeling tools help teams work together during CIM and PIM stages because they implement business logic which matches system operational needs.

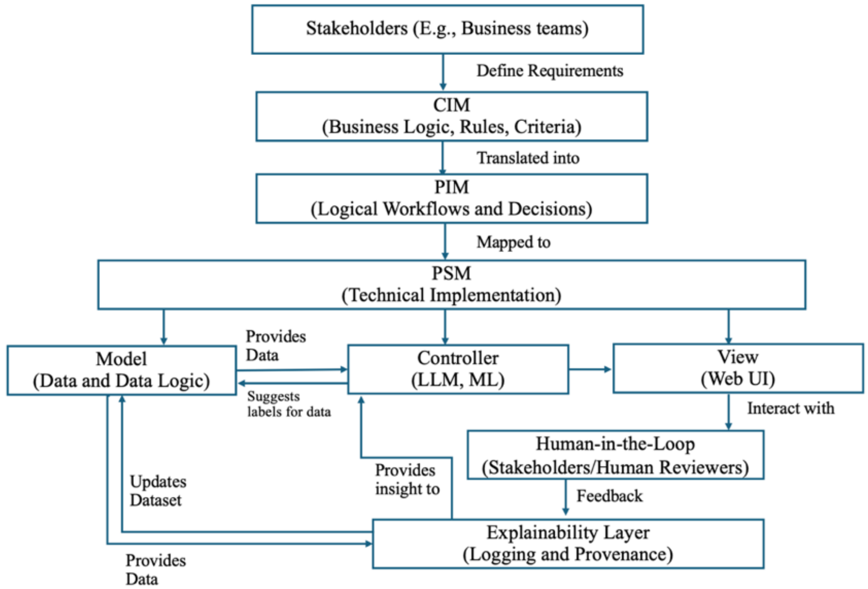

Figure 1: The conceptual architecture integrating MDA, MVC, LLM, human-in-the-loop validation and explainability.

3.3 Model-Driven Architecture Workflow

Following the principles of Model-Driven Architecture (MDA), the framework demonstrates a systematic transition from business objectives to technical implementation, as shown in FIGURE 2.

The CIM layer stakeholders develop business objectives and content-classification criteria through brief documentation which remains accessible for all participants. The system allows users to establish two rule types which consist of explicit content labeling standards and human verification protocols.

The PIM layer transforms business rules into automated workflows which produce full classification logic and state-transition definitions and data-linking structures. The logical model exists as conceptual diagrams which maintain independence from technology.

The PSM layer enables the transformation of logical workflows into technical implementations through particular technologies and MVC architectural components. The mapping method enables direct tracking of stakeholder requirements to system behavior.

The system enables stakeholders to change business logic through its organized workflow structure which supports their ability to handle changing requirements during maintenance and refinement work.

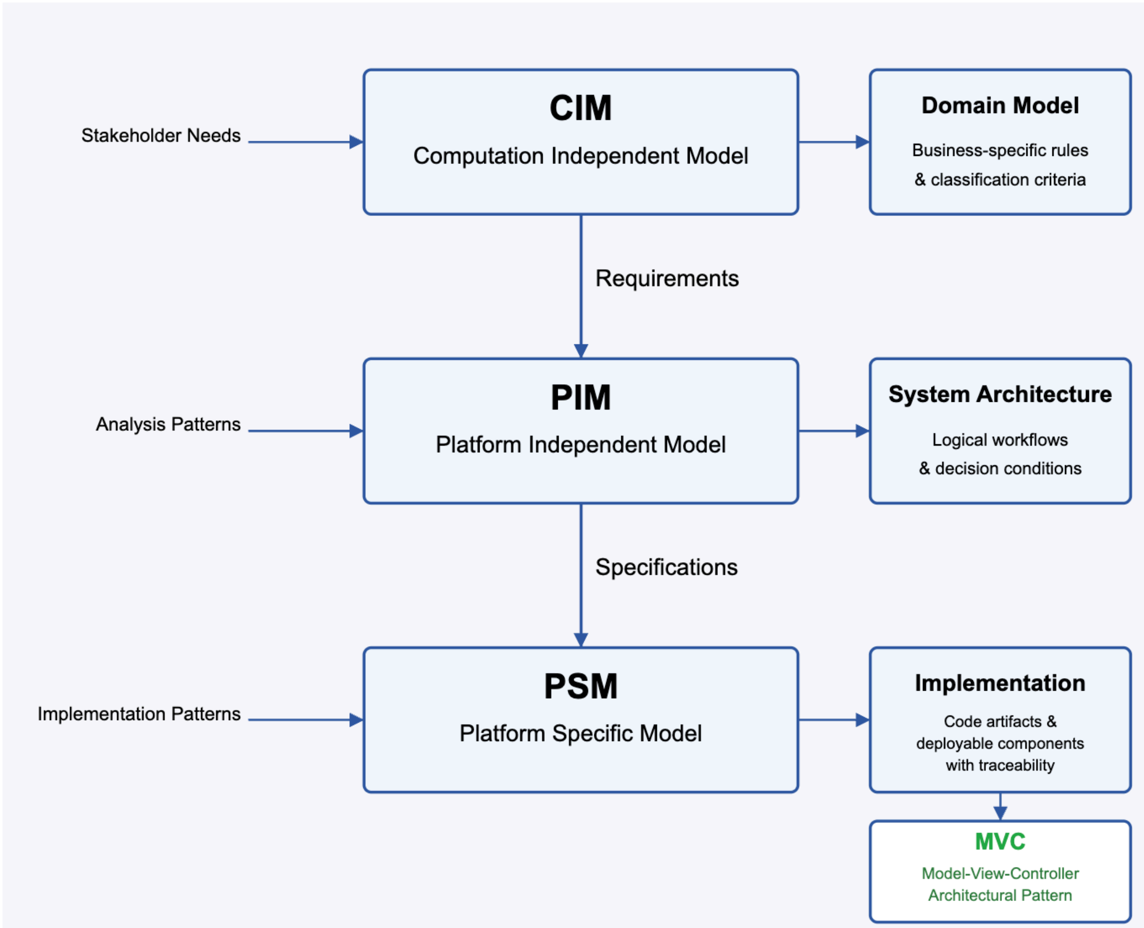

Figure 2: Model-Driven Architecture Workflow.

3.4 Mapping MDA Layers to MVC Components

The framework provides direct connections between MDA layers (CIM, PIM, PSM) to MVC components which enables stakeholders to track conceptual definitions through to practical system implementations. The mapping between these components appears in FIGURE 3, which allows stakeholders to track how business operations connect to the system while maintaining system alignment with business requirements.

3.5 LLM-Powered Interaction and Explainability

The conceptual model combines MDA and MVC and LLM components with HITL validation and an explicit explainability system as shown in FIGURE 4. Within this structure, the MVC

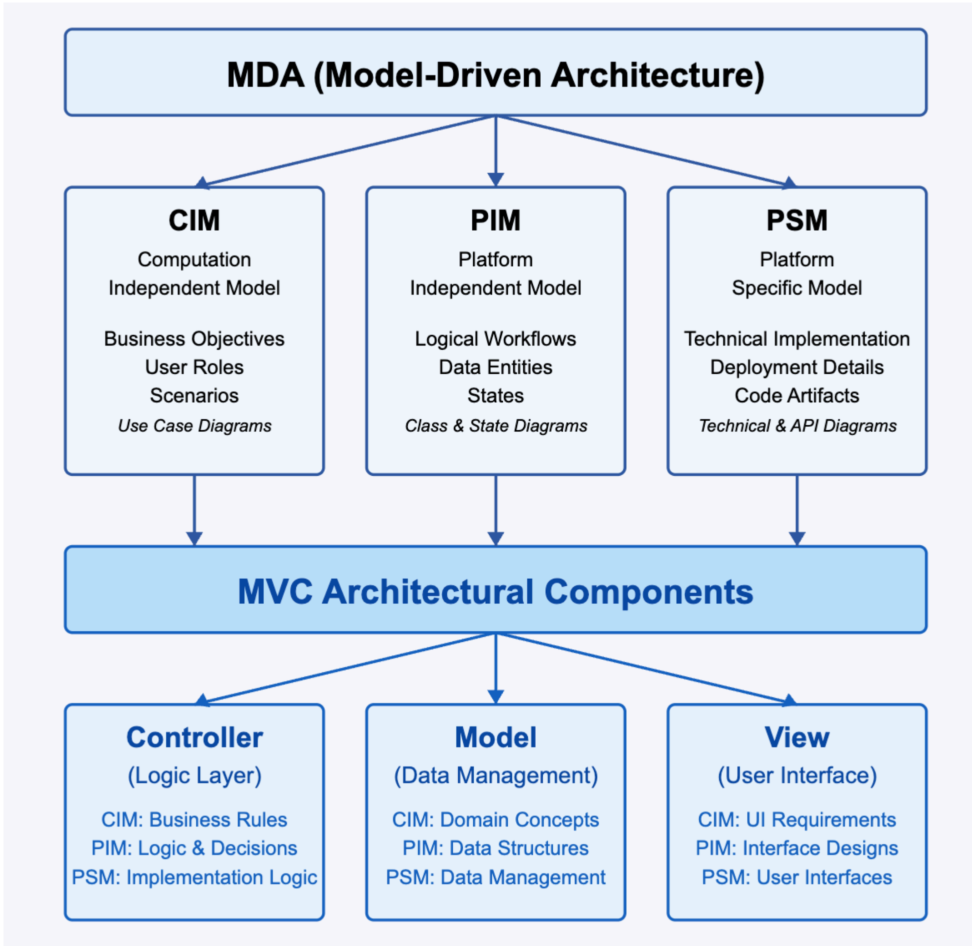

Figure 3: Mapping MDA Layers to MVC Components.

layer receives business, logical and technical rules from the MDA layer, enabling the controller to coordinate directly with the LLM engine. The LLM produces predicted labels and confidence scores which enable it to identify cases that can be processed automatically and cases that need human evaluation through the HITL mechanism.

The explainability layer maintains validated results and reviewer feedback through provenance metadata which allows for auditing and transparency and facilitates continuous improvement. The data from this layer returns to both the data management model and the controller's LLM/ML modules to enable dataset improvement and threshold adjustment during subsequent operations. The conceptual model unifies automated operations with human oversight and explainable systems to establish a unified system which generates transparent decisions that fulfill stakeholder requirements for marketing intelligence applications.

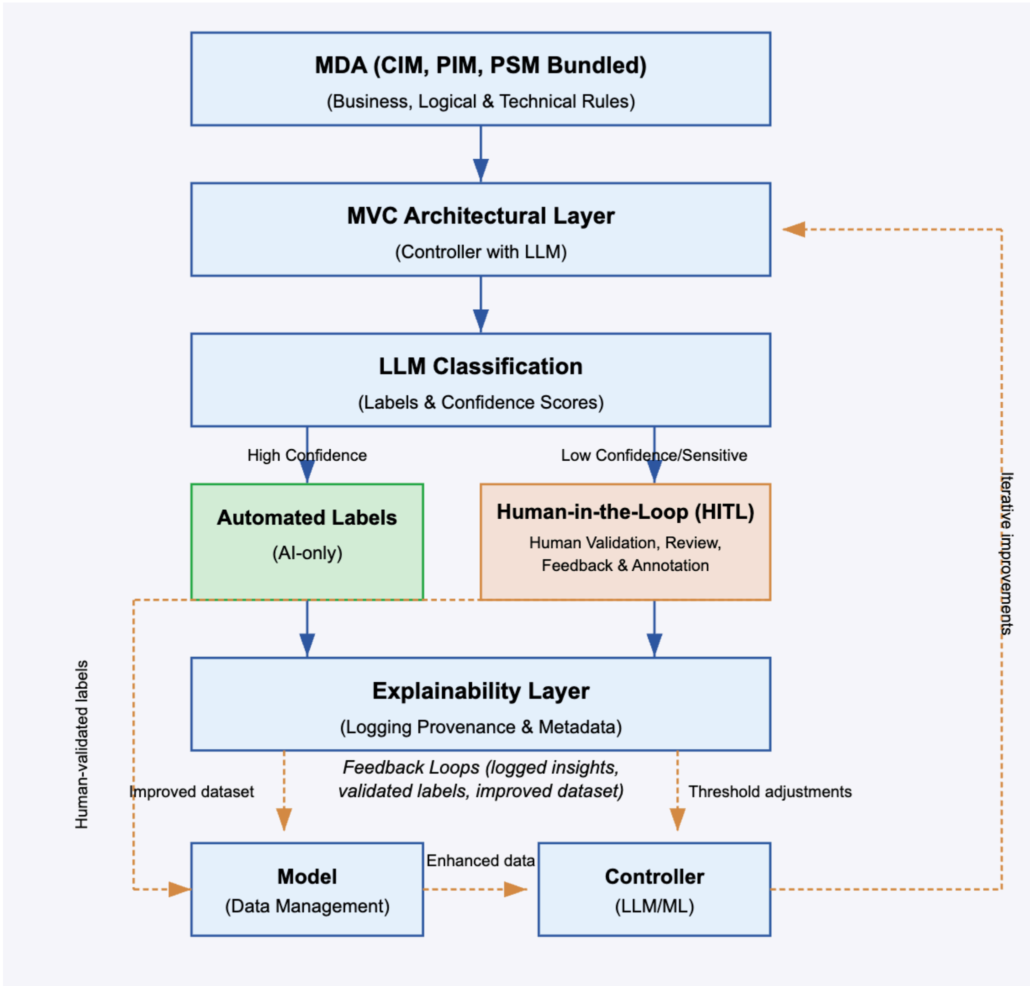

Figure 4: Conceptual diagram showing LLM-based classification integrated with Human-in-the-Loop validation and an explicit explainability layer.

3.6 Explainability Layer and Provenance Tagging

The framework contains an explainability layer according to Section 3.5 which enables users to track and understand every classification decision. The system tracks the origin of each label through three categories which include AI-generated labels, human-AI collaborative labels and human-generated labels. The system maintains an audit trail of all decisions by connecting provenance tags to metadata which contains confidence scores and reviewer comments that follow established rules from stakeholders.

The provenance system operates through three distinct categories which include AI-only and **z** and Human-only. The LLM generates High-confidence labels which get marked as AI-only and automatically finalized. The system sends cases with moderate confidence levels and sensitive information to human validation for AI+Human tagging. Labels created or replaced fully by reviewers are tagged Human-only. The system tracks review duration together with reviewer identification and content type and notes which explain the reasons behind approval or modification decisions.

The framework establishes three categories which TABLE 2, presents to show the distinction between automated tasks and semi-verified tasks and human-controlled tasks. The system enables transparency and trust through its connection of each classification to its confidence thresholds and reviewer feedback because these elements are essential for marketing environments that need accurate content and safe brand representation and full accountability.

Table 2: Label Provenance Types and Use Cases

Provenance Type	**Definition**	**Use Cases**
AI-only	LLM-generated, auto-accepted	Speed, low-risk content
AI+Human	LLM-generated, human-reviewed	Training data, analytics, sensitive topics
Human-only	Created manually by reviewer	High-stakes decisions, model error cases

The systematic approach to explainability goes further than basic classification outcome recording. The framework enables clear tracking of CIM-level business requirements on system technical behavior through its combination of provenance tags and reviewer annotations and confidence metrics in a single layer. The classification process enables organizations to learn from their experiences while ensuring that stakeholder-defined objectives remain the central priority.

3.7 Non-Technical Stakeholder Collaboration

The framework allows non-technical stakeholders including marketing and content strategy teams to actively participate in all development stages. At the CIM level stakeholders use visual modeling tools to define business objectives and logic and validation criteria. Through the View component stakeholders can take part in ongoing validation procedures which directly affects system outcomes and improvement initiatives.

The framework defines particular workflows for different roles which divides stakeholder responsibilities into business logic definition and human validation and technical system development thus enabling efficient collaboration and system evolution which matches stakeholder needs.

The proposed framework creates reliable trustworthy intelligent web applications by combining MDA business abstraction with MVC technical implementation and LLM automation and human-in-the-loop validation while following stakeholder-defined business objectives.

4. USE CASE: APPLICATION OF THE PROPOSED FRAMEWORK TO A CONTENT STYLE CLASSIFICATION SYSTEM

To illustrate how the proposed framework could operate in a real-world marketing context, a proof-of-concept demonstration was designed using the Aizhongchina Facebook page as a representative case.

Aizhongchina is a Thai-language media platform featuring translated news, lifestyle stories, and travel-related content about China. The page reaches approximately 290,000 followers and records about one million monthly impressions, making it a suitable scenario for evaluating the conceptual applicability of the model to marketing-oriented web intelligence.

A total of 200 posts were selected that 100 from Aizhongchina and 100 from comparable media outlets published between January and December 2024.

As shown in FIGURE 5, at the CIM stage, stakeholders collaboratively defined editorial and stylistic guidelines that distinguish "Match," "Not Match," and "Unclear" categories, ensuring a shared understanding among technical and marketing teams.

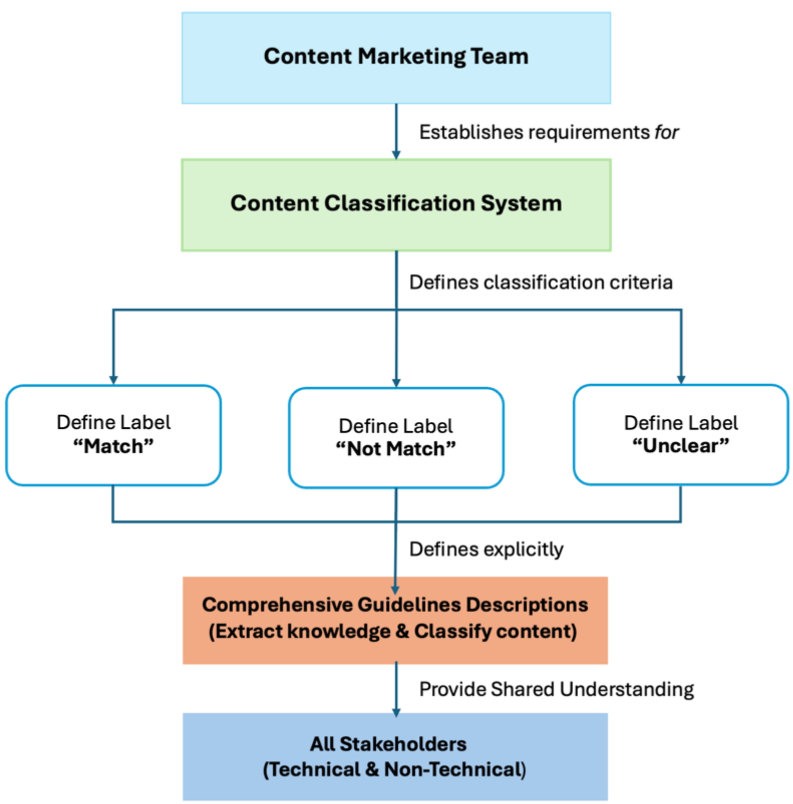

Figure 5: Diagram of CIM-level content classification labels and stakeholder guidelines.

During the PIM stage, these rules were modeled as logical workflows describing labeling conditions and human-validation criteria.

At the PSM stage, the workflows were conceptually mapped to an MVC-based structure as shown in FIGURE 6, in which the Model manages post metadata, the Controller invokes the LLM for prediction, and the View supports human validation for uncertain or context-sensitive cases. This process demonstrates how stakeholder-defined business logic can be translated into automated classification and selective human oversight through the proposed architecture.

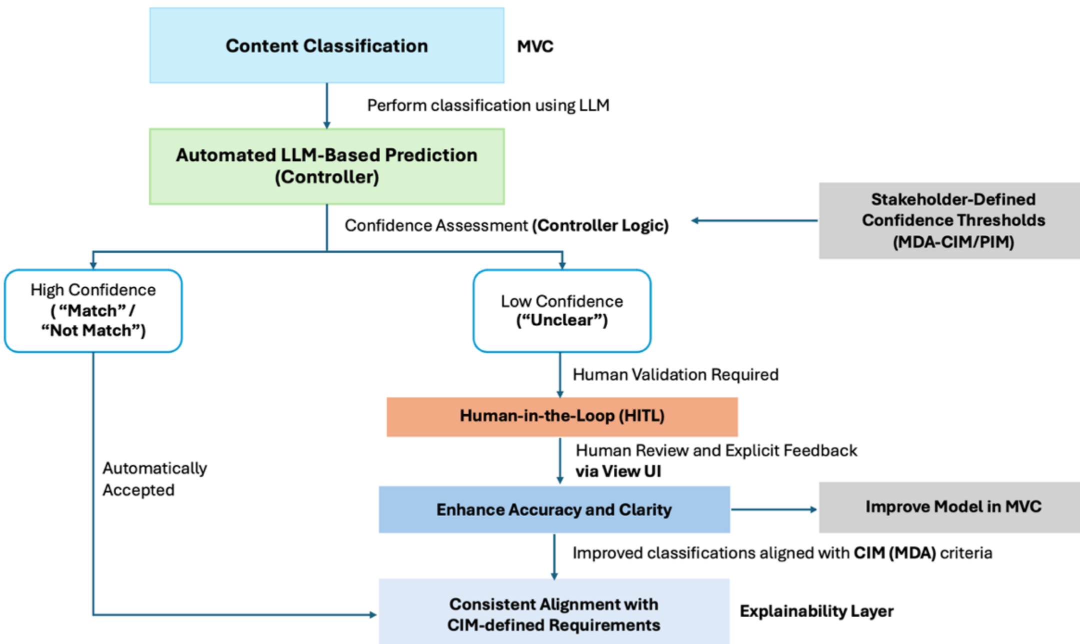

Figure 6: Diagram of MVC-based workflow integrating LLM predictions, human-in-the-loop validation, and explainability.

The 200 collected posts were first used to train the ChatGPT-5 model through the ChatGPT interface, allowing it to learn the distinction between the Aizhongchina content style and non-style posts. The labeled data, stored in a CSV file and annotated as Match and Not Match, provided the reference set for this initial learning phase.

After the learning phase, a separate subset of new posts was employed for testing. ChatGPT-5 was used to classify these unseen posts and generate confidence scores for each prediction. Cases with low confidence were assigned to the Unclear category, following the labeling logic and provenance definitions introduced earlier in TABLE 2.

A confidence threshold of 0.80 was applied to organize results into three provenance categories: AI-only, AI + Human, and Human-only.

As shown in TABLE 3, representative examples of each provenance category illustrate how the proposed framework integrates automated predictions with human validation and explainability mechanisms to ensure transparent, traceable, and brand-consistent decision making.

Table 3: Representative examples of provenance categories in the Aizhongchina dataset

Provenance	Post (Thai, full)	Translation (English)	Ground Truth	LLM Label	Confidence
AI-only	บรรยากาศช่วงเช้าที่ผ่านมา ณ ‘พระราชวังต้องห้าม’ (กู้กง) ปักกิ่งของวันหยุดยาววันชาติจีนวันแรก 1 ตุลาคม 2025... อ้ายจงไม่ได้ไปเยือนกู้กงนานแล้ว มีใครไปช่วงนี้บ้างครับ	Morning at the Forbidden City on October 1, 2025, China's National Day holiday. Aizhong notes he has not visited for a long time and invites readers to share.	Match	Match	0.95
AI-only	พื้นที่ต่างๆ ของจีนเฉลิมฉลองวันชาติ... ธงชาติจีนปลิวสะบัด... เมืองฉงชิ่ง ถนนสายหลักและสะพานล อยประดับด้วยสีแดงจีน	Regions across China celebrated National Day; flags fluttering and Chongqing's streets decorated in red.	Not Match	Not Match	0.87
AI+ Human	อากาศช่วงนี้ที่ปักกิ่งเริ่มหนาวแล้ว แต่บรรยากาศสวยมาก เดินเล่นแถวถนนหวังฝูจิ่ง เหมือนได้เห็นอีกมุมของเ มืองจีนจริง ๆ	The weather in Beijing is getting colder, but the scenery is beautiful. Walking around Wangfujing Street feels like seeing another side of China.	Match	Match	0.74
AI+ Human	จีนเจรจาการค้ากับอเมริกา รอบที่ 4 ที่สเปน... ถกกำแพงภาษี มาตรการควบคุมการส่งออก และปม TikTok	China–U.S. trade talks in Spain; tariffs, export controls, TikTok issue.	Match	Unclear	0.62
Human-only	พุทราแดงซินเจียง แสนอร่อย... เคี้ยวแล้วหนึบหนับหวานมาก...	Xinjiang red dates…chewy, sweet, healthy snack.	Not Match	Match	0.93
Human-only	ไทย–กัมพูชา ตกลงหยุดยิง ... PPTV รายงานว่าการหยุดยิงจะมี ผลเที่ยงคืนนี้	Thailand and Cambodia agreed to a ceasefire in Malaysia; PPTV reports it takes effect at midnight.	Match	Not Match	0.88

5. CONCLUSION

This research presents a model-driven and explainable framework that brings together MDA, MVC, LLM, and HITL methods for web intelligence in marketing. A propose framework builds on structured abstraction and provenance tagging to strengthen explainability, collaboration, and accountability and by using the Aizhongchina Facebook page as a use case, this research illustrates how the approach can be applied in real settings through three provenance categories that are AI-only, AI + Human, and Human-only.

Although this research remains conceptual, it shows that classification work can be managed with greater transparency when business rules and editorial guidelines are embedded directly into AI-driven workflows. In practice, this ensures that automated outputs stay consistent with brand tone and organizational goals. Our proposed framework can also be applied immediately to practical marketing tasks such as content labeling, feedback analysis, or brand monitoring, where both automation and human judgment are needed. Because this work focuses on conceptual demonstration rather than a full machine-learning experiment, it does not report quantitative measures such as accuracy or confusion matrices. Instead, it shows how MDA layers can be linked with MVC modules, LLM predictions, and HITL workflows to create traceable and accountable outcomes.

For future research, three directions are suggested. First, once deployed in a real-world environment, the framework should be evaluated in terms of explainability, usability, stakeholder satisfaction, and accuracy improvements compared with non–model-driven approaches. Second, researchers could develop automated methods to link CIM, PIM, and PSM more efficiently, reducing the manual effort needed when business rules or campaigns change. Finally, since this study mainly addresses text-based content, extending it to multimedia materials such as images, videos, and audio would help confirm its flexibility for broader web-intelligence applications.

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