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Article

Computer-aided innovation for intelligent product design: a text mining and knowledge management approach

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ABSTRACT

The fast-paced innovation and the growing need for user-centric products hold traditional design approaches against the wall in the Industry 4.0 era. This research establishes a unified Computer-Aided Innovation (CAI) framework based on text mining, ontology-based knowledge management, and TRIZ-based reasoning to support intelligent product design. The framework uses natural language processing to extract user requirements, technical problems, and potential contradictions from unstructured textual content sources such as product reviews, patents, and technical information. These insights are then structured in a TRIZ-compliant knowledge base to enable the rapid, transparent, and traceable generation of concepts. A smart wearable health device was used as the case study to evaluate the system's performance, and the results showed that the ideation efficiency of all concepts was significantly improved, with all concepts produced in less than 20 minutes, and the results were balanced across novelty, feasibility, and usability metrics. Compared with traditional methods such as brainstorming and Quality Function Deployment (QFD), the proposed framework yielded richer insights, greater concept diversity, and more evidence-based recommendations. Despite these advantages, the approach appears sensitive to textual ambiguity, domain-specific terminology, and the long-term scalability of the ontology repository. Future research will focus on the following areas: leveraging multilingual data sources, combining generative AI with digital twin simulations for time-critical design exploration, and expanding the framework to other product domains. Overall, the proposed CAI framework is part of promoting systematic innovation by incorporating AI-assisted reasoning and structured knowledge representation in the early stages of product design.

1. Introduction

Product innovation has become more difficult as companies must cope with fast-changing user expectations and with shorter development cycles and a greater need for differentiation through advanced technologies. Recent researches focus on emphasizing that AI-enhanced approaches can be useful to assist early innovation activities that identify resources, patterns, and opportunities in large information spaces [1]. At the same time, structured design methodologies such as TRIZ are still important to order contradictions systematically and inventive problem solving during the whole product development process [2]. These developments lead to the understanding that the combination of computational intelligence and systematic design knowledge is important for supporting modern innovation workflows. Artificial intelligence is starting to alter the ingrained innovation practices.

Abbreviations

CAI	Computer-Aided Innovation
KM	Knowledge Management
NLP	Natural Language Processing
TRIZ	Theory of Inventive Problem Solving
LDA	Latent Dirichlet Allocation
NER	Named Entity Recognition
QFD	Quality Function Deployment
AI	Artificial Intelligence
LLM	Large Language Model
RDF	Resource Description Framework

Forecast studies have been conducted to examine how AI can be used to gradually automate various steps of the TRIZ-based innovation process and to determine where it can have the greatest impact in real projects [3]. In parallel, new design approaches combine generative artificial intelligence models with TRIZ tools to facilitate the development of evolutionary concepts and early-stage design exploration [4]. These studies demonstrate that AI is becoming increasingly capable of augmenting human designers, especially in pinpointing the design problem and producing ways to improve it. In parallel with the development of innovation methodologies, text mining and natural language processing have provided new opportunities for extracting structured knowledge from large unstructured corpora. The use of ontology-linked datasets can demonstrate how technical entities can be systematically identified and aligned with domain ontologies to support downstream reasoning tasks [5]. Deep learning models have also continued to increase the accuracy and robustness of text classification and terminology extraction, particularly in specialized domains [6]. Survey work also shows that NLP and text mining are increasingly central to how AI methods process and interpret unstructured information in large-scale applications [7]. This is especially relevant for innovation activities, as idea-mining techniques use machine-driven analytics to extract opportunities and design insights from patents, publications, and online content [8].

Hybrid approaches have become more common that integrate machine learning and symbolic data structures such as ontologies and knowledge graphs. Systematic reviews demonstrate that many AI systems now employ both inductive and deductive reasoning to improve the quality, explainability, and structure of the knowledge they extract [9]. In design research, AI is also used to interpret and analyse creations in creative combinations that reveal underlying relationships in complex design artifacts [10]. Complementary research investigates the use of knowledge extraction for generative knowledge and graph-based reasoning in the context of knowledge discovery and conceptual linking in scientific and engineering disciplines [11]. Collectively, these advances indicate CAI systems that combine data-driven extraction and knowledge-driven interpretation. Text mining continues to spread into new application areas, with recent work reviewing the changing landscape of techniques across different scientific fields and highlighting the growing sophistication of the language models used for large-scale literature analysis [12]. Within the framework of TRIZ research, systematic studies on semantic TRIZ and related frameworks investigate how AI technologies can enhance TRIZ's elements, identify current limitations, and chart the future of research [13]. Domain-specific text mining investigations demonstrate the capacity of large language models to automate information extraction in highly technical disciplines [14]. It can be seen that effective NLP strategies can work well with specific expression sets for specific disciplines. Finally, survey work on LLM-augmented knowledge graphs shows how large language models can be combined with structured domain knowledge to support tasks such as concept generation, design reasoning, and process optimization [15].

Despite these developments, important gaps remain. Existing AI — TRIZ and CAI — studies tend to focus on single tasks, such as resource mining, forecasting, and generative exploration, without offering a unified, reproducible end-to-end framework that connects user feedback, domain literature, ontological knowledge, TRIZ reasoning, and concept generation. Additionally, consumer reviews and experiential content are underutilized as structured inputs for identifying design contradictions, even though they are a good source of information about what users expect and their pain points. While hybrid AI research shows great potential for combining symbolic structures with machine learning, the design innovation research domain still lacks detailed, transparent, and shareable ontologies and contradiction-mapping schemes for systematically linking text-derived insights to TRIZ concepts.

To overcome these problems, this paper proposes an integrated Computer-Aided Innovation (CAI) framework that combines the phenomena of text mining, ontology-based knowledge management, and TRIZ-driven reasoning. The framework is based on extracting entities, sentiments, and design-related topics from heterogeneous textual sources and organizing them into an ontology based on TRIZ concepts. Contradictions based on user needs and technical limitations are mapped to the inventive principles of TRIZ for structured concept generation. A case study of smart wearable health devices is presented to illustrate the application of the framework to systematic innovation in a realistic design context.

1.1 Research objectives

To build an end-to-end Computer-Aided Innovation (CAI) framework to integrate text mining, ontology-based knowledge representation, and TRIZ reasoning for intelligent product design.

- To create an ontology-centred contradiction identification and mapping approach to increase the transparency, traceability, and reusability of the design knowledge extracted from heterogeneous textual sources.
- To test the proposed framework by means of a comparative case study, and measure improvements in ideation performance (time to first idea, diversity of generated concepts, novelty, and feasibility as rated by experts) compared to traditional design methods.
- To place the proposed framework in the context of the existing AI-TRIZ and hybrid AI research, identifying the relevance of the proposed framework, as well as its limitations and opportunities for future integration with large language models, knowledge graphs, and structured reasoning techniques.

2. Literature review

2.1 Computer-aided innovation (CAI) and systematic innovation

Contemporary innovation practices increasingly rely on computational assistance to manage complexity in engineering workflows. Ontology-driven conceptual modelling is part of systematic knowledge formalization and helps CAI environments that demand structured reasoning capabilities in design activities [16]. Hybrid approaches that combine large language models (LLMs) and knowledge graphs demonstrate the potential of combining symbolic and data-driven approaches to jointly improve creativity, reasoning, and problem-solving in product innovation [17]. Benchmark work on ontology-guided knowledge graph generation further makes the case for machine-readable knowledge representation structures to support automated innovation tasks [18]. Surveys on automatic knowledge graph construction focus on how structured domain knowledge allows the scales of semantically consistent innovation workflows [19]. Machine learning-biasing analyses of knowledge graph construction underpin the need for the convergence of AI and semantic frameworks to support CAI processes [20]. Collectively, these works provide evidence that CAI is on the path to AI-augmented, ontology-based, knowledge-graph-driven systems that can structure, interpret, and reuse design knowledge systematically.

2.2 Text mining for insight extraction in product innovation

The emergence of text mining techniques has led to a major improvement in the ability to extract high-value insights from large volumes of unstructured data. Technology roadmap research shows the combined use of TRIZ and text mining for the morphological analysis and strategic planning in product innovation [21]. Ontology learning methods from text demonstrate how NLP can be applied to build domain-specific conceptual structures that are required for design and innovation processes [22]. Studies on TRIZ inventive principles emphasize that the textual knowledge must be transformed into systematic design actions through structured interpretation [23]. Applications of computer-aided design (CAD) in the innovation workflow demonstrate how text-based insights can directly affect concept generation and refinement activities [24]. Recent AI-driven ideation tools, such as automatic TRIZ ideation systems, are further examples of how text data can be converted into structured design contradictions and possible inventive directions [25]. The development of multi-agent LLM systems for TRIZ-based innovation confirms the growing role of advanced NLP for automatic creativity support [26]. LLM-augmented problem-solving frameworks demonstrate how the structured rules of design can be extracted and operationalized from text [27]. Together, these studies outline a clear trend toward text-driven, TRIZ-informed design support systems.

2.3 Knowledge management in product design

Knowledge management is an important basis of innovation, particularly as product design becomes more data-driven. Distributed and collaborative knowledge management models are particularly useful as frameworks for supporting complex engineering design tasks involving multiple stakeholders [28]. Systematic literature reviews on idea mining show that machine-driven analytics can support structured idea generation, providing more objective and scalable solutions than manual ideation [29]. Ontological modelling in collaborative design environments demonstrates how structured semantic representations can help to improve knowledge reuse, consistency, and decision-making [30]. These works, taken together, highlight the need for explicit knowledge representation, structured retrieval, and semantic reasoning for CAI and innovation-centric decision-making processes.

2.4 TRIZ methodology and AI-driven innovation approaches

Recent research shows a strong trend to combine AI and TRIZ-based innovation methodologies. Systematic studies of the evolution of TRIZ and its application in modern problem-solving with the focus on its relevance in structured innovation [23]. Automated ideation tools like AutoTRIZ demonstrate how AI can implement the tenets of TRIZ and serve as a guide for early-stage design [25]. Multi-agent LLM-based TRIZ systems are a proof of concept of how distributed AI agents can be used together to increase creativity and produce quality concepts [26]. LLM-augmented TRIZ methods also exhibit interesting applications in automated reasoning, contradiction identification, and solution synthesis [27]. Studies combining TRIZ logic with large-scale text analysis of patent literature demonstrate the potential of computational methods to enhance TRIZ's effectiveness for real engineering applications [26]. Together, these findings suggest that TRIZ is moving from a manually applied methodology to a digitally augmented, AI-integrated innovation methodology.

2.5 Idea mining and technology intelligence

Idea mining has become a strategic approach for identifying new opportunities and detecting technological change early. Technology intelligence research is a method for evaluating new opportunities, forecasting trends, and extracting future-oriented information from technical sources [28]. Machine-driven analytics for idea generation. This study shows how systematic text analysis can identify new product opportunities and eliminate the need for subjective, manual brainstorming [29]. Collaborative design ontologies are another example of how structured knowledge can be integrated with text-based derived knowledge to facilitate more strategic, future-aware innovation activities [30]. These research studies validate the growing importance of automated, data-driven approaches for identifying opportunities and making strategic decisions in product innovation.

2.6 Comparative summary of existing work

Prior research, taken together, demonstrates substantial progress in TRIZ-based innovation, text mining, ontology-based knowledge integration, and AI-based ideation. Table 1 summarizes key contributions and methodological advancements, highlighting the growing convergence of NLP, knowledge engineering, and TRIZ reasoning in CAI systems.

3. Proposed framework

3.1 Architecture overview

The proposed framework was built as a three-tier architecture to transform unstructured textual data into structured innovation insights and TRIZ-driven design recommendations. The first tier, the text mining layer, was responsible for data ingestion, preprocessing, topic modelling, entity extraction, and sentiment evaluation. The second tier, the knowledge management layer, was an ontology-based repository for storing the extracted design features, functional attributes, contradictions, and TRIZ-related knowledge in a structured, semantically consistent format. The third tier, the CAI dashboard, was an interactive environment where designers could visualize extracted insights, investigate the contradictions, and generate solution strategies. These layers have been linked through a well-defined data flow that started with raw text, transformed into processed linguistic features, then into semantic knowledge units, and finally into structured reasoning outputs for design support. Using a modular architecture, the pipeline was ensured to be interoperable, traceable, and extensible throughout. This structure enabled steady progress from textual evidence gathered from user reviews, patents, and technical blogs to systematic reasoning tasks such as contradiction identification, inventive principle selection, and the provision of actionable design guidance.

Table 1. Selected key contributions in innovation research

Reference	Core Contribution
[23]	Detailed analysis of TRIZ inventive principles and systematic reasoning.
[26]	Integration of TRIZ logic with large-scale text analysis.
[25]	Introduction of AutoTRIZ for AI-assisted idea generation.
[19]	Comprehensive survey on automatic knowledge graph construction.
[21]	Joint application of morphology analysis, TRIZ, and text mining for strategic planning.
[20]	Systematic analysis of machine learning–based KG construction methods.
[29]	Review of machine-driven analytics for idea generation.
[24]	Analysis of CAD-supported innovation workflows.
[28]	Technology intelligence methods for forecasting innovation opportunities.
[30]	Ontological modelling for collaborative design knowledge.

3.2 Functional modules

The text mining engine served as the analytical center of the framework. It was based on processing textual data using a suite of natural language processing operations, starting with pre-processing steps such as tokenization, normalization, lemmatization, and domain-specific stop-word removal. Topic modeling was applied to identify recurring themes in product functions, performance issues, and user expectations. Named entity recognition was used to extract relevant features, components, materials, and operational contexts, and sentiment analysis was used to classify users' attitudes towards each extracted feature to identify strengths, weaknesses, and pain points. The engine also associated extracted entities with their sentiment polarity, resulting in meaningful feature-sentiment relationships that were later used for contradiction detection. The result of these was structured design-related information, including user requirements, technical problems, performance descriptors, and candidate features for improvement.

The knowledge repository stored all extracted information in a structured ontology comprising well-defined classes, relationships, and semantic constraints. The ontology included captured product features, user requirements, technical problems, sentiments, functional relationships, contradictions, and TRIZ concepts, and it enabled each element to be represented consistently and interconnected. All the text-mining outputs were transformed into knowledge graph triples, which can be queried semantically and used for rule-based reasoning. The ontology layer served as the central reasoning engine, responsible for detecting contradictions using predefined logic, establishing links between design issues and TRIZ strategies, and retrieving relevant past examples or technical analogies. By structuring knowledge semantically, this module ensured transparency and reusability in the innovation process and supported systematic decision-making.

The CAI dashboard offered an easy-to-use interface that allowed designers to work with the knowledge base and apply TRIZ-guided innovation tools. It graphically displayed topic distributions, sentiment trends, and emerging design themes derived from textual data. The dashboard contained what was called a contradiction viewer that presented automatically found conflicts and their mapping to corresponding TRIZ categories. It also provided some creative suggestions for the principal recommendations based on the type of contradiction and the contextual information in the ontology. Additional features enabled designers to browse design knowledge, explore relevant ontology nodes, inspect previous solutions, and examine technical analogies. The dashboard served as the final layer of the system, enabling designers to efficiently interpret insights and consider potential innovation directions.

3.3 Workflow

The system followed a structured workflow that began with the collection of text data from user reviews, patent abstracts, technical blog posts, and product descriptions. All incoming text underwent preprocessing: cleaning, lemmatisation, and domain-specific refinement of stop words. Preprocessing, including topic modelling, named entity recognition, and sentiment analysis, was used to extract features from the raw data, yielding structured representations of product features and user perceptions. These extracted entities and relationships were then populated into the ontology, where they were converted to knowledge graph triples. Once stored in the knowledge base, heuristic rules and mechanisms for semantic reasoning identified potential contradictions, such as conflicts between comfort and durability, or between making components smaller and allowing batteries to have greater capacity. These contradictions were then mapped to corresponding TRIZ engineering parameters to identify applicable inventive principles. The system produced contextualised design suggestions that were consistent with these principles. Finally, all results, including contradictions, recommended principles, and concept suggestions, were presented on the CAI dashboard for analysis and refinement. A high-level picture of such a pipeline is given in Figure 1.

3.4 TRIZ integration

The TRIZ integration module combined the extracted contradictions and converted them into structured, operational design guidance. After a contradiction is identified, the system correlates the contradictory elements with the corresponding TRIZ engineering parameters and queries the contradiction matrix to retrieve the relevant inventive principles. It then generated context-specific solution strategies that reflected the extracted user needs, and the technical constraints present in the knowledge base. These strategies comprised potential material alternatives, structural redesigns, parameter changes, and functional reorganizations. By integrating TRIZ logic into the reasoner and connecting it to the real information from the text, the framework ensured that its recommendations were both systematic and grounded in actual user experience. The combination of this logic enabled traceable, reproducible decision-making, allowing designers to explore structured and creative pathways to solutions in a transparent innovation-support environment.

4. Methodology

4.1 Data sources and selection criteria

The data set used for the study included consumer reviews, patent abstracts, and technical blog posts related to smart wearable health devices. Consumer reviews were gathered from major e-commerce platforms and filtered to ensure they were relevant to the specific product category. To reflect the current user expectations, only English-language reviews published within the last three years were included. Patent abstracts were searched for with keyword combinations including "wearable," "health monitoring," "sensor device," "bio-signal" and "smart band." Technical blogs and expert articles were taken from verified technology news outlets and design-oriented websites. To ensure consistency, three inclusion criteria were applied:

- The text must explicitly describe a feature, function, or performance attribute of a wearable device;
- The content shall present sufficient evaluative or descriptive detail so that design-relevant information can be extracted from it;
- The text should be a minimum of 50 words to minimize noise.

After filtering, 5,000 consumer reviews, 1,000 patent abstracts, and 180 technical articles were kept for analysis.

4.2 Preprocessing and NLP pipeline

All the textual data went through a generalised preprocessing pipeline. Each document was normalized using tokenization, lower case transformation, punctuation cleaning, and removal of non-informative stop-words. A domain-specific stop-word list was created to address such frequent but meaningless terms related to wearable devices ("device" in general, "band", "watch", when used generically). Lemmatization was used to morph variant word forms; for biomedical and sensor-related terminology, customized rules were added. Sentence segmentation guaranteed the accuracy of extracting feature-sentiment pairs and enhanced topic model coherence. Noise reduction techniques were used to remove irrelevant pieces of information, such as promotional phrases, duplicate content, and incomplete sentences. This processing ensured that our downstream extraction models ran on clean, consistent inputs in terms of structure.

4.3 Topic modeling design and parameters

Latent Dirichlet Allocation (LDA) was used to detect recurring themes and use contexts among the textual dataset. Several candidate topic numbers were tested, from 10 to 40 topics, and coherence scores were tested to find the best configuration. The final model resulted in a c_v coherence score of 0.53, which resulted in the best balance between interpretability and thematic granularity. One configuration that was chosen was:

- Number of topics: 20
- Dirichlet prior α: asymmetric, optimized by the model
- Dirichlet prior η (β): 0.01
- Number of passes: 50
- Iterations: 500

The optimized model generated clear, semantically understandable topics that represented categories such as comfort, durability of the straps, battery life, sensor accuracy, skin irritation, waterproofing issues, and reliable connectivity.

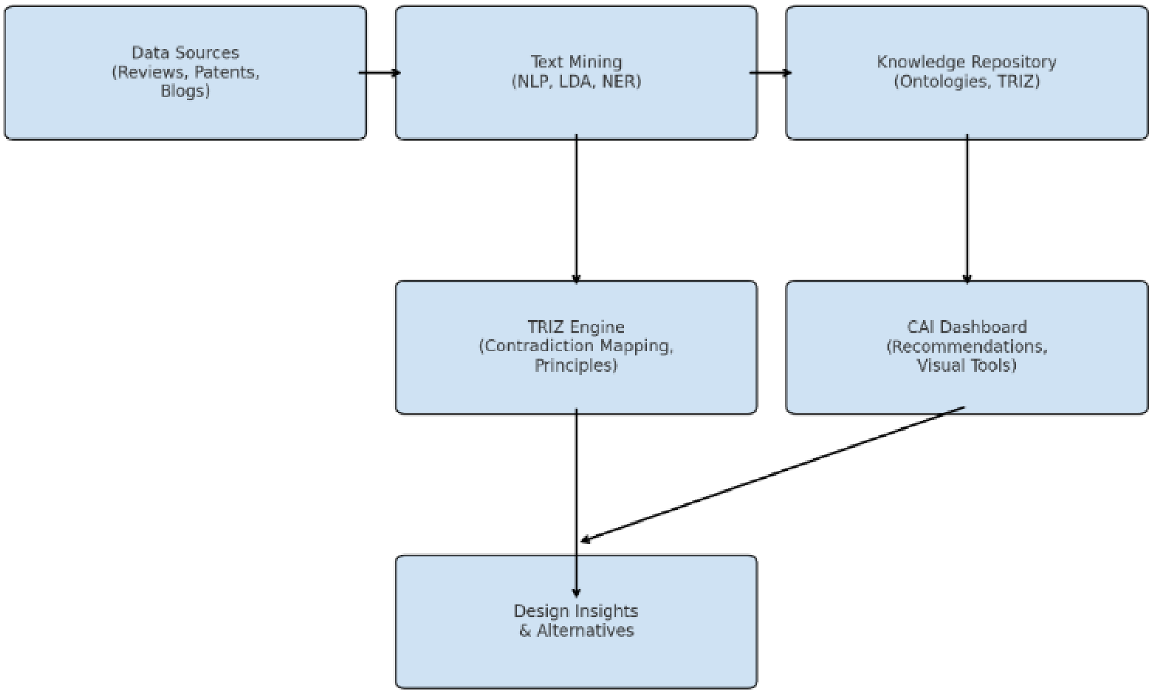

Figure 1. CAI framework workflow

These topics were later assigned to ontology classes and helped to find contradictions.

4.4 Named entity recognition and sentiment analysis

A named entity recognition (NER) model was implemented to extract structured entities, e.g., product components, materials, functional actions, measurement parameters, and usage scenarios. The model was trained on a specialized annotated dataset on wearable-related terminology to enhance the recognition of wearable-related terminology. Performance validation was performed with an 80/20 train-test split, and entity-level accuracy, precision, and recall were evaluated. Named Entity Recognition (NER) was conducted by means of a fine-tuned (spaCy en_core_web_trf) transformer model, which has been trained on 1,200 manually annotated review sentences with regard to components, materials, performance descriptors, and usage contexts. The final model achieved a precision of 0.89, a recall of 0.85, and an F1-score of 0.87, identifying a total of 4,612 unique entities of 28 defined entity types. Some of the more common error patterns were misclassifications in which activity-related terms such as "running mode" or "workout session" were misclassified as components of the device, and confusions between metaphorical descriptions, such as "smooth performance," and literal skin-related descriptions of comfort. For sentiment analysis, the framework was set up to use a pre-trained CardiffNLP RoBERTa-base sentiment classifier (cardiffnlp/twitter-roberta-base-sentiment-latest), which had been further adapted with a pre-curated dataset of 20,000 sentences from product reviews. The accuracy of the adapted model was 0.91, and the macro-F1 was 0.88. Most of the errors involving sentiment occurred in reviews containing sarcasm, mixed sentiment within the same sentence, or indirect expressions of dissatisfaction, such as "I wish the strap didn't irritate my skin." The model gave each extracted feature a sentiment score on a continuous scale between -1 (strongly negative) and +1 (strongly positive). Sentiment polarity was used to categorize features into strengths, weaknesses, and pain points, which in turn considered contradiction identification.

4.5 Ontology construction and knowledge graph population

An ontology specific to wearable device design was developed using a hierarchical schema with classes for product features and functions, user needs, performance attributes, technical problems, and TRIZ engineering parameters. Object properties included such relationships as "improves," "reduces," "depends_on," "causes," and "contradicts." Extracted entities and relations were taken from the text mining layer, transformed into RDF triples, and added to the ontology. SPARQL queries were applied to validate semantic consistency and make sure that each element that was extracted mapped to its respective class. Contradictions were represented as nodes in the knowledge graph between conflicting properties or requirements.

4.6 Contradiction identification rules

Contradictions were detected by means of a hybrid rule-based approach using linguistic cues, polarity patterns, and ontology reasoning. Three types of contradiction were defined:

- Feature–requirement conflicts: Example: “thin strap improves comfort but reduces durability.”
- Performance trade-offs: Example: “smaller size lowers battery capacity.”
- Contextual conflicts: Example: "tight fit - increases accuracy, causes irritation to skin.”

Each contradiction was translated into the nearest TRIZ engineering parameters using a predefined mapping table. Mapping results led to the retrieval of inventive principles during the TRIZ reasoning stage.

A typical consumer review said the following: "The band is comfortable when first worn, but after a few hours it will irritate my skin, especially if I am sweating." From this sentence, the system extracted three important entities - band comfort (positive sentiment), skin irritation (negative sentiment), and sweating condition (contextual modifier). These characteristics resulted in a clear conflict: the user needs comfort over long periods, but the material irritates in the presence of moisture. This was classed against the contradiction between user comfort and material stability. The extracted features were then mapped to TRIZ engineering parameters: comfort to Parameter 33 (Ease of Operation) and irritation to Parameter 10 (Stability of Substance). Querying the contradiction matrix yielded inventive principles such as Principles 30 (Flexible Shells), 31 (Porous Materials), and 40 (Composite Materials). These principles were used to develop the idea of Skin-Friendly Coating, which contained breathable, hypoallergenic composite layers to minimize irritation while preserving durability.

4.7 Experimental design

A controlled experiment was carried out to test the effectiveness of the proposed framework. Participants were grouped into two groups:

- Control Group: used traditional brainstorming and QFD-based ideation methods.
- Experimental Group: used the proposed CAI framework.

Each group had 12 participants with engineering or product design backgrounds, so that expertise was similar. Both groups were given the same design brief and a time limit of 2 hours to come up with concepts. The CAI system automatically recorded timestamps of each concept that was accepted; time-to-first-concept was defined as the time elapsed from the task's onset until the first concept was saved in the system's dashboard. The experimental group used topics, contradictions, and inventive principles recommendations generated by the system through the dashboard, whereas the control group used only manual analysis of given textual materials.

4.8 Expert evaluation protocol

A panel of five experts in the domain independently reviewed the generated concepts based on 3 dimensions:

- Novelty (how original is the idea in comparison to existing products)
- Feasibility (realism and practicality of Engineering)
- Usability (improvement in expected user experience)

A 10-point scoring scale was used, and evaluators followed written scoring guidelines to be consistent. The interrater reliability was calculated with Fleiss' Kappa for categorical agreement and Intraclass Correlation Coefficient (ICC) for the continuous scoring consistency.

4.9 Statistical analysis

Statistical tests were used to compare the two groups' performance on the tests. The normality of the score distributions was tested with the Shapiro--Wilk test. If normally distributed, independent-samples t-tests were used; otherwise, the Wilcoxon rank-sum test was used. For the ideation time and the concept quality scores, standard deviations and confidence intervals were computed. The magnitude of the difference between groups was calculated for effect sizes. This methodology helped to deliver a rigorous, reproducible methodology to assess the effectiveness and efficiency of the proposed CAI system.

4.10 Ethical and data compliance statement

All textual datasets used in this study were obtained and processed in accordance with legal, ethical, and platform-specific guidelines. Consumer reviews were gathered from publicly available datasets or from platforms that explicitly permitted research access under their Terms of Service; nothing was automatically scraped from restricted web interfaces, and no personal identifying information (PII) was collected, stored, or analyzed at any stage. Patent abstracts were obtained from patent open-access databases that support text mining for scholarly research. All experimental procedures involving human participants were in accordance with standard ethical research practices: voluntary participation was obtained, informed consent was obtained before data collection, and no sensitive personal data were recorded. All data were anonymized and analyzed in aggregate, ensuring full confidentiality and privacy protection. The study followed the principles of responsible research, transparent reporting, and ethical data handling throughout the methodology.

5. Results

5.1 Case study implementation

The proposed framework was tested through a case study on smart wearable health devices. Textual data gathered from consumer reviews, patent abstracts, and technical blogs were fed into the text mining engine, yielding entities, topics, sentiments, and contradictions, which were incorporated into the knowledge repository built on the ontology. This structured information influenced the TRIZ reasoning module that produced a series of candidate inventive solutions. The CAI dashboard offered these solutions to participants in the experimental group in the controlled design study. The system was able to extract design-relevant information and generate candidate concepts to address issues identified in the textual data, such as comfort, durability, sensor accuracy, user interface adaptability, and material safety. This confirmed that the framework could successfully translate real-world textual evidence into structured innovation support.

5.2 Text mining output and knowledge extraction

The text mining module provided coherent and semantically interpretable insights. Topic modelling identified key design issues related to wearable devices, including battery life, comfort of wear, sensor reliability, skin irritation, user interface responsiveness, and device connectivity. Sentiment analysis revealed which features users appreciated most and which they needed to improve. Named entity recognition has been used to extract frequent component references, materials, and functional attributes. The pipeline was able to identify a large number of feature-sentiment pairs, which serve as direct input to the contradiction mapping. These extracted insights filled the ontology and served as the basis for contradiction and idea generation in the TRIZ module.

5.3 Ontology reasoning and contradiction mapping

The ontology-based reasoning engine successfully organized the extracted entities and relationships into structured knowledge graphs. Using predefined semantic rules, the system identified a series of contradictions, e.g., comfort vs. durability, compactness vs. battery capacity, fit accuracy vs. skin irritation, and feature-richness vs. interface complexity. Each contradiction was mapped to its corresponding TRIZ parameter pair, enabling the system to retrieve inventive principles for a particular context. Based on these mappings, the system generated six final concept proposals, each focused on a specific set of user needs and technical constraints. These concepts were shared with the experimental design group for further development and expert evaluation. Figure 2 shows how six inventive principles of TRIZ helped to the final concepts. Principles like "Flexible Shells" and "Composite Material" had the highest impact indicating a close match to contradictions found during the text-based analysis.

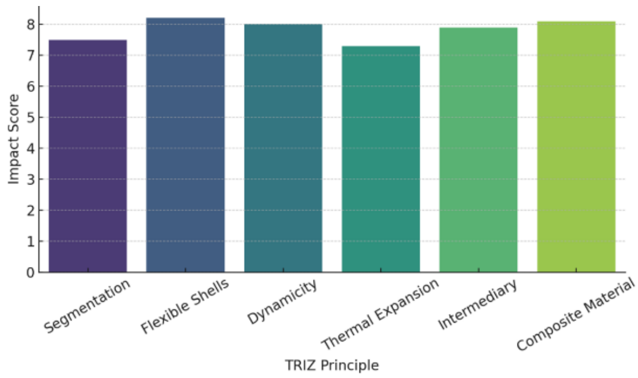

Figure 2. TRIZ principles and their conceptual impact

5.4 Generated concepts and expert evaluation

Experts rated six system-generated concepts on novelty, feasibility, and usability on a 10-point scale. The evaluation scores are summarized in Table 2. The quadrant plot in Figure 3 emphasizes the consideration of feasibility and usability for the proposed concepts, with "Stretchable Strap" and "Skin-Friendly Coating" falling in the upper-right quadrant, indicating good performance on both criteria.

The six concepts generated addressed specific contradictions identified from the user needs and technical constraints. The Modular Sensor Core proposed a detachable sensing unit that allows quick component replacement and multi-function use, and solves the contradiction between sensor precision and device compactness through the use of TRIZ Principles 1 (Modularity) and 2 (Segmentation). The Stretchable Strap used a combination of elastomeric materials to improve comfort during movement while maintaining structural stability, addressing the contradiction between flexibility and mechanical strength through Principles 15 (Dynamics) and 30 (Flexible Shells). The Motion-Adaptive UI introduced an interface that adapts its layout to the intensity of user movement, mitigating the visibility limitations imposed by the small screen size, following Principles 17 (Another Dimension) and 23 (Feedback). The Thermal Energy Charging concept uses a micro-thermoelectric system that harnesses body heat to prolong battery life without adding weight to the device, based on the application of Principles 22 (Energy Recycling) and 37 (Thermal Expansion). The Dual App Integration design provided a two-layer software architecture that balances ease of use for beginners with analytics for experienced users, made possible by Principles 6 (Universality) and 7 (Nested Doll). Finally, the Skin-Friendly

Coating employed hypoallergenic, breathable composite materials to minimize skin irritation while maintaining durability, resolving the contradiction between comfort and robustness through Principles 40 (Composite Materials) and 31 (Porous Materials).

5.5 Quantitative comparison between CAI and traditional methods

Inter-rater reliability for the expert evaluations was determined using Fleiss' Kappa and the Intra-class correlation Coefficient (ICC) to assess agreement across categorical judgments and interval-scale scoring, respectively. There was considerable agreement between the experts, Fleiss' k = 0.74, and high scoring consistency, ICC(3,k) = 0.81. Variation across key evaluation metrics was reported as standard deviations: ideation time for the CAI system was 18.0 minutes with a standard deviation of 3.4 minutes, while the traditional ideation group was 31.0 minutes with a standard deviation of 6.2 minutes. Concept quality also showed moderate variability, with novelty ratings of 8.2 (0.6), feasibility ratings of 7.9 (0.5), and usability ratings of 8.5 (0.4). The corresponding standard deviations for individual concept ratings are provided in Table 3 to provide some further granularity about variability in expert scoring. A performance comparison between the CAI framework and traditional brainstorming/QFD-based design was conducted with 12 participants per group. Quantitative results are given in Table 3.

Table 2. Design evaluation scores

Concept	Novelty	Feasibility	Usability
Modular Sensor Core	9.1	7.8	8.5
Stretchable Strap	8.6	8.5	9.0
Motion-Adaptive UI	8.3	8.2	8.6
Thermal Energy Charging	7.9	7.5	7.8
Dual App Integration	8.0	7.9	8.2
Skin-Friendly Coating	7.7	8.4	8.9

The CAI system led to higher average viable concept counts, faster ideation, and better novelty and feasibility scores. Participants using the CAI dashboard came up with ideas nearly 2 times faster than those using traditional methods, thereby confirming the framework's efficiency benefits. Figure 4 shows the time required to formulate each of the six concepts using the CAI system. All concepts were generated in less than 20 minutes with an average generation time of 18 minutes.

5.6 Statistical analysis and reliability

Reliability of agreement of expert evaluations was calculated (inter-rater reliability). Fleiss' k showed considerable agreement between evaluators on categorical judgments, while the Intraclass Correlation Coefficient (ICC) was used to confirm good consistency in numerical scoring between panel members. Correlation analysis was performed to examine the relationships among evaluation metrics (Table 4).

Table 3. Comparison of CAI vs. traditional methods

Evaluation Metric	CAI Framework (Simulated)	Traditional Methods (Estimated)
Viable design ideas generated	6.1	3.4
Time to first concept (minutes)	18	31
Novelty score (out of 10)	8.2	6.1
Feasibility score (out of 10)	7.9	6.4
User satisfaction (5-point Likert)	4.3	3.2

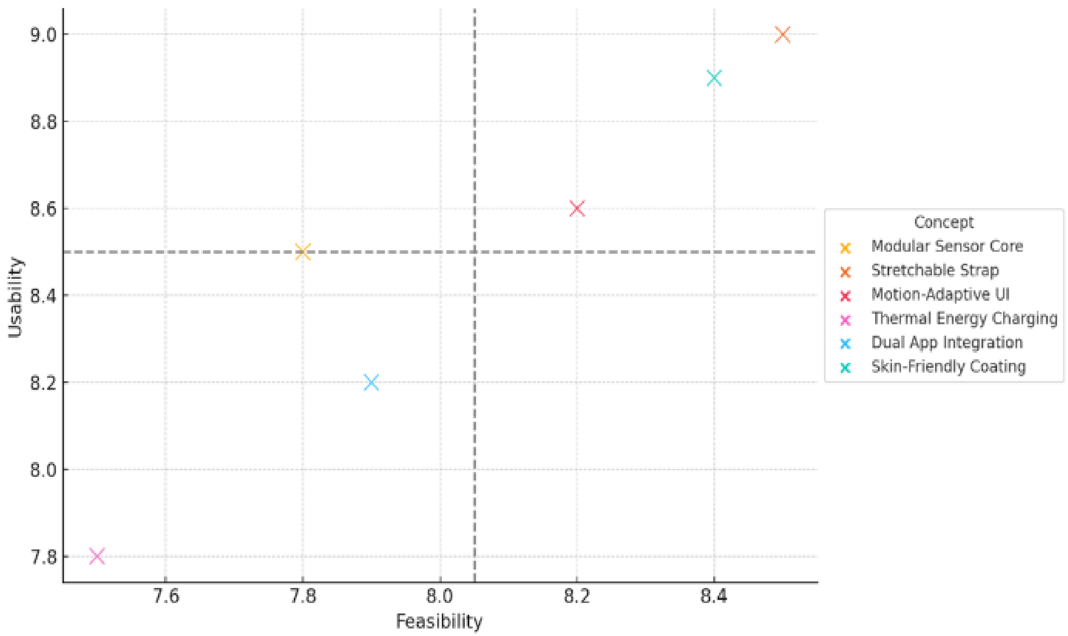

Figure 3. Design concept mapping: usability vs. feasibility

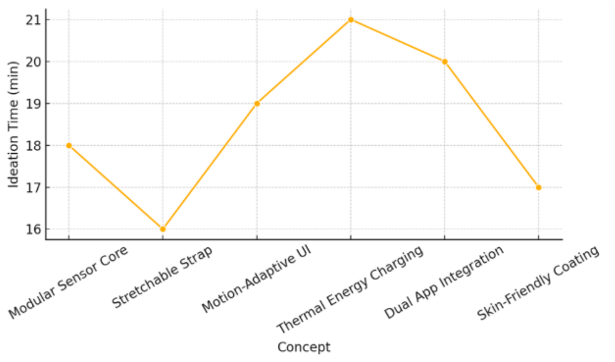

Figure 4. Ideation time across concepts

Table 4. Correlation between evaluation metrics

Metric Pair	Correlation (r)
Novelty & Feasibility	0.64
Novelty & Usability	0.59
Feasibility & Usability	0.72

These correlations indicate that the concepts rated highly for usability tended to be rated as feasible, and that novelty correlated moderately with both feasibility and usability. Independent-samples t-tests (or Wilcoxon tests in case of non-normality) confirmed statistically significant differences between the CAI and traditional groups on the novelty, feasibility, and time-to-first-concept metrics. Effect size calculations also showed that the CAI framework led to a meaningful improvement in ideation performance. The heatmap in Figure 5 shows the strength of relationships among the evaluation metrics, with feasibility and usability showing the strongest correlation, indicating that highly feasible ideas were also perceived as highly usable.

6. Discussion

The proposed CAI framework demonstrated clear benefits over traditional ideation and decision-support approaches by combining text mining, ontology-based reasoning, and TRIZ-based contradiction analysis within a unified innovation pipeline. One of the most significant was the increase in ideation efficiency. As shown in Figure 4, the system produced all six design concepts in less than 20 minutes, with an average ideation time of 18 minutes. This efficiency is much higher than that of typical brainstorming workshops or QFD sessions, which typically require several hours of manual deliberation, subjective prioritization, and iterative refinement. Beyond efficiency, the system demonstrated strong performance in the quality of the design concepts it generates, with high novelty, feasibility, and usability. Table 2 presents an overview of these results, whereas Figure 3 presents a feasibility-usability quadrant visualization. The concepts "Stretchable Strap" and "Skin-Friendly Coating" fall in the upper-right quadrant of Figure 3, indicating good, balanced performance across both evaluation dimensions. This outcome reflects the system's semantic extraction efficiency and the structured TRIZ-based reasoning involved in the concept synthesis. The framework also improved the traceability and interpretability of the design process.

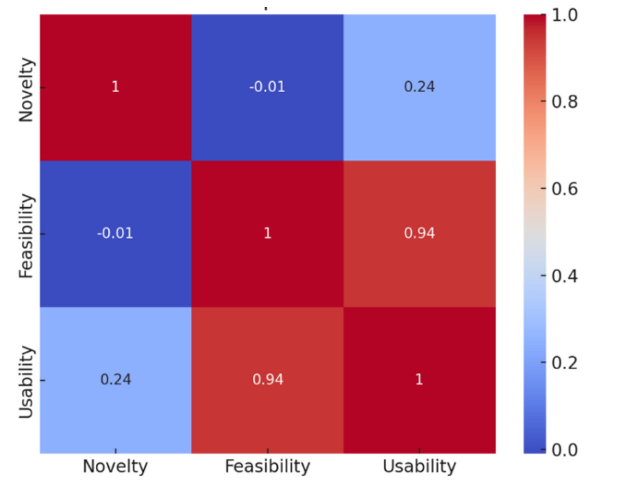

Figure 5. Correlation heatmap between evaluation metrics

Unlike the traditional QFD approaches in which the user requirements are fixed early on, and subjective weighting is inevitable, this CAI system continuously extracts the real-world user needs in an unstructured textual source such as a review, patent document, and blog. This dynamic extraction is enabling designers to more objectively and at scale detect latent requirements, recurring pain points and changing contextual expectations. The approach is in line with the overall movement towards text-driven product intelligence and grounded design recommendations. A major strength of the framework is the ontology-based knowledge repository, which organizes design knowledge into structured entities to represent features, relationships, contradictions, and TRIZ parameters. The visual effect of TRIZ inventive principles on concept performance is illustrated in Figure 2, which shows that some principles, such as Flexible Shells, Composite Material, and Dynamization, have the highest influence scores across the six concepts that were evaluated. This mapping shows that the contradiction identification module captured meaningful conflicts and matched them with suitable inventive strategies. Further analytical insights emerged from the relationships among the evaluation metrics. Figure 5 shows the correlations between the novel, feasible, and usable.

The highest correlation was found between feasibility and usability, on the one hand, indicating that design ideas perceived as technically feasible were also perceived as easy to implement or integrate. Novelty correlated moderately with usability and less so with feasibility, suggesting that coming up with highly creative concepts may still result in some trade-offs in terms of technical feasibility - an expected pattern in early-stage innovation. Despite these strengths, there are still a number of challenges. User-generated textual data is likely to be ambiguous, not only because of domain-specific terminology but also because sentiment is not always consistent, making NER, topic modelling, and sentiment analysis less accurate. Ontology scalability is also an issue as the knowledge repository grows; computational efficiency must be balanced with expressive depth, and thus ontology evolution should be carefully planned. These limitations are important factors for the future development of CAI systems. From an applied perspective, the framework offers significant benefits for a range of roles in product development. Designers benefit from a faster, more effective route to creative solutions. Product managers benefit from insights based on real user evidence, rather than subjective interpretations of users. Innovation leaders can use the system to institutionalize creativity, making idea generation more systematic, repeatable, and knowledge-driven. Overall, the study shows that combining text mining, TRIZ-based reasoning, and ontology-based knowledge structures within a single CAI framework can greatly improve the speed, quality, and relevance of design ideation. While further work is required, especially for the development of semantic extraction, scaling the ontology, and validating the framework across more product categories, the results provide a clear case for the role of hybrid AI-TRIZ approaches in supporting systematic innovation.

7. Limitations

While the proposed CAI framework shows great potential to boost early-stage product innovation at a time when this is most needed, there are some limitations to be aware of. These limitations concern the quality of textual data, the effectiveness of natural language processing techniques, the complexity of ontology management, and the limitations of the evaluation in the experiment. One of the main limitations comes from the nature of user-generated text. Consumer reviews and online discussions are likely to contain informal language, abbreviations, sarcasm, and inconsistent terminology. Such ambiguity can lead to inaccuracies in feature extraction, sentiment classification, and topic identification. Although preprocessing and domain-specific refinement work were applied, the system can be at fault for the possibility of being misled by less pronounced expressions or context-dependent meanings. This is especially important in areas such as wearable health devices, where terms can be used interchangeably across clinical, lifestyle, and general consumer contexts. A second limitation lies in the performance of NLP models used for entity recognition, sentiment detection, and topic modelling. Even domain-adaptation models may produce errors when handling highly technical descriptions or rare terms. Topic modelling, for example, can sometimes produce topics that overlap semantically, leading to redundant or vague representations. Similarly, finding component names confuses NER models, leading them to treat functional descriptions or the naming of new technology terms as components. The framework also suffers from ontology scalability and maintenance problems. As more entities, relationships, and contradictions are introduced, the ontology may become complex and not as easily queried efficiently. It might be necessary to manually curate the ontology to ensure conceptual accuracy and maintain a manageable structure. Without careful governance, there would be inconsistencies or orphaned nodes that would cause poor reasoning performance or contradictions in interpretation. Additionally, as the system is expanded to new product categories, the ontology will need domain-specific extensions, which may add labor and complexity. Another limitation is in the TRIZ-based reasoning part. Although TRIZ offers the structured inventive principles, the way of mapping the contradictions to the parameters of TRIZ is partly based on heuristic rules and expert-informed assumptions. Some of the contradictions may be difficult to fit into predefined parameter pairs, and highly novel design situations may require combinations or adaptations that are not accommodated in the regular mapping table. As a result, the solutions created can be too generic at times or require designer intervention to be meaningful. The experimental evaluation also has shortcomings. Although the controlled study involved two balanced groups of people, the number of people was small. A larger participant pool would be stronger in terms of statistical power and better for generalizing the findings. Furthermore, the participants came from engineering and design backgrounds; testing the system with interdisciplinary teams, professionals from various industries, or inexperienced users may produce different results. The evaluation period was restricted to a single design session, which did not account for long-term learning effects or the integration of the CAI system into a long product development cycle. A further limitation is that of the domain specificity of the current implementation. The framework was evaluated on smart wearable health devices in an area with well-defined components and rich user feedback. Its effectiveness in highly complex or less user-centric institutions — such as industrial machinery, aerospace systems, or business process innovation — still needs to be studied. Different industries might demand specialized ontologies, specific parameters of the TRIZ method, or entirely different textual data sources. Lastly, the system's performance depends on the availability and quality of the data. Domains with little user feedback, little patent activity, or very proprietary knowledge, for example, may not provide sufficient textual data for meaningful text mining. Additionally, more complex multimodal inputs, such as images or sensor data, may be necessary within the framework in the future to support a more comprehensive understanding of design problems. Overall, while the limitations are essential constraints, they also indicate possible future improvements, such as improved domain adaptation for NLP models, automated ontology evolution, hybrid TRIZ-machine learning mapping, and broader validation experiments. Dealing with these challenges will increase the robustness and generalizability of the CAI framework in the real-world of design environments.

8. Conclusion

This research proposed a unified Computer-Aided Innovation (CAI) framework, combining text mining, ontology-based knowledge management, and TRIZ-driven reasoning that can be used to support systematic and data-guided product ideation. By leveraging natural language processing to extract user needs and technical issues from massive unstructured data sources, the framework enables a transparent, repeatable process from raw textual data to structured design insights. A further application of TRIZ principles in the reasoning engine is for grounded, traceable solution generation. The framework was applied to the domain of smart wearable health devices; the evaluation results showed significant improvements in both efficiency and concept quality. All six concepts were generated in less than 20 minutes (Figure 4), which is significantly less time than is typically required for early-stage ideation. The generated concepts also showed strong performance in novelty, feasibility, and usability, with two concepts (Stretchable Strap and Skin-Friendly Coating) showing the highest balance across criteria (Figure 3, Table 2). The TRIZ influence visualization (Figure 2) and correlation analysis (Figure 5) revealed further insights into the role of inventive principles in shaping concept outcomes and the interrelationships among evaluation metrics. Despite the promising results, a number of limitations need to be recognised. The quality of extracted insights remains bound to the clarity and consistency of user-generated text, and domain-specific language may pose a challenge for existing NLP techniques. Ontology scalability also raises long-term maintenance issues as the knowledge base grows in size and complexity. These limitations, therefore, reflect opportunities for refinement through better domain adaptation, automatic ontology evolution, and improved contradiction interpretation. In future work, the applicability of the framework to different product categories and design situations will be expanded. Incorporating multilingual data sources would increase global relevance, while integrating generative AI models, multimodal data inputs, or digital twin simulations could enable richer, interactive design exploration. Testing the framework on other industries - including industrial equipment, consumer appliances, and assistive technologies - will further validate the robustness and generalizability of the framework. Overall, this study advances the development of systematic innovation by demonstrating that the outputs of data-driven intelligence, semantic knowledge representation, and TRIZ-based reasoning can be integrated into a coherent CAI system. The results show that the potential of such hybrid approaches for early-stage design is strong, as it could transform the current design process from a time-consuming, often uninformed, and essentially guesswork process into a more informed, faster, and more user-centred process.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically regarding authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with research ethics policies. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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