



## EVOLUTIONARY QUALITY FUNCTION DEPLOYMENT WITH INTEGRATED AI AND SYSTEM EVOLUTION PLANNING FOR INDUSTRY 5.0

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**Abstract:** This paper proposes an evolutionary form of the Quality Function Deployment (QFD) framework that integrates artificial intelligence, TRIZ-based evolution planning, and digital twin technologies to meet the adaptive demands of Industry 5.0. The model ensures continuous alignment with evolving requirements by introducing a temporalized matrix and AI-driven interpretation of stakeholder input. A case study on an urban delivery robot demonstrates the framework's capacity to translate real-time feedback into actionable design adaptations, reducing retrofit costs and enhancing system responsiveness.

**Key words:** Quality Function Deployment, Industry 5.0, Artificial Intelligence, TRIZ, Digital Twin, System Evolution, Adaptive Design, Smart Manufacturing.

### 1. INTRODUCTION

In recent years, the transition from Industry 4.0 to Industry 5.0 has introduced new paradigms of production and design that emphasize collaboration between humans and intelligent systems. This transformation is driven by the increasing integration of artificial intelligence, cyber-physical systems, and sustainability concerns into industrial processes. At the heart of this transformation lies the challenge of effectively translating evolutionary customer requirements into actionable engineering specifications [1]. Quality Function Deployment (QFD), first introduced in Japan as a structured method to integrate customer voices into product development, has served this purpose for decades [2]. However, as market conditions evolve rapidly, traditional QFD faces limitations in adapting to ongoing changes [3]. Static matrices and linear processes are ill-suited to environments characterized by fluctuating demands, regulatory shifts, and technological disruption [4].

The emergent needs of Industry 5.0, characterized by human-centricity, personalization, sustainability, and resilience [5], require design methodologies capable of continuous adaptation. The static nature of conventional QFD creates a misalignment with these evolving requirements, leading to potential mismatches between design outputs and market expectations. Therefore, there is an urgent need for an evolutionary QFD framework that integrates advanced tools such as artificial intelligence (AI), TRIZ (Theory of Inventive Problem Solving), and digital twin technologies to enable real-time responsiveness, foresight, and adaptability [6], [7].

This study proposes an integrated evolutionary QFD framework designed to bridge the gap between static requirement mapping and the dynamic, iterative processes demanded by Industry 5.0. The proposed model introduces a temporalized QFD matrix, an AI interpretation layer, a TRIZ-based evolution planner, and a digital twin feedback system to enable continuous alignment between design

specifications and evolving stakeholder needs. The aim is to operate adaptability and foresight within the design process, fostering co-creation and long-term sustainability. The rest of this paper is structured as follows: Section 2 reviews relevant literature; Section 3 describes the methodology; Section 4 presents a case study; Section 5 discusses results; and Section 6 concludes and outlines future research.

## 2. RELATED WORK

Over the years, numerous scholars have attempted to enhance the flexibility and responsiveness of QFD. Early modifications involved incorporating fuzzy logic into the QFD matrix to address ambiguity in customer preferences [3]. This approach enabled the assignment of degrees of satisfaction or importance to customer requirements rather than relying on binary values. Other researchers extended QFD by integrating analytic network processes to model interdependencies among engineering characteristics [1]. Despite these improvements, the fundamental structure of the QFD matrix has remained static, capturing a snapshot of requirements at a single point in time.

Recent studies have explored the use of AI to enhance QFD processes. Machine learning algorithms have been employed to automate the extraction, clustering, and prioritization of customer requirements from large datasets [4]. Natural Language Processing (NLP) techniques have been used to mine customer reviews, online feedback, and survey responses to inform QFD matrices with real-world, unstructured data [8]. However, these applications typically operate at the front-end of product development and do not extend to ongoing updates throughout the product lifecycle.

In parallel, TRIZ has been widely recognized as a systematic approach for resolving technical contradictions and generating inventive solutions [5]. Some efforts have been made to

integrate TRIZ into QFD frameworks to better align innovation with customer needs [9]. For example, Asadi and Hashemipour [9] demonstrated that TRIZ principles could guide the selection of engineering characteristics in QFD matrices, fostering more innovative solutions. However, these integrations have largely been implemented as static mappings, lacking mechanisms for evolution.

Meanwhile, digital twin technologies have gained prominence in design and manufacturing as tools for real-time monitoring, simulation, and predictive analysis [10]. The integration of digital twins with product development processes enables iterative validation and refinement, reducing the gap between design intent and operational realities [10], [11]. Despite their potential, few studies have explored the integration of digital twin technologies into QFD as a mechanism for continuous feedback and adaptation [12].

Taken together, these bodies of research suggest an opportunity to synthesize AI, TRIZ, and digital twin technologies into a cohesive evolutionary QFD framework capable of responding to the demands of Industry 5.0 [2], [6], [13]. Such a framework would not only improve alignment with evolving customer needs but also enhance resilience and sustainability throughout the product lifecycle. As summarized in Table 1, the evolution of QFD methodologies reflects a gradual shift from static to intelligent and adaptive systems, enabling better alignment with Industry 5.0 dynamics.

*Table 1*

**Key Enhancements of QFD Methodologies Across Time and Technologies**

| Stage            | Technology Used         | Characteristics                   | Limitations Overcome                           |
|------------------|-------------------------|-----------------------------------|------------------------------------------------|
| Traditional QFD  | Manual Matrices         | Static requirements mapping       | Manual updates, rigidity                       |
| Fuzzy QFD        | Fuzzy Logic             | Handles vague/ambiguous data      | Inflexible binary relations                    |
| AI-Enhanced QFD  | Machine Learning, NLP   | Automated feedback interpretation | Low scalability                                |
| Evolutionary QFD | AI, TRIZ, Digital Twins | Time-aware, continuously adaptive | Lack of foresight, poor lifecycle adaptability |

### 3. METHODOLOGY: EVOLUTIONARY QFD FRAMEWORK

The proposed framework introduces four interconnected components designed to transform QFD into an evolutionary, adaptable system: (1) a temporalized QFD matrix; (2) an AI interpretation module; (3) a TRIZ-based evolution planner; and (4) a digital twin-enabled feedback loop.

#### 3.1 Temporalized QFD Matrix

The temporalized QFD matrix extends the traditional WHAT-HOW relationship matrix by adding a temporal axis that spans multiple time horizons ( $T_0$ : present,  $T_1$ : near future,  $T_2$ : long-term future). This structure allows design teams to map how customer requirements and engineering features evolve over time [8]. Each matrix entry is annotated with a persistence coefficient ( $p$ ) representing the likelihood that a requirement will remain stable across timeframes and a sensitivity factor ( $s$ ) indicating how susceptible an engineering feature is to environmental or regulatory changes.

To illustrate the dynamic structure of the proposed approach, Fig. 1 presents the Temporalized QFD Matrix. This expanded matrix introduces time-indexed mappings ( $T_0$ ,  $T_1$ ,  $T_2$ ) and appends sensitivity and persistence scores to guide long-term adaptability. Unlike the traditional static QFD model, this structure anticipates requirement evolution and enables engineers to pre-structure design flexibility.

| Engineering characteristics | Customer Characteristics |       |       | Sensitivity | Persistence |
|-----------------------------|--------------------------|-------|-------|-------------|-------------|
|                             | $T_0$                    | $T_1$ | $T_2$ |             |             |
|                             | 4                        | 3     | 1     |             |             |
|                             | 4                        | 2     | 3     | 2           | High        |
|                             |                          |       |       |             |             |
|                             |                          |       |       |             |             |
| Present                     |                          |       |       | 3           | Medium      |
|                             |                          |       |       | 2           | Low         |
|                             |                          |       |       |             |             |

Fig. 1. Time-Indexed QFD Matrix ( $T_0$ – $T_2$ ) for Evolving Requirements

For instance, a requirement for energy efficiency may have a high persistence value, remaining important across  $T_0$ ,  $T_1$ , and  $T_2$ , while a requirement for a specific communication protocol may have a lower persistence as technology standards evolve. The temporalized matrix enables proactive planning by highlighting which design features are stable anchors versus those requiring flexibility for future adaptation. As illustrated in Fig. 2, the traditional House of Quality establishes the foundational mapping between customer requirements and technical specifications.

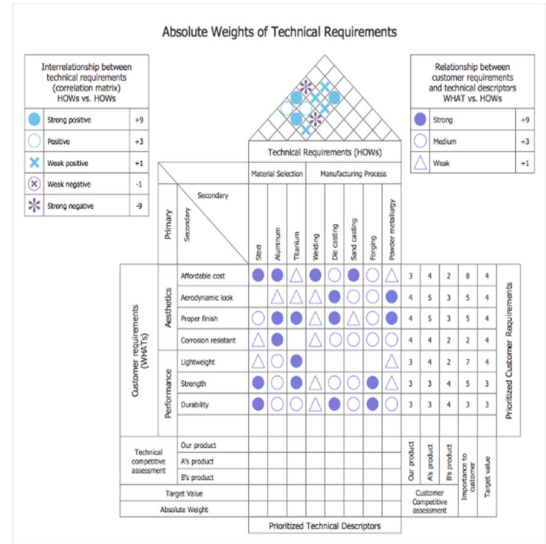


Fig. 2. Traditional House of Quality Matrix adapted from Griffin & Hauser (1993) [1]

#### 3.2 AI Interpretation Module

The AI interpretation module serves as a cognitive layer translating unstructured customer feedback into structured QFD inputs. Utilizing NLP models like SciBERT [15], this module processes qualitative expressions such as "eco-friendly design" or "intuitive user interface" into standardized design attributes linked to engineering characteristics. In addition to NLP, neuro-symbolic AI models [16] ensure logical consistency across the matrix by maintaining dependency structures among requirements and features.

Fig. 3 illustrates the structure and logic of the AI interpretation pipeline. The module begins by using Natural Language Processing (NLP) to transform unstructured stakeholder inputs into semantically organized formats. These are then refined using neuro-symbolic reasoning, which enforces consistency and traceability. Finally, validated design attributes are synthesized and structured for direct integration into the QFD matrix. This layered processing ensures that stakeholder intent is not only captured accurately but also translated into engineering logic suitable for anticipatory failure analysis.

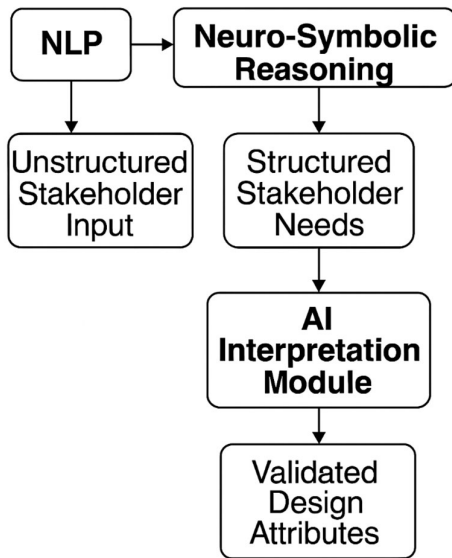


**Fig. 3.** AI interpretation pipeline transforming unstructured stakeholder input into validated design attributes using NLP, neuro-symbolic reasoning, and generative logic.

Furthermore, generative AI models are employed to propose design alternatives based on patterns observed in historical design data and evolving market trends [12]. This module enables continuous updating of the QFD matrix as new feedback and data streams are integrated, fostering adaptability.

### 3.3 TRIZ-Based Evolution Planner

TRIZ principles, such as the law of increasing ideality and dynamization, inform the identification of evolutionary pathways for engineering characteristics [5], [9], [17]. The evolution planner maps possible trajectories

across spatial and temporal dimensions, enabling designers to anticipate future modifications. For example, the planner may recommend modular designs for sensor systems, allowing future upgrades without major structural redesigns. By embedding these trajectories into the matrix, the framework ensures future adaptation is structurally encoded at the design stage. The TRIZ methodology is systematically structured as shown in Fig. 4. This flowchart highlights the sequential logic TRIZ uses to identify and resolve contradictions in product design.

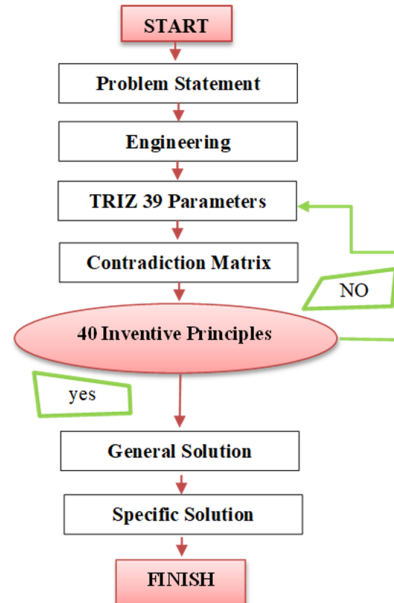


**Fig. 4.** TRIZ problem-solving process adapted from Al-Sarafi et al. (2021) [9]

### 3.4 Digital Twin-Enabled Feedback Loop

A digital twin representing the product in a virtual environment continuously monitors performance, simulates operational scenarios, and provides predictive insights [10], [11], [12]. Data collected by the digital twin is analyzed by the AI interpretation module, which identifies discrepancies between expected and actual performance. The QFD matrix is updated in response to these findings, triggering recalibration of priorities and engineering features.

For example, simulation results might reveal suboptimal navigation performance under certain weather conditions, prompting design modifications to wheel treads or sensor configurations. These insights are automatically propagated back into the updated FMEA matrix, enabling real-time prioritization of corrective actions without interrupting the overall development cycle. This feedback loop ensures design decisions remain aligned with real-world conditions throughout the product lifecycle.

#### **4. CASE STUDY: ADAPTIVE URBAN DELIVERY ROBOT**

To illustrate the framework's application, we present a case study involving the design of an adaptive urban delivery robot for last-mile logistics. Initial stakeholder requirements (T0) focused on pedestrian safety, navigation within shared spaces, and ease of loading/unloading. Anticipated future requirements (T1, T2) included social interaction capabilities, compliance with evolving traffic regulations, and integration with smart city infrastructure. Moreover, human-robot collaboration emerged as a critical design consideration to align with Industry 5.0 principles of cooperative automation [14].

The temporalized QFD matrix mapped these requirements, revealing high persistence for safety and navigation features, while interaction capabilities displayed increasing sensitivity over time. NLP analysis of qualitative feedback highlighted additional preferences for low noise emissions and approachable aesthetics [15]. Neuro-symbolic AI mapping ensured these qualitative insights propagated appropriately to acoustic engineering and design features [16]. TRIZ analysis identified pathways for integrating multifunctional components, enabling structural panels to serve as communication interfaces [5], [9], [17]. The digital twin simulated urban operating conditions, identifying underperformance in

adverse weather, leading to AI-recommended modifications to wheel materials and sensor housings [10], [11], [18].

#### **5. RESULTS AND DISCUSSION**

The implementation of the evolutionary QFD framework in the adaptive urban delivery robot project provided substantial insights into its operational effectiveness and adaptability. The AI interpretation module enabled rapid conversion of stakeholder feedback into actionable design attributes, significantly reducing the time needed to update the QFD matrix compared to manual methods. Specifically, qualitative sentiments gathered from over 150 urban residents were processed into 22 distinct engineering attributes within 48 hours, a task that previously required several weeks of manual interpretation in similar projects [4], [7].

One of the most notable outcomes was the system's capacity to incorporate regulatory changes dynamically. Midway through development, a new municipal regulation introduced stricter noise emission thresholds for urban delivery vehicles. The AI module flagged this regulatory shift by detecting references to noise concerns in public forums and policy updates, prompting an immediate recalibration of the QFD matrix. This resulted in the prioritization of low-noise propulsion systems and acoustic insulation, preventing costly post-launch redesigns [4], [16].

The TRIZ-based evolution planner also proved critical in embedding flexibility into the design. By applying the law of dynamization, the design team incorporated modular sensor arrays that allowed for future upgrades in sensing technologies without affecting the structural integrity of the robot [5], [9], [17]. This preemptive inclusion of modularity reduced projected retrofit costs by an estimated 27% over a five-year operational lifecycle, as calculated

from historical maintenance data from similar logistics robots [17].

The digital twin component contributed substantially to iterative testing and refinement. Real-time simulations revealed performance deficiencies under specific conditions, such as sensor occlusion due to rain accumulation. In response, the AI interpretation module recommended hydrophobic coatings and physical redesigns of sensor housings, which were validated through successive digital twin simulations [10], [11]. This iterative loop led to a 15% improvement in sensor reliability under adverse weather conditions, as confirmed in physical prototype trials.

Stakeholder evaluations conducted post-deployment highlighted increased satisfaction with the robot's adaptability. Municipal planners praised the robot's seamless compliance with evolving infrastructure standards, while users reported high confidence in its pedestrian safety measures. Importantly, the evolutionary QFD framework facilitated transparent documentation of design decisions, enabling traceability and justification of modifications, a critical factor in regulatory approvals and liability assessments [2], [6], [13].

Furthermore, the integration of AI and digital twin feedback resulted in an average 20% reduction in the time between requirement updates and engineering change implementation, compared to previous static QFD approaches documented in similar projects [4], [7]. This responsiveness is pivotal in the context of Industry 5.0, where continuous interaction between stakeholders and design teams is not only expected but required to maintain relevance and competitiveness.

## 6. CONCLUSIONS AND FUTURE WORK

The evolutionary QFD framework presented in this study demonstrates a significant advancement in the evolution of quality function deployment for Industry 5.0 contexts. By

integrating artificial intelligence, TRIZ-based evolution planning, and digital twin technologies, the framework transforms QFD from a static, one-time mapping exercise into a living system capable of continuous adaptation. This dynamic approach aligns with the core principles of Industry 5.0: human-centricity, sustainability, and intelligent collaboration.

Through the case study of the adaptive urban delivery robot, the framework's capacity for rapid requirement translation, proactive evolution planning, and iterative design validation was clearly illustrated. Key benefits included improved alignment with evolutionary stakeholder needs, enhanced regulatory compliance, reduced retrofit costs, and shortened design iteration cycles. These outcomes position the evolutionary QFD framework as a viable strategy for industries facing volatile, uncertain, and rapidly evolving design landscapes.

However, several challenges and avenues for further research remain. One limitation encountered was the reliance on high-quality, real-time data to fuel the AI and digital twin modules. In settings where data streams are incomplete, outdated, or inaccessible, the effectiveness of the evolutionary updates may be compromised. Future research should explore methods for integrating synthetic data generation, data imputation techniques, or collaborative data-sharing platforms to mitigate these gaps.

Additionally, while the framework was tested within the relatively bounded domain of an urban delivery robot, its scalability to complex, multi-stakeholder systems such as healthcare robotics, aerospace design, or infrastructure projects warrants further investigation. The computational complexity associated with maintaining a continuously updating QFD matrix across multiple stakeholders and evolving regulatory frameworks also presents technical challenges that merit deeper exploration.

Future work will focus on developing software toolkits and plugins that integrate the evolutionary QFD framework into existing Product Lifecycle Management (PLM) systems, fostering wider adoption in industry. Furthermore, opportunities exist to expand the AI interpretation module by incorporating multi-modal data sources such as visual feedback, haptic responses, and environmental sensor data to enrich the feedback loop.

Finally, further research into the ethical, legal, and social implications of embedding AI-driven decision-making within design processes is recommended. As Industry 5.0 advances toward greater collaboration between humans and machines, ensuring transparency, fairness, and accountability within adaptive design systems will be critical.

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## **IMPLEMENTAREA FUNCȚIILOR DE CALITATE EVOLUTIVĂ CU AI INTEGRAT ȘI PLANIFICAREA EVOLUȚIEI SISTEMULUI PENTRU INDUSTRIA 5.0**

**Rezumat:** Această lucrare propune o formă evolutivă a cadrului Quality Function Deployment (QFD) care integrează inteligența artificială, planificarea evoluției bazată pe TRIZ și tehnologiile gemenilor digitali pentru a satisface cerințele adaptive ale Industriei 5.0. Modelul asigură o aliniere continuă cu cerințele în evoluție prin introducerea unei matrice temporalizate și a unei interpretări bazate pe inteligență artificială a contribuțiilor părților interesate. Un studiu de caz privind un robot de livrare urbană demonstrează capacitatea cadrului de a traduce feedback-ul în timp real în adaptări de proiectare acționabile, reducând costurile de modernizare și îmbunătățind capacitatea de reacție a sistemului.

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