

A Two-Phase Fuzzy Quality Function Deployment Framework for Customer-Driven Intelligent Design of Hotel Service Robots

Ali Jamea

ali@qzuie.edu.cn

Quanzhou University of Information Engineering

Adam Ismaeel

Quanzhou University of Information Engineering

Gaosheng Ye

Quanzhou University of Information Engineering

Yuexiang Du

Quanzhou University of Information Engineering

Xiaohu Chen

Quanzhou University of Information Engineering

Article

Keywords: Fuzzy QFD, service robots, intelligent design, human-robot interaction (HRI), customer requirements (CRs), AI-based systems

Posted Date: October 16th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11048456/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.
[Read Full License](#)

Additional Declarations: No competing interests reported.

A Two-Phase Fuzzy Quality Function Deployment Framework for Customer-Driven Intelligent Design of Hotel Service Robots

Ali Jamea^{1,*}, Adam Ismaeel¹, Gaosheng Ye¹, Yuexiang Du¹, Xiaohu Chen¹

¹ Quanzhou University of Information Engineering. Quanzhou, Fujian Province, China, Email: ali@qzuie.edu.cn.

* Corresponding author

Corresponding Author:

Ali Jamea: Email: ali@qzuie.edu.cn, ORCID: 0000-0003-3707-5877

Co-Authors:

Adam Ismaeel: adam@qzuie.edu.cn, 0009-0002-3437-189X

Gaosheng Ye: ygs2025@qzuie.edu.cn, 0009-0008-8300-5873

Yuexiang Du: duyuexiang@qzuie.edu.cn, 0009-0004-7717-2676

Xiaohu Chen: chenxiaohu@qzuie.edu.cn, 0009-0000-8932-3700

Author Contributions

Ali Jamea: Conceptualization, methodology, validation, formal analysis, investigation, data curation, writing original draft, writing review & editing.

Adam Ismaeel: Data curation, visualization, writing review & editing.

Gaosheng Ye: Validation, writing original draft, writing review & editing.

Yuexiang Du: Methodology, validation, writing review & editing.

Xiaohu Chen: Supervision, project administration, resources, writing review & editing.

Abstract

Service robots are increasingly deployed in hospitality environments, where successful design depends not only on mechanical and operational performance but also on context awareness, safe human–robot interaction, reliability, adaptive behavior, ethical AI, and user acceptance. However, early-stage design methods provide limited systematic support for translating subjective stakeholder requirements into prioritized intelligence-oriented design capabilities and corresponding enabling technologies (ETs) under uncertainty. This study proposes a two-phase fuzzy QFD framework in which CRs are first mapped to intelligent design attributes (IDAs), after which the resulting priorities are translated into ETs. Linguistic judgments are represented using triangular fuzzy numbers and defuzzified through graded mean integration representation. As prospective extensions, the study outlines CIDPI and ECC for future integration of multidimensional and ethical information; these constructs are not applied in the present case because their required inputs were not collected. The methodology is illustrated through an expert-based hotel service robot design case involving 22 participants from Fujian Province, China, including hotel managers, frequent hotel guests, robotics engineers, and AI ethics specialists. Within this demonstration context, context awareness and perception, safe human–robot interaction, and operational reliability emerged as the highest-priority IDAs, while AI-based perception and control, sensor fusion and autonomous navigation, and machine learning for adaptive behavior were the highest-priority ETs. Sensitivity analyses indicated that the dominant rankings remained stable within the predefined perturbation ranges. The proposed framework provides a traceable basis for linking stakeholder requirements with intelligent design priorities and technology-selection decisions during early-stage hotel service robot design.

Keywords: Fuzzy QFD; service robots; intelligent design; human-robot interaction (HRI); customer requirements (CRs); AI-based systems.

1. Introduction

The integration of intelligent service robots into the hospitality sector has transformed hotel operations, including room delivery, cleaning, concierge assistance, and guest guidance (Ivanov et al., 2019; Kuo et al., 2017; I. Tussyadiah, 2020). This transformation is driven by advances in artificial intelligence (AI) and automation, which enable complex functionalities such as personalized recommendations and seamless IoT integration (Ivanov & Webster, 2019).

Service robots operating in public environments face unique design constraints characterized by high social interaction and environmental unpredictability (W. Liu et al., 2025). Successful systems must integrate sophisticated movement, social interaction capabilities, and real-time adaptability. Consequently, the design imperative has moved beyond standard mechanical performance toward cognitive capabilities that enable context-aware and socially appropriate behavior (Xin & Liu, 2025). Conventional robot design procedures typically prioritize basic functional metrics such as speed, payload, or battery life over the cognitive and adaptive capabilities essential for service environments (van der Schoor & Göhlich, 2023). Service success in hospitality depends fundamentally on a robot's ability to perceive context, make nuanced decisions, and operate reliably under uncertain conditions (Wirtz et al., 2018).

Recent studies on behavioral intelligence and customer-centric operational design emphasize that intelligent service systems should be designed around users' behavioral expectations and value creation (Mende et al., 2019). However, existing research provides limited methodological guidance for systematically translating these subjective customer expectations into quantifiable IDAs, creating a critical bottleneck in service robot conceptual design. CRs such as “adaptability”, “safety”, and “operational consistency” remain ambiguous during requirements engineering. Consequently, critical IDAs particularly context awareness and ethical interaction—are often underspecified or implemented without systematic prioritization. Many deployed systems exhibit inadequate operational reliability when facing real-world variability, necessitating systematic methods to embed prioritized intelligent design principles early in conceptual design — a gap practically significant given the accelerating global deployment of service robots in hospitality environments and the associated commercial, operational, and safety risks of under-specified intelligent design requirements (Honig & Oron-Gilad, 2018; Tuomi et al., 2021).

This study is positioned as a context-specific, exploratory methodological demonstration conducted within the hospitality environment of Fujian Province, China. Accordingly, the resulting priority rankings are interpreted as baseline estimates for the studied context and are not assumed to represent hotel service-robot preferences across East Asia or other cultural settings. Cross-regional and cross-cultural replication is therefore required before broader empirical generalization.

The study pursues four objectives: (1) to identify and prioritize CRs related to operational intelligence, safety, interaction, and autonomy in hotel service robots; (2) to develop a two-phase fuzzy QFD framework that translates CRs into IDAs; (3) to translate prioritized IDAs into enabling engineering technologies; and (4) to demonstrate the procedural applicability and robustness of the proposed framework through an illustrative hotel service-robot design case.

Accordingly, the following research questions are addressed:

RQ1: Which CRs receive the highest priority within the studied Fujian hotel-service context?

RQ2: How can CRs be systematically translated into IDAs and subsequently into ETs through a two-phase

fuzzy QFD framework?

RQ3: To what extent do the resulting IDA and ET priority rankings remain stable under predefined perturbations of CR importance weights?

This study makes three specific contributions. First, it extends conventional QFD from physical-attribute prioritization to the prioritization of cognitive and interaction-oriented capabilities, including context awareness, safe human–robot interaction, adaptive behavior, and ethical-AI compliance. Second, it establishes a traceable two-phase translation from CRs to IDAs and subsequently to ETs. Third, it specifies CIDPI and ECC as conceptual avenues for future research on multidimensional prioritization and bounded ethical modulation; because their required inputs were unavailable, they are not treated as implemented or validated components of the present demonstration.

A key methodological decision in this study is the adoption of a two-phase fuzzy QFD architecture rather than a conventional single house of quality (HoQ). Traditional QFD frameworks typically translate CRs directly into engineering characteristics, assuming that technical specifications can be derived in a single mapping process. However, intelligent service robot design involves an intermediate layer of cognitive and interaction-oriented capabilities—such as context awareness, adaptive behavior, safe human–robot interaction, and ethical AI compliance—that cannot be represented adequately as conventional engineering characteristics. Directly linking CRs to ETs would obscure this conceptual transition and reduce design traceability. The proposed two-phase architecture therefore decomposes the design process into two sequential mappings: CRs are first translated into prioritized IDAs, which are subsequently mapped to the ETs required for implementation. This hierarchical decomposition improves design transparency, preserves traceability between stakeholder needs and engineering decisions, and provides a more systematic foundation for prioritizing intelligent technologies during early-stage conceptual design.

Accordingly, the two-phase architecture should be viewed not simply as a computational extension of conventional fuzzy QFD, but as a conceptual redesign of the quality deployment process for intelligent systems whose customer expectations must first be translated into cognitive capabilities before engineering technologies can be meaningfully prioritized, Figure 1.

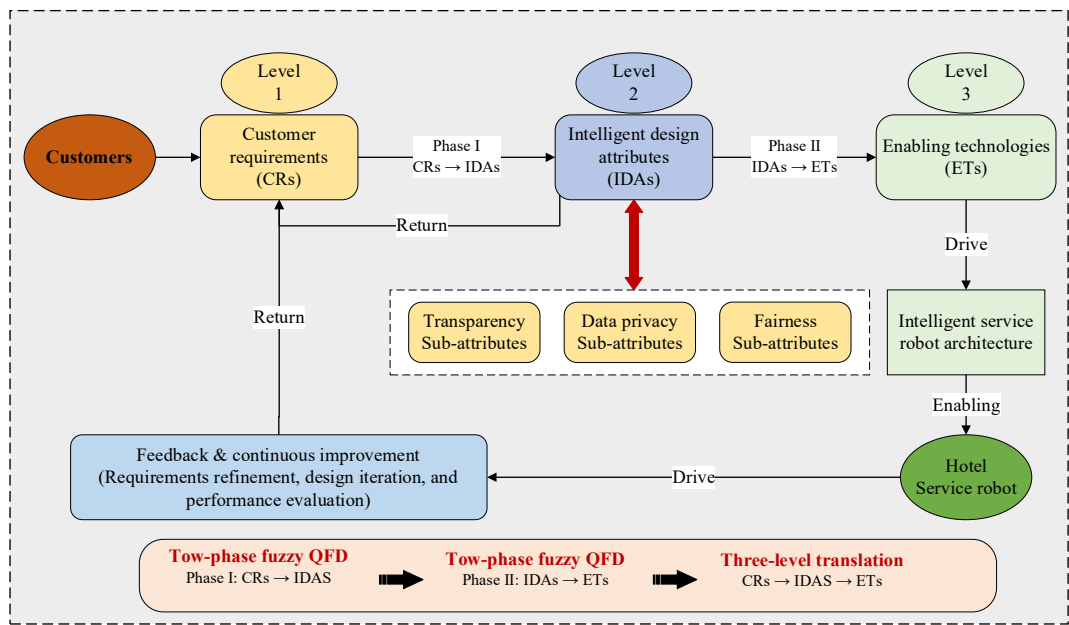


Figure 1. The proposed two-phase fuzzy QFD conceptual architecture

The proposed framework extends conventional fuzzy QFD through a two-phase, three-level translation architecture, with ethical AI represented through IDA6 and numerical modulation reserved as a prospective extension. The three principal levels comprise CRs, IDAs, and ETs, while ethical AI considerations are incorporated within the IDA evaluation and subsequent priority adjustment rather than treated as an independent translation level, Table 1. Whereas traditional QFD maps CRs directly to engineering characteristics, and conventional fuzzy QFD extends this with fuzzy arithmetic for handling linguistic uncertainty, the present framework introduces the following structured decomposition.

This two-phase, three-level architecture advances conventional fuzzy QFD by representing intelligent capabilities explicitly between CRs and engineering technologies. Ethical AI is incorporated through IDA6 and its transparency, privacy, and fairness sub-attributes; a numerical ECC-based modulation mechanism is reserved for future validation when appropriate ethical-rating data are available.

Table 1. Comparison between conventional fuzzy QFD and the proposed two-phase fuzzy QFD framework

Dimension	Conventional fuzzy QFD	Proposed framework
Primary objective	Translate CRs into technical or engineering characteristics under uncertainty	Translate CRs into IDAs and subsequently into ETs under uncertainty
Translation structure	Typically, single-stage or direct CR → technical-characteristic mapping	Two-phase, three-level mapping: CRs → IDAs → ETs
Intermediate design level	Generally absent or represented implicitly through technical characteristics	Explicit IDA level connecting customer expectations with intelligent functional capabilities
Phase I	CRs are directly related to technical characteristics	CRs → IDAs, identifying and prioritizing the intelligent capabilities required by stakeholders
Phase II	Usually not explicitly separated from the initial QFD mapping	IDAs → ETs, translating prioritized intelligent capabilities into enabling engineering technologies
Treatment of uncertainty	Fuzzy linguistic judgments are used to represent uncertainty in CRs and relationship strengths	TFNs are applied throughout both phases, with GMIR defuzzification used to obtain comparable priority rankings
Ethical AI integration	Typically absent or treated as an external design constraint	Embedded within the IDA evaluation through IDA6 and its transparency, data privacy, and fairness sub-attributes, with bounded priority modulation through the ECC
Composite prioritization	Primarily based on fuzzy relationship strengths and customer-importance weights	Conventional fuzzy-QFD priorities are reported in the present demonstration; CIDPI is specified only as a prospective multidimensional extension requiring future empirical validation.
Engineering traceability	Primarily CR → technical characteristics	CRs → IDAs → ETs → representative engineering implementation modules, providing explicit traceability from stakeholder requirements to technology selection
Robustness assessment	Often limited to the resulting fuzzy priority ranking	Includes CR-weight sensitivity analysis and an approximate assessment of propagation between Phase I and Phase II; CIDPI/ECC robustness remains outside the empirical scope.

The remainder of this paper is organized as follows. Section 2 reviews relevant literature on intelligent service robot design, ETs, and fuzzy QFD applications. Section 3 describes the research methodology, including the fuzzy computational model and expert panel composition. Section 4 presents the illustrative demonstration and results from both phases of the fuzzy QFD analysis. Section 5 discusses the findings, implications, and limitations. Section 6 concludes the paper and outlines future research directions.

2. Literature Review

Service robots are defined as systems that perform useful tasks for humans or equipment excluding industrial automation applications (Chen et al., 2023; Franke et al., 2026). In hospitality contexts, service robots must navigate dynamic environments, interact with diverse users, and maintain operational reliability over extended periods (Giuliani et al., 2010; Tung & Au, 2018). The design of such systems requires integration of mechanical engineering, control systems, sensor fusion, and increasingly, AI-based decision-making (Licardo et al., 2024). Research has established that user acceptance of service robots depends not only on functional performance but also on perceived intelligence, safety, and social appropriateness (Gursoy et al., 2019; Lu et al., 2019; Shin & Jeong, 2020). These factors are inherently subjective and context-dependent, creating a measurement challenge for design teams.

To position the proposed fuzzy QFD framework within its theoretical context, this subsection reviews the principal theoretical traditions from which the study draws. Three established frameworks provide complementary lenses for interpreting this study's contributions: HRI theory, service-dominant logic (SDL), and human-centered AI (HCAI) principles. HRI theory establishes that safe, natural, and socially appropriate interaction is central to service robot effectiveness (Goodrich & Schultz, 2008). This study's IDAs are directly grounded in HRI theory, extending its prescriptions into the fuzzy QFD design methodology. SDL conceptualizes service as a process of value co-creation between providers and customers, emphasizing that value is created collaboratively through interactions and customer experiences (Vargo & Lusch, 2004). Extending this perspective to hotel service robotics, the present study argues that context awareness, communication quality, and ethical AI compliance should be treated as primary IDAs because they directly influence customer value co-creation during human–robot service encounters.

HCAI principles emphasize that AI systems should be designed to augment human capabilities while maintaining human oversight, transparency, and accountability (Shneiderman, 2022). The explicit incorporation of ethical AI compliance as a measurable design variable in this study reflects HCAI principles and aligns with EU AI Act requirements on transparency and human oversight.

Value-sensitive design (VSD) provides a complementary theoretical lens for integrating ethical considerations into engineering practice. VSD emphasizes the proactive identification and navigation of value tensions during the design process, rather than treating ethics as a post-hoc compliance exercise. The

operationalization of ethical AI compliance through measurable sub-attributes (transparency, data privacy, fairness) in this study aligns with VSD's directive to make values explicit and traceable in design decisions (Friedman, 1996; Friedman et al., 2013; Umbrello et al., 2021).

The technology acceptance model and its extension, the unified theory of acceptance and use of technology (UTAUT), have been extensively applied to predict user acceptance of service robots. Both frameworks link perceived usefulness and ease of use to behavioral intention, demonstrating that subjective perceptions of system intelligence directly influence adoption outcomes (Davis, 1989; Venkatesh et al., 2003). These models are retained as supporting acceptance literature but do not receive equivalent theoretical prominence, as they explain why CRs exist rather than how they should be translated into engineering specifications.

The fuzzy QFD framework developed here complements these theoretical traditions. HRI theory specifies the behavioral dimensions of safe and socially appropriate interaction; SDL grounds requirements in service value creation; and HCAI ensures ethical dimensions are formally engineered rather than informally assumed. The fuzzy QFD mechanism provides the structured translation apparatus from these theoretical constructs to prioritized engineering decisions. Collectively, these theoretical perspectives provide the conceptual justification for the seven IDAs adopted in this study and establish the foundation for systematically translating subjective CRs into quantifiable engineering priorities through the proposed two-phase fuzzy QFD framework. By integrating insights from HRI, SDL, HCAI, and VSD, the proposed methodology bridges established theory with engineering implementation, thereby strengthening both the theoretical rigor and practical traceability of intelligent service robot design.

Three IDAs consistently emerge as critical issues in the literature: context awareness and perception enable a robot to sense, interpret, and act upon knowledge regarding its surroundings, user intent, and service task (Abowd et al., 1999; Dey, 2001). For service robots, context awareness facilitates meaningful social interaction by enabling appropriate communication and behavior (Fong et al., 2003). Effective context awareness requires integration of multiple sensors, fusion algorithms, and human-like cues that enhance user comprehension of robotic actions (Schepers et al., 2022).

Safe HRI is non-negotiable for robots operating in public spaces (De Santis et al., 2008). Safety requires adherence to structured standards that minimize collision and injury risks through defined safe distances, speed limits, and emergency functions (Di Cosmo et al., 2019; Gualtieri et al., 2022). Beyond physical safety, ethical compliance protocols must address privacy, fairness, and non-intrusive communication crucial for maintaining guest trust in multicultural settings (Fosch-Villaronga & Mahler, 2021; I. P. Tussyadiah et al., 2020). Operational reliability and robustness refer to a robot's capacity to function safely over extended periods in uncertain environments (Hawes et al., 2017). Reliability metrics must differentiate between theoretical advertised capabilities and verified operational performance, often formalized through reference ontologies (Haidegger et al., 2013). Sustaining high reliability depends on advanced control software, including fast reaction times and strategic recovery planning (Nguyen & Sreenath, 2021; Pezzato et al., 2023).

The realization of prioritized IDAs requires specific ETs. AI algorithms form the necessary foundation for intelligent control, enabling autonomous navigation, path planning, and dynamic manipulation (Levine et al., 2018). Deep learning techniques, trained on extensive datasets, allow robots to learn complex sensorimotor policies for tasks such as grasping cluttered objects (Levine et al., 2018; Li et al., 2025). Sensor fusion integrates data from multiple modalities (vision, lidar, tactile, audio) to build robust environment

representations. Predictive maintenance and reliability management monitor component health and schedule interventions before failures occur (Zonta et al., 2020). The growing deployment of AI-enabled robots in public service environments has intensified scholarly attention to ethical design dimensions. Modern AI governance literature identifies multiple ethical dimensions beyond the commonly cited transparency, privacy, and fairness triad. These include explainability; the ability of the system to articulate the rationale for its decisions, accountability; traceability of decisions to responsible agents, human oversight; preservation of human control over automated processes, contestability; the ability of users to challenge system outputs, and safety governance; systematic management of risks arising from AI-driven decisions (Galgano, 2026; Jobin et al., 2019).

Most existing QFD studies neglect ethical design requirements, treating ethics as a post-hoc compliance concern rather than a formal design variable. This study advances this frontier by operationalizing three measurable ethical sub-attributes—transparency, data privacy, and fairness—as core quantitative components of IDA6. Four additional sub-attributes—explainability, accountability, human oversight, and contestability—are formally acknowledged as complementary conceptual dimensions aligned with EU AI Act and OECD AI Principles, but are reserved for full operationalization in future empirical studies to maintain methodological focus and avoid conceptual inflation. This distinction is maintained consistently throughout the manuscript.

Fuzzy QFD has been applied extensively in product development, supplier selection, and sustainable design (Younesi & Roghanian, 2015). QFD integrated with fuzzy regression for robot selection, demonstrating that fuzzy methods effectively handle subjective engineering judgments (Okoli & Pawlowski, 2004). However, existing fuzzy QFD applications focus predominantly on environmental and economic attributes (i.e., energy efficiency, recyclability, lifecycle cost) rather than on cognitive and interactional design attributes.

Although previous studies have made important contributions to service robot design and fuzzy QFD methodology, several limitations remain. First, existing fuzzy QFD applications focus on product sustainability (environmental and economic) rather than on IDAs such as context awareness and ethical AI. Second, no prior study has systematically linked CRs for perceived intelligence to the specific ETs (e.g., machine learning architectures, sensor fusion methods) required for implementation. Third, the social and ethical dimensions of intelligent service robots remain underexplored in formal design frameworks, with existing studies treating them as implicit rather than formally quantifiable design variables.

Recent advances in embodied AI—where large language models (LLM) are coupled with robotic control policies to enable natural-language-commanded manipulation and navigation—promise to reshape how context awareness (IDA1) and adaptive behavior (IDA4) are implemented (Shaji et al., 2026). Research has demonstrated that LLM-based agents can serve as core reasoning components within robotic cognitive architectures, enabling spatial reasoning, instruction interpretation, and adaptive plan revision based on environmental feedback (Kim et al., 2025). Explainable robotics, an emerging subfield at the intersection of XAI and HRI, addresses the transparency sub-attribute of ethical AI compliance (IDA6) by generating human-interpretable rationales for robot navigation and interaction decisions; recent systems integrating vision-language models with heat-map-based explanation mechanisms have demonstrated real-time, natural-language justifications for autonomous robot behavior (Sotomi et al., 2025).

Recent empirical studies have systematically reviewed XAI techniques for service robots, identifying transparency mechanisms that enhance user trust during navigation and task execution. Foundation models for robotics pretrained on internet-scale vision-language data offer a path to dramatically reduce the

engineering effort required for AI-based perception (ET1) and machine learning for adaptive behavior (ET3), potentially altering their relative priority rankings as these technologies mature (Brohan et al., 1 C.E.; Firoozi et al., 2025). Multimodal perception research combining vision, language, audio, and tactile sensing is increasingly relevant to multimodal user interaction (IDA5), suggesting that the three-modality scope of the present IHR realizes (ET5) definition may require expansion; recent extensions of VLA models to incorporate contact audio perception, alongside bioinspired multisensory frameworks integrating visual, tactile, and auditory, demonstrate that comprehensive environmental understanding benefits from broader sensor integration (Wei et al., 2025).

Finally, digital twins in robotics—virtual replicas of physical robots used for simulation-based design optimization and predictive maintenance—directly support predictive maintenance (ET4) and offer a pathway for virtual validation of fuzzy QFD priority rankings before physical prototype (Sun et al., 2026). Robotic digital twins provide lifecycle-spanning capabilities from virtual prototyping to predictive maintenance, functioning as cognitive sandboxes for safe policy learning and rigorous hypothesis testing prior to real-world deployment (Levi et al., 2026).

The contributions of this study are threefold: (1) a two-phase intelligence-oriented QFD architecture that extends established fuzzy QFD methodology to the domain of intelligent service robot design, decomposing the design problem into CR-to-IDA and IDA-to-ET phases; (2) explicit ethical AI operationalization with three measurable sub-attributes traceable to CRs; and (3) structured traceability from subjective intelligence perception CRs to ETs, enabling design teams to justify engineering investments on the basis of customer evidence, together with integration of cognitive attributes into formal engineering decision-making via fuzzy arithmetic, Table 2.

Table 2. Comparative positioning of the present study within recent fuzzy QFD literature

Study & Method	Application domain	Intelligence attributes?	Ethical AI?	Main limitation
Fuzzy QFD (Vinodh et al., 2017).	Consumer electronics sustainability	No	No	Environmental focus only; no cognitive attributes
Fuzzy QFD + Regression (Karsak, 2008).	Industrial robot selection	No	No	Industrial context; no HRI or social requirements
Fuzzy QFD + ARIZ (Z. Liu et al., 2024).	Sweeping robot design	Partial (functional)	No	Cognitive/social/ethical attributes absent
GRA-Fuzzy QFD (Wang & Yang, 2023).	Craft product design	No	No	Product aesthetics; no intelligent attributes
QFD + ORESTE (Shi et al., 2022).	Engineering characteristics (general QFD)	No	No	No service robot context or intelligence
Current study: Two-phase Fuzzy	Hotel service robot intelligent design	Yes (7 IDAs incl. context	Yes (3 measurable sub-	Single case; China-based; no longitudinal outcome

Study & Method	Application domain	Intelligence attributes?	Ethical AI?	Main limitation
QFD		awareness, safe HRI, adaptive behavior, ethical AI)	attributes with indicators; aligned with EU AI Act & OECD principles)	validation

2.6 Ethical AI operationalization scope

Ethical AI compliance (IDA6) is operationalized through three measurable sub-attributes—transparency, data privacy, and fairness—while formally acknowledging explainability, accountability, human oversight, and contestability as complementary dimensions aligned with the EU AI Act and the OECD AI Principles (Development, 2019; Galgano, 2026; Jobin et al., 2019). This selection is grounded in three critical criteria for integration into the fuzzy QFD framework:

First, Quantifiability. Each selected sub-attribute can be expressed through verifiable engineering indicators suitable for inclusion in the fuzzy QFD relationship matrix:

- Transparency: Percentage of robot decisions with accessible audit logs; proportion of actions accompanied by clear behavioral explanations.
- Data Privacy: Proportion of sensor data processed on-device versus transmitted/stored; number of identifiable guest data points collected per interaction.
- Fairness: Variance in service response time across guest demographic groups; consistency of task completion quality across user categories.

Table 3 shows each theoretical framework to the specific IDAs, ETs, and methodological choices derived from it to make the theoretical contribution explicit. This mapping demonstrates that the fuzzy QFD framework is not merely described by these theories but is operationally grounded in them.

Table 3. Theoretical foundations and design mapping

Theory	Derived IDAs	Enabled ETs	Methodological choice
HRI theory (Goodrich & Schultz, 2008)	IDA1, IDA2, IDA5	ET1, ET2, ET5	Inclusion of social-interaction criteria in CR elicitation; safety-first weighting in HoQ
SDL (Vargo & Lusch, 2004)	IDA1, IDA4, IDA6	ET1, ET3, ET6	Guest and manager inclusion in expert panel; value-co-creation as design priority criterion
HCAI (Shneiderman, 2022)	IDA6, IDA7	ET5, ET6	Ethical AI as explicit IDA with measurable sub-attributes; transparency-privacy-fairness triad
VSD (Friedman, 1996; Friedman et al., 2013; Friedman & Hendry, 2026)	IDA6	ET6	Stakeholder deliberation for ethical sub-attribute selection; operationalizability criterion

3. Methodology

Figure 2 summarizes the methodological workflow of the demonstrated two-phase fuzzy-QFD framework, including stakeholder elicitation, Phase I and Phase II mappings, fuzzy aggregation, and conventional robustness assessment. CIDPI and ECC, where shown, should be read as optional conceptual extensions for future data-enabled validation rather than operations performed in the present case study.

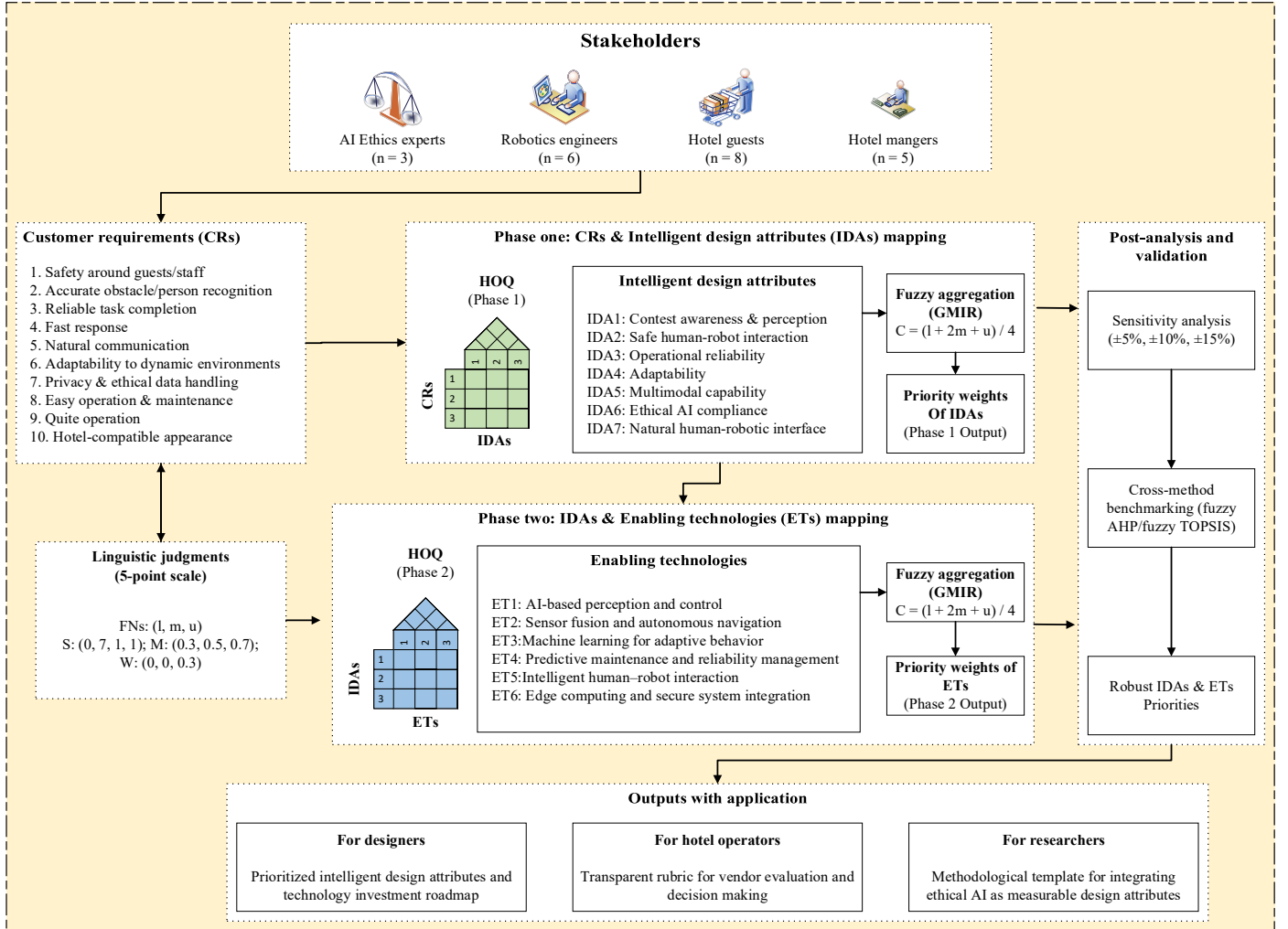


Figure 2. A two-phase fuzzy QFD framework methodological workflow

This layered architecture transforms the fuzzy QFD outputs from abstract priority rankings into an actionable engineering blueprint. As presented in Table 4, each layer directly maps to one or more IDAs and ETs, ensuring that every engineering decision can be traced back to stakeholder requirements through the fuzzy QFD chain. The architecture is intended as a reference template; specific implementations may reorder or merge layers depending on hardware constraints and hotel operational contexts.

Table 4. Mapping between architecture layers IDAs and ETs

Architecture layer	Main components	Supported IDAs	Related ETs
CRs	CR1–CR10	All	—
Fuzzy QFD decision	TFN, GMIR	All	All
Functional modules	IDA1–IDA7	IDA1–IDA7	—
Perception	RGB-D, LiDAR, IMU	IDA1, IDA2	ET1

Architecture layer	Main components	Supported IDAs	Related ETs
Decision	Visual SLAM, RL, Semantic Mapping	IDA1, IDA4	ET2, ET3
Motion	Differential Drive, A*, Safety Controller	IDA2, IDA3	ET2
HRI	NLP, GUI, Gesture Recognition	IDA5, IDA7	ET5
Cloud/Edge	Fleet Learning, Predictive Maintenance	IDA3, IDA6	ET4, ET6
Hotel service robot	Physical Platform	All	All

3.1 Methodology validation and application assumptions

This study is based on the following assumptions:

- Expert judgments represent approximate preferences under uncertainty;
- Rankings are context-specific to hotel service robots in Fujian, China;
- Outputs represent relative priorities, not absolute performance metrics;
- No physical robot deployment is included.

3.2 Methodology procedures design

This research develops a two-phase fuzzy QFD framework to translate stakeholder requirements into prioritized IDAs and ETs for hotel service robots. The framework comprises two sequential translation phases: Phase I maps CRs to IDAs. Phase II maps prioritized IDAs to ETs. Each phase represents linguistic judgments using triangular fuzzy numbers (TFNs). Aggregated fuzzy priorities are maintained throughout the sequential computation, while GMIR defuzzification is applied to obtain crisp scores for reporting and ranking. The scope is limited to indoor hotel service robots performing delivery, guidance, and waste collection tasks. The study does not cover outdoor operation, industrial robotics, or general-purpose social robots. All 22 participants were recruited from Fujian Province, China, and provided informed consent prior to participation. Consequently, results are primarily valid for Fujian, China hospitality contexts; cross-cultural replication in Europe, North America, and Southeast Asia is required before these crisp values can be generalized. No physical robot deployment was conducted because the study focuses on conceptual design prioritization under uncertainty.

3.2.1 Data collection and multi-stakeholder panel

A structured expert elicitation process was conducted in accordance with the approved ethics protocol, and inputs were obtained from a multi-stakeholder panel comprising the stakeholders shown in Table 5. All participants provided informed consent prior to participation.

Table 5. Composition of the multi-stakeholder elicitation panel

Stakeholder group	n	Role in elicitation
Hotel managers	5	Identify CRs; rate CR importance
Hotel guests (frequent travelers, ≥ 4 stays/year, prior robot exposure)	8	Identify CRs; rate CR importance
Robotics engineers (≥ 3 years in autonomous systems)	6	Define IDAs, ETs; rate HoQ relationships
Academic experts in AI ethics (faculty/postdoctoral researcher, published in AI ethics or HRI ethics)	3	Evaluate ethical sub-attributes for face validity
Total	22	

Hotel managers and hotel guests rated the importance of each customer requirement using a four-point linguistic scale (Very important, Important, Fair, and Weak). Robotics engineers rated the relationship strengths between CRs and IDAs and between IDAs and ETs. Table 6 summarizes the elicitation responsibilities of each stakeholder group; AI ethics specialists evaluated the ethical sub-attributes used to operationalize IDA6 for face validity, Figure 3.

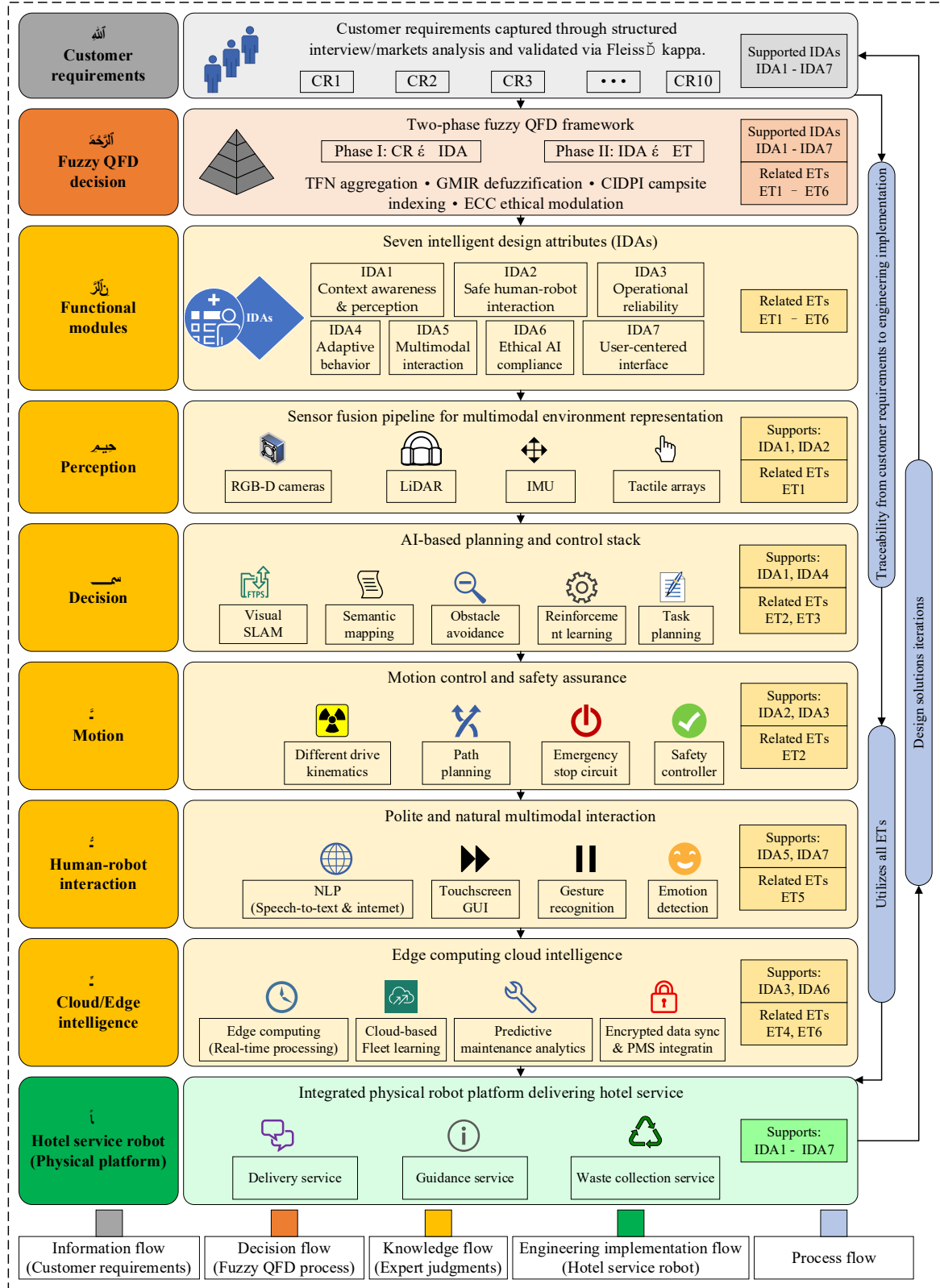


Figure 3. Customer-driven intelligent hotel service robot design integrated architecture

Table 6 summarizes the elicitation responsibilities of each stakeholder group across the five rating tasks underlying the fuzzy QFD computation. This clarifies which group performed each rating task. Inter-rater agreement was assessed using Fleiss' kappa, yielding mean $\kappa = 0.74$ (range 0.68–0.81), indicating substantial agreement (Fleiss, 1971).

Table 6. Stakeholder rating responsibilities by task

Rating task	Managers	Guests	Engineers	AI ethics experts
CR identification	Yes	Yes	No	No
CR importance rating	Yes	Yes	No	No
CR–IDA relationship rating	No	No	Yes	No
IDA–ET relationship rating	No	No	Yes	No
Ethical sub-attribute face validity	No	No	Optional	Yes

Ethics approval and informed consent

The study involved 22 adult participants. All methods involving human participants were carried out in accordance with the Declaration of Helsinki and relevant institutional guidelines and regulations. The research protocol was reviewed and approved by the Institutional Review Board of Quanzhou University of Information Engineering (Approval No. QZUIE-IRB-2026-0072; approval letter issued 25 June 2026). Written informed consent was obtained from all participants before data collection. The approved protocol covered the stakeholder questionnaire, linguistic rating scales, and House of Quality relationship matrices. Responses were anonymized for analysis, and no personally identifiable information is reported in this manuscript.

3.2.2 Description of the ET identification procedure

Candidate ETs were identified through a structured literature-based technology screening followed by expert evaluation. In the first stage, studies published between 2018 and 2025 concerning intelligent service robots, autonomous mobile service systems, human–robot interaction, robotic perception, navigation, adaptive intelligence, reliability management, and secure computing were reviewed to identify technologies directly relevant to implementation of the seven IDAs. Technologies were retained when they supported at least one IDA, represented an implementable sensing, hardware, software, control, interaction, or computational capability, and had reported applicability to autonomous or intelligent service-robot systems. Functionally overlapping technologies were consolidated to minimize conceptual duplication, resulting in an initial set of 12 candidate ETs.

In the second stage, the six robotics engineers independently assessed the relevance of each candidate technology to the seven IDAs using the linguistic relationship-strength scale adopted in the fuzzy QFD model. The individual judgments were subsequently aggregated using the expert-aggregation procedure described in Section 3.3, and the six highest-ranked technologies were retained for the Phase II HoQ. Fleiss' κ was used as a supplementary measure of inter-rater agreement. The resulting ET set therefore represents the technologies judged by the participating engineering experts to provide the strongest implementation support for the IDAs within the specific hotel service-robot design scenario considered in this study.

3.2.3 Justification of expert panel size

The sample size of $n=22$ requires explicit methodological justification. Panels of 10–30 domain experts are widely documented as adequate for convergent judgment tasks (Dalkey & Helmer, 1963; Turoff & Linstone, 1975). Therefore, the present methodology is consistent with these precedents and exceeds the minimum recommended size of 10–15 for fuzzy QFD applications requiring Fleiss’ kappa assessment. In addition, the multi-stakeholder structure spanning hotel managers, guests, engineers, and ethics experts provides complementary expertise coverage that partially compensates for the moderate aggregate panel size.

No formal a priori power analysis was conducted, as standard parametric power calculations do not directly apply to fuzzy expert-elicitation rank-order tasks; for exploratory fuzzy QFD studies, panels exceeding $n=15$ are generally considered adequate to obtain a stable rank order under Fleiss’ kappa assessment, a threshold the present panel ($n=22$) exceeds (Z. Liu et al., 2024; Wang & Yang, 2023).

3.2.4 Linguistic variables and fuzzy representation

To represent uncertainty in stakeholder judgments, linguistic evaluations were converted into TFNs, denoted as (l, m, u) , where l is the lower bound, m the modal value, and u the upper bound. The linguistic terms and corresponding TFNs are presented in Table 7.

Table 7. CR importance scale

Linguistic term	Notation	Triangular fuzzy number (l, m, u)
Very important	VI	(0.7, 1.0, 1.0)
Important	I	(0.5, 0.7, 1.0)
Fair	F	(0.3, 0.5, 0.7)
Weak	W	(0.0, 0.5, 0.5)

A fuzzy treatment, rather than a simple crisp weighted-scoring matrix, was adopted because the linguistic terms used by stakeholders to describe IDAs (e.g., “safe interaction,” “adaptive behavior,” “privacy protection”) have inherently vague and overlapping boundaries that resist precise numerical encoding. A crisp scoring approach would force each expert judgment into a single point value, artificially implying a level of precision that the underlying judgments do not possess and potentially masking disagreement that is meaningfully captured by the spread between the lower and upper bounds of a TFN. Where relationships between CRs and IDAs were expressed with their corresponding fuzzy values as illustrated in Table 8.

Table 8. CRs and IDAs relationship strength scale

Linguistic term	Notation	Triangular fuzzy number (l, m, u)
Strong	S	(0.7, 1.0, 1.0)
Medium	M	(0.3, 0.5, 0.7)
Weak	W	(0.0, 0.1, 0.4)

3.3 Computational model

Before constructing the two HoQ matrices, the individual linguistic judgments provided by the relevant stakeholder groups were converted into TFNs and aggregated to obtain representative group-level fuzzy evaluations. Because no differential weighting was assigned to experts within the same stakeholder group, an equal-weight component-wise arithmetic aggregation was adopted.

Let the judgment provided by expert “ e ” for evaluation item x_{ij} be presented as:

$$x_{ij}^{(e)} = (l_{ij}^{(e)}, m_{ij}^{(e)}, u_{ij}^{(e)}) \quad (1)$$

Where l , m , and u denote the lower, modal, and upper values of the corresponding TFN. For a stakeholder group comprising K experts, the aggregated fuzzy judgment is calculated as:

$$\tilde{x}_{ij}^{agg} = \left(\frac{1}{k} \sum_{e=1}^k l_{ij}^{(e)}, \frac{1}{k} \sum_{e=1}^k m_{ij}^{(e)}, \frac{1}{k} \sum_{e=1}^k u_{ij}^{(e)} \right) \quad (2)$$

Where $\tilde{x}_{ij}^{agg}$ represents the aggregated fuzzy evaluation for item i relative to criterion j , and K denotes the number of experts participating in the corresponding rating task.

This aggregation procedure was applied separately to the stakeholder judgments according to their assigned elicitation roles. Hotel managers and hotel guests provided the CR-importance evaluations, whereas robotics engineers provided the CR-IDA and IDA-ET relationship evaluations. The resulting aggregated TFNs were subsequently used as inputs to the Phase I and Phase II fuzzy HoQ calculations. This separation preserves the distinct knowledge contributions of customer-side and engineering stakeholders while providing a consistent fuzzy representation of within-group judgments.

3.3.2 Phase I: CRs mapping to IDAs fuzzy QFD

The first HoQ establishes the relationship between CRs and IDAs.

Let:

- CR_i : Customer requirement “ i ”;
- IDA_j : IDA attribute “ j ”;
- $\tilde{w}_i$: Fuzzy importance of CR_i ;
- $\tilde{R}_{ij}$: Fuzzy relationship strength between CR_i and IDA_j .

Step 1: Aggregation

Fuzzy importance weight of each intelligent design attribute IDA_j was calculated as:

$$\tilde{W}_{IDA_j} = \sum_{i=1}^n (\tilde{w}_i \otimes \tilde{R}_{ij}) \quad (3)$$

Where $\otimes$ denotes fuzzy multiplication.

Step 2: Defuzzification

Each fuzzy IDA weight is converted into a crisp score as follows:

$$C_j = (l_j + 2m_j + u_j) / 4 \quad (4)$$

Step 3: Ranking

To reflect relative design priority under uncertainty, IDAs are ranked in accordance with descending crisp score as:

$$IDA_1 > IDA_2 > \dots > IDA_n \quad (5)$$

3.3.3 Phase II: IDAs mapping to ETs fuzzy QFD

The second HoQ maps the prioritized IDAs to the candidate ETs. To preserve fuzzy uncertainty across the two-phase framework, the aggregated fuzzy IDA priority weights obtained in Phase I are used directly as the weighting inputs to Phase II. The defuzzified Phase I scores are retained only for ranking and reporting purposes and are not used as the computational inputs to the Phase II HoQ.

Let $\tilde{W}_{IDA_j}$ denote the aggregated fuzzy priority weight of IDA_j obtained from Phase I, and $\tilde{R}_{jk}$ the fuzzy relationship strength between IDA_j and ET_k . The fuzzy priority of each enabling technology is computed as:

Step 1: Technology scoring

$$\tilde{W}_{ET_k} = \sum_{j=1}^m (\tilde{W}_{IDA_j} \otimes \tilde{R}_{jk}) \quad (6)$$

The resulting fuzzy ET priorities are subsequently defuzzified using GMIR to obtain crisp values for final ranking. Accordingly, fuzzy uncertainty is preserved throughout the CR-IDA-ET computational chain, while crisp values are introduced only for comparative ranking and interpretation.

Step 2: Defuzzification

$$C_k = (l_k + 2m_k + u_k) / 4 \quad (7)$$

Step 3: Ranking

ETs are ranked by crisp values to identify the most critical ETs for implementing prioritized IDAs.

3.3.4 Justification of GMIR defuzzification method

The GMIR formula $C = (l + 2m + u)/4$ was selected because it assigns greater weight to the modal value (m), which represents the expert's best point estimate, and has been adopted in prior fuzzy QFD service design studies facilitating cross-study comparability. Comparative sensitivity analyses indicated that centroid and signed-distance defuzzification methods preserved the ranking structure with mean shifts of ± 0.8 and ± 0.6 crisp units respectively, indicating that the GMIR choice does not materially affect substantive conclusions. It is emphasized that GMIR is adopted here for consistency with prior literature rather than on the basis of a formal theoretical proof of superiority over alternative defuzzification methods (Chou, 2003; Junior et al., 2022; Zhang et al., 2022).

3.3.5 Proposed CIDPI extension for future validation

For future studies with complete component-level data, CIDPI is proposed as a composite index that could

integrate normalized customer importance, relationship strength, ethical performance, and implementation feasibility. The formulation below defines the prospective extension; it is not calculated or used to rank IDAs in the present demonstration.

For prospective application, the CIDPI for the j^{th} intelligent design attribute is defined as:

$$CIDPI_j = \alpha C_j + \beta R_j + \gamma E_j + \delta F_j \quad (8)$$

Where:

- C_j : Normalized customer importance associated with IDA_j , obtained from the CR-weighting process;
- R_j : Aggregated fuzzy relationship score derived from the HoQ;
- E_j : Normalized ethical sub-score reflecting the contribution of transparency, privacy, and fairness to IDA_j ;
- F_j : Implementation feasibility score, which evaluates the engineering maturity of the corresponding ETs.

The weighting coefficients satisfy

$$\alpha + \beta + \gamma + \delta = 1, \quad (9)$$

Where:

$$\alpha = 0.35, \beta = 0.30, \gamma = 0.20, \delta = 0.15$$

The illustrative coefficient vector ($\alpha = 0.35, \beta = 0.30, \gamma = 0.20, \delta = 0.15$) represents a proposed starting configuration for future empirical calibration. These coefficients are not validated by the present case and should be elicited and sensitivity-tested in an independent dataset before operational use.

The implementation feasibility score was categorized into three maturity levels:

- 1.0: Mature technologies suitable for immediate implementation;
- 0.7: Emerging technologies requiring moderate development;
- 0.5: Experimental technologies with limited engineering readiness.

If validated with complete inputs, CIDPI could support comparison across multiple design dimensions while preserving the conventional fuzzy-QFD ranking as a separately reported baseline. Its empirical usefulness, discrimination, and effects on rank remain subjects for future research.

3.4 Ethical-AI attribute modeling and prospective modulation

Ethical AI was incorporated into the proposed framework as a composite IDA6 to ensure that ethical considerations are systematically represented during early-stage conceptual design. The attribute is organized into two complementary layers, as illustrated in Figure 4.

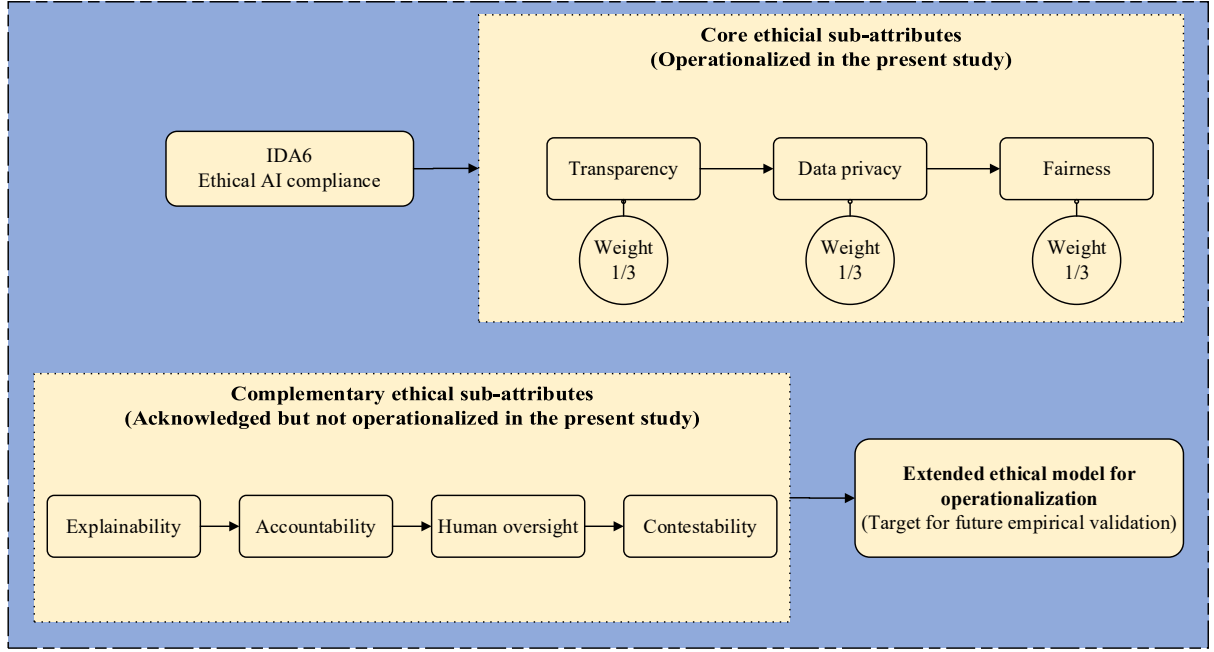


Figure 4. Ethical AI sub-attribute model (IDA6)

3.4.1 Proposed ECC extension for future validation

ECC is proposed as a future multiplicative extension for studies that collect numerical transparency, data privacy, and fairness ratings for every IDA. The formulation would permit bounded ethical modulation of conventional priorities, but it is not applied in the present case because the necessary ratings were not collected.

The ECC for IDA_j is defined as:

$$ECC_j = 1 + \lambda \left(\frac{t_j + d_j + f_j}{3} \right) \quad (10)$$

Where:

- t_j : Normalized transparency score of IDA_j ;
- d_j : Normalized data privacy score;
- f_j : Normalized fairness score; and
- λ : ECC modulation parameter.

For prospective application, $\lambda = 0.10$ is presented as an illustrative bounded modulation setting. This value is not empirically calibrated or sensitivity-tested in the present study and must be validated with independent ethical-rating data before operational use.

Under the proposed normalization, $0 \leq t_j, d_j, f_j \leq 1$ and $\lambda = 0.10$ would bound ECC_j within $[1.00, 1.10]$. This bounded range is a design property of the prospective formulation, not an observed result of the present case study.

In a future empirical application, an ethically modulated priority could be calculated as:

$$Q_j^{(E)} = Q_j \times ECC_j \quad (11)$$

Where:

Q_j : Defuzzified technical priority of IDA_j obtained from Phase I;

$Q_j^{(E)}$: Prospective ethically adjusted priority of IDA_j in a future empirical application.

The three AI-ethics specialists provided face validation of the transparency, data-privacy, and fairness constructs but did not supply numerical $t_j, d_j, or f_j$ ratings. Their contribution supports the conceptual definition of IDA6; it does not support empirical ECC values.

4. Illustrative demonstration: Intelligent design of a hotel service robot

4.1 Illustrative demonstration context

A hypothetical hotel service robot design scenario is used to illustrate the application of the proposed framework. No physical robot was deployed; this is a numerical demonstration of the method, using a prototype hotel service robot under active development as the illustrative subject. The robot is designed to operate 24/7 in indoor hotel environments, responsible for delivering amenities, guiding guests to rooms, and collecting waste from guest floors. The robot must interact safely with guests and staff while navigating corridors, elevators, and lobbies.

The hotel service robot case was selected because hospitality environments combine complex human–robot interaction, operational uncertainty, and diverse stakeholder requirements, making them well suited for demonstrating the proposed customer-driven two-phase fuzzy QFD methodology. The case is intended to illustrate the methodological applicability of the framework rather than to validate the performance of a specific robotic platform.

4.1.1 Customer requirements (CRs)

Ten stakeholder requirements were identified from hotel stakeholders and guests to reflect the intelligent service robot context. The CR set below replaces prior sustainability-oriented requirements with intelligence-focused requirements aligned with the paper’s scope, Table 9.

Table 9. CRs for intelligent hotel service robot design

No.	Customer requirement	Linguistic importance
CR1	Safe movement around guests and staff	VI
CR2	Accurate recognition of obstacles and people	VI
CR3	Reliable completion of delivery and guidance tasks	VI
CR4	Fast response to user requests	I
CR5	Natural and polite human–robot communication	VI
CR6	Ability to adapt to dynamic hotel environments	I
CR7	Privacy protection and ethical data handling	I
CR8	Easy operation and maintenance	F
CR9	Quiet and comfortable operation	F
CR10	Attractive and hotel-compatible appearance	F

4.1.2 Phase I fuzzy QFD analysis

Seven IDAs were derived from the literature review and expert elicitation. IDAs are formally defined as measurable design variables derived from perceived intelligence requirements, Table 10. IDAs encompass: Context awareness & perception (IDA1), Safe human–robot interaction (IDA2), Operational reliability (IDA3), Adaptive behavior (IDA4), Multimodal interaction (IDA5), Ethical AI compliance (IDA6), and User-centered interface (IDA7). Based on that, each IDA was mapped against the CRs in the HoQ matrix.

Table 10. Phase I HoQ matrix: CRs & IDAs with fuzzy relationship

	IDA	IDA1	IDA2	IDA3	IDA4	IDA5	IDA6	IDA7
CR								
CR1	VI	S	S	M	W	W	M	W
CR2	VI	S	M	S	M	W	W	W
CR3	VI	M	M	S	M	W	W	W
CR4	I	S	M	M	S	W	W	W
CR5	VI	M	S	W	M	S	W	S
CR6	I	S	M	M	S	W	W	W
CR7	I	W	M	W	W	W	S	W
CR8	F	W	W	S	W	W	W	W
CR9	F	W	W	M	W	W	W	W
CR10	F	W	W	W	W	M	W	S
Crisp score C_j		24.3 ± 1.4	22.7 ± 1.3	21.9 ± 1.2	20.5 ± 1.1	19.8 ± 1.1	15.4 ± 0.9	14.1 ± 0.9
	S: Strong	M: Medium	W: Weak	VI: Very important	I: Important	F: Fair		

1. Correlation analysis of HoQ “Roof” among IDAs

To complete the HoQ structure and support qualitative design trade-off awareness, Table 11 presents a qualitative expert-derived interaction map capturing the perceived interactions among the seven IDAs. This matrix is explicitly positioned as a directional guidance tool only; correlation signs were assigned by the robotics engineer panel ($n = 6$) based on consensus discussion of technical and operational interdependencies, using the symbols: ++ (strong positive), + (weak positive), − (weak negative), — (strong negative), and No (no meaningful interaction).

Table 11. IDA-IDA qualitative expert-derived interaction map

IDA	IDA1	IDA2	IDA3	IDA4	IDA5	IDA6	IDA7
IDA1	=	+	+	++	+	—	No
IDA2	+	=	+	No	No	+	No
IDA3	+	+	=	−	No	No	No
IDA4	++	No	−	=	+	−	No
IDA5	+	No	No	+	=	+	++
IDA6	—	+	No	−	+	=	+
IDA7	No	No	No	No	++	+	=

++:	Strong positive	+:	Weak positive	No:	No interaction	−:	Weak negative	—:	Strong negative	=:	Neutral
-----	-----------------	----	---------------	-----	----------------	----	---------------	----	-----------------	----	---------

As illustrated in Table 11, the most consequential trade-off identified by the panel is the strong negative interaction between IDA1 (context awareness and perception) and IDA6 (ethical AI compliance, particularly

the privacy sub-attribute): higher-fidelity context awareness typically requires continuous multimodal sensing (cameras, audio, RFID tracking of guests), which directly increases data-privacy exposure. Conversely, IDA1 exhibits a strong positive synergy with IDA4 (adaptive behavior), since improved environmental perception directly enables more effective adaptive responses, and IDA5 (multimodal interaction) shows a strong positive synergy with IDA7 (user-centered interface design), as richer interaction modalities and interface design are mutually reinforcing. Design teams should treat the IDA1–IDA6 trade-off explicitly: investment in perception capability should be paired with privacy-preserving design measures (e.g., on-device processing, data minimization, auditable access logs) rather than treated as an independent budget line, as illustrated in Figure 5.

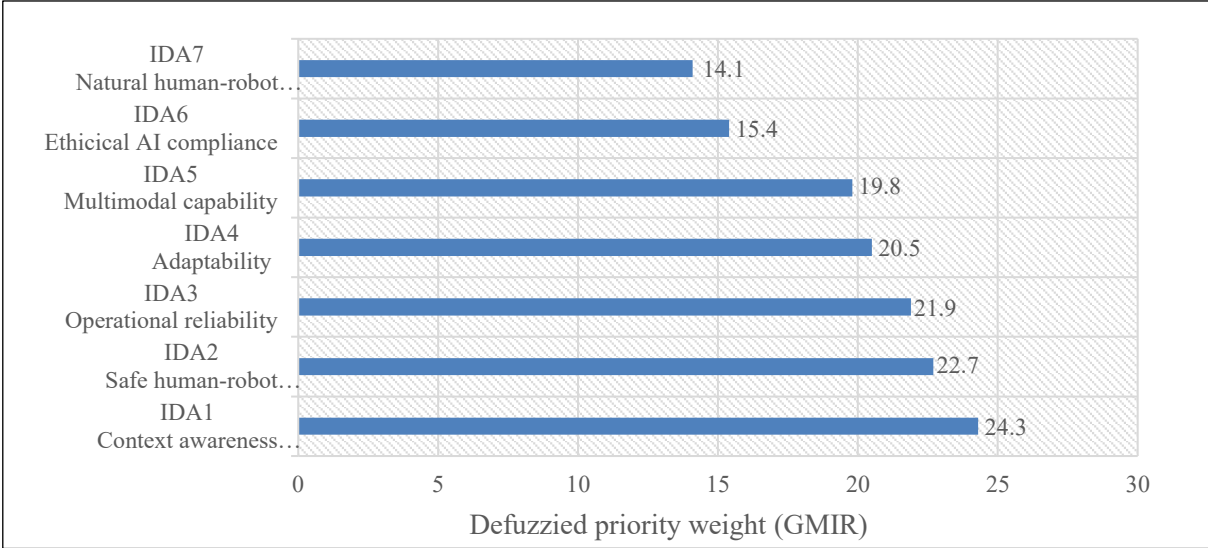


Figure 5. Phase I priorities weights of IDAs

2. Phase I results: Prioritization of IDAs

To anchor each IDA to verifiable engineering measures, Table 12 provides illustrative measurable indicators for each IDA. These indicators are intended as representative examples rather than an exhaustive or validated metrology and should be refined in collaboration with implementing engineering teams.

Table 12. Illustrative measurable indicators for IDAs

Category	IDA	Illustrative measurable indicator(s)
Core measurable	IDA1	Object/obstacle detection range (m) and recognition accuracy (%); false-positive/false-negative rate of person detection in corridor environments.
Core measurable	IDA2	Minimum maintained safe distance from guests/staff (m); emergency-stop response latency (ms); collision incident rate per 1,000 operating hours.
Core measurable	IDA3	Mean time between failures (MTBF, hours); task completion rate (%) for delivery/guidance/waste-collection tasks; unplanned downtime (hours/month).
Core measurable	IDA4	Route re-planning success rate under environmental change (%); time to adapt to a new floor layout (minutes); reduction in repeated navigation errors over time.
Core measurable	IDA5	Number of supported interaction modalities (voice, touchscreen, gesture); speech recognition accuracy in ambient noise (%); guest-rated communication clarity (Likert scale).
Core	IDA6	Transparency: percentage of robot decisions with an accessible audit log. Privacy: proportion of sensor data

Category	IDA	Illustrative measurable indicator(s)
measurable		processed on-device vs. transmitted/stored. Fairness: variance in service response time across guest demographic groups.
Core measurable	IDA7	User-reported ease-of-use score (Likert scale); task completion time for first-time users; number of interface steps required for common requests.

3. Phase II results: prioritization of ETs

Six ETs were identified through a two-step process: (1) a systematic literature review of service robot design papers yielded an initial set of twelve candidate technologies; (2) the robotics engineer panel (n=6) rated each candidate for relevance to the seven prioritized IDAs, retaining the top six by consensus (Fleiss’ $\kappa > 0.70$), as illustrated in Figure 6.

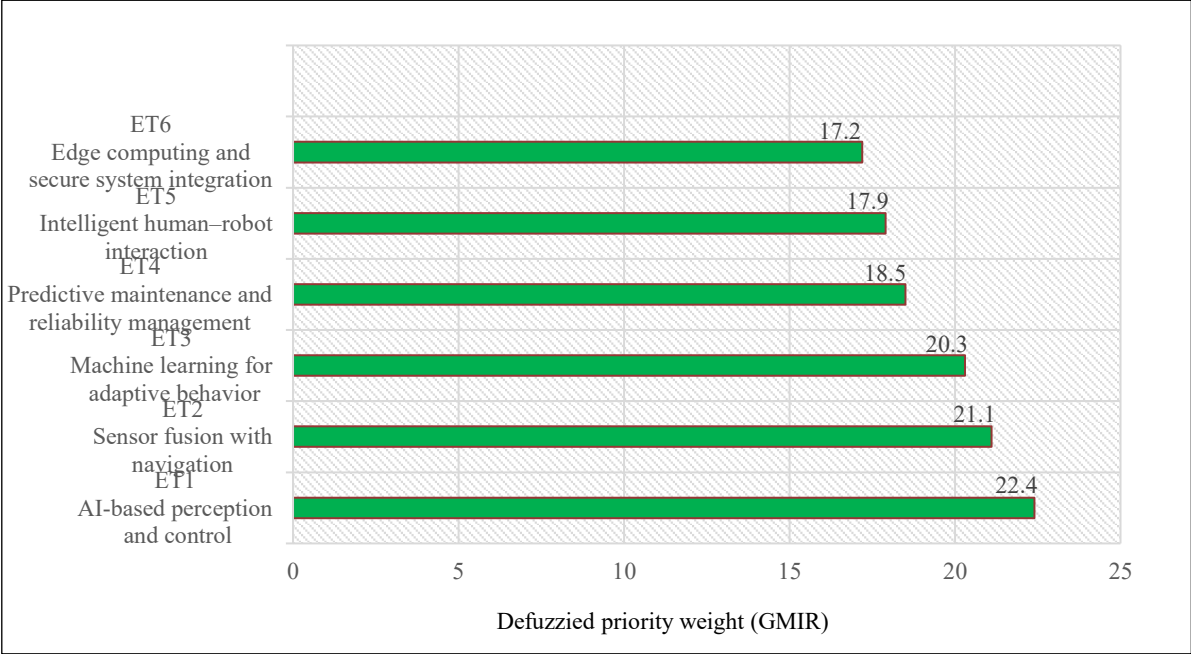


Figure 6. Phase II priority weights of ETs

A critical limitation of Phase II is that the IDA mapping to ET is treated as approximately linear: each ET is assigned a primary IDA link, whereas real systems involve non-linear interdependencies where multiple ETs jointly enable individual IDAs. To partially address this, the IDA Link column in Table 13 reports all IDAs materially supported by each ET.

Table 13. Phase II results ranked ETs with crisp priority scores

Rank	Enabling Technology (ET)	Crisp score	Design Implication	IDA Link
1	AI-based perception and control	22.4 ± 1.3	Core intelligence layer	IDA ₁
2	Sensor fusion and autonomous navigation	21.1 ± 1.2	Robust indoor operation	IDA ₁ , IDA ₂
3	Machine learning for adaptive behavior	20.3 ± 1.1	Personalization and adaptation	IDA ₄
4	Predictive maintenance and reliability management	18.5 ± 1.0	Continuous service availability	IDA ₃
5	Intelligent human-robot interaction	17.9 ± 1.0	Multilingual guest communication	IDA ₅
6	Edge computing and secure system integration	17.2 ± 0.9	Low-latency autonomous decisions	IDA ₁ , IDA ₆

4.1.3 Phase II fuzzy QFD analysis

The prioritized ETs identified through the second phase of the fuzzy QFD framework were further translated into representative engineering implementation modules to demonstrate how the proposed methodology supports the transition from conceptual design to system realization. Rather than prescribing a specific hardware configuration, the mapping establishes the functional relationships between ETs, IDAs, and representative implementation components, thereby providing a traceable engineering reference for design teams.

- ET1: AI-based perception and control primarily support IDA1 by enabling environmental sensing, object recognition, and autonomous perception. Representative implementation components include multimodal vision sensors, LiDAR, simultaneous localization and mapping (SLAM), object detection algorithms, and semantic environment representation. Together, these modules provide the perceptual foundation required for autonomous operation in dynamic hotel environments.
- ET2: Sensor fusion and autonomous navigation support IDA1 and IDA2 by integrating heterogeneous sensor data into a unified localization and navigation framework. Typical implementation functions include multi-sensor fusion, localization, path planning, dynamic obstacle avoidance, and safety monitoring, enabling robust navigation while maintaining safe interaction with guests and staff.
- ET3: Machine learning for adaptive behavior realizes IDA4 through data-driven decision-making and continuous behavioral improvement. Representative implementation modules include reinforcement learning, continual learning, guest preference modeling, and anomaly detection, allowing the robot to adapt its behavior to changing operational conditions and user preferences.
- ET4: Predictive maintenance and reliability management corresponds to IDA3 by continuously monitoring the health status of critical hardware components. Typical implementation functions include equipment condition monitoring, battery health assessment, thermal management, fault prediction, and maintenance scheduling, thereby improving long-term operational availability.
- ET5: Intelligent human–robot interaction realizes IDA5 by integrating speech, visual, and graphical interaction channels. Representative components include speech recognition, natural language understanding, multimodal dialogue management, graphical user interfaces (GUIs), gesture recognition, and multilingual communication modules to facilitate intuitive interaction with hotel guests.
- ET6: Edge computing and secure system integration supports IDA1 and IDA6 by enabling real-time processing while protecting sensitive information. Representative implementation functions include edge inference, distributed computing, secure data synchronization, encrypted communication, and privacy-preserving data management, thereby supporting both computational efficiency and ethical AI requirements.

4.2 Robustness and sensitivity analysis

4.2.1 Sensitivity analysis design

To validate the stability of the fuzzy QFD rankings under uncertainty in input judgments, a systematic sensitivity analysis was conducted using independent one-at-a-time perturbations of each CR importance weight at $\pm 5\%$, $\pm 10\%$, and $\pm 15\%$ relative to its baseline value, while holding the remaining CR weights constant. The complete Phase I and Phase II calculations were recomputed under each scenario. Rank changes

were assessed using rank-reversal counts and Spearman rank correlation relative to the baseline ordering.

This approach is methodologically preferable to simultaneous proportional scaling of all weights because independent perturbations test whether the rank order is robust to idiosyncratic variation in any single requirement, which is the realistic uncertainty pattern in stakeholder elicitation.

Results confirm that the top three IDAs: IDA1 = 24.3, IDA2 = 22.7, IDA3 = 21.9 remain stable in rank order across all perturbation scenarios; no rank reversals occurred among these three attributes. Among the lower-ranked IDAs (IDA4-IDA7), minor rank fluctuations occur at $\pm 15\%$ perturbation, particularly between IDA4 and IDA5, suggesting that these two attributes should be treated as approximately equivalent design priorities in practical applications. The ranking of Ethical AI compliance (IDA6) remains stable across all perturbation scenarios, indicating that its moderate priority (rank 6) is not an artifact of specific input weights.

4.2.2 Approximate assessment of uncertainty propagation between Phase I and Phase II

Because the proposed framework adopts a sequential CR-IDA-ET structure, uncertainty originating in Phase I may propagate to the engineering priorities generated in Phase II. In the present formulation, the aggregated fuzzy priority weights of the IDAs obtained from Phase I are propagated directly as weighting inputs to the Phase II HoQ. GMIR defuzzification is applied only after the fuzzy ET priorities have been computed, thereby preserving the fuzzy representation of uncertainty across the two-phase translation process.

The $\pm 15\%$ sensitivity analysis of CR-importance weights provides a deterministic assessment of the conventional two-phase fuzzy QFD rankings. CIDPI, ECC, and cross-method benchmarking are outside the empirical scope of the present study.

Within the CR weight perturbation scenarios examined, uncertainty affected the magnitudes of conventional fuzzy QFD priorities more than the ordering of the dominant IDAs and ETs. This result should be interpreted as a deterministic robustness assessment rather than a comprehensive probabilistic analysis. Future studies may employ Monte Carlo or Bayesian methods and may validate the proposed CIDPI and ECC extensions using complete component-level and ethical-rating datasets.

4.3 Preliminary customer-stakeholder subgroup analysis

To explore whether differences in customer-side stakeholder perspectives influence the prioritization of IDAs, an exploratory subgroup analysis was conducted using the CRs importance evaluations provided separately by hotel managers ($n = 5$) and hotel guests ($n = 8$). Because the CR-IDA relationship strengths were evaluated exclusively by the robotics-engineer panel ($n = 6$), the subgroup analysis did not construct fully independent stakeholder-specific HoQ matrices. Instead, the engineer-derived CR-IDA relationship matrix was held constant, while the subgroup-specific CR importance weights from hotel managers and guests were independently propagated through the Phase I fuzzy QFD model. This procedure isolates differences attributable to stakeholder perceptions of requirement importance while maintaining a common technical relationship structure.

The subgroup analyses reproduced the principal priorities of the aggregated model, with IDA1 and IDA2 remaining among the highest-priority attributes for both stakeholder groups. Differences were observed primarily among the remaining IDAs. Hotel guests assigned relatively greater priority to IDA5, reflecting greater emphasis on communication quality and interaction experience during hotel service encounters. In contrast, hotel managers assigned relatively greater priority to IDA3, consistent with their concern for service

continuity, system availability, and maintenance efficiency. These results suggest that although the principal intelligent-design priorities are broadly consistent, secondary priorities may vary according to stakeholder role. Because the subgroup sample sizes are limited, these findings should be interpreted as exploratory rather than statistically generalizable.

5. Discussion

The proposed two-phase fuzzy QFD framework provides a structured approach for translating CRs into prioritized IDAs and ETs for early-stage conceptual design. By introducing an intermediate layer of IDAs, the framework better captures the characteristics of intelligent service systems, where customer expectations regarding perception, interaction, adaptability, and ethical AI must first be translated into functional design capabilities before engineering technologies can be prioritized. This structured decision process enhances design transparency and traceability while supporting systematic engineering decision-making under uncertainty.

Beyond its methodological contribution, the findings provide several engineering insights. The consistently high priorities assigned to context awareness and perception, safe human–robot interaction, and operational reliability indicate that customers place greater value on robust intelligence and dependable operation than on advanced interactive features alone. Correspondingly, AI-based perception and control, sensor fusion with autonomous navigation, and machine learning for adaptive behavior emerged as the key ETs, suggesting that perception-driven intelligence should form the technological foundation of intelligent service robots before more sophisticated interaction capabilities are introduced.

The integrated system architecture further demonstrates the practical applicability of the proposed methodology by establishing explicit traceability from stakeholder requirements to representative software and hardware implementation modules. Rather than relying primarily on expert intuition, engineering teams can use the framework to justify technology selection and resource allocation through systematically prioritized customer evidence. CIDPI and ECC are retained only as prospective extensions that may support multidimensional prioritization and bounded ethical modulation after independent data collection, calibration, and validation.

The reported CR weight perturbation analysis provides preliminary evidence that the dominant fuzzy QFD rankings are stable within the tested ranges. Future research should evaluate cross-method convergence using independently implemented fuzzy-AHP and fuzzy-TOPSIS models with fully reported numerical inputs and outputs.

From a practical perspective, the framework offers value for both hotel operators and robotics developers. Hotel managers can use the methodology to align technology investment with customer priorities, thereby reducing the risk of emphasizing technically sophisticated but operationally less valuable functions. Robotics developers can apply the prioritization results to guide technology selection and engineering resource allocation while incorporating transparency, privacy, and fairness directly into the conceptual design process rather than treating ethical AI as a post-development compliance requirement.

Despite these contributions, several limitations constrain interpretation of the findings. First, the study constitutes an expert-based methodological demonstration rather than empirical validation through physical robot deployment; consequently, the reported priority values represent early-stage design guidance rather than

measured operational performance. Second, all participants were recruited within a single regional hospitality context in Fujian Province, China, and the resulting rankings should therefore not be generalized to other cultural or geographic settings without replication. Third, the present two-phase formulation approximates relationships between IDAs and ETs through additive fuzzy mappings, whereas practical intelligent robotic systems may exhibit nonlinear, interdependent, and networked technology relationships. Fourth, the present ethical-AI model operationalizes transparency, data privacy, and fairness, while explainability, accountability, human oversight, and contestability are acknowledged but not numerically incorporated. Finally, the current uncertainty-propagation analysis is based on deterministic sensitivity scenarios rather than a full probabilistic treatment. Future research should therefore combine cross-cultural stakeholder studies, physical or digital-twin-based prototype validation, network-based IDA-ET dependency modeling, broader ethical-AI operationalization, and probabilistic uncertainty analysis. In addition, CIDPI and ECC are presently conceptual extensions: their component inputs, ethical ratings, calibration, and sensitivity behavior require independent empirical validation before they can be used for decision support.

Future research should focus on prototype implementation, cross-cultural empirical validation, and digital twin-enabled verification to further evaluate and refine the proposed framework in real-world engineering applications. Furthermore, future applications should report CIDPI and ECC as analytically separate outputs to prevent double counting. E_j would contribute only to CIDPI, whereas ECC_j would modulate only the conventional priority Q_j . Neither proposed construct contributes to the rankings reported here.

6. Conclusion

This study developed and demonstrated a two-phase fuzzy QFD framework for the customer-driven conceptual design of hotel service robots. Through a hierarchical CR-IDA-ET architecture, the framework systematically translates CRs into IDAs and subsequently into ETs. It incorporates fuzzy uncertainty throughout both translation phases and represents ethical-AI considerations through IDA6, while numerical ethical modulation remains a prospective extension requiring future empirical validation.

The demonstrated framework advances intelligent engineering design by establishing a sequential CR-IDA-ET translation that improves traceability and by representing ethical-AI compliance explicitly through IDA6. The proposed CIDPI and ECC formulations extend the research agenda but are not included in the empirical findings of this study.

The illustrative hotel service-robot case demonstrates the procedural application of the conventional two-phase fuzzy QFD method. Context awareness and perception, safe human–robot interaction, and operational reliability were the highest-priority IDAs, while AI-based perception and control, sensor fusion with autonomous navigation, and machine learning for adaptive behavior were the highest-priority ETs. CR weight perturbations preserved the dominant ranking structure within the tested ranges.

More broadly, the proposed framework extends conventional fuzzy QFD from a product-oriented prioritization tool into a systematic methodology for intelligent engineering design. By integrating customer-centered intelligence, ethical AI, engineering traceability, and computational decision support within a unified framework, the proposed framework provides a potentially transferable methodological structure for customer-driven intelligent product and service-system design. Its applicability beyond hotel service robots should be established through cross-domain replication, empirical implementation, and prototype-based validation.

Acknowledgments:

This research was supported by Quanzhou University of Information Engineering, School of Mechanical and Electrical Engineering (No. 249 Bodong Street, Fengze District, Quanzhou City, Fujian Province, People's Republic of China), which provided resources and institutional support for the research, authorship, and publication of this article.

Declaration of Generative AI Use:

During the preparation of this work, the authors used DeepSeek exclusively for language refinement and grammar correction. After using this tool, the authors reviewed and edited the content as necessary and take full responsibility for the content of the published article.

Declaration of Interest Statement:

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding Statement

The authors received no specific funding for this work.

Data Availability Statement:

The aggregated fuzzy-QFD matrices and conventional priority results supporting the illustrative case are reported in the article. CIDPI and ECC were not empirically calculated and therefore have no associated case-study dataset. Available anonymized supporting data may be obtained from the corresponding author upon reasonable request, subject to participant consent and applicable ethical and institutional restrictions.

Ethical Approval and Consent to Participate

This study involved human participants and was conducted in accordance with the Declaration of Helsinki. All methods were carried out in accordance with relevant guidelines and regulations. The study protocol was reviewed and approved by the Institutional Review Board of Quanzhou University of Information Engineering (Approval No. QZUIE-IRB-2026-0072). Written informed consent was obtained from all individual participants prior to their participation. All participant data were anonymized, and no personally identifiable information is included in this manuscript.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
HRI	Human-robot interaction
CRs	Customer requirements
QFD	Quality function deployment
Fuzzy QFD	Fuzzy quality function deployment
IDAs	Intelligent design attributes
ETs	Enabling technologies
HoQ	House of quality
CIDPI	Customer-driven intelligent design priority index
ECC	Ethical compliance coefficient
HCAI	Human-centered artificial intelligence
SDL	Service-dominant logic
VSD	Value-sensitive design
LLM	Large language model
VLA	Vision–language–action
XAI	Explainable artificial intelligence
TFNs	Triangular fuzzy numbers
GUI	Graphical user interface
RFID	Radio frequency identification
MTBF	Mean time between failures

References

- Abowd, G. D., Dey, A. K., Brown, P. J., Davies, N., Smith, M., & Steggles, P. (1999). Towards a better understanding of context and context-awareness. *International Symposium on Handheld and Ubiquitous Computing*, 304–307.
- Brohan, A., Brown, N., Carbajal, J., Chebotar, Y., Chen, X., Choromanski, K., Ding, T., Driess, D., Dubey, A., & Finn, C. (1 C.E.). others. 2023. Rt-2: Vision-language-action models transfer web knowledge to robotic control. *ArXiv Preprint ArXiv:2307.15818*.
- Chen, M., Wang, X., Law, R., & Zhang, M. (2023). Research on the frontier and prospect of service robots in the tourism and hospitality industry based on international core journals: a review. *Behavioral Sciences*, 13(7), 560.
- Chou, C.-C. (2003). The canonical representation of multiplication operation on triangular fuzzy numbers. *Computers & Mathematics with Applications*, 45(10–11), 1601–1610.
- Dalkey, N., & Helmer, O. (1963). An experimental application of the Delphi method to the use of experts. *Management Science*, 9(3), 458–467.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340.
- De Santis, A., Siciliano, B., De Luca, A., & Bicchi, A. (2008). An atlas of physical human–robot interaction. *Mechanism and Machine Theory*, 43(3), 253–270.
- Development, O. for E. C. and. (2019). *Recommendation of the council on artificial intelligence*. OECD.
- Dey, A. K. (2001). Understanding and using context. *Personal and Ubiquitous Computing*, 5(1), 4–7.
- Di Cosmo, V., Giusti, A., Vidoni, R., Riedl, M., & Matt, D. T. (2019). Collaborative robotics safety control application using dynamic safety zones based on the ISO/TS 15066: 2016. *International Conference on Robotics in Alpe-Adria Danube Region*, 430–437.
- Firoozi, R., Tucker, J., Tian, S., Majumdar, A., Sun, J., Liu, W., Zhu, Y., Song, S., Kapoor, A., & Hausman, K. (2025). Foundation models in robotics: Applications, challenges, and the future. *The International Journal of Robotics Research*, 44(5), 701–739.
- Fleiss, J. L. (1971). Measuring nominal scale agreement among many raters. *Psychological Bulletin*, 76(5), 378.
- Fong, T., Nourbakhsh, I., & Dautenhahn, K. (2003). A survey of socially interactive robots. *Robotics and Autonomous Systems*, 42(3–4), 143–166.
- Fosch-Villaronga, E., & Mahler, T. (2021). Cybersecurity, safety and robots: Strengthening the link between cybersecurity and safety in the context of care robots. *Computer Law & Security Review*, 41, 105528.
- Franke, S., de Koster, R., Reining, C., Celik, H., & Kirchheim, A. (2026). Automated and Autonomous Mobile Robots in Warehousing: Definitions, Autonomy Levels, and Research Directions. *Journal of Intelligent & Robotic Systems*.
- Friedman, B. (1996). Value-sensitive design. *Interactions*, 3(6), 16–23.
- Friedman, B., & Hendry, D. G. (2026). *Value sensitive design: Shaping technology with moral imagination*. The MIT Press.
- Friedman, B., Kahn Jr, P. H., Borning, A., & Hultgren, A. (2013). Value sensitive design and information systems. In *Early engagement and new technologies: Opening up the laboratory* (pp. 55–95). Springer.
- Galgano, N. Z. (2026). The 2024 EU Regulation on Artificial Intelligence: A Perspective. *European Business Law Review*, 37(3), 459–490.
- Giuliani, M., Lenz, C., Müller, T., Rickert, M., & Knoll, A. (2010). Design principles for safety in human-robot interaction. *International Journal of Social Robotics*, 2(3), 253–274.
- Goodrich, M. A., & Schultz, A. C. (2008). Human–robot interaction: a survey. *Foundations and Trends® in Human–Computer Interaction*, 1(3), 203–275.
- Gualtieri, L., Rauch, E., & Vidoni, R. (2022). Development and validation of guidelines for safety in human-robot collaborative assembly systems. *Computers & Industrial Engineering*, 163, 107801.
- Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management*, 49, 157–169.
- Haidegger, T., Barreto, M., Gonçalves, P., Habib, M. K., Ragavan, S. K. V., Li, H., Vaccarella, A., Perrone, R., & Prestes, E. (2013). Applied ontologies and standards for service robots. *Robotics and Autonomous Systems*, 61(11), 1215–1223.

- Hawes, N., Burbridge, C., Jovan, F., Kunze, L., Lacerda, B., Mudrova, L., Young, J., Wyatt, J., Hebesberger, D., & Kortner, T. (2017). The strands project: Long-term autonomy in everyday environments. *IEEE Robotics & Automation Magazine*, 24(3), 146–156.
- Honig, S., & Oron-Gilad, T. (2018). Understanding and resolving failures in human-robot interaction: Literature review and model development. *Frontiers in Psychology*, 9, 861.
- Ivanov, S., Gretzel, U., Berezina, K., Sigala, M., & Webster, C. (2019). Progress on robotics in hospitality and tourism: a review of the literature. *Journal of Hospitality and Tourism Technology*, 10(4), 489–521.
- Ivanov, S., & Webster, C. (2019). *Conceptual framework of the use of robots, artificial intelligence and service automation in travel, tourism, and hospitality companies*.
- Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence*, 1(9), 389–399.
- Junior, J. B. G., Hékis, H. R., Costa, J. A. F., de Andrade, Í. G. M., dos Santos Cabral, E. L., Castro, W. R. S., de Medeiros Florentino, D. R., de Oliveira Barreto, T., & da Costa Júnior, J. F. (2022). Application of the QFD-fuzzy-SERVQUAL methodology as a quality planning tool at the surgical centre of a public teaching hospital. *BMC Medical Informatics and Decision Making*, 22(1), 8.
- Karsak, E. E. (2008). Robot selection using an integrated approach based on quality function deployment and fuzzy regression. *International Journal of Production Research*, 46(3), 723–738.
- Kim, C., Kim, K., Oh, M., Baek, H., Lee, J., Jung, D., Woo, S., Woo, Y., Tucker, J., & Firoozi, R. (2025). E2map: Experience-and-emotion map for self-reflective robot navigation with language models. *2025 IEEE International Conference on Robotics and Automation (ICRA)*, 12811–12817.
- Kuo, C.-M., Chen, L.-C., & Tseng, C.-Y. (2017). Investigating an innovative service with hospitality robots. *International Journal of Contemporary Hospitality Management*, 29(5), 1305–1321.
- Levi, E., Kordova, S., & Tahan, M. (2026). Digital Twin Integration for Enhancing Robotic Fastening Systems in Industrial Automation. *Systems*, 14(4), 372.
- Levine, S., Pastor, P., Krizhevsky, A., Ibarz, J., & Quillen, D. (2018). Learning hand-eye coordination for robotic grasping with deep learning and large-scale data collection. *The International Journal of Robotics Research*, 37(4–5), 421–436.
- Li, L., Li, L., Li, M., & Liang, K. (2025). AI-Driven Robotics: Innovations in Design, Perception, and Decision-Making. *Machines*, 13(7), 615.
- Licardo, J. T., Domjan, M., & Orehovački, T. (2024). Intelligent robotics—A systematic review of emerging technologies and trends. *Electronics*, 13(3), 542.
- Liu, W., Xin, X., & Zheng, C. (2025). The effect of behaviorally anthropomorphic service robots on customers' variety-seeking behavior: an analytical examination of social presence and decision-making context. *Frontiers in Robotics and AI*, 12, 1503622.
- Liu, Z., Liang, X., Chen, X., & Wen, X. (2024). Design of a sweeping robot based on fuzzy QFD and ARIZ algorithms. *Heliyon*, 10(19).
- Lu, L., Cai, R., & Gursay, D. (2019). Developing and validating a service robot integration willingness scale. *International Journal of Hospitality Management*, 80, 36–51.
- Mende, M., Scott, M. L., Van Doorn, J., Grewal, D., & Shanks, I. (2019). Service robots rising: How humanoid robots influence service experiences and elicit compensatory consumer responses. *Journal of Marketing Research*, 56(4), 535–556.
- Nguyen, Q., & Sreenath, K. (2021). Robust safety-critical control for dynamic robotics. *IEEE Transactions on Automatic Control*, 67(3), 1073–1088.
- Okoli, C., & Pawlowski, S. D. (2004). The Delphi method as a research tool: an example, design considerations and applications. *Information & Management*, 42(1), 15–29.
- Pezzato, C., Corbato, C. H., Bonhof, S., & Wisse, M. (2023). Active inference and behavior trees for reactive action planning and execution in robotics. *IEEE Transactions on Robotics*, 39(2), 1050–1069.
- Schepers, J., Belanche, D., Casaló, L. V., & Flavián, C. (2022). How smart should a service robot be? *Journal of Service Research*, 25(4), 565–582.

- Shaji, S., Huppertz, F., Mitrevski, A., & Houben, S. (2026). From language to action: Can llm-based agents be used for embodied robot cognition? *ArXiv Preprint ArXiv:2603.03148*.
- Shi, H., Mao, L.-X., Li, K., Wang, X.-H., & Liu, H.-C. (2022). Engineering characteristics prioritization in quality function deployment using an improved ORESTE method with double hierarchy hesitant linguistic information. *Sustainability*, 14(15), 9771.
- Shin, H. H., & Jeong, M. (2020). Guests' perceptions of robot concierge and their adoption intentions. *International Journal of Contemporary Hospitality Management*, 32(8), 2613–2633.
- Shneiderman, B. (2022). *Human-centered AI*. Oxford University Press.
- Sotomi, O., Kodi, D., & Arab, A. (2025). Trust Through Transparency: Explainable Social Navigation for Autonomous Mobile Robots via Vision-Language Models. *ArXiv Preprint ArXiv:2504.05477*.
- Sun, Y., Fu, Z., Li, P., Xu, Y., Xiong, Z., & Ji, J. (2026). Robotic Digital Twin: A Lifecycle Perspective from Design to Application and Maintenance—A Review. *CHAIN*, 3(1), 37–52.
- Tung, V. W. S., & Au, N. (2018). Exploring customer experiences with robotics in hospitality. *International Journal of Contemporary Hospitality Management*, 30(7), 2680–2697.
- Tuomi, A., Tussyadiah, I. P., & Stienmetz, J. (2021). Applications and implications of service robots in hospitality. *Cornell Hospitality Quarterly*, 62(2), 232–247.
- Turoff, M., & Linstone, H. A. (1975). *"The" Delphi method: techniques and applications*. Addison-Wesley Publ.
- Tussyadiah, I. (2020). A review of research into automation in tourism: Launching the Annals of Tourism Research Curated Collection on Artificial Intelligence and Robotics in Tourism. *Annals of Tourism Research*, 81, 102883.
- Tussyadiah, I. P., Zach, F. J., & Wang, J. (2020). Do travelers trust intelligent service robots? *Annals of Tourism Research*, 81, 102886.
- Umbrello, S., Capasso, M., Balistreri, M., Pirni, A., & Merenda, F. (2021). Value sensitive design to achieve the UN SDGs with AI: A case of elderly care robots. *Minds and Machines*, 31(3), 395–419.
- van der Schoor, M. J., & Göhlich, D. (2023). Integrating sustainability in the design process of urban service robots. *Frontiers in Robotics and AI*, 10, 1250697.
- Vargo, S. L., & Lusch, R. F. (2004). Evolving to a new dominant logic for marketing. *Journal of Marketing*, 68(1), 1–17.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view1. *MIS Quarterly*, 27(3), 425–478.
- Vinodh, S., Manjunatheshwara, K. J., Karthik Sundaram, S., & Kirthivasan, V. (2017). Application of fuzzy quality function deployment for sustainable design of consumer electronics products: a case study. *Clean Technologies and Environmental Policy*, 19(4), 1021–1030.
- Wang, T., & Yang, L. (2023). Combining GRA with a fuzzy QFD model for the new product design and development of Wickerwork Lamps. *Sustainability*, 15(5), 4208.
- Wei, X., Zhang, H., Cao, X., Xie, S., Ge, W., Li, Y., & Wang, C. (2025). Audio-VLA: Adding Contact Audio Perception to Vision-Language-Action Model for Robotic Manipulation. *ArXiv Preprint ArXiv:2511.09958*.
- Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: service robots in the frontline. *Journal of Service Management*, 29(5), 907–931.
- Xin, X., & Liu, W. (2025). Exploring the balance between functionality and aesthetics: an analytical framework and pragmatic consideration of the anthropomorphism of service robots. *Frontiers in Psychology*, 16, 1555395.
- Younesi, M., & Roghanian, E. (2015). A framework for sustainable product design: a hybrid fuzzy approach based on quality function deployment for environment. *Journal of Cleaner Production*, 108, 385–394.
- Zhang, H., Xu, Z., Qian, H., & Su, X. (2022). Failure mode and effects analysis based on Z-numbers and the graded mean integration representation. *CMES-Computer Modeling in Engineering and Sciences*, 134(2), 1005–1019.
- Zonta, T., Da Costa, C. A., da Rosa Righi, R., De Lima, M. J., Da Trindade, E. S., & Li, G. P. (2020). Predictive maintenance in the Industry 4.0: A systematic literature review. *Computers & Industrial Engineering*, 150, 106889.

