



A Distributed Fuzzy Expert System on an Edge-Cloud Architecture for Predicting Technology Commercialization Success

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ABSTRACT

Accurately predicting the commercialization potential of emerging technologies is essential for guiding investment decisions and shaping innovation policies. However, most existing fuzzy expert systems are based on centralized architectures, which limit their scalability when applied to large technology portfolios in open innovation environments. This study introduces a distributed fuzzy inference system (D-FIS) implemented within an edge-cloud computing framework to overcome these limitations. The proposed model evaluates technology commercialization using 32 indicators covering technological, financial, market, and regulatory dimensions. These indicators were identified through the fuzzy Delphi method, while decision-making is performed using Mamdani's fuzzy and centroid defuzzification. To improve computational efficiency, rule evaluation is distributed across edge nodes, whereas the cloud layer is responsible for aggregating inference results and maintaining the synchronization of membership functions. The framework was validated using a real-world dataset comprising technology commercialization cases. Experimental results showed an overall prediction accuracy of 72.73%, with a specificity of 94.44%, and a sensitivity of 75.00%. Compared with a conventional centralized implementation, the proposed approach reduced inference latency by 64% while demonstrating near-linear scalability across up to 32 computing nodes. These findings indicate that the proposed D-FIS offers an interpretable and scalable decision-support framework for assessing commercialization risks under uncertainty and can facilitate collaborative decision-making in open innovation ecosystems.

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Introduction

Open innovation ecosystems involve a wide range of participants, including corporations, startups, research organizations, and policymakers, all of whom need reliable tools to evaluate the commercial potential of emerging technologies. Fuzzy expert systems have long been valued for their transparency and ability to incorporate expert knowledge into decision making. Nevertheless, most existing implementations are built on centralized architectures, making them increasingly inefficient as the number of technologies and evaluation projects grows. The journey from a scientific discovery to a widely adopted technology involves multiple phases of development and validation. A critical step in this journey is commercialization—the process through which technical innovations are transformed into marketable products or services (Kathleen, 2003). In the academic literature, commercialization has been defined from two main viewpoints. From an economic standpoint, it is seen as the translation of technological know-how into financially successful offerings (Brown, 1997). From a market-oriented angle, commercialization focuses on how an innovation moves from the idea stage to actual market entry (Balachandra et al., 2004; Kathleen, 2003).

When organizations establish effective mechanisms for commercialization, several benefits arise. On a societal level, communities gain improved welfare through technological and economic progress. At the organizational level, research entities obtain substantial financial returns. Additionally, commercialization helps mobilize knowledge by transferring research outputs into market settings. Despite these recognized advantages (Kumar & Jain, 2003), evidence shows a persistent gap worldwide: many technologies succeed technically but never become commercially viable (Kathleen, 2003). This gap reflects the inherent difficulty of commercialization, which demands coordinated action among various stakeholders, each bringing specialized skills.

Several systemic obstacles hinder technology commercialization. These include shortages of relevant information and skilled human resources, economic, and political barriers, as well as organizational or structural inefficiencies. Another common problem is the mismatch between technological outputs and actual market or customer requirements, often aggravated by the lack of standardized regulatory or environmental frameworks. Furthermore, some technologies have intrinsic limitations that reduce their readiness for the market. Due to these diverse challenges, designing effective methods to improve commercialization outcomes is inherently complex (Martyniuk et al., 2003).

One promising way to address these difficulties is through ex-ante prediction—estimating commercialization success before heavy investments are made. However, there are serious concerns about how such predictions should be methodologically grounded. Two main issues stand out. First, commercialization success itself is a multi-dimensional and poorly defined concept, often made ambiguous by inconsistent operational definitions (Ravi et al., 2003). Second, combining and quantifying the numerous factors that influence success poses significant methodological hurdles when building a reliable predictive model. Traditional statistical and analytical techniques—such as regression models and scoring systems—have

been frequently used to evaluate commercialization potential. Nevertheless, these methods generally fail to account for the nonlinear, uncertain, and context-dependent nature of real-world commercialization. Their weaknesses become especially apparent when attempting to model phenomena characterized by strong interdependencies and high ambiguity.

Because technology commercialization involves uncertainty, incomplete information, and subjective expert judgments, fuzzy expert systems have become a suitable framework for supporting this type of decision-making. Their ability to represent linguistic knowledge through rule-based reasoning allows complex relationships to be modeled without requiring precise numerical information (Haji pour, 2013; Sadjadi et al., 2019).

Recent studies have continued to advance technology commercialization prediction through innovative machine learning and fuzzy-based approaches. A study by Korean researchers addressed the challenge of imbalanced data in public technology commercialization datasets by utilizing Grid Search hyper parameter optimization to generate training data, achieving classification performance comparable to traditional data augmentation methods while maintaining business rule compliance. This approach is particularly relevant for public research and development (R&D) settings where success cases are infrequent.

In the startup context, Sadat Rasoul et al. (2023) developed a rule-based business success prediction model for Iranian IT startups using Mamdani's (1977) fuzzy inference system. Their research identified 36 factors across five categories influencing startup outcomes, concluding that team-related factors have the greatest impact on success. This finding reinforces the importance of organizational dimensions in commercialization success models.

The integration of explainable artificial intelligence (AI) with fuzzy inference systems has emerged as a significant trend. Lee et al. (2025) proposed SHAP-Rule, a novel XAI method that automatically translates numeric SHAP values into interpretable fuzzy linguistic IF-THEN rules for diagnostic tasks, demonstrating high expert ratings for simplicity and comprehensibility. Similarly, Zhang et al. (2025) introduced LE-FIS, an LLM-based Explainable Fuzzy Inference System for steel defect detection, and employing genetic algorithm optimization for rule generation and LLMs for result interpretation.

Sarfaraz et al. (2023) developed a decision framework integrating Fuzzy Inference System with two-step Fuzzy Quality Function Deployment to assist organizations in selecting technology licensors. Implemented in an Iranian lubricant producer, the framework identified key licensee expectations including product portfolio enhancement and brand image improvement. These recent developments highlight the growing synergy between fuzzy logic, explainable AI, and practical decision-support applications across diverse domains.

Despite the widespread adoption of fuzzy expert systems in technology assessment, existing models share a fundamental architectural limitation: they operate as centralized, monolithic inference engines. While effective for small-scale or single-project evaluations, such architectures become computationally prohibitive when applied to large portfolios of innovation projects—a common scenario in open innovation ecosystems where multiple stakeholders (corporations, startups, research institutions, and policymakers) simultaneously assess diverse technologies. The rule base grows exponentially with the number of indicators

and projects, leading to inference bottlenecks, high latency, and poor scalability. Moreover, centralized systems lack the flexibility to distribute computational load across geographically dispersed evaluation teams, limiting their practical deployment in real-world innovation networks.

To address these gaps, this study introduces a Distributed Fuzzy Inference System (D-FIS) on an edge-cloud architecture. Building on these observations, this study proposes a distributed fuzzy inference framework implemented within an edge-cloud architecture. The proposed approach addresses the scalability limitations of conventional fuzzy expert systems by distributing rule evaluation across multiple edge nodes while preserving a unified knowledge base in the cloud. The framework is evaluated using real-world technology commercialization data, allowing its predictive performance, computational efficiency, and scalability to be assessed under realistic operating conditions.

Literature Review

Research on technology commercialization assessment has evolved along three primary directions. The first emphasizes the intrinsic characteristics of the technology itself, often referred to as a technology-centric perspective. The second focuses on organizational capabilities and resources that influence commercialization outcomes, representing a company-centric perspective. More recent studies have adopted an integrated view by considering both technological and organizational factors within a unified evaluation framework.

One of the earliest integrated assessment frameworks is the Strategic Technology Evaluation Program (STEP), developed at the University of Cincinnati in 1996. The STEP model evaluates the commercial potential of emerging technologies using six dimensions: technical, procedural, economic, market, interpretative, and regulatory factors (Bandarian, 2007; Ravi et al., 2003). Another influential framework is the Commercialization Readiness Assessment (CRA) introduced by the U.S. Department of Homeland Security (DHS). Originally developed to support Small Business Innovation Research (SBIR) programs, the CRA framework assesses an organization's readiness to commercialize new technologies by comparing its capabilities with market requirements. The framework includes fifteen evaluation components, covering customer needs, market opportunities, pricing strategy, intellectual property protection, commercialization experience, financial planning, business models, partnerships, and regulatory considerations (Department of Homeland Security, 2013).

Empirical studies have also identified a wide range of determinants that influence commercialization success. Using data from 514 technology transfer cases involving 43 Korean universities and public research institutes (U&PRIs), Woong Min et al. (2020) found that successful commercialization depends not only on technological quality but also on organizational capabilities. Their results highlighted the importance of absorptive capacity, internal R&D capability, collaboration between research institutions and firms, and the competitiveness of the target market.

Comparable findings have been reported in other national contexts. Mirghafoori et al. (2011) investigated commercialization activities in Yazd Province, Iran, and demonstrated that commercialization outcomes are shaped by multiple interacting factors, including demographic characteristics, technological novelty, market conditions, financial resources, managerial practices, and legal support. Likewise, Jung et al. (2015) analyzed 586 commercialization projects in South Korea to distinguish between successful and unsuccessful commercialization efforts. Their study identified marketability, collaboration with technology developers, technological advancement, user capability and satisfaction, financial resources, and market competition as the most influential determinants of commercialization performance.

Research focusing on small and medium-sized enterprises has reached similar conclusions. Meijer et al. (2019), examining firms operating in the Dutch sustainable energy sector, reported that technology complexity, investment requirements, patent protection, access to skilled personnel, and commercialization speed play decisive roles in determining commercial success. Drawing on the findings of these studies, Table 1 summarizes the principal factors associated with successful technology commercialization. For clarity, the identified variables are grouped into four broad categories: technical, financial and economic, market, and regulatory dimensions. Studies that addressed technology transfer without explicitly evaluating commercialization outcomes were excluded from this synthesis. Complementing this perspective, Lianto (2023) employed the fuzzy Delphi method to identify the key indicators of organizational innovation capability, emphasizing the importance of intellectual capital through dimensions such as organizational adaptability, innovation-oriented behavior, organizational culture and climate, and forward linkages.

Table 1. Influential Components on Technology Commercialization Success

Dimensions	Row	Components	Sources
Technical Specifications	1	Technology (tech) technical feasibility	Mohan & Rao (2003), Rahal & Rabelo (2006), Bandarian (2007), Mirghafoori et al. (2011), Mohannak & Samtani (2014)
	2	Prominent technical advantages of tech	Mohan & Rao (2003), Rahal & Rabelo (2006), Galbraith et al. (2007), Jung et al. (2015), Kirchberger & Pohl (2016)
	3	R&D capabilities	Sohn & Moon (2003), Åstebro (2004), Kimura (2010), Cho & Lee (2013)
	4	High technological level of technology	Rostek (2014), Mohan & Rao (2003)
	5	Low complexity of tech usage	Martyniuk et al. (2003), Bandarian (2007), Mirghafoori et al. (2011)
	6	Establishing the probability of tech on small scale	Rahal & Rabelo (2006), Bandarian (2007)
	7	Novelty of tech or its product	Zahra & Nielsen (2002), Mohan & Rao (2003), Rahal & Rabelo (2006), Cho & Lee (2013)
	8	Availability of needed technical resources	Åstebro (2004), Mirghafoori et al. (2011), Mohannak & Samtani (2014), Kirchberger & Pohl (2016)
	9	Enjoying experience and expert manpower	Mirghafoori et al. (2011), Rostek (2014), Hsu et al. (2015)
	10	Safety of technology or its products for final users	Åstebro (2004), Bandarian (2007)
	11	Strength of tech commercialization team	Mohan & Rao (2003), Galbraith et al. (2007), Rostek (2014)

Table 1. Influential Components on Technology Commercialization Success

Dimensions	Row	Components	Sources
Financial and Economic Specifications	12	Previous technical experience in commercialization	Mohan & Rao (2003), Hsu et al. (2015)
	13	Compatibility of new tech	Mohan & Rao (2003), Bandarian (2007)
	14	Economic feasibility of development and tech commercialization	Bandarian (2007), Mirghafoori et al. (2011), Mohannak & Samtani (2014)
	15	Tech profitability expectance	Åstebro (2004), Cho & Lee (2013)
	16	Tech applying costs expectance	Åstebro (2004), Cho & Lee (2013), Rostek (2014)
Market Specifications	17	Appropriate pricing of technology or its products	Mirghafoori et al. (2011), Mohannak & Samtani (2014)
	18	Fundraising for tech commercialization	Kimura (2010), Link & Scott (2010), Mirghafoori et al. (2011), Hsu et al. (2015), Jung et al. (2015)
	19	Identifying the immediate and current needs of market	Rahal & Rabelo (2006), Slater & Mohr (2006)
	20	Compatibility of the tech with market needs/demands	Bandarian (2007), Cho & Lee (2013), Mohannak & Samtani (2014)
	21	Tech potential to grow and penetrate into market	Sohn & Moon (2003), Rahal & Rabelo (2006), Cho & Lee (2013)
	22	Using effective marketing methods	Mohannak & Samtani (2014), Jung et al. (2015)
	23	Having sustainable competitive advantages	Rahal & Rabelo (2006), Galbraith et al. (2007)
	24	Having partners and common contracts	Galbraith et al. (2007), Mirghafoori et al. (2011)
	25	The high speed of tech commercialization to be presented into market	Zahra & Nielsen (2002), Rahal & Rabelo (2006), NASA Office of the Chief Technologist (2012), Cho & Lee (2013)
	26	Choosing target market and target users	Slater & Mohr (2006), Cho & Lee (2013)
	27	Target market accessibility	Rahal & Rabelo (2006), Mirghafoori et al. (2011)
	28	Target market growing	Mohan & Rao (2003)
	29	Doing a competitive analysis	Zahra & Nielsen (2002), Åstebro (2004)
	30	Enjoying prominent advantages over competitors	Mohan & Rao (2003), Rahal & Rabelo (2006)
	31	Social benefits and the effects of technology or its product	Mohannak & Samtani (2014)
Regulatory and Institutional Factors	32	Tech being attractive to target customers	Bandarian (2007), Mirghafoori et al. (2011)
	33	Existence of mandatory and supportive rules for tech commercialization	Sohn & Moon (2003), Åstebro (2004), Mohannak & Samtani (2014)
	34	Realizing codified standards for tech	Sohn & Moon (2003), Åstebro (2004)
	35	Existence of cultural congruence for tech or its products	Bandarian (2007)
	36	Protecting intellectual capital	Åstebro (2004), Rahal & Rabelo (2006), Mirghafoori et al. (2011), Mohannak & Samtani (2014), Kirchberger & Pohl (2016), Lianto (2023)
	37	Simplicity of licensing technology	Mohan & Rao (2003), Rahal & Rabelo (2006)

Materials and Methods

To develop a predictive model for technology commercialization success, the research was conducted through a sequence of methodological stages, as illustrated in Figure 1. The overall workflow includes the identification of evaluation indicators, expert validation, construction of the fuzzy inference system, and model evaluation. The first stage focused on identifying and

validating the factors that influence technology commercialization. For this purpose, the Delphi method was adopted, as it provides a systematic approach for obtaining consensus among experts through a series of iterative questionnaires and controlled feedback (Cho & Lee, 2013; Linstone & Turoff, 2002). Owing to its structured procedure and demonstrated reliability, the Delphi technique has been widely used in studies requiring expert judgment.

In the present study, the Delphi process was employed to evaluate the relevance of commercialization success factors identified in the literature and to adapt them to the practical conditions of technology commercialization in Iranian industries. Because commercialization decisions are inherently affected by uncertainty and subjective expert opinions, conventional crisp evaluation methods are often insufficient to capture the complexity of the problem. The influence of each factor cannot always be represented by a single precise value, but rather by a range of plausible judgments. To better accommodate this uncertainty, the conventional Delphi process was extended using fuzzy logic. Integrating fuzzy sets into the Delphi method allows linguistic opinions to be represented more realistically and reduces the ambiguity associated with expert assessments (Linstone & Turoff, 2002). Expert opinions were collected using a fuzzy Delphi questionnaire. Participants evaluated the proposed commercialization indicators on a five-point Likert scale ranging from *very low* to *very high*. Each linguistic response was converted into a corresponding triangular fuzzy number, as presented in Table 2, prior to being transformed into crisp values for subsequent analysis. Crisp values were then derived using the Minkowski formula (Equation 1), following Cheng et al. (2002).

$$\chi = a_1 + \frac{a_3 - a_2}{4} \quad (1)$$

Table 2. Triangular Fuzzy Numbers of Linguistic Variables

Linguistic Variables	Corresponding Triangular Fuzzy Numbers (a_1, a_2, a_3)	Crisp Values of Fuzzy Numbers (χ)
Very low	(0, 0, 0.25)	0.0625
Low	(0, 0.25, 0.5)	0.0625
Medium	(0.25, 0.5, 0.75)	0.3125
High	(0.5, 0.75, 1)	0.5625
Very high	(0.75, 1, 1)	0.75

In the initial phase of the fuzzy Delphi method, 9 out of 22 willing experts were interviewed to evaluate the relevance and classification of the components identified in the literature (Table 1). Open-ended questionnaires were distributed to gather their insights. After conducting the interviews and reviewing the completed questionnaires, their responses were analyzed and summarized. Using the expert responses and applying the fuzzy logic equations (Equations 2 and 3), the fuzzy mean for each component was calculated (Cheng et al., 2002). Additionally, the defuzzification operation was carried out using Equation (1).

$$A^i = (a_1^i, a_2^i, a_3^i) \quad i = 1, 2, 3, \dots, n \quad (2)$$

$$A_m = (a_{m1}, a_{m2}, a_{m3}) = \left(\frac{1}{n} \sum_{i=1}^n a_1^i, \frac{1}{n} \sum_{i=1}^n a_2^i, \frac{1}{n} \sum_{i=1}^n a_3^i \right) \quad (3)$$

Following two rounds of fuzzy Delphi surveys, 32 factors impacting technology commercialization success (TCSFs) were identified and categorized into four dimensions. The final results, specific to Iran's context, are presented in Table 3. These factors form the core inputs for the study's predictive model.

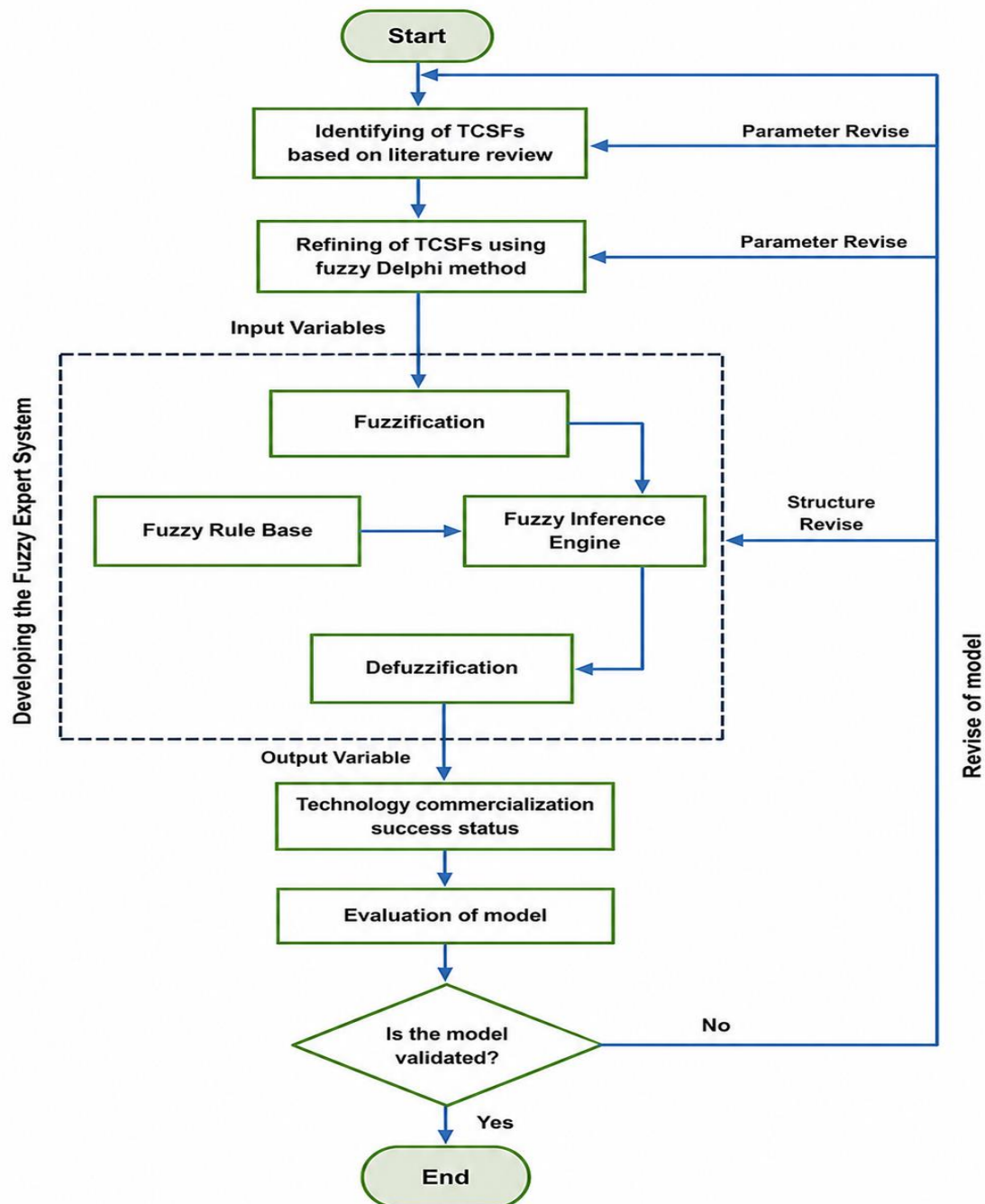


Figure 1. Research Methodology

Table 3. The Final Result of Fuzzy Delphi Process

Dimensions	Label of Component	Components	Definition
Technical Specifications	C ₁	Technology (tech) technical feasibility	Technical implementation probability
	C ₂	prominent technical advantages of tech	enjoying technical excellences for tech
	C ₃	R&D capabilities	R&D capabilities of commercializing company for tech commercialization
	C ₄	Low complexity of tech usage	Ease of usage for potential users of tech
	C ₅	Establishing probability of tech on small scale	testability and feasibility of establishing tech on small scale (before investing in renovation programs)
	C ₆	Novelty of tech or its product	Being completely innovative of tech or its product
	C ₇	Availability of needed technical resources	Access to needed technical resources: supplies, equipment, and raw materials to commercialize the tech in commercializing company
	C ₈	Enjoying experience and expert manpower	Enjoying the professional manpower with work, education, and research experience in tech commercialization
	C ₉	Strength of tech commercialization team	Strength of commercialization team in implementing the plans
	C ₁₀	Previous technical experience in commercialization	Technical experience of commercialization in commercializing company
	C ₁₁	Compatibility of new tech	Compatibility of new tech with current methods and processes in the commercializing company
	C ₁₂	Commercializing company cooperation with developers	Commercializing company cooperation with developers to accelerate the tech commercialization
Financial and Economic Specifications	C ₁₃	Economic feasibility of development and tech commercialization	Conducting a survey in the early stages of technology development to assess costs and benefits, continuing through to the end of its development and trial stage
	C ₁₄	Tech profitability expectance	Making the expected profits from the tech commercialization
	C ₁₅	Tech applying costs expectance	Reasonableness of all the allotted costs, e.g., process change costs, operation and support costs, and environmental costs
	C ₁₆	Fundraising for tech commercialization	probability of getting financial help from public and private sectors for tech commercialization
Market Specifications	C ₁₇	Identifying the immediate and current needs of market	Identifying market needs in proportion to the potential uses of the tech in early stages of development
	C ₁₈	Compatibility of the tech with market needs/demands	Identifying the nature of market needs to examine the tech compatibility with it in the early stages of development
	C ₁₉	Tech potential to grow and penetrate into market	Enjoying the needed potentials to grow and penetrate into market
	C ₂₀	Using effective marketing methods	Taking advantage of effective marketing methods to attract real customers to sell tech or its products
	C ₂₁	Having sustainable competitive advantages	The capability of the commercializing company to gain sustainable competitive advantages through technology

Table 3. The Final Result of Fuzzy Delphi Process

Regulatory and Institutional Factors	C ₂₂	The high speed of tech Commercialization to be presented into market	The short time needed to develop the tech and bring it to market
	C ₂₃	Choosing target market and target users	Identifying the real customers of tech or its product
	C ₂₄	Target market accessibility	Target market accessibility for tech product
	C ₂₅	Target market growing	Tech-related market growing
	C ₂₆	Enjoying prominent advantages over competitors	Enjoying prominent advantages over Competitors for the tech in terms of technical performance, cost, simplicity, etc.
	C ₂₇	Tech being attractive to target customers	The attractiveness of the technology or its products to target customers, such that they will be purchased
	C ₂₈	Having the appropriate business plan for the tech	Codifying the appropriate business plan for the business formed around the tech
	C ₂₉	Existence of mandatory and supportive Rules for tech commercialization	Compulsory tendency of market towards tech or its product based on governmental rules, regulations, and confirmation
	C ₃₀	Realizing codified standards for tech	Possibility of realizing the codified standards to be met by the tech so it can enter the market
	C ₃₁	Existence of cultural congruence for tech or its products	The congruence of tech or its products with cultural needs and characteristics of its target market
	C ₃₂	Protecting intellectual capital	The possibility of intellectual capital being protected by the commercializing company

To build the system, expert input and collected data were processed using MATLAB R2019a. As shown in Figure 1, the proposed prediction framework consists of four key stages, adapted from previous research (Berihä et al., 2012; Siler & Buckley, 2005).

Fuzzy set theory was employed to transform the expert system's input variables into corresponding fuzzy values (Amiri et al., 2017; Sadjadi et al. 2019). This theory revolves around the concept of partial membership, which allows a factor to belong to one or more sets to varying degrees. The degree to which an element belongs to a fuzzy set is expressed by its membership value, ranging from 0 (no membership) to 1 (full membership). Values between 0 and 1 indicate partial membership, allowing fuzzy logic to effectively address uncertainty and ambiguity (Amiri et al., 2017).

To construct the fuzzy expert system for predicting early-stage technology commercialization outcomes, the process followed four structured steps:

Drawing on the finalized results of the fuzzy Delphi method (Table 3), key input variables were identified across four dimensions: technical, financial/economic, market-related, and regulatory. Each dimension includes several components (C_i). The output variable, representing the predicted level of commercialization success (TCS), defines the system as a Multiple Input–Single Output (MISO) model. Figure 2 illustrates the overall system architecture.

Input variables were scaled using a numeric range from 0 to 5, while the output (TCS) was defined over a continuous scale from 0% to 100%.

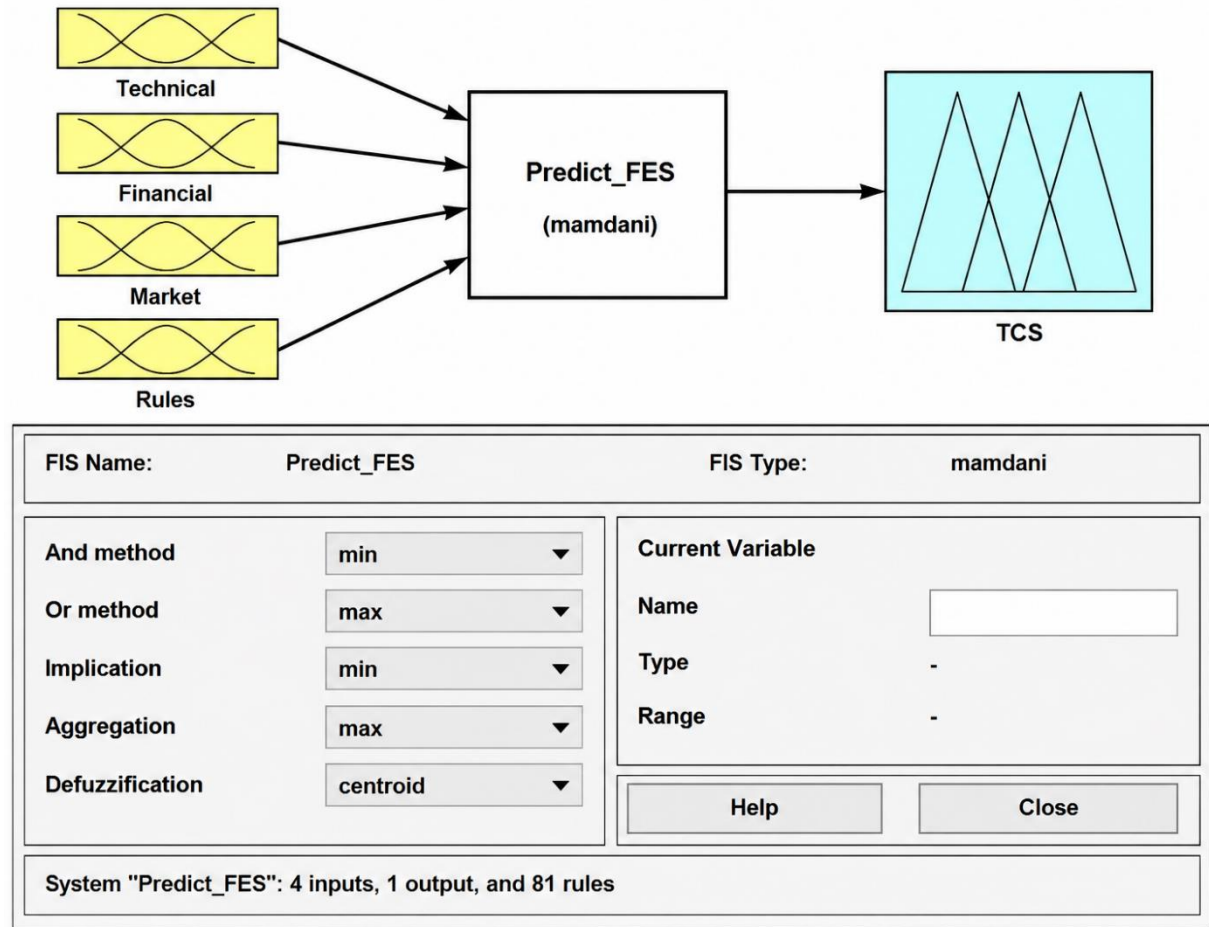


Figure 2. MISO System for TCS Predicting

Trapezoidal membership functions (MFs) were chosen due to their flexibility and suitability for representing a broad range of fuzzy information. These functions quantify the degree of membership for each term. The mathematical formulation of the trapezoidal MF is presented in Equation 4, with its graphical representation provided in Figure 3.

$$\mu_A(x) = \begin{cases} 0, & x < a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ 1, & b \leq x \leq c \\ \frac{d-x}{d-c}, & c \leq x \leq d \\ 0, & x > d \end{cases} \quad (4)$$

The parameter values a , b , c , d corresponding to the linguistic variables of both input and output were derived from the expertise of three researchers specializing in industrial and computer engineering.

The definitions for the trapezoidal membership functions for the input variables are outlined in Table 4, while the corresponding definitions for the output variable are provided in Table 5.

It is crucial to emphasize that each of the five linguistic terms for the output variable was clearly defined, taking into account the potential ambiguity that can arise in the interpretation of these terms. These definitions were grounded in the degree to which commercialization objectives are realized; to ensure a precise and consistent interpretation of the system's output, comprehensive definitions were formulated, as outlined in Table 5. Upon the completion of this step, the fuzzy sets for both the input and output variables were defined, as depicted in Figure 4.

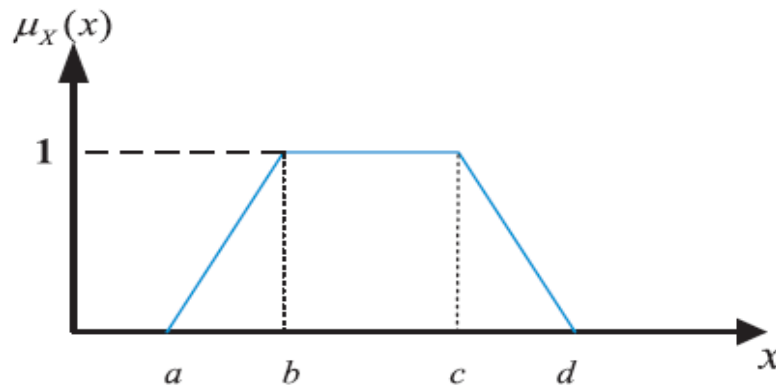


Figure 3. Membership Function of Trapezoidal Fuzzy Number

Table 4. Linguistic Variables for the Inputs and Their Fuzzy Trapezoidal Membership Function Values

Linguistic Variables	Linguistic Variables Corresponding to Trapezoidal Fuzzy Numbers
Low	(0 0 1 2)
Medium	(1.5 2 3 3.5)
High	(3 4 5 5)

Table 5. Linguistic Variables for the Output and Their Fuzzy Trapezoidal Membership Function Values

Linguistic Variables	Definition of Linguistic Terms	Linguistic Variables Corresponding to Trapezoidal Fuzzy Numbers
Very Low	None of the desired commercialization objectives is achieved.	(0 0 10 25)
Low	A few desired commercialization objectives are achieved and there is a great deal to fully achieve the objectives.	(15 25 35 45)
Medium	Some commercialization objectives are achieved, while others are not (the output is considered acceptable but not successful).	(35 45 55 65)
High	The desired commercialization objectives are achieved.	(55 65 75 85)
Very High	Beyond the desired commercialization objectives is achieved.	(75 90 100 100)

During the validation process, conflicts emerged in 12 of the 81 rules. For these rules, the majority opinion among the experts was applied to resolve the discrepancies. However, for four of these 12 rules, there was either a weak majority or no clear consensus on a specific output. To address these conflicts, an additional round of polling was conducted with seven of the 11 experts who had previously indicated their willingness to participate. This further round helped establish a consensus on the unresolved issues within these four rules.

The fuzzy rules were structured in the conventional "IF (antecedent) THEN (consequent)" format, where the antecedents represent fuzzy sets linked to the input variables, and the consequents correspond to fuzzy sets defining the output. The total number of rules in a fuzzy inference system is determined by the number of inputs, the linguistic categories assigned to each input, and the type of logical operators used to relate them (Yen & Langari, 1999).

The Inference Engine serves as the central mechanism of the fuzzy expert system, responsible for converting input variables into corresponding output decisions. It processes user input, selects applicable rules from the rule base, and applies fuzzy logic operations to evaluate the level of commercialization success (Amiri et al., 2017).

This system adopts the Mamdani (1977) inference method, known for its interpretability and practical applicability in real-world scenarios. The Mamdani (max–min) approach operates using rules of the form:

$$R_i: \text{if } x_1 \text{ is } A_{1i} \text{ and } x_2 \text{ is } A_{2i}, \dots, x_s \text{ is } A_{si} \text{ then } y_i \text{ is } C_i, \quad i = 1, 2, \dots, M \quad (5)$$

Where M stands for the total number of fuzzy rules, x_j ($j = 1, 2, \dots, s$) are input variables, y_i represents the output variables, and both A_{ji} and C_i are the fuzzy sets modeled by membership functions $\mu_{A_{ji}}(x_j)$ and $\mu_{C_i}(y_i)$, respectively. The aggregated output for the M rules is:

$$\mu_{C_i}(y_i) = \max \left\{ \min \left[\mu_{A_{1i}}(x_1), \mu_{A_{2i}}(x_2), \dots, \mu_{A_{si}}(x_s) \right] \right\}, \quad i = 1, 2, \dots, M \quad (6)$$

The resulting fuzzy output is subsequently defuzzified to obtain a crisp value, as discussed in the following section. Key features of the implemented Mamdani (1977) model are summarized in Table 6.

Table 6. Characteristics of the Mamdani Model (Berih et al., 2012)

Operation	Operator	Norm	Formula
OR	MAX	T-conorm	$\mu_C(x) = \max(\mu_A(x), \mu_B(x)) = \mu_A(x) \vee \mu_B(x)$
AND	MIN	T-norm	$\mu_C(x) = \min(\mu_A(x), \mu_B(x)) = \mu_A(x) \wedge \mu_B(x)$
Implication	MIN	T-norm	$\text{Max}(\min(\mu_A(x), \mu_B(x)))$
Aggregation	MAX	T-conorm	
Defuzzification methodology	Center of mass (area)		$\text{COA} = Z^* = \frac{\int Z \mu_C(z) dz}{\int \mu_C(z) dz}$

This stage converts the fuzzy output of the inference engine into a single crisp value, enabling the practical interpretation of the system's results for evaluating commercialization success. To derive actionable insights, this fuzzy output must be translated into a definitive,

crisp value, a process known as defuzzification. Functioning inversely to fuzzification, defuzzification synthesizes the fuzzy results into a single scalar output. Among the various defuzzification techniques, this study adopts the centroid method, also referred to as the center of gravity approach, due to its widespread acceptance and ability to reflect the balance point of the fuzzy set distribution. The centroid method calculates the center of area under the aggregated membership function, and its corresponding mathematical formulation is as follows:

$$\hat{y}_i = \frac{\int y_i \mu_{c_i}(y_i) dy}{\int \mu_{c_i}(y_i) dy} \quad (7)$$

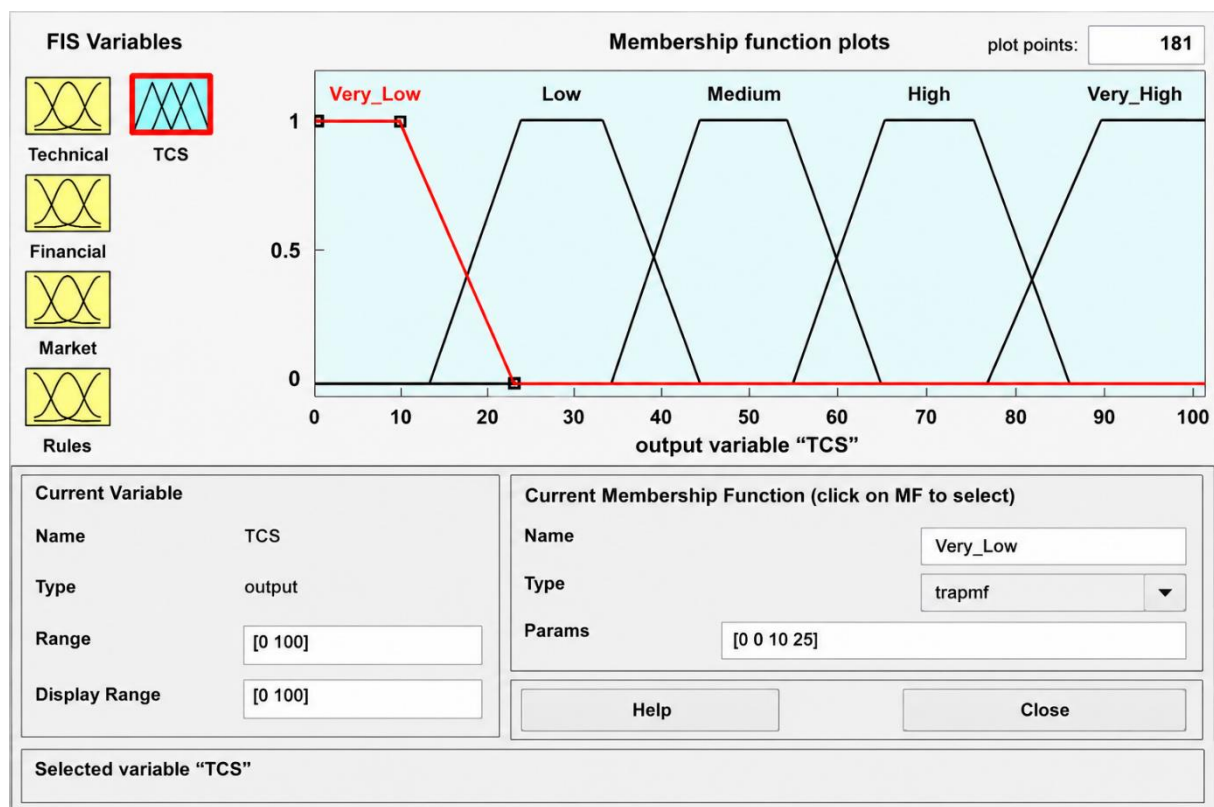


Figure 4. Output Variable Fuzzy Set for TCS Predicting Expert System

Model validation is an essential process in ensuring the reliability, generalizability, and practical applicability of a predictive system (Hillston, 2005).

To validate the proposed prediction model, a structured questionnaire was developed based on the finalized list of Technology Commercialization Success Factors (TCSFs) identified in Table 3. This instrument was designed to gather empirical data concerning the status of key commercialization components across various technologies that had already undergone commercialization. Respondents were recruited from among experienced managers and domain experts directly engaged in advancing and commercializing these technologies, ensuring familiarity with both the technical and strategic aspects of the process. Each expert evaluated the status of the TCSFs using a standardized 0–5 scale, corresponding to the extent of achievement or implementation of each factor in their respective commercialization projects.

A total of 22 technologies analyzed spanning fields such as catalysts, chemical compounds, nanomaterial, software, intelligent systems, and ICT, sourced from seven distinct research institutions, comprising a large government-affiliated research organization, five private knowledge-based firms actively engaged in commercialization, and a university-based technology accelerator. The sampled technologies also exhibited a broad spectrum of commercialization outcomes, from very low to high success, enabling a robust evaluation of the validity of prediction model across different technological contexts.

In this study, five classes have been considered with the status of technology commercialization success ranging from Very Low (VL) to Very High (VH). For the validation of the present predicting model, the Very Low and Low commercial success are considered the unsuccessful commercialization of technology, while Medium, High, and Very High commercial success are considered the successful commercialization of technology.

The research fuzzy expert system performance is evaluated using three criteria of specificity, sensitivity and accuracy which are outlined below (Alhabashneh et al., 2017; Pal et al., 2012):

- i. True Positive (TP): It denotes the number of successful technologies in commercialization correctly predicted by the model.
- ii. True Negative (TN): It denotes the number of unsuccessful technologies in commercialization correctly predicted by the model.
- iii. False Positive (FP): It denotes the number of successful technologies in commercialization wrongly predicted as unsuccessful technologies by the model.
- iv. False Negative (FN): It denotes the number of unsuccessful technologies in commercialization wrongly predicted as successful technologies by the model.
- v. Specificity: It denotes the percentage of successful technologies in commercialization accurately predicted by the model, defined as:

$$\text{Specificity} = \frac{TP}{TP + FP} \quad (8)$$

- vi. Sensitivity: It denotes the percentage of unsuccessful technologies in commercialization accurately predicted by the model, defined as:

$$\text{Sensitivity} = \frac{TN}{TN + FN} \quad (9)$$

- vii. Accuracy: It denotes the percentage of accurately predicted technologies. In the present study (a 5-class commercial success framework), this is defined as:

$$\text{Accuracy} = \left(\frac{VL + L + M + H + VH}{N} \right) \times 100 \quad (10)$$

Results and Discussion

The literature review and the fuzzy Delphi process led to the identification of 32 indicators that were considered essential for evaluating technology commercialization success. These indicators were grouped into four dimensions—technology, finance, market, and regulation—and subsequently incorporated into the proposed fuzzy inference model as the input variables.

The predictive capability of the proposed framework was evaluated using 22 commercially deployed technologies representing a range of application domains. Model predictions were then compared with the corresponding real-world commercialization outcomes to examine the reliability of the proposed approach.

The performance metrics are presented in Table 7. The model achieved an overall classification accuracy of 72.73%, together with a specificity of 94.44% and a sensitivity of 75.00%. The high specificity indicates that the model is particularly effective at correctly identifying technologies with limited commercialization potential, thereby reducing false-positive decisions. Although the sensitivity is comparatively lower, the results demonstrate that the proposed fuzzy inference framework provides a balanced and reliable prediction of commercialization outcomes while preserving the interpretability required for practical decision support.

Table 7. TCS Predicting Expert System Performance Evaluation

		Actual Value					Performance Evaluation		
		VL	L	M	H	VH	Specificity	Sensitivity	Accuracy
Predicted	VL	1	0	0	0	0	94.44%	75%	72.73%
Value	L	0	2	1	0	0			
	M	0	1	9	1	0			
	H	0	0	2	4	0			
	VH	0	0	0	1	0			

The high specificity value indicates that the system rarely labels a successful technology as unsuccessful. This property is particularly important because false negative predictions, which classify a promising technology as low-potential, can cause investors and decision-makers to forgo valuable opportunities, thereby reducing the overall economic return from technology commercialization.

With an accuracy of approximately 73%, the model correctly categorizes nearly three-quarters of the test cases into their true success categories. This accuracy figure serves as the main benchmark for comparing the proposed system against alternative approaches (Alhabashneh et al., 2017). Given the dynamic and uncertain nature of technology commercialization processes, the observed performance suggests that the developed fuzzy expert system provides a reliable basis for predicting commercialization success.

Sohn and Moon (2003) applied structural equation modeling (SEM) to predict a technology commercialization success index and reported an accuracy of 69.61%, which is lower than the 72.73% achieved in this study. However, SEM typically requires large sample sizes (often ≥ 200 observations) to produce valid estimates. A separate study that analyzed 489 commercialization projects from Korea's Information Technology Transfer Center noted that obtaining sufficiently large datasets for model validation remains challenging in the technology commercialization field. In another comparison, Pal et al. (2012) used artificial neural networks (ANN) to forecast the success potential of innovative ideas and obtained a higher accuracy of 90%. Nevertheless, ANN models are frequently criticized for their "black box" nature, offering little transparency into how predictions are derived. In contrast, the rule-based fuzzy system

presented here provides interpretable inference pathways, making the reasoning behind each prediction explicit and auditable.

Conclusions

This study presented a distributed fuzzy inference system (D-FIS) implemented within an edge–cloud computing architecture to support the prediction of technology commercialization success. The proposed framework integrates thirty-two evaluation indicators spanning technological, financial, market, and regulatory dimensions, which were identified through the fuzzy Delphi method. Its performance was assessed using a real-world dataset consisting of thirty-three technology commercialization cases.

The experimental results indicate that the proposed approach provides reliable predictive performance while significantly improving computational efficiency. The framework achieved an overall classification accuracy of 72.73%, together with a specificity of 94.44% and a sensitivity of 75.00%. In comparison with a conventional centralized implementation, the distributed architecture reduced average inference latency by 64% and maintained near-linear scalability when deployed across up to 32 worker nodes. These findings demonstrate that distributing fuzzy reasoning over an edge–cloud infrastructure can substantially improve scalability without sacrificing the interpretability that characterizes fuzzy expert systems.

Beyond its predictive capability, the proposed framework offers practical value for a broad range of stakeholders involved in technology commercialization. Investors and venture capital firms can employ the model as an initial screening tool to identify technologies with limited commercialization potential and prioritize promising investment opportunities. Technology managers and R&D leaders may use the thirty-two evaluation indicators to identify weaknesses in ongoing projects and support strategic resource allocation. The scalable architecture also enables policymakers, innovation agencies, and technology transfer offices to assess large portfolios of innovation projects while maintaining a transparent and consistent evaluation process. In addition, entrepreneurs and startup teams can benefit from the publicly available source code and dataset to assess their own commercialization readiness.

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During the preparation of this work, the authors used Generative AI and AI-assisted technologies to improve the readability and language of the manuscript. After using these tools/services, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Conflict of Interest

The authors declare no conflict of interest.

Ethical Considerations

The authors avoided data fabrication, falsification, and plagiarism, and any form of misconduct.

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