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A Fuzzy-Inference-Based Hybrid Crowdfunding Model for Proportional Funding Allocation to Micro, Small, and Medium Enterprises

Yuthsi Aprilinda[1*], Harco Leslie Hendric Spits Warnars[1], Elfindah Princes[2], Devi Fitrianah[3]

[1] BINUS Graduate Program - Doctor of Computer Science, Computer Science Department, Bina Nusantara University, Jakarta 11480, Indonesia
[2] BINUS Graduate Program - Master of Information Systems Management, Information Systems Management Department, Bina Nusantara University, Jakarta 11480, Indonesia
[3] BINUS Graduate Program - Master of Computer Science, Computer Science Department, Bina Nusantara University, Jakarta 11480, Indonesia

Corresponding Author Email: yuthsi.aprilinda@binus.ac.id

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ABSTRACT

Micro, small, and medium enterprises (MSMEs) often face financing constraints that conventional lending and single-mode crowdfunding schemes may not adequately address. Donation-based crowdfunding can support socially oriented ventures, whereas peer-to-peer (P2P) lending is more suitable for enterprises with stronger repayment capacity. This study develops a rule-based hybrid crowdfunding model that allocates funding proportionally between these two mechanisms. Following the Design Science Research Methodology, the model incorporates a Mamdani-type fuzzy inference system (FIS) to translate four dimensions—Financial Performance (FP), Business Maturity and Risk (BMR), Social Impact (SI), and Project Narrative (PN)—into a funding-allocation index. Each input is represented by three linguistic levels, producing an 81-rule inference base. The rules were formulated through a structured elicitation process involving five experts, and inter-rater agreement was assessed using Fleiss' kappa. The model was then demonstrated using five hypothetical, expert-informed MSME profiles rather than observed financial or crowdfunding data. In these illustrative examples, index values assigned by the authors show how the resulting index determines complementary proportions of P2P lending and donation funding, allowing the allocation to vary with the financial and social characteristics represented in each profile. The examples illustrate how fuzzy rule-based reasoning could operationalize a continuous funding split under uncertain and partly qualitative inputs. The study contributes a conceptual decision-support framework for hybrid MSME crowdfunding. Its practical effectiveness, robustness, and generalizability remain to be established through testing with real-world data, sensitivity analysis, and evaluation by platform users and independent experts.

1. INTRODUCTION

Micro, small, and medium enterprises (MSMEs) are widely acknowledged as a fundamental pillar of economic growth, particularly in emerging economies. Beyond contributing significantly to the gross domestic product (GDP), MSMEs support employment generation and local economic resilience. In many developing nations, MSMEs account for over 90% of all business entities and contribute up to 40% of national income. Despite their strategic importance, recent global reports indicate a staggering $5.2 trillion annual financing gap for MSMEs in emerging markets, with nearly 41% of formal MSMEs having unmet credit needs [1, 2]. This financial exclusion highlights the inability of traditional financial systems to effectively meet the dynamic needs of small enterprises.

In many developing contexts, MSMEs still depend on conventional financing mechanisms such as bank loans and cooperatives. However, these sources often impose stringent collateral requirements, complex administrative processes, and high interest rates, which typically range from 10% to over 24% annually in certain emerging markets. Furthermore, slow disbursement times and rigid documentation hurdles often lead to high rejection rates for small-scale entrepreneurs. These systemic barriers create an urgent need for a paradigm shift toward more inclusive financing. Consequently, financial technology (Fintech) has emerged as a disruptive solution to bridge this gap by offering decentralized and data-driven funding alternatives that bypass traditional intermediaries [3].

Among various fintech innovations, crowdfunding has emerged as a prominent alternative that enables direct interaction between fund seekers and contributors through digital platforms. This study specifically focuses on donation-based crowdfunding and peer-to-peer (P2P) lending-based crowdfunding as the primary components for the proposed model. These two schemes are selected because they represent

the two ends of the MSME spectrum: the socially driven motivation (donation) and the commercially driven sustainability (lending). While donation-based models prioritize social value without repayment burdens, P2P lending offers structured financial returns for investors [4].

Despite their advantages, these crowdfunding models are typically implemented independently, resulting in a fragmented financing ecosystem. This binary approach, either pure donation or pure lending fails to accommodate the "hybrid" nature of MSMEs, which often embody both commercial potential and significant Social Impact (SI) [5]. While studies in the Indonesian context have examined crowdfunding for SMEs across separate donation-, reward-, asset-, and equity-based categories, they lack a dynamic and mathematical framework for real-time allocation [6]. Consequently, there is a scarcity of research that addresses the "missing middle" -a segment of MSMEs that are too commercial for pure donation but too risky for pure lending. Most existing models fail to provide a proportional mechanism that can adaptively balance social contributions and debt obligations [7].

To address these limitations, this study proposes a conceptual hybrid proportional crowdfunding model that integrates Donation and P2P Lending within a unified framework. The model introduces a proportional allocation mechanism that dynamically determines the composition of funding based on four synthesized dimensions: Financial Performance (FP), Business Maturity and Risk (BMR), SI, and Project Narrative (PN). To handle the inherent uncertainty and subjectivity in evaluating these qualitative indicators, a Mamdani-type fuzzy inference system (FIS) is incorporated.

Accordingly, this study aims to develop a rule-based, adaptive crowdfunding framework that overcomes the limitations of single-model approaches. This study seeks to answer the following research question: How can an FIS-based hybrid model be designed to dynamically integrate donation and P2P lending schemes for MSME proportional funding allocation under uncertainty? To demonstrate the feasibility of the proposed approach, a simulation using illustrative scenarios is conducted. Through this approach, the study seeks to contribute both theoretically, by extending existing crowdfunding frameworks, and practically, by outlining a conceptual decision-support framework with potential relevance for financial inclusion in emerging economies, subject to future empirical validation.

The remainder of this paper is organized as follows: Section 2 reviews the related literature on MSME financing and FISs. Section 3 describes the research methodology based on the Design Science Research Methodology (DSRM) framework. Section 4 presents the results of the proposed conceptual model, the mathematical formulation, and the simulation. Section 5 discusses the findings, Section 6 concludes the study, and Section 7 outlines directions for future research.

2. RELATED WORK

2.1 Crowdfunding models for micro, small, and medium enterprise financing

Crowdfunding has emerged as a prominent alternative financing mechanism that leverages digital platforms to connect fund seekers with a large number of contributors. It has been widely recognized for its ability to reduce reliance on traditional financial intermediaries and improve access to capital for small businesses. Recent studies highlight that crowdfunding supports entrepreneurial activities, fosters innovation, and enhances funding accessibility for MSMEs [8, 9].

Among the various crowdfunding models, donation-based crowdfunding and P2P lending-based crowdfunding are the most commonly adopted. Donation-based models are typically associated with social or community-driven initiatives, where contributors do not expect financial returns, while P2P lending models focus on financial returns through structured repayment mechanisms [10]. These models have been increasingly integrated into digital financial ecosystems to promote financial inclusion, particularly for underserved MSMEs.

Information asymmetry and credit risk remain the primary challenges in digital lending platforms. Recent work [11] addressed these issues by designing a structured P2P lending framework aimed at mitigating credit risk through improved platform evaluation. While their model focuses on student lending, a different domain, its principles of risk mitigation and framework design are cited here as a methodological parallel applicable to MSME financing, where information transparency is often limited, rather than as direct empirical evidence for MSME crowdfunding.

2.2 Hybrid crowdfunding approaches

To address the limitations of single-model crowdfunding, several studies have explored hybrid or combined crowdfunding schemes. A notable example in the Indonesian context is the inclusive crowdfunding model for the rural agriculture sector, which integrates donation-based elements with debt-based mechanisms [12]. Similarly, earlier research introduced models integrating charitable elements such as Sadaqah with microfinancing to support social welfare and business development [13].

However, most existing hybrid studies primarily focus on static financing designs or life-cycle costs rather than developing adaptive mechanisms to dynamically determine the composition of funding types [14]. There is a clear lack of frameworks that can automatically calculate the "proportion" of donation versus lending based on the real-time profile of the borrower.

2.3 Fuzzy inference systems in decision support

To address decision-making challenges under uncertainty, FIS have been widely applied across various domains, including financial forecasting and risk assessment. Unlike traditional binary logic, FIS enables the modeling of imprecise and qualitative information through linguistic variables and rule-based reasoning, which is essential for complex socio-economic environments [15]. The core advantage of FIS lies in its ability to transform subjective human expertise into a structured mathematical framework through four main stages: fuzzification, rule base construction, inference engine, and defuzzification.

The theoretical foundation of this study is built upon a prior systematic literature review which identified four pillar components essential for a sustainable crowdfunding ecosystem: crowdfunding models, technology, trust, and regulation [16]. While the previous work established these critical factors, this research translates them into a functional computational model. Specifically, the 'Trust' and 'Regulation' components from the previous study are operationalized

through the PN and BMR variables, while the 'Technology' aspect is addressed through the implementation of the FIS as a knowledge-based decision engine.

Recent studies have demonstrated the effectiveness of FIS in multi-criteria decision-making (MCDM), particularly in financial contexts where data may be incomplete or vague. For instance, fuzzy-based approaches have been utilized to evaluate creditworthiness by integrating both quantitative financial ratios and qualitative entrepreneur characteristics. In the realm of information systems, researchers have increasingly adopted Mamdani-type inference for its intuitive nature and Sugeno-style for its computational efficiency in automated systems [17].

The application of intelligent systems, particularly fuzzy logic, has shown significant efficacy in handling uncertainty across various domains. For instance, Berbiche et al. [18] demonstrated how fuzzy logic-based automation, specifically using the Mamdani approach, can enhance decision-making efficiency and resilience in volatile environments by mitigating uncertainties. This underscores the potential of fuzzy-based engines in domains involving imprecise risk and social variables; this supply-chain application is cited as a methodological parallel for Mamdani-based automation rather than direct evidence from the crowdfunding domain, and is extended here to financial contexts where risk and social variables are often imprecise.

In the context of MSME funding, FIS is particularly relevant due to the high degree of uncertainty in business sustainability and digital readiness. Recent literature highlights that fuzzy logic can bridge the gap between SI and financial risk, allowing for a more nuanced evaluation than rigid scoring models [15]. By utilizing a set of "If-Then" rules, FIS can dynamically process multiple inputs such as FP, BMR, SI, and PN to produce a single, optimized output representing the proportional allocation of funding. This flexibility ensures that the decision-making process is not only robust but also interpretable for both the platform providers and the fund seekers.

2.4 Synthesis, research gap, and contribution

A critical synthesis of the contemporary literature narrows to one specific, largely unaddressed problem: the fuzzy-based, continuous proportional allocation of funding between donation-based and P2P lending schemes for MSME crowdfunding. To clearly delineate this boundary and systematically justify the novelty of this research relative to that specific problem, a comprehensive comparative matrix of prominent studies is established in Table 1.

Table 1. Comparative literature matrix and research gap analysis

Ref.	Author(s) and Year	Crowdfunding Model	Decision Method / Core Approach	Proportional Allocation?	Target Operational Domain
[12]	Suasih et al. (2022)	Inclusive Crowdfunding	Descriptive Qualitative	No	Rural Agriculture (Indonesia)
[13]	Aderemi and Ishak (2020)	Donation	Qualitative Descriptive & Inductive	No	MSME / Micro Enterprises
[19]	Sutthibutr et al. (2024)	Not crowdfunding (supply chain)	Fuzzy Multi-Criteria	No	Supply chain (aggregate production planning)
[20]	Zhang et al. (2020)	P2P Lending	Deep Learning Framework	No	General
[21]	Wahjono et al. (2021)	General Crowdfunding	Descriptive Conceptual	No	MSME (Indonesia)
[22]	Panitkulpong et al. (2023)	Equity Crowdfunding	Conceptual Framework	No	General (Thailand)
[23]	Gunduz et al. (2026)	Reward-based (Kickstarter)	Deep Learning & Meta-Heuristics	No	E-Commerce / General Projects
(*)	This Study	Hybrid (Donation & P2P)	Fuzzy Inference System (FIS)	YES (Dynamic Engine)	MSME (F&B Sector)

Note: MSMEs = micro, small, and medium enterprises, P2P = peer-to-peer, F&B = food and beverage.

As summarized in Table 1, the present approach differs from prior fuzzy-based decision models, including the fuzzy multi-criteria approach of Sutthibutr et al. [19] and comparable fintech risk-assessment frameworks, primarily in producing a continuous proportional allocation rather than a discrete classification or risk score; it likewise differs from deep-learning-based crowdfunding prediction models (e.g., studies [20, 23]) in generating a prescriptive allocation rather than a predictive evaluation. Building on this comparison, three fundamental research gaps are identified in the current literature:

(1). Methodological silo (binary outcomes): High-tech computational models, such as the deep learning frameworks by Zhang et al. [20] and the state-of-the-art generative AI approach by Gunduz et al. [23], are strictly designed for binary or evaluative outcomes (e.g., success vs. failure or credit risk levels). These models lack prescriptive capabilities to dynamically optimize funding structures for campaigns falling into intermediate evaluation bands. Meanwhile, existing fuzzy frameworks like Sutthibutr et al. [19] remain applied outside the crowdfunding domain.

(2). Rigid funding structures: Existing crowdfunding literature assumes single-silo architectures. Empirical frameworks targeting local contexts, including inclusive models [12], general MSME startup books [21], equity investor models [22], and ethical Islamic finance (*Qard-al-Hasan*) [13], channel capital through non-fluid, single-model mechanisms. There is a distinct absence of an automated system that computationally integrates Donation and P2P lending into a unified proportional allocation framework.

(3). Domain disconnect: Broad e-commerce crowdfunding models [23] fail to address the specific socio-commercial constraints of local MSMEs in emerging economies, such as the volatile Food and Beverage (F&B) sector. Conversely, localized qualitative studies [12, 13, 21] lack the mathematical precision needed to scale these models into digital platforms.

It should be clarified that references [11, 18, 19, 23] are cited throughout this manuscript as methodological

references, illustrating relevant fuzzy-based or data-driven techniques from adjacent domains (student lending, supply-chain management, and e-commerce crowdfunding prediction), rather than as directly related studies on proportional donation-lending allocation for MSME crowdfunding, which remains the specific and largely unaddressed problem this study targets.

To bridge these gaps, this study proposes a hybrid proportional crowdfunding model driven by a Mamdani-type FIS. The explicit contributions are threefold:

(1). Prescriptive dynamic allocation engine: Shifting from evaluative binary predictions [20, 23], the proposed FIS serves as a prescriptive engine that handles vague indicators to automatically calculate a crisp hybrid index (z*).

(2). Mathematical integration of dual-silo funding: This model breaks the single-silo rigidity [4, 6] by introducing a mathematical framework where z* dynamically splits capital into complementary lending (PL) and donation (PD) proportions (PL + PD = 100%).

(3). Socio-technical optimization for MSMEs: By synthesizing 11 expert-validated metrics into 4 robust variables (FP, BMR, SI and PN), this model offers a structured, rule-based calibration approach illustrated for the F&B MSME domain in emerging markets, pending empirical validation.

3. METHODOLOGY

This study employs the DSRM to develop and evaluate the hybrid proportional crowdfunding model. DSRM is chosen for its focus on creating and evaluating innovative artifacts to solve identified organizational and social problems in the information systems domain [24].

3.1 Research framework

The research process is structured into six iterative stages as follows:

(1). Problem identification and motivation: Recognizing the financial gap in MSMEs and the limitations of single-model crowdfunding.

(2). Objectives for a solution: Designing a hybrid funding mechanism that provides proportional allocation through a rule-based decision support system.

(3). Design and development: Constructing the hybrid proportional model and the FIS engine.

(4). Demonstration: Conducting simulations using representative MSME datasets to test the model's functionality.

(5). Evaluation: Assessing the internal validity and consistency of the fuzzy rule base through structured expert validation (Fleiss' Kappa inter-rater agreement).

(6). Communication: Reporting the findings through this scholarly publication.

3.2 Proposed hybrid crowdfunding model

The proposed hybrid crowdfunding model integrates MSME profiles as inputs and processes them through a rule-based FIS. The model consists of three layers: Input Layer (Profile Data), Processing Layer (FIS Engine), and Output Layer (Proportional Allocation). Figure 1 illustrates the logical flow of the system, showcasing how MSME characteristics are transformed into a hybrid funding structure.

The proposed hybrid crowdfunding model, illustrated in Figure 1, is structured into three integrated layers: the Input Layer, the Processing Layer, and the Output Layer. Input Layer (MSME Profiles): The system accepts four primary multi-criteria variables: FP, BMR, SI, and PN. These variables represent the dual nature of the hybrid model combining commercial viability with social contribution goals. Processing Layer (Mamdani FIS engine): Functioning as a knowledge-driven, rule-based agent, this layer utilizes a Mamdani-type FIS. It undergoes three critical stages: Fuzzification of crisp inputs, evaluation of a Knowledge Base consisting of 81 heuristic rules, and defuzzification using the Centroid of Area (CoA) method. Output Layer (proportional capital allocation): The resulting hybrid index (z*) ranging from 0 to 100 determines the final funding split. This index is processed into PL and PD proportions, which are then converted into the actual allocated lending amount (L_{amount}) and allocated donation amount (D_{amount}). This architecture ensures that capital allocation is not binary, but adaptive to the specific profile and risk-impact balance of each MSME. This figure demonstrates how input variables are transformed into a proportional funding output through the FIS engine, highlighting the adaptive nature of the model.

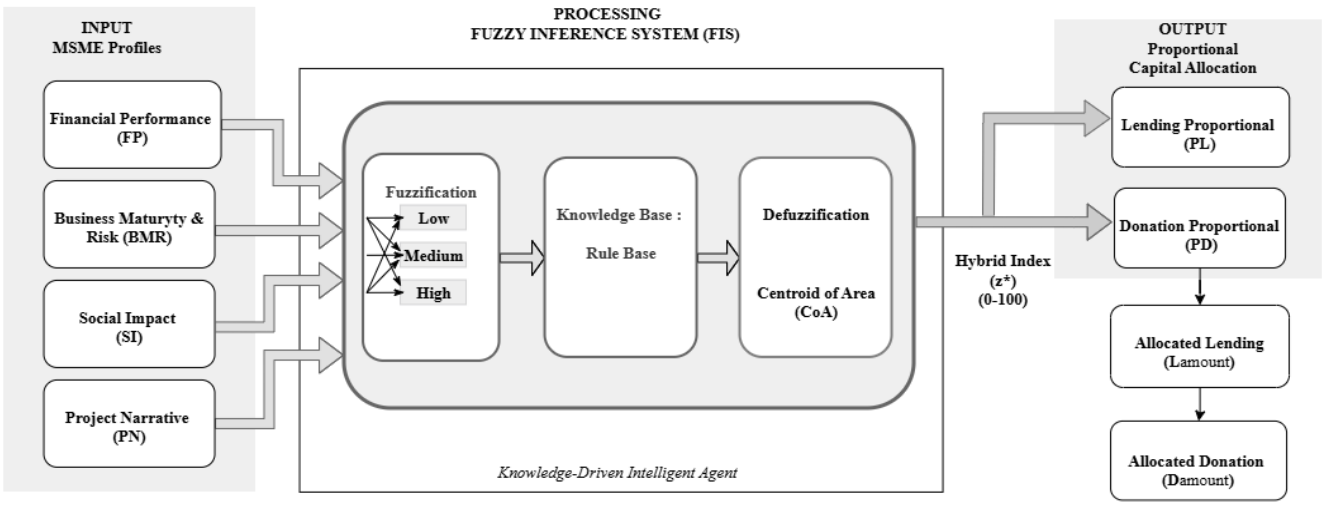


Figure 1. Proposed hybrid proportional crowdfunding model

3.3 Fuzzy inference system design

The core of the decision support system is a Mamdani-type FIS. It should be noted that the proposed system is a rule-based FIS rather than a learning-based or self-adaptive model; the term "intelligent" is therefore avoided in this manuscript, and the system is instead described as knowledge-based and rule-driven to accurately reflect its underlying mechanism.

3.3.1 Fuzzification and input variables

This four-dimensional structure is grounded in a four-pillar framework (crowdfunding models, technology, trust, regulation) from a prior systematic literature review [16]: Trust and Regulation are operationalized through BMR and PN, while Technology is addressed through the FIS engine itself. Other potentially relevant factors, such as market potential, repayment history, platform-level trust, and investor behavior, are excluded as an explicit scope boundary rather than an oversight, and are identified as future extensions.

The model utilizes four primary input variables, mapped to linguistic sets (Low, Medium, High) using trapezoidal membership functions (MFs) for the Low and High categories and triangular MFs for the Medium category. The variable-to-indicator mapping is defined in Table 2, and the exact numerical breakpoints for every MF are reported in Table 3.

Table 2. Mapping of micro, small, and medium enterprise (MSME) indicators to fuzzy input variables

Fuzzy Variable	Code	Indicators (From Empirical Analysis)	Rationale for Hybrid Model
Financial Performance	FP	Monthly Revenue, Net Profit, Cash Flow	Crucial for debt repayment capacity in the lending portion
Business Maturity and Risk	BMR	Business Age, Legality Status (NIB), Certifications (PIRT/Halal)	Essential for risk mitigation and market readiness
Social Impact	SI	Number of Employees, Community Involvement	Primary driver for attracting donation-based funding
Project Narrative	PN	Business Story/Narrative, Purpose of Funds	Vital for social sympathy and donor engagement

Note: FP = Financial Performance, BMR = Business Maturity and Risk, SI = Social Impact, PN = Project Narrative.

Table 3. Membership function (MF) parameters for input variables (0–100 scale)

Variable	Low (Trapezoidal: a, b, c, d)	Medium (Triangular: a, b, c)	High (Trapezoidal: a, b, c, d)
FP	[0, 0, 25, 40]	[30, 50, 70]	[60, 85, 100, 100]
BMR	[0, 0, 30, 45]	[35, 55, 75]	[65, 80, 100, 100]
SI	[0, 0, 20, 35]	[25, 50, 75]	[65, 85, 100, 100]
PN	[0, 0, 30, 40]	[30, 55, 80]	[70, 90, 100, 100]

Note: Values denote the [a, b, c, d] breakpoints of each trapezoidal function or the [a, b, c] breakpoints of each triangular function, where membership equals 1 between the inner breakpoints and 0 outside the outer breakpoints, with linear interpolation in between. FP = Financial Performance, BMR = Business Maturity and Risk, SI = Social Impact, PN = Project Narrative.

3.3.2 Rule base construction

The rule base is constructed to map the relationship between the four input variables and the two funding outputs. To ensure the fuzzy space is entirely covered, the number of rules is determined by the combination of linguistic scales across all input variables (L^n). Since the system utilizes 4 input variables (n = 4), each with 3 linguistic labels (L = 3), the Rule Base consists of 81 rules (3^4 combinations). These rules determine the balance between Lending and Donation based on expert knowledge. Examples of the rules are provided in Table 4. The complete set of 81 rules is provided in Appendix A (Table A1) to ensure full reproducibility. To assess the internal stability of the rule base, a monotonicity consistency check was performed across all 81 rules: for every pair of rules differing by one linguistic level in a single input variable, the corresponding output level was verified to never decrease as the driving input increased. This check confirmed 100% consistency (108/108 adjacent-level comparisons for Lending as a function of FP and BMR; 108/108 for Donation as a function of SI and PN), indicating that the rule base behaves monotonically and without internal contradictions across the complete input space.

Table 4. Sample of fuzzy inference rules

Rule ID	FP	BMR	SI	PN	Output: Lending	Output: Donation
R73	High	High	Low	Low	High	Low
R18	Low	Medium	High	High	Low	High
R41	Medium	Medium	Medium	Medium	Medium	Medium

Note: FP = Financial Performance, BMR = Business Maturity and Risk, SI = Social Impact, PN = Project Narrative.

The rule base was validated through a structured, two-stage expert elicitation protocol involving a panel of five domain experts: two P2P/MSME lending practitioners, two academics specializing in FISs, and one active MSME mentor affiliated with a regional business incubation program (e.g., Rumah BUMN or a regional Cooperative Office). This composition was intended to jointly cover the financial, technical, and social dimensions of the model rather than to achieve statistical representativeness. In the first stage (individual elicitation), each expert independently defined the boundaries of the linguistic categories (Low/Medium/High) and proposed candidate rules in an IF-THEN format, each accompanied by a self-rated confidence score (1–5). In the second stage, a group discussion (approximately two hours) was held to clarify discrepancies between experts, vote on conflicting rules, and consolidate the individual submissions into a single

rule base; where two proposed rules shared an identical antecedent but differed in consequent, the conflict was resolved through confidence weighting, retaining the consequent with the higher average expert confidence rating. Inter-rater agreement was quantified using Fleiss' kappa [25, 26] with a target of $\kappa \geq 0.61$ (Substantial Agreement); rules falling below $\kappa = 0.41$ were revisited in an additional clarification session. Following this process, overall agreement reached the Substantial category ($\kappa = 0.69$). It should be clarified that this Fleiss' Kappa value reflects the level of agreement among the five experts during rule construction-that is, the internal consistency of the expert panel's judgments-and is not a measure of the model's classification accuracy or predictive validity against independent, ground-truth samples; the experts participated in constructing the rules themselves rather than independently classifying pre-existing cases.

3.3.3 Inference and defuzzification

The inference engine uses the MIN-MAX method. For defuzzification, the CoA method is applied to produce a crisp value z^* representing the funding percentage:

$$z^* = \frac{\int \mu A(z) z dz}{\int \mu A(z) dz}$$

3.4 Mathematical model for proportional allocation

The ultimate goal of the proposed model is to derive a balanced funding structure that reflects the MSME dual characteristics. The mathematical logic for the proportional allocation is defined as follows:

3.4.1 Output normalization

The FIS produces a defuzzified crisp value z^*, where $z^* \in [0, 100]$. This value represents the hybrid index, indicating the tendency of an MSME towards either a commercial or a social orientation. To determine the specific amount for each funding type, we define the Total Funding Requirement (T_f) requested by the MSME.

3.4.2 Proportional calculation

The allocation of P2P lending (L) and donation (D) is calculated based on the following equations:

Lending proportion (PL): The proportion of funding that must be repaid (lending) is directly proportional to the hybrid index score z^*:

$$PL = \frac{z^*}{100} \quad (1)$$

Donation proportion (PD): The proportion of funding provided as a social contribution (donation) is the complement of the PL:

$$PD = 1 - PL = \frac{100 - z^*}{100} \quad (2)$$

3.4.3 Capital allocation formula

Based on the proportions derived, the actual capital amount for each scheme is formulated as:

$$L_{\text{amount}} = Tf \times PL \quad (3)$$

$$D_{\text{amount}} = Tf \times PD \quad (4)$$

where,

•L_{amount}: Total capital allocated through the P2P lending scheme.

•D_{amount}: Total capital allocated through the donation scheme.

•Tf: Total funding required by the MSME ($L_{\text{amount}} + D_{\text{amount}} = Tf$).

3.4.4 Allocation constraints

To ensure the sustainability of the platform and the MSME, the model follows these logical constraints:

•If $z^* \rightarrow 100$, the MSME is deemed highly commercial, and the funding structure shifts heavily toward P2P Lending.

•If $z^* \rightarrow 0$, the MSME is deemed to have a high SI with low financial capacity, shifting the structure toward Donation.

•The model ensures that $0 \leq PL, PD \leq 1$, providing a flexible transition between the two funding silos.

3.5 Simulation setup and data collection

To demonstrate the artifact, an illustrative example is prepared. The data used for this illustration involve:

(1) Expert judgment: Used to validate the weights of the input variables and the fuzzy rules.

(2) Representative dataset: A set of five illustrative MSME profiles is constructed by the authors as hypothetical, expert-informed cases (i.e., synthetic input combinations designed to reflect plausible real-world characteristic ranges in emerging economies), rather than being sampled from actual MSME financial records or historical crowdfunding transactions; this is done to test the model's responsiveness under controlled, clearly labeled conditions. Three additional contrasting scenarios are constructed in the same manner. The eligibility scores and hybrid index values reported in Section 4 are illustrative values assigned by the authors to demonstrate the allocation mechanism; they were not obtained by executing the complete rule base.

(3) Expert validation: The reliability of the underlying rule base is assessed through a structured Fleiss' kappa inter-rater agreement procedure involving a panel of five domain experts (see Section 3.3.2), rather than through large-scale benchmarking against real crowdfunding platform data at this stage.

4. RESULTS

This section presents a simulation demonstration of the primary artifact of this research: the model of the hybrid proportional crowdfunding system. This demonstration illustrates how the model integrates multi-dimensional MSME data into a unified proportional funding logic and should be read as an illustrative simulation rather than a formal empirical evaluation.

4.1 Model of hybrid proportional crowdfunding

The primary outcome of this study is the proposed conceptual model of hybrid proportional crowdfunding for MSMEs. The model integrates donation-based crowdfunding and P2P lending-based crowdfunding within a unified framework to address the limitations of single-model

approaches.

The architecture of the proposed model consists of three main components: MSME input variables, a decision-support mechanism based on an FIS, and a proportional funding allocation mechanism. MSME characteristics, including FP, BMR, SI, and PN, are used as inputs to the system. These inputs are processed by the FIS to generate an eligibility score, which serves as the basis for determining the proportion of funding.

Unlike conventional crowdfunding systems that rely on a single funding mechanism, the proposed model dynamically allocates funding between donation and lending schemes. This allows the system to adapt to varying MSME conditions, ensuring that funding decisions reflect both financial feasibility and social considerations.

4.2 Logical flow of the artifact

The model operates through three integrated conceptual stages:

(1). Multi-criteria data fusion: The model accepts disparate data types (quantitative financial ratios and qualitative social narratives) and treats them as co-dependent variables.

(2). Fuzzy reasoning engine: Unlike rigid scoring models, this conceptual framework uses linguistic rules to bridge the gap between "hard information" (bankability) and "soft information" (social value).

(3). Dynamic split-funding output: The final output is not a rejection or acceptance, but a proportional ratio (z^*), which creates a customized hybrid campaign.

4.3 Implementation and functionality demonstration

To demonstrate the conceptual model, its MFs and rule base were specified as described below. The MFs were designed to reflect the non-linear relationship between business maturity and social contribution.

4.3.1 Membership function analysis

The transition between "Low", "Medium", and "High" categories in the model is designed using triangular and trapezoidal functions to accommodate the ambiguity in MSME reporting. The model is designed to map these qualitative inputs into a crisp numerical hybrid index.

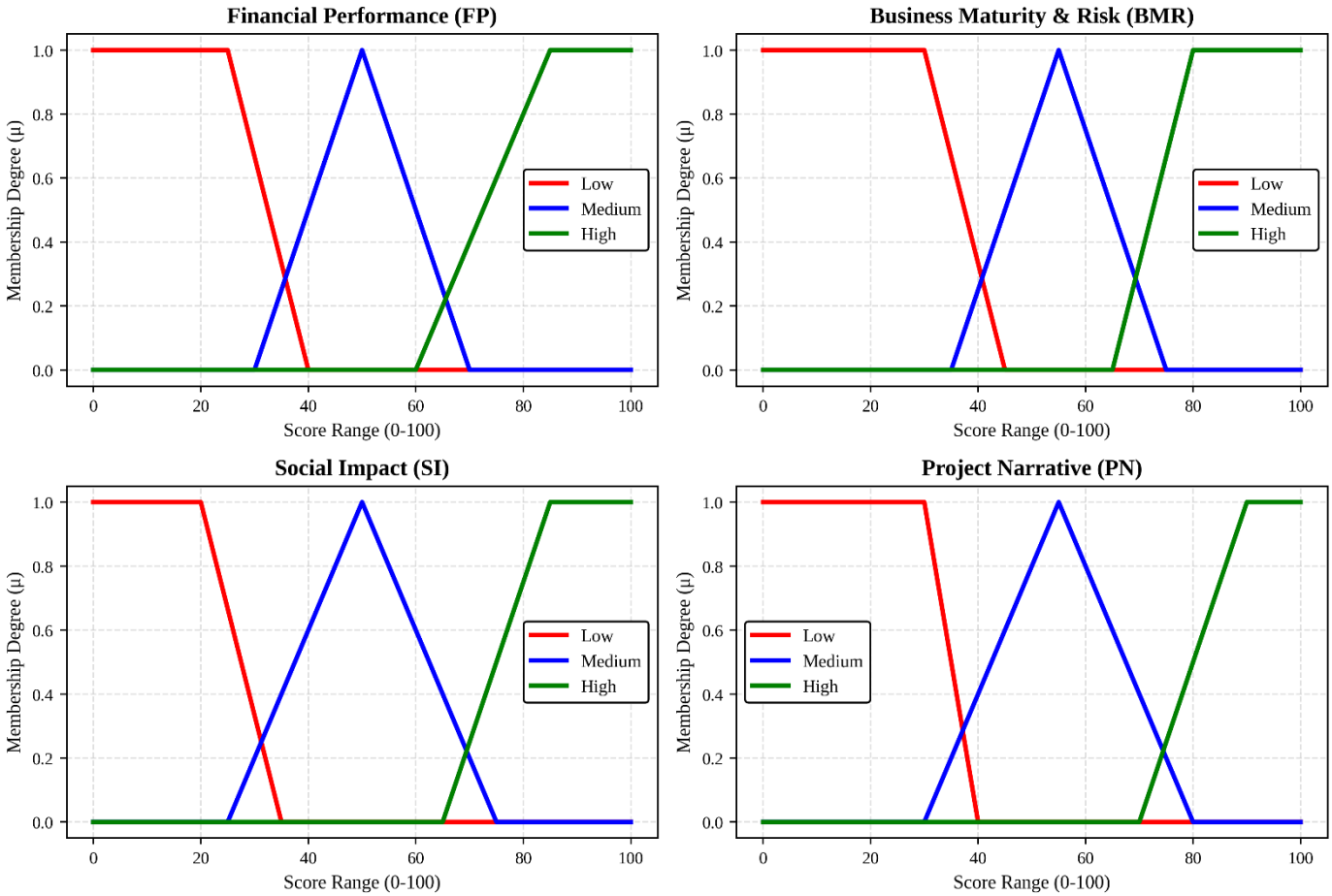


Figure 2. Visualization of membership functions (MFs) for model inputs

Figure 2 illustrates the MFs for the four input variables: FP, BMR, SI, and PN. To handle the inherent uncertainty and imprecision in MSME data, each variable is mapped into three linguistic terms: Low, Medium, and High.

A combination of trapezoidal and triangular geometries is employed to define these sets. The trapezoidal shape is utilized for the 'Low' and 'High' categories to represent regions of absolute certainty at the extremes of the scale. For instance, in the FP variable, a score below 25 is definitively categorized as 'Low' (μ = 1.0), while a score above 85 is fully 'High'. Conversely, the triangular MF is assigned to the 'Medium' category to identify a specific peak (e.g., score 50) that best represents a moderate state. A critical feature of this design is the overlap between linguistic sets (e.g., the intersection between Low and Medium ranges). This fuzziness ensures a smooth transition in decision-making; for example, in the

BMR graph, a score of 40 carries both 'Low' and 'Medium' membership degrees. This allows the system to avoid rigid binary thresholds, reflecting the complex reality of MSME profiles where a business might exhibit characteristics of two categories simultaneously. Each variable's thresholds are specifically tuned based on expert judgment: FP and BMR emphasize risk mitigation by maintaining a wider 'Low' range to protect lenders from default. SI and PN provide a broader 'Medium' range to capture the diverse social contributions and storytelling qualities of Indonesian MSMEs. These thresholds were not set arbitrarily: they were informed jointly by expert judgment and a preliminary review of the 25th and 75th percentile (P25/P75) distribution of the corresponding indicators observed in a small sample of MSME profiles, which guided the boundary placement between the 'Low', 'Medium', and 'High' categories. Nonetheless, because this preliminary sample is small and the final boundaries still reflect expert adjustment rather than a full empirical calibration study, the thresholds directly influence the final allocation: for instance, narrowing the FP 'Low' boundary would reclassify borderline MSMEs into the 'Medium' category, shifting the resulting hybrid index and, consequently, the lending-donation split. A formal sensitivity analysis of these boundaries is not conducted in the present study and is identified in the Limitations as a specific direction for future work. These MFs serve as the foundation for the subsequent fuzzy inference process, transforming crisp input data into granular linguistic information for proportional capital allocation.

4.4 Simulation setup

To illustrate the behavior of the proposed conceptual model, a lightweight illustration is constructed using hypothetical data representing MSMEs with different characteristics. The illustration includes five MSME cases with varying levels of FP, BMR, SI, and PN.

For each MSME, an eligibility score is assigned by the authors to illustrate the mechanism. These scores are then used to calculate the proportion of funding allocated to donation-based and lending-based crowdfunding. The illustration is designed to represent diverse MSME conditions, ranging from high-performing businesses with low risk to lower-performing businesses with higher uncertainty.

Table 5. Micro, small, and medium enterprise (MSME) input variables for simulation

MSME	Financial Performance (FP)	Business Maturity & Risk (BMR)	Social Impact (SI)	Project Narrative (PN)
M1	0.80	0.20	0.70	0.75
M2	0.65	0.40	0.60	0.70
M3	0.50	0.60	0.65	0.55
M4	0.40	0.70	0.50	0.45
M5	0.75	0.30	0.80	0.80

Note: FP, BMR, SI, and PN are normalized scores on a 0–1 scale. Before fuzzification, each value is converted to the 0–100 scale used in Table 3 by multiplying by 100 (e.g., FP = 0.80 for M1 becomes 80).

The illustrative values provide a structured picture of the intended behavior of the proposed model, rather than a formal evaluation. Table 5 presents the input variables representing different MSME conditions, ranging from high-performing and low-risk enterprises to those with higher uncertainty.

4.5 Simulation results and case analysis

The expected behavior of the conceptual model is illustrated through three simulated scenarios, representing the spectrum of MSMEs in emerging economies.

The illustrative values show how the proposed model is intended to adjust funding allocation dynamically based on MSME characteristics. MSMEs with higher eligibility scores receive a larger proportion of lending-based funding, indicating their suitability for financial-based financing mechanisms.

In contrast, MSMEs with lower eligibility scores are allocated a higher proportion of donation-based funding, reflecting the need for more supportive and less risky financing options. For MSMEs with moderate eligibility scores, the model produces a balanced allocation between lending and donation, demonstrating its flexibility in handling intermediate conditions.

These illustrative values suggest that integrating an FIS with a proportional allocation mechanism could enable adaptive and context-aware decision-making. Within the illustrated scenarios, the model captures the dual economic and social characteristics of MSMEs, allowing for more inclusive funding allocation compared to traditional single-model approaches.

It should be emphasized that this simulation is a demonstration of the proposed conceptual model's expected behavior, not a validation or empirical evaluation, and it does not constitute large-scale empirical testing. The findings illustrate, within the five simulated scenarios only, that the proposed rule-based mechanism can produce differentiated funding allocations for MSME profiles with different characteristics; no claim of general feasibility, applicability, or scalability beyond these scenarios is made. The eligibility scores in Table 6 and the hybrid index values in Table 7 are illustrative values assigned by the authors; they are not outputs obtained by executing the rule base.

Table 6 shows the eligibility scores assigned to the five profiles, which represent how multiple criteria would be aggregated into a single decision variable. The assigned values reflect that MSMEs with stronger FP and lower risk levels tend to obtain higher eligibility scores. The eligibility score S is the hybrid index z* of Section 3.4 rescaled from the 0–100 scale to the 0–1 scale (S = z*/100). Consequently, PL = S and PD = 1 − S (Eqs. (1) and (2)), and the percentages reported in Table 7 correspond to z* and 100 − z*.

Based on these scores, Table 8 illustrates the proportional funding allocation. The values illustrate how the model is intended to adjust the balance between lending and donation mechanisms. High-scoring MSMEs (e.g., M1 and M5) receive a greater proportion of lending-based funding, while lower-scoring MSMEs (e.g., M4) rely more on donation-based support.

Table 6. Illustrative eligibility scores assigned to the five profiles

MSME	Eligibility Score (S = z*/100)	Eligibility Level
M1	0.80	High
M2	0.65	Medium-High
M3	0.45	Medium
M4	0.30	Low
M5	0.75	High

Note: MSME = micro, small, and medium enterprise.

Table 7. Illustrative scenarios across different micro, small, and medium enterprise (MSME) profiles

Case ID	Profile Focus	FP	SI	BMR	DR	Hybrid Index (z*, 0–100)	P2P Lending Proportion (PL, % = z*)	Donation Proportion (PD, % = 100 − z*)
Case 1	Commercial-Oriented	85	20	15	90	82.5	82.5%	17.5%
Case 2	Social-Impact Focus	30	90	40	50	28.4	28.4%	71.6%
Case 3	Balanced Growth	55	55	30	60	51.2	51.2%	48.8%

Note: FP = Financial Performance, BMR = Business Maturity and Risk, SI = Social Impact, PN = Project Narrative.

Table 8. Funding allocation results

MSME	P2P Lending Proportion (PL = S, 0–1)	Donation Proportion (PD = 1 − S, 0–1)
M1	0.80	0.20
M2	0.65	0.35
M3	0.45	0.55
M4	0.30	0.70
M5	0.75	0.25

Note: MSME = micro, small, and medium enterprise.

Within the scope of these illustrative cases, the illustrative values show how the proposed model is intended to capture the heterogeneity of MSME conditions and produce differentiated funding recommendations without relying on rigid classification thresholds; broader validation is required before generalizing this behavior.

To further illustrate the qualitative behavior of the proposed model, Table 7 presents three additional scenarios (Cases 1–3) that were constructed directly on the 0–100 scale of Table 3 to represent contrasting profile archetypes. These scenarios are newly constructed and are not drawn from the five profiles in Table 5; like those profiles, they are hypothetical and do not constitute an independent dataset. As shown in Table 7, the assigned values yield consistent and intuitive funding allocations across these different business characteristics.

Commercial-oriented MSMEs (Case 1) receive a significantly higher proportion of lending-based funding due to strong FP and low risk. In contrast, social-impact-focused MSMEs (Case 2) are allocated a larger proportion of donation-based funding, reflecting their higher social contribution but relatively lower financial feasibility.

For balanced MSMEs (Case 3), the model generates a near-equal distribution between lending and donation mechanisms. These illustrative values show the intended behavior of the model across diverse MSME conditions while maintaining logical consistency in funding allocation.

5. DISCUSSION

The illustrative examples indicate that the proposed hybrid proportional crowdfunding model is intended to offer a flexible approach to MSME financing, dynamically adjusting the allocation between donation- and lending-based mechanisms according to MSME characteristics, in contrast to conventional single-mode crowdfunding models.

In the illustrative examples, MSMEs with higher eligibility scores receive a greater proportion of lending-based funding, while those with lower scores rely more on donation-based support. This finding aligns with the fundamental principle of financial feasibility, where financially stronger entities are better suited for loan-based financing. At the same time, the model incorporates social considerations by allocating donation-based funding to MSMEs with higher uncertainty, which is consistent with the objectives of financial inclusion discussed in previous research.

The proposed model extends existing hybrid crowdfunding approaches by introducing a proportional allocation mechanism that dynamically determines the composition of funding. While earlier studies have explored combinations of donation and lending schemes, these approaches are often static or context-specific. In contrast, this study illustrates a framework designed to be adaptable across different MSME conditions, as illustrated within the five hypothetical profiles in Section 4. This highlights a key contribution of the research in addressing the gap between conceptual hybrid models and operational decision-making mechanisms.

Furthermore, the integration of the FIS enhances the model's ability to handle uncertainty and multi-criteria evaluation. Consistent with previous studies on fuzzy-based decision systems, the use of linguistic variables and rule-based reasoning allows the model to capture qualitative aspects of MSME characteristics that cannot be easily quantified. This capability is particularly important in MSME contexts, where incomplete or imprecise information is common.

Beyond applying fuzzy scoring to funding allocation, the theoretical contribution is twofold, and each is mechanistically distinct from existing fuzzy decision-making models. First, prior fuzzy-based approaches, including fuzzy MCDM [19] and deep-learning prediction models [20, 23], are designed to produce a single discrete or ordinal output, such as a ranking, an approval/rejection decision, or a success-probability score for one financing channel. In contrast, the proposed mechanism maps the defuzzified hybrid index (z*) directly into a continuous split ratio simultaneously governing two complementary funding channels (PL and PD, where PL + PD = 100%); to the authors' knowledge, this continuous, simultaneous dual-channel allocation logic has not been formalized in the existing fuzzy crowdfunding literature, which instead treats donation-based and lending-based mechanisms as separate, non-interacting decisions. Second, the model operationalizes the four-pillar framework (crowdfunding models, technology, trust, regulation) from a prior systematic literature review [16] into this computational decision structure, bridging conceptual crowdfunding theory and an implementable decision-support artifact.

Another potential implication of this study, contingent on future empirical validation, is its conceptual contribution to financial inclusion discussions. By combining financial and social funding mechanisms at the design level, the proposed conceptual model is intended to accommodate a broader range of MSME profiles, including those that may not meet the requirements of traditional lending systems; this is a design intention rather than a demonstrated outcome, since the model has not been tested with real crowdfunding platforms or MSME beneficiaries. If validated in future work, this direction would align with the growing emphasis on inclusive fintech solutions aiming to address financing gaps for underserved sectors.

However, several limitations should be explicitly

acknowledged. First, and most importantly, the results reported in this study demonstrate the conceptual feasibility of the proposed allocation mechanism only; because validation relies on five hypothetical, expert-informed profiles rather than real MSME financial data or historical crowdfunding cases (see Section 3.5), no claim of predictive accuracy, generalizability, or real-world performance is made, and the three additional scenarios in Table 8 are likewise hypothetical, author-constructed profiles rather than an independent dataset. Second, the model assumes a simplified linear relationship between eligibility score and funding allocation. Third, evaluation is currently limited to expert validation of the rule base (Section 3.3.2); formal user evaluation, comparison with existing decision methods, and sensitivity analysis of membership-function thresholds remain to be conducted, and the five simulated cases, while spanning commercial-to-social-impact extremes, do not constitute a stress test against edge cases, adversarial inputs, or independent expert-assigned scores, so robustness beyond the illustrated scenarios cannot be claimed. Fourth, the model focuses on MSME-side profile variables and excludes demand-side factors whose omission could materially change real-world outcomes: investor risk appetite and preferences could alter actual funds raised regardless of the model's recommended split; undisclosed repayment history could cause the model to overstate the eligibility of a financially distressed but well-narrated MSME; prevailing market conditions could shift realistic funding availability independent of an MSME's profile; and platform-level risk policy could impose caps or floors that override the model's proportional recommendation. Future research will address these points through real-world datasets, sensitivity and robustness analysis, and formal expert/user evaluation, including direct comparison between model-generated allocations and independent expert-assigned allocations, on operational crowdfunding platforms.

Overall, the findings suggest that the proposed hybrid crowdfunding model offers a promising approach to enhancing MSME financing by integrating rule-based decision-making with flexible funding mechanisms. The model not only contributes to the theoretical development of crowdfunding systems but also provides practical insights for the design of more inclusive and adaptive financial platforms.

6. CONCLUSIONS

This study has developed and illustrated, through a conceptual model and illustrative simulation, a rule-based Hybrid Proportional Crowdfunding approach intended to address the rigid financing structures currently available for MSMEs. By moving beyond the traditional binary approach (all-or-nothing), the proposed model offers a more granular and adaptive capital allocation mechanism.

6.1 Summary of contributions

The primary contribution of this research is the development of a conceptual and mathematical framework that integrates Donation-based and P2P Lending schemes into a single proportional output. The application of an FIS has illustrated potential effectiveness, within the simulated scenarios, in handling the qualitative uncertainty inherent in MSME profiles, such as SI and PN. The illustrative examples show how the model is intended to adjust funding proportions dynamically: rewarding high-financial-performance MSMEs with greater debt capacity while protecting social-impact-oriented enterprises through a higher donation ratio.

6.2 Research implications

Theoretically, this research enriches the literature on Information Systems and FinTech by providing a formal logic for hybridity in digital finance. Practically, the model serves as a conceptual decision-support prototype for crowdfunding platform operators and MSME mentors, illustrating a possible approach to designing more inclusive and sustainable funding campaigns, pending further empirical validation. This approach reduces the "missing middle" gap, ensuring that MSMEs with blended value can access the right type of capital at the right time.

7. FUTURE WORK

This study opens several opportunities for future research to further enhance the proposed hybrid proportional crowdfunding model. First, future studies may incorporate real-world MSME datasets to validate the robustness and practical applicability of the model in real crowdfunding environments. Empirical validation would provide stronger evidence of the model’s effectiveness in diverse economic contexts. Second, the current model adopts a linear proportional allocation mechanism based on the eligibility score. Future research may explore more advanced allocation approaches, such as non-linear models or optimization-based techniques, to achieve more precise and context-sensitive funding decisions. Third, the design of the FIS can be further refined by incorporating additional input variables, such as market conditions, business sustainability indicators, or behavioral factors of MSME owners. This would enhance the model’s ability to capture more complex real-world dynamics.

In addition, future work may focus on developing a prototype or implementing the proposed model within an actual crowdfunding platform. Such implementation would enable usability testing, system performance evaluation, and user acceptance analysis.

Finally, integrating the model with emerging financial technologies, such as machine learning or blockchain-based crowdfunding systems, may further improve transparency, scalability, and trust in digital funding platforms.

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REFERENCES

[1] Ummah, H.R., Sonjaya, A., Jamaludin, J. (2024). Sharia fintech: Crowdfunding as MSMEs financing. Al-Muamalat: Jurnal Ekonomi Syariah, 11(1): 115-136. https://doi.org/10.15575/am.v11i1.28808

[2] Omarini, E. (2018). Peer-to-peer lending: Business model analysis and the platform dilemma. International Journal of Finance, Economics and Trade, 2(3): 31-41. https://doi.org/10.19070/2643-038X-180005

[3] Ayyagari, M., Juarros, P., Martinez Peria, M.S., Singh, S. (2021). Access to finance and job growth: Firm-level evidence across developing countries. Review of Finance, 25(5): 1473-1496. https://doi.org/10.1093/rof/rfab003

[4] Belleflamme, P., Lambert, T., Schwienbacher, A. (2014). Crowdfunding: Tapping the right crowd. Journal of Business Venturing, 29(5): 585-609. https://doi.org/10.1016/j.jbusvent.2013.07.003

[5] Zhang, X., Liu, X.P., Wang, X.H., Zhao, H.K., Zhang, W. (2022). Exploring the effects of social capital on crowdfunding performance: A holistic analysis from the empirical and predictive views. Computers in Human Behavior, 126: 107011. https://doi.org/10.1016/j.chb.2021.107011

[6] Mustafida, R., Fauziah, N.N., Kurnia, Z.N. (2021). The development of Islamic crowdfunding in Indonesia and its impact towards SMEs. Hasanuddin Economics and Business Review, 4(3): 20-29. https://doi.org/10.26487/hebr.v4i3.2547

[7] Ferrer, J.M., Ulrich, K., Blanco-González-Tejero, C., Caño-Marín, E. (2023). Investors' confidence in the crowdlending platform and the impact of Covid-19. Journal of Business Research, 155: 113433. https://doi.org/10.1016/j.jbusres.2022.113433

[8] Cumming, D.J., Vanacker, T., Zahra, S.A. (2021). Equity crowdfunding and governance: Toward an integrative model and research agenda. Academy of Management Perspectives, 35(1): 69-95. https://doi.org/10.5465/amp.2017.0208

[9] Shneor, R., Wenzlaff, K., Boyko, K., Baah-Peprah, P., Odorovi, A., Okhrimenko, O. (2024). The European crowdfunding market report 2023. Kristiansand: University of Agder-Crowdfunding Research Center. https://doi.org/10.5281/zenodo.10617956

[10] Edward, M.Y., Fuad, E.N., Ismanto, H., Atahau, A.D.R., Robiyanto. (2023). Success factors for peer-to-peer lending for SMEs: Evidence from Indonesia. Investment Management and Financial Innovations, 20(2): 16-25. https://doi.org/10.21511/imfi.20(2).2023.02

[11] Izang, A.A., Ajayi, O.F., Junaid, O., Nwigwe, B., Onyeka, P.O. (2024). Design and evaluation of a peer-to-peer student lending platform to mitigate information asymmetry and credit risk. Ingénierie des Systèmes d'Information, 29(3): 885-894. https://doi.org/10.18280/isi.290309

[12] Suasih, N.N.R., Budhi, M.K.S., Wijaya, P.Y. (2022). Inclusive crowdfunding scheme as capital source alternative for rural agriculture in Indonesia. In IOP Conference Series: Earth and Environmental Science, 977: 012053. https://doi.org/10.1088/1755-1315/977/1/012053

[13] Aderemi, A.M.R., Ishak, M.S.I. (2020). Crowdfunding as an alternative mode of financing for micro and small enterprises: A proposed qard-al-hasan contract. International Journal of Islamic Economics and Finance (IJIEF), 3(3): 95-118. https://doi.org/10.18196/ijief.3235

[14] Wang, Y.F., Ibrahim, O. (2025). Enhancing crowdfunding success with machine learning and visual analytics: Insights from Chinese platforms. IEEE Access, 13: 68097-68110. https://doi.org/10.1109/ACCESS.2025.3546265

[15] Sun, Y., Cai, N.N., Dong, Y.Z., Shi, B.F. (2022). Assessing and predicting small industrial enterprises' credit ratings: A fuzzy decision-making approach. International Journal of Forecasting, 38(3): 1158-1172. https://doi.org/10.1016/j.ijforecast.2022.01.006

[16] Aprilinda, Y., Warnars, H.L.H.S., Princes, E., Fitrianah, D. (2025). Critical components in building a crowdfunding model: A systematic review. In 2025 4th International Conference on Creative Communication and Innovative Technology (ICCIT), Cirebon, Indonesia, pp. 1-7. https://doi.org/10.1109/ICCIT65724.2025.11166885

[17] Volosencu, C. (2020). Fuzzy Systems-theory and applications. IntechOpen. https://doi.org/10.5772/intechopen.87799

[18] Berbiche, N., Hlyal, M., El Alami, J. (2024). Enhancing supply chain resilience and efficiency through fuzzy logic-based decision-making automation in volatile environments. Ingénierie des Systèmes d'Information, 29(1): 191-203. https://doi.org/10.18280/isi.290120

[19] Sutthibutr, N., Hiraishi, K., Chiadamrong, N. (2024). A fuzzy multi-criteria decision-making for optimizing supply chain aggregate production planning based on cost reduction and risk mitigation. Journal of Open Innovation: Technology, Market, and Complexity, 10(4): 100377. https://doi.org/10.1016/j.joitmc.2024.100377

[20] Zhang, Z.M., Niu, K., Liu, Y. (2020). A deep learning based online credit scoring model for P2P lending. IEEE Access, 8: 177307-177317. https://doi.org/10.1109/ACCESS.2020.3027337

[21] Wahjono, S.I., Marina, A., Fam, S.F., Rasulong, I. (2021). Crowdfunding as a business innovation to finance SMEs for sustainable development goals to anticipating the impact of corona virus pandemic disease (COVID-19) in Indonesia. In Proceedings of the 4th International Conference on Sustainable Innovation 2020-Accounting and Management (ICoSIAMS 2020), Yogyakarta, Indonesia, pp. 315-323. https://doi.org/10.2991/aer.k.210121.044

[22] Panitkulpong, K., Saengnoree, A., Deebhijarn, S., Teerawatananond, T. (2023). The factors influencing investor intentions to invest in equity crowdfunding in Thailand: A conceptual framework. In 2023 15th International Conference on Information Technology and Electrical Engineering (ICITEE), Chiang Mai, Thailand, pp. 329-333. https://doi.org/10.1109/ICITEE59582.2023.10317667

[23] Gunduz, H., Klein, M., Bayrak Meydanoglu, E.S. (2026). Crowdfunding as an e-commerce mechanism: A deep learning approach to predicting success using reduced generative AI embeddings. Journal of Theoretical and Applied Electronic Commerce Research, 21(1): 28. https://doi.org/10.3390/jtaer21010028

[24] Peffers, K., Tuunanen, T., Rothenberger, M.A., Chatterjee, S. (2007). A design science research methodology for information systems research. Journal

of Management Information Systems, 24(3): 45-77. https://doi.org/10.2753/MIS0742-1222240302
[25] Cumming, D.J., Leboeuf, G., Schwienbacher, A. (2020). Crowdfunding models: Keep-it-all vs. all-or-nothing. Financial Management, 49: 331-360. https://doi.org/10.1111/fima.12262
[26] Zadeh, L.A. (1965). Fuzzy sets. Information and Control, 8(3): 338-353. https://doi.org/10.1016/S0019-9958(65)90241-X

NOMENCLATURE

FP	Financial Performance Index, {Low, Medium, High}
BMR	Business Maturity and Risk Index, {Low, Medium, High}
SI	Social Impact Index, {Low, Medium, High}
PN	Project Narrative and Storytelling Index, {Low, Medium, High}
$\mu A(z)$	Membership function of fuzzy set A, (0,1)
CoA	Center of Area: The defuzzification method used to find the centroid
z^*	Defuzzified crisp output value (hybrid index), 0 – 100
PL	Peer-to-Peer (P2P) Lending Proportion, %
PD	Donation-based Funding Proportion, %
Tf	Total Funding Requirement requested by MSME
L_{amount}	Capital amount allocated for Lending scheme, Currency
D_{amount}	Capital amount allocated for Donation scheme, Currency

APPENDIX

Table A1. Complete fuzzy rule base for hybrid proportional crowdfunding model (81 rules)

#	FP	BMR	SI	PN	Lending	Donation
R1	Low	Low	Low	Low	Low	Medium
R2	Low	Low	Low	Medium	Low	Medium
R3	Low	Low	Low	High	Low	High
R4	Low	Low	Medium	Low	Low	Medium
R5	Low	Low	Medium	Medium	Low	Medium
R6	Low	Low	Medium	High	Low	High
R7	Low	Low	High	Low	Low	High
R8	Low	Low	High	Medium	Low	High
R9	Low	Low	High	High	Low	High
R10	Low	Medium	Low	Low	High	Medium
R11	Low	Medium	Low	Medium	Medium	Medium
R12	Low	Medium	Low	High	Medium	High
R13	Low	Medium	Medium	Low	Medium	Medium
R14	Low	Medium	Medium	Medium	Medium	High
R15	Low	Medium	Medium	High	Medium	High
R16	Low	Medium	High	Low	Medium	High
R17	Low	Medium	High	Medium	Medium	High
R18	Low	Medium	High	High	Low	High
R19	Low	High	Low	Low	High	Medium
R20	Low	High	Low	Medium	High	Medium
R21	Low	High	Low	High	Medium	Medium
R22	Low	High	Medium	Low	High	Medium
R23	Low	High	Medium	Medium	Medium	Medium
R24	Low	High	Medium	High	Medium	High
R25	Low	High	High	Low	Medium	Medium
R26	Low	High	High	Medium	Medium	High
R27	Low	High	High	High	Medium	High
R28	Medium	Low	Low	Low	High	Medium
R29	Medium	Low	Low	Medium	Medium	Medium
R30	Medium	Low	Low	High	Medium	High
R31	Medium	Low	Medium	Low	Medium	Medium
R32	Medium	Low	Medium	Medium	Medium	High
R33	Medium	Low	Medium	High	Medium	High
R34	Medium	Low	High	Low	Medium	High
R35	Medium	Low	High	Medium	Medium	High
R36	Medium	Low	High	High	Low	High
R37	Medium	Medium	Low	Low	High	Medium
R38	Medium	Medium	Low	Medium	High	Medium
R39	Medium	Medium	Low	High	Medium	Medium
R40	Medium	Medium	Medium	Low	High	Medium
R41	Medium	Medium	Medium	Medium	Medium	Medium
R42	Medium	Medium	Medium	High	Medium	High
R43	Medium	Medium	High	Low	Medium	Medium
R44	Medium	Medium	High	Medium	Medium	High
R45	Medium	Medium	High	High	Medium	High

R46	Medium	High	Low	Low	High	Low
R47	Medium	High	Low	Medium	High	Medium
R48	Medium	High	Low	High	High	Medium
R49	Medium	High	Medium	Low	High	Medium
R50	Medium	High	Medium	Medium	High	Medium
R51	Medium	High	Medium	High	Medium	Medium
R52	Medium	High	High	Low	High	Medium
R53	Medium	High	High	Medium	Medium	Medium
R54	Medium	High	High	High	Medium	High
R55	High	Low	Low	Low	High	Medium
R56	High	Low	Low	Medium	High	Medium
R57	High	Low	Low	High	Medium	Medium
R58	High	Low	Medium	Low	High	Medium
R59	High	Low	Medium	Medium	Medium	Medium
R60	High	Low	Medium	High	Medium	High
R61	High	Low	High	Low	Medium	Medium
R62	High	Low	High	Medium	Medium	High
R63	High	Low	High	High	Medium	High
R64	High	Medium	Low	Low	High	Low
R65	High	Medium	Low	Medium	High	Medium
R66	High	Medium	Low	High	High	Medium
R67	High	Medium	Medium	Low	High	Medium
R68	High	Medium	Medium	Medium	High	Medium
R69	High	Medium	Medium	High	Medium	Medium
R70	High	Medium	High	Low	High	Medium
R71	High	Medium	High	Medium	Medium	Medium
R72	High	Medium	High	High	Medium	High
R73	High	High	Low	Low	High	Low
R74	High	High	Low	Medium	High	Low
R75	High	High	Low	High	High	Low
R76	High	High	Medium	Low	High	Low
R77	High	High	Medium	Medium	High	Low
R78	High	High	Medium	High	High	Low
R79	High	High	High	Low	High	Low
R80	High	High	High	Medium	High	Low
R81	High	High	High	High	High	Medium

Note: FP = Financial Performance, BMR = Business Maturity and Risk, SI = Social Impact, PN = Project Narrative. Rules R18, R41, and R73 correspond to the illustrative examples in Table 4 of the main manuscript. All 81 rules cover the complete combinatorial space of $3^4 = 81$ input configurations, and were verified to contain no duplicate or missing combinations.