A Fair and Transparent Credit Evaluation Mechanism for SMEs Using Blockchain

***Abstract*— This paper introduces the design and implementation of a fair and transparent decentralized Blockchain-based credit evaluation framework for Small and Medium Enterprises (SMEs). Overcoming the limitations of centralized credit scoring such as lack of Information availability, high cost, and rating manipulations, the study employs Subjective logic, pairwise comparisons, and the Cumulative belief degree (CBD) method to generate borrower scores and credit risk. Implemented on the Ethereum Blockchain using Solidity and Ganache, the framework offers a transparent, fair, and inclusive credit assessment mechanism for SMEs. By incorporating peer opinions, the research enhances the accuracy of credit risk assessments, contributing to the evolving field of decentralized finance and Blockchain applications in fintech. The study's originality lies in its innovative combination of Blockchain technology with qualitative credit assessments using Subjective logic and CBD to address the shortcomings of traditional credit scoring systems for SMEs.**

Keywords—Credit Evaluation, SMEs (Small and Medium Enterprises), Blockchain, Peer-to-peer Lending, DeFi (Decentralized Finance)

I. Introduction

Small and Medium Enterprises (SMEs) are the lifeline of economies across the globe. According to the World Bank, they account for roughly 90 percent of all businesses and more than half of all employment internationally. SMEs contribute significantly to the GDP and employment worldwide and promote balanced regional development. However, owing to their small size and lack of resources, many struggle to withstand the day-to-day business crises. Lack of timely access to finance has been the most prevalent challenge for SMEs [1]. Due to their relatively opaque nature, financial institutions consider these firms risky. Financial institutions lending to these businesses ask for formal and standard documents about the firm's economic activities, which small firms do not maintain. This creates challenges for banks and other lending institutions in accurately evaluating the creditworthiness of these enterprises, potentially leading to their negligent behavior toward SMEs' financial needs.

Most credit screening and rating mechanisms financial institutions employ are quantitative. However, small firms do not generate, keep, or publish standardized business information and thus rely upon relationship lending. This form of credit access is restricted to a minimal set of firms with established relationships with bank managers or credit officials [2]. Without such connections, most firms turn to informal lending sources with very high-interest rates. Peer-to-peer (P2P) lending has emerged as an alternative source of financing for small businesses [3]. By connecting borrowers directly with individual investors, P2P lending platforms have disrupted traditional lending models and facilitated access to credit for many businesses that may have otherwise struggled to obtain financing. But Sha (2022) shows that these platforms generate their internal credit ratings, which are likely to be manipulated by the platform [4]. Borrowers might pay the owners of these centralized lending platforms to acquire higher credit ratings.

Blockchain technology has provided a more transparent and decentralized mechanism for peer-to-peer lending [5]. By leveraging the transparency and immutability of blockchain, these platforms can create a lending environment that is more objective and less susceptible to manipulation. Smart contracts and decentralized identity systems allow for a more accurate, transparent, and efficient evaluation of borrower creditworthiness while protecting sensitive information's privacy [6]. Blockchain technology in peer-to-peer lending enables the creation of tamper-resistant credit histories, reducing the risk of fraudulent activities and enhancing the overall trust and credibility within the lending ecosystem.

This paper presents a fair and transparent decentralized credit screening and scoring framework for Blockchain-Based Peer-to-Peer SME Lending, considering their unique characteristics. The parameters of credit scoring in the relatively new credit ecosystem, such as P2P lending, differ slightly from that of traditional lending. Factors like lending to peers and peer opinion that can carry significant credit information have no parallels in the existing literature. One of the most important sources of information about a firm's creditworthiness is its immediate partner firms, especially those with whom it engages in direct buying or selling activities. These partner firms can provide valuable insights into the financial health and performance of the subject firm.

This study blends the quantitative financial variable-based credit scoring criteria with peer opinion to enable a better credit screening mechanism. It uses the Subjective logic approach to obtain and process peer opinion and classifies credit risk using the Cumulative Belief degree (CBD) mechanism. The paper provides the following mechanisms for decentralized peer-to-peer SME lending:

- Credit screening mechanism using Credit limit and Credit risk.
- User score and rating of a borrower
- Credit risk and rating for individual credit requests

The rest of the paper is organized as follows: Section II reviews the relevant literature in the area and organizes them into subcategories to reflect the concepts of crowd opinion and reputation theory used in our framework. Section III describes the Credit screening process and its various parameters, including the user score and rating calculation. Section IV discusses the peer opinion gathering and processing mechanism for a credit request. Section V explains the credit risk and rating calculation. Section VI shows the framework's implementation over Ethereum Blockchain using Solidity, Remix IDE, and Ganache. The last section concludes the paper with a discussion on applicability, limitations, and further research directions.

II. Literature Review

Credit rating plays a critical role in evaluating borrowers and efficiently allocating credit based on their creditworthiness. However, the recent banking crisis shed light on the challenges faced by the traditional credit rating model, especially in assessing smaller borrowers [3]. The limited availability of data makes it difficult to gauge the creditworthiness of new and small business borrowers. This has resulted in a huge credit gap for SMEs. To address this issue, peer-to-peer markets have emerged as a promising alternative, demonstrating their potential to complement traditional lending markets, particularly for smaller borrowers. The exponential growth of online peer-to-peer lending marketplaces has opened opportunities to explore novel lending models that rely on the collective screening efforts of multiple peers. These market-based, non-hierarchical structures offer significant screening advantages, particularly in leveraging soft information.

Compared to traditional financial intermediaries, online P2P platforms have lowered the barrier to entry for both borrowers and lenders to partake in lending transactions and implemented more convenient procedures [7]. As a result, many academic literature articles have exploded in discussions of credit scoring frameworks for peer-to-peer lending. It is essential to note, however, that most of these platforms and frameworks are centralized and centered on consumer finance, where credit scoring criteria coalesce around the personal characteristics of borrowers. In microfinance, these approaches range from leveraging collective intelligence to relying on individual judgments through online peer-to-peer lending platforms.

A. Peer-to-Peer Credit Rating and Scoring Criteria

Peer-to-peer platforms utilize various credit scoring models, encompassing traditional, machine learning, and hybrid approaches that combine both methods [8]. The true ex-ante default probability relies on the borrower's attributes and specific loan characteristics, such as loan amount, terms, and other relevant elements [3]. Hence, the credit scoring models consider multiple factors in calculating credit scores, such as borrower and loan characteristics, social influence, borrower behavior, platform reputation, and network structure. This includes standard variables like repayment history, income, collateral, education level, and social network connections.

Numerous studies have investigated the impact of these factors on credit risk in peer-to-peer lending networks. Zhou et al. (2018) discovered that borrower and loan attributes like age, income, and education level significantly affected credit ratings, as did loan characteristics like amount, term, and purpose [9]. Social network structure has also been studied regarding its effect on credit ratings. Niu et al. (2019) find a significant correlation between social network information and loan default and conclude that social network information can significantly improve loan default prediction performance [10]. Additionally, big data and machine learning techniques have been leveraged to increase sophistication and improve the performance of credit rating methods. However, the centralized platforms-based credit ratings suffer from manipulation, which disadvantages small firms.

B. Peer and Crowd Opinion in Credit Rating

The concept that economic transactions are intertwined with social relationships has long been recognized in academic literature [11]. Many platforms are actively embracing and harnessing these effects. This trend underscores the significance of understanding the nuances of friendship relations in economic transactions. Liu et al. (2015) show that friendships influence economic decisions, acting as pipes, prisms, and relational herding signals [12]. As pipes, borrowers' friends are more inclined to offer loans than strangers.

If proximity enables access to soft information typically unavailable in traditional finance, then P2P lending could offer pricing and accessibility benefits to prospective borrowers. Traditional banking literature has extensively demonstrated that relationships and soft information are crucial in screening and mitigating moral hazards [13]. P2P lending takes advantage of the crowd's collective wisdom [14]. The fundamental concept behind crowdfunding is that individuals in the crowd may share connections through networks, expertise, or exposure to local economic risks.

Leveraging friendship networks for borrowing and lending activities sets online P2P lending apart from traditional lenders like banks. Liu et al. (2015) show that the number of friends a borrower has and the number of friends bidding on a loan increase the likelihood of successful funding, leading to reduced interest and ex-post-default rates [12].

C. Reputation Theory in Credit Rating

Reputation theory, first proposed by Kreps and Wilson (1982), assumes that a player's reputation reflects their historical records and characteristics [15]. In finance, reputation theory has proven crucial in addressing moral hazard problems and controlling default risk. Diamond (1989) was one of the pioneering researchers to utilize reputation theory in finance [16]. He demonstrated how reputation is a powerful constraint and incentive to control moral hazard problems.

In peer-to-peer lending, reputation mechanisms are crucial in assessing consumers' creditworthiness [17]. Such platforms impose a borrower's reputation based on their historical performance. Indicating that reputation is a significant factor in loan allocation and borrowers with superior past performance are likelier to obtain loans at lower interest rates. When creditworthiness information is scarce, lenders rely on the wisdom of the masses, but when more signals are available through the market, they rely on their judgment. When their creditworthiness is questioned, borrowers endeavor to maintain a positive reputation, and direct communication with lenders can correct any incorrect conclusions drawn from hard data [14].

III. The Credit Decision Process and Key Criteria

This section describes the credit decision process and the employed criteria. When an SME puts a credit request on the network, the model checks if the amount is within the borrower's credit limit. If so, the credit request is broadcasted to the network for peer approval. The borrower profile, including user score and rating based on borrowing, lending, and opinion history, is also attached with the credit request details to provide network members with a summary view of the borrower's credit profile. Peers with their knowledge about the borrower's creditworthiness then respond with a probability of ability on the borrower's part to repay the loan. Then the comprehensive credit attribute of the borrower is combined with peer opinion to calculate the credit risk and rating. The credit request is open for peer bidding if the credit risk is below the network's threshold. This credit decision process is outlined below in Fig. 1.

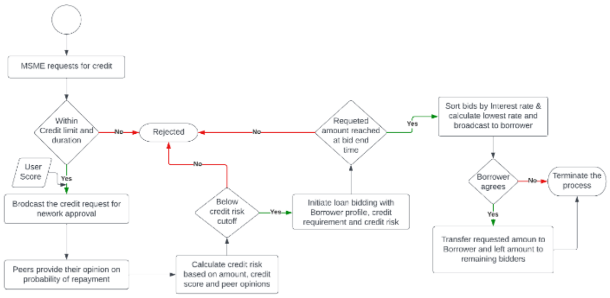

Fig. 1. Credit Screening and Risk Scoring Process

Key Credit parameters used in the credit decision process are user score and rating (based on the historical financial record), credit Limit of the borrower, and credit risk and rating for individual credit requests. The section below discusses how each one of these parameters is calculated.

A. *User Score and User Rating*

Almost all formal lending mechanisms employ a credit score factoring various quantitative and qualitative economic variables. FICO is the most widely used credit scoring method that Fair Isaac Corporation developed worldwide. The most important criterion determining credit score is a borrower's credit history regarding repayments, delays, and defaults. In our model, SMEs can perform three tasks on the network: Borrow, Invest, and provide opinions on peer loan requests. Hence, the user score is made up of three scores, namely Borrowing Score, Lending Score, and Opinion Accuracy Score. We list the formulas to calculate the above three scores in (1), (2) and (3). The normalization function is formulated using the Hyperbolic Tangent function [18].

$$\textit{Borrowing Score (BS)} = \frac{1}{1+e^{-0.1\left(\frac{TRA}{AI}-\frac{TDA}{AI}\right)}} \qquad (1)$$

$$\textit{Lending Score (LS)} = \frac{1}{1+e^{-0.1\left(\frac{LA}{AI}-\frac{TC}{AI}\right)}} \qquad (2)$$

$$\textit{Opinion Accuracy score (OAS)} = \frac{1}{1+e^{-0.1(NCA-NIA)}} \qquad (3)$$

Where TRA is the total repayment amount on previous loans, TDA is the total default amount, LA is the total lending amount by the user, TC is the total credit taken, NCA is the number of correct opinions on peer loans, NIA is the number of incorrect opinions, and AI is the annual income of the user. The variables in the first and second equations have been divided by annual income to negate its effect on the user score and rating, or else the bigger firms will have higher scores and ratings.

To consolidate individual scores into a user score and rating, we need to rank these scores according to their relative significance. The determination of weights for prioritization is a subjective task [19]. When we do not have available data to determine criterion weight objectively, taking expert opinion is a preferred choice [20]. Pairwise Comparison is the most efficient method among Rating, Point Allocation, Ratio, Ranking, Pairwise Comparison, and Trade-off [21].

We obtained expert opinion through pairwise comparison, and table I depicts the pairwise comparison matrix based on the aggregated pairwise comparisons of the expert group for the three criteria. To determine the weights, the geometric means of each row were first computed, followed by the normalization procedure to derive the weights for the primary criteria.

TABLE I. USER SCORE CRITERIA WEIGHTS USING PAIRWISE COMPARISON

	Borrowing Score	**Lending Score**	**Opinion Accuracy Score**	**Geo Mean**	**Normalized Weights**
Borrowing Score	1.00	4.84	6.97	3.23	0.74
Lending Score	0.21	1.00	1.26	0.64	0.15
Opinion Accuracy Score	0.14	0.79	1.00	0.48	0.11
			Total	4.35	1

Based on these weights, the user score can be calculated as in (4):

$$\textit{User Score}(S) = 0.74 * (BS) + 0.15 * (LS) + 0.11 * (OAS) \qquad (4)$$

User rating follows from the user score. User rating R= {1,2…5} corresponds to User Score S= {0-0.2, 0.2-0.4, 0.4-0.6, 0.6-0.8, 0.8-1} respectively. A higher rating of a user reflects that the user has shown more financial discipline in the network.

B. *Credit Limit*

A credit limit defines how much credit a business should have given its income, revenue, or asset levels. It helps avoid the overexposure of a firm to debt, thus preventing its default. We begin with a low initial credit limit to prevent the likelihood of default and prevent moral hazard before the borrower builds their credit history and reputation in the network. We list the formulae to calculate the Credit limit Ratio and amount below in (4) and (5).

$$\textit{Credit Limit Ratio}\ (CLR) = 0.1 + (\textit{User score} - 0.5) \qquad (5)$$

$$\textit{Credit Limit}\ (CL) = (CLR * \textit{Income}) - \textit{outstanding credit} + \textit{outstanding investment} \qquad (6)$$

C. *Credit Risk and Credit Rating*

Loan and borrower attributes have been widely used in credit risk assessment models. Incorporating peer opinion into credit risk models for peer-to-peer lending can provide valuable information about borrowers' creditworthiness. It can also provide insights into the social and financial behavior of borrowers. Peer opinions can complement the traditional credit scoring models when used with other factors [22].

In our Credit risk model, we combine the credit request attributes and user score with peer opinions to calculate the overall credit risk. The model uses Cumulative belief degree to calculate credit risk using the following factors:

- Borrowing Score

- Lending Score
- Opinion Accuracy Score
- Loan size (Credit amount requested/ Credit limit of the borrower)
- Peer opinion Score

IV. Peer Opinion Score using Subjective Logic

Subjective logic deals with subjective beliefs about the world and uses "opinion" to represent such beliefs [23]. It is ideally adapted for modeling and analyzing uncertain situations and unreliable data sources. For instance, subjective logic finds applications in modeling and analyzing trust and Bayesian networks. The different categories are represented by symbols *b, d,* and *u* as *(7),* and they satisfy certain properties:

$$b + d + u = 1 \, ; b, d, u \in [0,1] \tag{7}$$

Where b represents the degree of trust or belief, d represents the degree of untrust or disbelief, and u represents its uncertainty [24].When the credit request by a borrower is broadcasted for peer approval in the network, the peers provide a probabilistic value about the likelihood of repayment by the borrower. This provides us the value for trust(belief) and distrust(disbelief) about the borrowing peer. The uncertainty is calculated by looking at the accuracy of previous opinions of the approver.

Peers who provide opinions about others' creditworthiness are most likely to provide a true opinion because their user score depends on their opinion accuracy. Further, to make this more accurate, these opinions are weighted by the volume of financial interaction between them so that those with more skin in the game get a higher say. An observation of significant importance is that the source of soft information in this context is the pool of investors. Individual investors with connections to prospective borrowers possess proximate knowledge and information within this pool. The peer opinion score on a credit request is calculated as below using subjective logic methods following [24] and [25]. First, we obtain the individual opinions from peers on a credit request as (8):

$$\begin{gathered} \omega_{i\to j} \coloneqq \{b_{i\to j}, d_{i\to j}, u_{i\to j}\} \\ b_{i\to j}, d_{i\to j}, u_{i\to j} \in [0,1] \\ b_{i\to j} + d_{i\to j} + u_{i\to j} = 1 \end{gathered}$$

where, $\omega_{i\to j}$ is the opinion vector from peer i to borrower j and $b_{i\to j}, d_{i\to j}, u_{i\to j}$ represent belief, disbelief, and uncertainty, respectively. According to the subjective logic model (9):

$$\begin{cases} b_{i\to j} = \left(1 - u_{i\to j}\right) \dfrac{\alpha_i}{\alpha_i + \beta_i} \\ d_{i\to j} = \left(1 - u_{i\to j}\right) \dfrac{\beta_i}{\alpha_i + \beta_i} \\ u_{i\to j} = 1 - s_{i\to j} \end{cases} \tag{9}$$

Where α_i is the peer opinion of repayment likelihood, β_i is the default likelihood and $s_{i\to j}$ is the certainty of the opinion by the peer calculated by his accuracy of historical approvals as (10),

$$s_{i\to j} = \frac{Number\ of\ Correct\ Opinions}{Number\ of\ Total\ Opinions} \tag{10}$$

For example, if peer A opines that B has a 90% probability of repaying the requested credit, α_i becomes 0.9, and β_i becomes 0.1. The uncertainty here comes from the accuracy of the recommender's historical opinions. If he has ten opinions in the past on peer loans and 7 of those opinions have turned out to be correct, $s_{i\to j}$ becomes 0.7 and $u_{i\to j}$ 0.3. All the peer opinions obtained are combined using weights proportional to their financial interaction volume with the borrower. After being weighted, the recommended opinions are combined into a common opinion in the form of $\omega_{x\to j}^{rec} \coloneqq \{b_{x\to j}^{rec}, d_{x\to j}^{rec}, u_{x\to j}^{rec}\}$ which is called the recommended opinion:

$$\begin{cases} b_{x\to j}^{rec} = \dfrac{1}{\sum_{x\in X}} \displaystyle\sum_{x\in X} \delta_{x\to j} b_{x\to j}, \\ d_{x\to j}^{rec} = \dfrac{1}{\sum_{x\in X} \delta_{x\to j}} \displaystyle\sum_{x\in X} \delta_{x\to j} d_{x\to j}, \\ u_{x\to j}^{rec} = \dfrac{1}{\sum_{x\in X} \delta_{x\to j}} \displaystyle\sum_{x\in X} \delta_{x\to j} u_{x\to j} \end{cases} \tag{11}$$

Where $\delta_{x\to j}$ represents the financial interaction volume calculated by total lending and borrowing between x and j, and x $\in$ X is a set of peers who gave their opinions on borrower j's credit request. The peer opinion score(P) on a credit request is then calculated as (12):

$$\text{P} = b_{x\to j}^{rec} * u_{x\to j}^{rec} \tag{12}$$

V. Credit Risk and Credit Rating Calculation Using Cumulative Belief Degree

In section 3, we calculated the credit limit based on a borrower's income and user score. Here, we build on them incrementally to estimate the risk of a credit request submitted to the network by an SME following the method used by [19]. Fig. 2 below provides the criteria being used to calculate the credit risk.

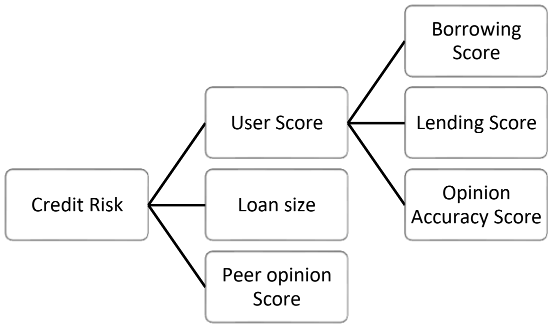

Fig. 2. Criteria for credit risk

The criteria mentioned in Fig. 2 for calculating credit risk have already been defined in III(A). We list and explain the credit risk calculation steps below.

A. Criteria weights

We have seen how to calculate different scores needed to calculate credit risk. To aggregate those scores, it is required to prioritize them to reflect their relative importance. This is done using the pairwise comparison of criteria by experts and aggregating them. We explained this process while determining the weights in user score calculation. The same process is employed here. Table II provides the weight of the three main criteria of the credit risk calculation.

TABLE II. MAIN CRITERIA WEIGHTS USING PAIRWISE-COMPARISON

	User Score	Loan Size	Peer Opinion Score	Geo Mean	Normalized Weights
User Score	1.00	7.24	7.32	3.76	0.78
Loan Size	0.14	1.00	0.48	0.41	0.08
Peer Opinion Score	0.14	2.08	1.00	0.66	0.14
			Total	4.82	1.00

We already calculated the weights of the subcriteria in section three. The final weights are calculated by multiplying the criteria weight with the subcriteria weights. It is shown in table III, which provides us with the final weights for parameters used in credit risk and rating calculation.

TABLE III. FINAL WEIGHTS FOR CREDIT RISK CALCULATION

Criteria	Subcriteria	Criteria weights	Subcriteria weights	Final Weights
User Score		0.78		
	Borrowing Score		0.74	0.57
	Lending Score		0.15	0.12
	Opinion Accuracy Score		0.11	0.09
Loan Size		0.08		0.08
Peer Opinion Score		0.14		0.14
			Total	1.000

B. Criteria scores

The criteria score is obtained using the formulas discussed in sections III and IV. To illustrate the process of Credit risk calculation, we fill the scores in table IV with dummy numbers representing various criteria scores. We have taken the same values just above average for all the variables to visualize whether the credit risk and rating calculated at the end of this section come to be around the average mark.

TABLE IV. CRITERIA SCORES

Criteria	Borrowing Score	Lending Score	Opinion Accuracy Score	Loan Size	Peer opinion Score
Name	k1	k2	k3	k4	k5
Score	0.6	0.6	0.6	0.6	0.6

C. Representing Data with cumulative belief degrees

To transform the scores using Cumulative Belief Degrees (CBDs), we define a linguistic term set comprising five terms: S = {s}, i.e. (0,1,...,4) wherein the credit ratings are mapped to linguistic terms as: S_0 :E, S_1: D, S_2: C, S_3: B, S_4: A.

1) Defining transformation parameters

To analyze the scores, we transform the criteria scores into belief degrees on linguistic term sets. This is done using triangular fuzzy numbers defined for each criterion and linguistic terms. We define a fuzzy triangular number with three parameters for each criterion to represent the most preferred (x^*) and least preferred (x^-) scores based on conventional linguistic hierarchical structures.

The triangular fuzzy number representation of a linguistic term i is (a^L, a^C, a^R), where "L" and "R" stand for the left and right supports, respectively, and "C" represents the central value. Since there are five distinct linguistic concepts, it is necessary to formulate five distinct fuzzy numbers. For benefit criteria (where a larger attribute value indicates a greater preference), the triangular fuzzy numbers are defined as (13):

$$\begin{aligned}
&\text{For } s_0; (a_0^L, a_0^C, a_0^R) = \left(x_k^-, x_k^-, \tfrac{x_k^*-x_k^-}{4}\right),\\
&\text{For } s_1; (a_1^L, a_1^C, a_1^R) = \left(x_k^-, \tfrac{x_k^*-x_k^-}{4}, \tfrac{x_k^*-x_k^-}{2}\right),\\
&\text{For } s_2; (a_2^L, a_2^C, a_2^R) = \left(\tfrac{x_k^*-x_k^-}{4}, \tfrac{x_k^*-x_k^-}{2}, \tfrac{3(x_k^*-x_k^-)}{4}\right),\\
&\text{For } s_3; (a_3^L, a_3^C, a_3^R) = \left(\tfrac{x_k^*-x_k^-}{2}, \tfrac{3(x_k^*-x_k^-)}{4}, x_k^*\right),\\
&\text{For } s_4; (a_4^L, a_4^C, a_4^R) = \left(\tfrac{3(x_k^*-x_k^-)}{4}, x_k^*, x_k^*\right).
\end{aligned} \quad (13)$$

For the cost criteria (the greater the attribute value, the lesser its preference), the triangular fuzzy numbers are defined (14):

$$\begin{aligned}
&\text{For } s_0; (a_0^L, a_0^C, a_0^R) = \left(\tfrac{3(x_k^--x_k^*)}{4}, x_k^-, x_k^-\right),\\
&\text{For } s_1; (a_1^L, a_1^C, a_1^R) = \left(\tfrac{x_k^--x_k^*}{2}, \tfrac{3(x_k^--x_k^*)}{4}, x_k^-\right),\\
&\text{For } s_2; (a_2^L, a_2^C, a_2^R) = \left(\tfrac{x_k^--x_k^*}{4}, \tfrac{x_k^--x_k^*}{2}, \tfrac{3(x_k^--x_k^*)}{4}\right),\\
&\text{For } s_3; (a_3^L, a_3^C, a_3^R) = \left(x_k^*, \tfrac{x_k^--x_k^*}{4}, \tfrac{x_k^--x_k^*}{2}\right),\\
&\text{For } s_4; (a_4^L, a_4^C, a_4^R) = \left(x_k^*, x_k^*, \tfrac{x_k^--x_k^*}{4}\right).
\end{aligned} \quad (14)$$

Since all the Credit rating and risk criteria in our model range between 0 and 1, the transformation parameters for benefit & cost criteria are calculated using the formulae above and presented in table V. In our model, only loan size is a cost criterion, as the greater its value, the less its preference (because of higher risk). The rest are benefit criteria as the greater their value, the more they are preferable (lower risk).

TABLE V. TRANSFORMATION PARAMETERS FOR BENEFIT AND COST CRITERIA

Variables	Benefit	Cost
X*	1	0
X¯	0	1
S0	(0, 0, 0.25)	(0.75, 1, 1)
S1	(0, 0.25, 0.5)	(0.5, 0.75, 1)
S2	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75)
S3	(0.5, 0.75, 1)	(0, 0.25, 0.5)
S4	(0.75, 1, 1)	(0, 0, 0.25)

2) Transformation of scores to belief degrees

Belief degrees are essential representations of decision-makers expectations and encompass diverse measurement scales. Each score must be transformed into belief degrees to effectively handle scores within separated risk classes. These belief degrees form the belief structure, representing the general belief about a specific criterion, with each belief degree being an element of this structure.

We transform the scores into belief degrees using the transformation parameters listed in table V. The criterion k for credit request (x) is transformed into belief degrees(β_{ks}) based on the membership functions associated with linguistic terms (μ_{sk}) as follows [26]:

For a given x_k

If $x_k^- \leq x_k \leq x_k^*$ (or $x_k^* \leq x_k \leq x_k^-$ for cost criteria)

$$\beta_{ki} = \mu_{si}(x_k),\ \forall i \qquad (15)$$

If $x_k < x_k^-$(or $x_k > x_k^-$ for cost criteria)

$$\beta_{k0} = 1, \beta_{k1} = \beta_{k2} = \beta_{k3} = \beta_{k4} = 0, \qquad (16)$$

If $x_k > x_k^*$ (or $x_k < x_k^*$ for cost criteria)

$$\beta_{k4} = 1, \beta_{k0} = \beta_{k1} = \beta_{k2} = \beta_{k3} = 0. \qquad (17)$$

When a criterion's score falls between the most and least preferable values, the degree of belief is determined using (15). Nonetheless, suppose a score in a benefit criterion is lower than the least preferred value (or higher than the least preferred value in a cost criterion). In that case, it indicates an extremely unfavorable situation that belongs to the worst rating category. Therefore, in (16), we attribute a degree of belief of 1 to the S_0 category and 0 to the other categories. Conversely, if a score in a benefit criterion is higher than the most preferable value, it indicates a very favorable situation. It should unquestionably be assigned to the highest rating category. In (17), we attribute a degree of belief of 1 to the S_4 category and 0 to the other categories.

Fig. 3 depicts the calculation of membership degrees for the "Borrowing score" criterion with a value of 0.6. Here α and θ represent the degree of membership of the provided score in the sets S_2 and S_3, respectively. In the CBD strategy, these membership levels serve as belief levels. In this instance, α = 0.6 represents the degree of belief associated with the S_2 credit rating, while θ = 0.4 corresponds to the degree of belief associated with the S_3 credit rating. There is no intersection between the score 0.6 and the sets representing S_0, S_1, and S_4 credit ratings, so the belief degrees of the score 0.6 in these sets are all equal to zero.

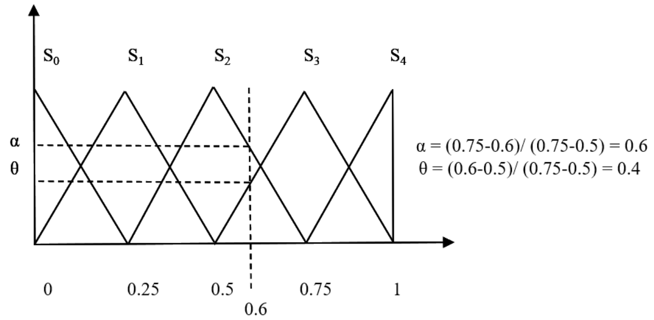

Fig. 3. Belief Degree Calculation example

β_{20}= $\mu_{S0}(0.6)$ = 0 (there is no intersection of S_0 and 0.6 line)
β_{21}= $\mu_{S1}(0.6)$ = 0 (there is no intersection of S_1 and 0.6 line)
β_{22}= $\mu_{S2}(0.6)$ = 0.6 (α in Figure 3)
β_{23}= $\mu_{S3}(0.6)$ = 0.4 (θ in Figure 3)
β_{24}= $\mu_{S4}(0.6)$ = 0 (there is no intersection of S_4 and 0.6 line)

Accordingly, we calculate the belief degree scores for all the criteria and fill in table VI below. The belief degree of all the benefit criteria is the same in the example because we have considered the same scores in this case for simplicity. But we can see that for the same score of the cost criterion, the membership score belongs to a lower rating of s_1.

TABLE VI. BELIEF DEGREE SCORES FOR ALL CRITERIA

Variables	Type	Scores	Belief Degree				
			S0	S1	S2	S3	S4
k1	Benefit	0.6	0	0	0.6	0.4	0
k2	Benefit	0.6	0	0	0.6	0.4	0
k3	Benefit	0.6	0	0	0.6	0.4	0
k4	Cost	0.6	0	0.4	0.6	0	0
k5	Benefit	0.6	0	0	0.6	0.4	0

3) Calculation of cumulative belief degrees

CBD structures are utilized to depict the credit rating of a credit request as a distribution among various credit risk classes. At the level of a particular linguistic term, the CBD is defined as the aggregated belief degrees of terms with greater or equal belief degrees. CBDs are calculated using (18) based on the belief degrees computed for each criterion in the preceding section.

$$C(I_k) = \{(\gamma_{ki}, S_i), i = 0, \dots, m\}, \forall k \;\; \gamma_{ki} = \textstyle\sum_{p=i}^{m} \beta_i \qquad (18)$$

where γ_{ki} is the CBD related to criterion k at threshold level i. For example, {(0.6, s_2), (0.4, s_3)} belief structure can be transformed to the cumulative belief structure of {(1, s_0), (1, s_1), (1, s_2), (0.4, s_3), (0, s_4)}. Similarly, we calculate the CBD for each criterion and present it in table VII.

TABLE VII. CUMULATIVE BELIEF DEGREE SCORES FOR ALL CRITERIA

Variables	Type	Scores	Cumulative Belief Degree				
			S_0	S_1	S_2	S_3	S_4
k_1	Benefit	0.6	1	1	1	0.4	0
k_2	Benefit	0.6	1	1	1	0.4	0
k_3	Benefit	0.6	1	1	1	0.4	0
k_4	Cost	0.6	1	1	0.6	0	0
k_5	Benefit	0.6	1	1	1	0.4	0

D. Specifying Credit Ratings

1) Aggregation of cumulative belief degrees

The aggregation of belief degree scores is achieved at a specific linguistic term level by multiplying the weights by the cumulative belief degree scores at that level which can be seen in (19). This process allows us to combine the credit rating information from different criteria while accounting for their relative importance.

$$C(I) = \{(\gamma_i, s_i), i = 0, \dots, 4\}, \text{ where } \gamma_i = \sum_k w_k \gamma_{ki} \quad (19)$$

The aggregated scores calculated using (19) are presented in table VIII. The CBDs for each linguistic term notated by γ_i represent the membership degree/general belief degree of the credit request having a credit rating s_i or higher.

TABLE VIII. AGGREGATED BELIEF DEGREE SCORES

Variables	Scores	Weight	Belief Degree				
			S0	S1	S2	S3	S4
k1	0.6	0.57	1	1	1	0.4	0
k2	0.6	0.12	1	1	1	0.4	0
k3	0.6	0.09	1	1	1	0.4	0
k4	0.6	0.08	1	1	0.6	0	0
k5	0.6	0.14	1	1	1	0.4	0
		γ_i	1	1	0.97	.37	0

2) Credit Risk and Credit Rating for a credit request

We can use the aggregated belief degree scores to evaluate the credit risk and rating. We define risk for each belief class and derive the individual belief scores for each of these classes which is shown in table IX.

TABLE IX. AGGREGATED BELIEF DEGREE SCORES

Belief	S0	S1	S2	S3	S4
Risk	0.8 - 1.0	0.6 - 0.8	0.4 – 0.6	0.2 - 0.4	0 – 0.2
Average Risk (AR)	0.9	0.7	0.5	0.3	0.1
γ_i	1	1	0.97	.37	0
β_i	0	0.03	0.60	0.37	0

Based on these, we calculate credit risk R as (20):

$$R = \sum_{si} AR_i * \beta_i \quad (20)$$

= 0*0.9 + 0.03*0.7 + 0.60*0.5 + 0.37*0.3 + 0*0.1 =0.43

So, the risk on the credit request of the user, in this case, turns out to be 43 percent, which is in line with the fact that we filled scores with just above average scores, and hence the risk is just a little below the average mark. Credit rating follows from the credit risk. Credit rating R= {A, B, …, E} corresponds to credit risk S= {0-0.2, 0.2-0.4, 0.4-0.6, 0.6-0.8, 0.8-1} respectively. A higher credit rating reflects lower credit risk on a credit request. So, in the above example, the credit rating is C.

VI. A Proof-of-Concept Implementation

A. *Credit rating Contract Execution*

We used Ethereum Blockchain, the most popular for creating smart contracts and developing applications to implement the above framework. We write the code using Solidity and use Remix IDE as a compiler. Ganache is used to simulate the local Ethereum Blockchain. Fig. 4 below shows the proof of concept for the credit scoring mechanism.

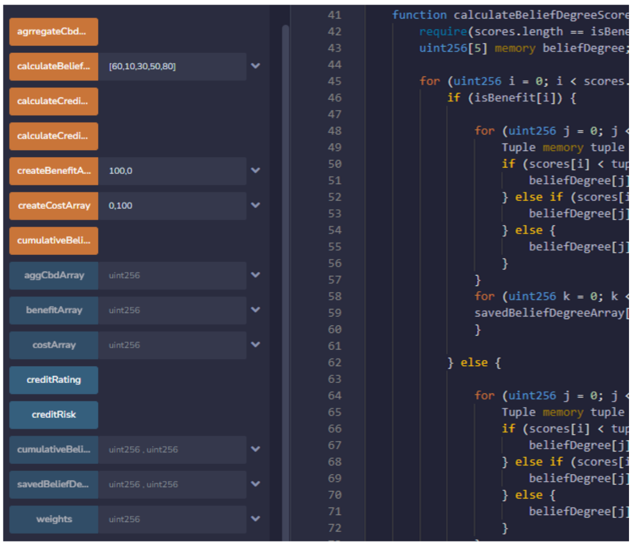

Fig. 4. Proof-of-concept implementation for the proposed credit risk and rating framework

The code was deployed on the local Ethereum Blockchain simulated using Ganache. The execution parameters for the same are shown in table X.

TABLE X. EXECUTION OF CREDIT RATING SMART CONTRACT

transaction hash	true Transaction mined and execution succeed
block hash	0x24757ac5282638b8311794de8b5b64238e9ee469043001e724c2120b54699d7f
block number	0x4c380675acdf4ad7ce18be58140fd1bb808bcf458a4439df904be919770fb63d
contract address	1
from	0xd9145CCE52D386f254917e481eB44e9943F39138
to	0x5B38Da6a701c568545dCfcB03FcB875f56beddC4
gas	creditrating.(constructor)
transaction cost	2163857 gas
execution cost	1882126 gas
input	1704110 gas
	0x608...20033

B. *Cost and Throughput analysis*

For scalability experiments, we have considered the setup and restrictions in terms of gas limits (approx. 15000000 per block) and mining periodicity (i.e., 15 seconds) of the public Ethereum main network [27]. The combined cost of all the functions in calculating a single credit rating comes out to be 1240977 gases. Dividing the gas limit per block of the Ethereum blockchain with this cost produces a throughput of approximately nine credit ratings per block, as shown in table XII.

TABLE XI. COST AND THROUGHPUT

Gas Limit Per Block (Ethereum)		**12000000**
Credit Rating	**Functions**	
	Belief Degree	420495

	Cumulative Belief Degree	532201
	Aggregate CBD	207109
	Credit Risk	81172
Gas Cost/Credit Rating	**Total**	1240977
Credit Rating/ Block		9

To visualize the number of credit ratings generated using this framework, we plotted it against time (in minutes) in Fig. 5. It can also be seen that approx. 36 Credit ratings can be generated per minute, and in one hour, it can carry out 2160 such calculations.

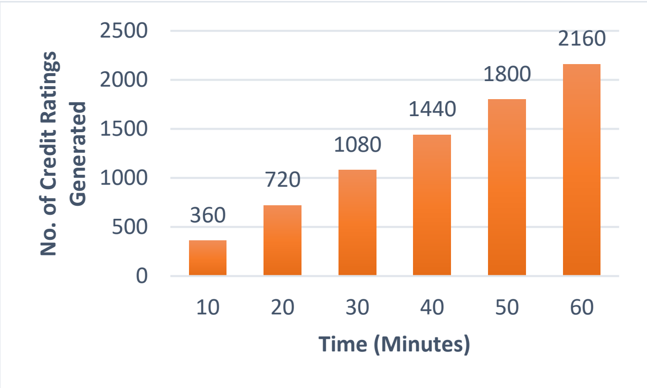

Fig. 5. Credit Rating Processing capacity

VII. CONCLUSION

In this paper, we have created and demonstrated a decentralized Blockchain-based credit screening and scoring framework for SME peer-to-peer lending networks. It includes mechanisms to calculate user scores and ratings of SMEs in the network, their credit limit, and the risk and rating of credit requests they submit. We have incorporated peer opinion into credit risk calculation as peers have information about the creditworthiness of businesses. The peer opinion was obtained and quantified using subjective logic, and the cumulative belief degree method was employed to determine the credit risk and rating. We also implemented the framework on Ethereum by writing the credit rating smart contract in Solidity and employing it using Remix IDE and Ganache.

By creating mechanisms to calculate user scores, SME ratings, credit limits, and credit request risk evaluations, we aimed to address the challenges associated with traditional centralized credit scoring systems. By incorporating peer opinions, we harnessed the collective wisdom of the network participants, which further enhances the accuracy and reliability of credit risk assessments. The utilization of Ethereum and the development of a credit-rating smart contract written in Solidity demonstrated the practical implementation of our proposed framework.

The implications of our research have the potential to impact the SME lending landscape positively. Our framework can significantly impact the SME lending landscape by providing more transparent, trustworthy, and inclusive credit screening and scoring mechanisms. By reducing the dependence on centralized credit agencies, we empower SMEs with fairer access to capital, fostering economic growth and entrepreneurship.

However, we acknowledge that our research has some limitations. It's just a starting point for decentralized credit scoring, and each of the steps in the framework can be improved to enable better screening of SMEs for credit. While we incorporated peer opinions to enhance credit risk calculations, further research could explore ways to incentivize active and accurate participation from peers in the lending network. Also, there is a broad scope to add other SME and loan attributes to make the credit risk calculation more comprehensive. The availability of real data on the parameters used in the framework will help find more accurate weights and add more precision to the credit risk calculation.

Our research contributes to the growing knowledge of decentralized finance and Blockchain applications. By proposing and implementing a novel credit screening and scoring framework for SME peer-to-peer lending, we aspire to stimulate discussions and inspire future innovations in fintech and decentralized financial systems. With continuous development and refinement, our framework can foster financial inclusion for SMEs, unlocking new avenues for economic prosperity and growth.

REFERENCES

[1] Yoshino, N., & Taghizadeh Hesary, F. (2016). Major Challenges Facing Small and Medium-Sized Enterprises in Asia and Solutions for Mitigating Them. ADBI Working Paper 564. http://dx.doi.org/10.2139/ssrn.2766242

[2] Osano, H. M., & Languitone, H. (2016). Factors influencing access to finance by SMEs in Mozambique: case of SMEs in Maputo central business district. Journal of Innovation and Entrepreneurship, 5(13). https://doi.org/10.1186/s13731-016-0041-0

[3] Iyer, R., Khwaja, A., Luttmer, E., & Shue, K. (2009). Screening in New Credit Markets: Can Individual Lenders Infer Borrower Creditworthiness in Peer-to-Peer Lending? Harvard University, John F. Kennedy School of Government, Working Paper Series. https://doi.org/10.2139/ssrn.1570115

[4] Sha, Y. (2022). Rating manipulation and creditworthiness for platform economy: Evidence from peer-to-peer lending. International Review of Financial Analysis, 84, 102393. ISSN 1057-5219. https://doi.org/10.1016/j.irfa.2022.102393.

[5] Baber, H. (2020). Blockchain-Based Crowdfunding. In R. Righi, A. Alberti, & M. Singh (Eds.), Blockchain Technology for Industry 4.0. Blockchain Technologies. Springer, Singapore. https://doi.org/10.1007/978-981-15-1137-0_6

[6] Roman, D., & Stefano, G. (2016). Towards a Reference Architecture for Trusted Data Marketplaces: The Credit Scoring Perspective. In 2016 2nd International Conference on Open and Big Data (OBD), Vienna, Austria (pp. 95-101). IEEE. https://doi.org/10.1109/OBD.2016.21

[7] Pope, D., & Sydnor, J. (2008). What's in a Picture? Evidence of Discrimination from Prosper.com. Monetary Economics eJournal, 46. https://doi.org/10.1353/jhr.2011.0025

[8] Gao, G., Caglayan, M., Li, Y., & Talavera, O. (2020). Expert imitation in P2P markets. The Manchester School, 89. https://doi.org/10.1111/manc.12321

[9] Zhou, G., Zhang, Y., & Luo, S. (2018). P2P Network Lending, Loss Given Default and Credit Risks. Sustainability, 10(4), 1010. https://doi.org/10.3390/su10041010

[10] Niu, B., Ren, J., & Li, X. (2019). Credit Scoring Using Machine Learning by Combing Social Network Information: Evidence from Peer-to-Peer Lending. Information, 10(12), 397. https://doi.org/10.3390/info10120397

[11] Granovetter, M. (1985). Economic Action and Social Structure: The Problem of Embeddedness. American Journal of Sociology, 91(3), 481–510. http://www.jstor.org/stable/2780199

[12] Liu, D., Brass, D., Lu, Y., & Chen, D. (2015). Friendships in Online Peer-to-Peer Lending: Pipes, Prisms, and Relational Herding. MIS Quarterly, 39(3), 729-742. http://dx.doi.org/10.2139/ssrn.2251155

[13] Petersen, M., & Rajan, R. (1994). The Benefits of Lending Relationships: Evidence from Small Business Data. Journal of Finance, 49, 3-37. https://doi.org/10.1111/j.1540-6261.1994.tb04418.x

[14] Yum, H., Lee, B., & Chae, M. (2012). From the Wisdom of Crowds to My Own Judgment in Microfinance Through Online Peer-to-Peer Lending Platforms. Electronic Commerce Research and Applications, 11, 469–483. https://doi.org/10.1016/j.elerap.2012.05.003

[15] Kreps, D., & Wilson, R. (1982). Reputation and Imperfect Information. Journal of Economic Theory, 27, 253-279. https://doi.org/10.1016/0022-0531(82)90030-8

[16] Diamond, D. W. (1989). Reputation Acquisition in Debt Markets. Journal of Political Economy, 97(4), 828–862. http://www.jstor.org/stable/1832193

[17] Guo, Y., Jiang, S., Zhou, W., et al. (2021). A predictive indicator using lender composition for loan evaluation in P2P lending. Financial Innovation, 7(49). https://doi.org/10.1186/s40854-021-00261-1

[18] Xiao, F., Honma, Y., & Kono, T. (2005). A simple algebraic interface capturing scheme using hyperbolic tangent function. International Journal for Numerical Methods in Fluids, 48, 1023-1040. https://doi.org/10.1002/fld.975.

[19] Gül, S., Kabak, O., & Topcu, I. (2018). A multiple criteria credit rating approach utilizing social media data. Data & Knowledge Engineering, 116. https://doi.org/10.1016/j.datak.2018.05.005.

[20] Yurdakul, M., & Ic, Y. (2004). AHP approach in the credit evaluation of the manufacturing firms in Turkey. International Journal of Production Economics, 88, 269-289. https://doi.org/10.1016/S0925-5273(03)00189-0.

[21] Başar, A., Kabak, O., & Topcu, I. (2016). A Decision Support Methodology For Locating Bank Branches: A Case Study in Turkey. International Journal of Information Technology & Decision Making, 16. https://doi.org/10.1142/S0219622016500462.

[22] Freedman, S., & Jin, G. Z. (2017). The Information Value of Online Social Networks: Lessons from Peer-to-Peer Lending. International Journal of Industrial Organization, 51, 185-222.

[23] Jøsang, A. (2001). A Logic for Uncertain Probabilities. International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 9. https://doi.org/10.1142/S0218488501000831.

[24] Liu, Y., Li, K., Jin, Y., Zhang, Y., & Qu, W. (2009). A novel reputation computation model based on subjective logic for mobile ad hoc networks. Future Generation Computer Systems, 27, 547-554. https://doi.org/10.1016/j.future.2010.03.006.

[25] Kang, J., Xiong, Z., Niyato, D., Ye, D., Kim, D. I., & Zhao, J. (2019). Toward Secure Blockchain-Enabled Internet of Vehicles: Optimizing Consensus Management Using Reputation and Contract Theory. IEEE Transactions on Vehicular Technology, PP, 1-1. https://doi.org/10.1109/TVT.2019.2894944.

[26] Kabak, O., & Ruan, D. (2011). A Cumulative Belief Degree-Based Approach for Missing Values in Nuclear Safeguards Evaluation. IEEE Transactions on Knowledge and Data Engineering, 23, 1441-1454. https://doi.org/10.1109/TKDE.2010.60.

[27] [14] Antal, C., Cioara, T., Antal, M., & Anghel, I. (2021). Blockchain Platform For COVID-19 Vaccine Supply Management. IEEE Open Journal of the Communications Society, 1-1. https://doi.org/10.1109/OJCS.2021.3067450