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A Systematic Literature Review

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The elements of the Peer-to-peer (P2P) lending system

A Systematic Literature Review

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ABSTRACT

Peer-to-peer (P2P) lending systems have gained governments' attention to create an inclusive society, but establishing such systems remain challenging. Specifically, the elements making up such a system are not known. This research aims to understand the main elements of P2P lending systems and their interconnections. For this, we conducted a Systematic Literature Review to investigate the elements that build the complex arrangement of the P2P lending system. Our review identified five categories of elements that build an integral part of the P2P lending system: Data and Processing, Business, Organizational, Policy and Governance, and Culture. Although technical aspects have gained much attention, social aspects need to be considered carefully. We conclude that P2P lending systems are context-dependent. Moreover, the interaction and the combination of each element influence the whole design of the system. These elements can assist the government in designing a socially accepted P2P lending system that contributes to an inclusive society.

CCS CONCEPTS

• **Social and professional topics** → Professional topics; Computing and business; Socio-technical systems.

KEYWORDS

P2P lending system, Credit Scoring, Inclusive society, Financial inclusion

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1 INTRODUCTION

Traditionally, banks lend money to companies and individuals by implementing a credit scoring system to assess the creditworthiness of the customers. The need for decision support for analyzing banking customers' credit risk has emerged since the 1970s to replace the manual evaluation method (Do, Luong, Nguyen, & Mai, 2019). This has been the domain of large financial organizations often focused on profit maximization. Recently, there has been a shift to more distributed systems based on peer-to-peer interactions without large dominating parties. Governments want to direct this development process to ensure that the resulting systems will be accepted by society. In particular, ensuring the inclusion of those groups who had no or limited access to financial resources. This has given rise to the question of what such a system would look like, and in particular, what its elements are. This can help the governments determine their role in such a system and develop regulations and policies to steer these P2P systems in the desired societal direction.

Crook et al. (2007, p. 1448) defined credit scoring as "the assessment of the risk associated with lending to an organization or an individual". Credit scoring provides information about the likelihood of a lender defaulting in the future (Tsai, Hsub, & C.Yen, 2014), the clusters of good and bad borrowers (Hand & Henley, 1997; Baesens et al., 2003), and future unexpected behavior (Lessmann et al., 2015). The quantitative score of borrowers' credibility is calculated based on various individual attributes, including personal profiles and financial capabilities (Crook, Edelman, & Thomas, 2007). A proper design of the credit scoring model is crucial. A small fraction of misclassification of credit scoring significantly impacted profitability (Lessmann et al., 2015). Moreover, the inability to predict the failure might induce various social costs to the lenders (Tsai, 2014) and the continuity of the lending platforms (Ye, Dong, & Ma, 2018). Yet, there is limited insight into the elements of the design.

Credit scoring systems can be implemented in banking institutions and online Peer-to-Peer (P2P) lending platforms. The focus of this study is the credit scoring system in P2P lending. P2P lending platforms enable direct interaction between lenders and borrowers without financial intermediaries (Luo et al., 2011). Therefore, P2P lending platforms have an opportunity to reach customers that have not been served by traditional banking sectors (Kohardinata et al., 2020). From the government's point of view, P2P lending extends the coverage of credit circulations and improves the strength of economic resilience (Rizal, Maulina, & Kostini, 2018). P2P lending has become a prospective alternative in the disbursement of credit, even during the financial crisis (Gopal & Schnabl, 2020).

However, the P2P lending system is faced with the challenges of inclusiveness which is further complicated by different and even opposing stakeholders' interests. Inclusiveness in the financial context refers to the unbanked, low-income market, and people in remote areas' ability to access financial services including payment and lending facilities (Dev, 2006). The government encourages P2P lending companies to prioritize credit to the unbanked market and micro-small-medium enterprises (MSMEs). However, the indicators

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and measurements to assess the inclusiveness remain unclear. Moreover, the inclusiveness issue is strongly related to the stakeholders' complexity. P2P lending involves stakeholders varying from government authorities, IT companies, MSMEs, investors, and borrowers. Each stakeholder could have different concerns, therefore, conflict of interest among them is likely to occur. A narrow focus on profit and minimizing risks can exclude prospective entrepreneurs, which is not desirable for society. As such, governments have a high interest in creating an inclusive financial system.

Driven by this complexity, we argue that understanding the elements of the system is crucial to help us design the system properly and ensure that we have recognized the challenges attached to each element in a structured way. However, to the best of our knowledge, no single paper explicitly addresses the elements for designing a P2P lending credit scoring system. This study aims to identify elements involved in the end-to-end arrangement of the P2P lending system.

The remaining part of the paper is structured as follows. Section 2 provides the literature background; section 3 explains the methodology, research questions, and research protocol; section 4 presents the analysis, and section 5 provides conclusions.

2 LITERATURE BACKGROUND

Numerous research studied the technical aspects of credit scoring in general. Two notable Systematic Literature Reviews (SLR) have been conducted by Lessmann et al. (2015) and Dastile et al. (2021) to provide a comprehensive overview of credit scoring research. Both SLRs do not differentiate the implementation of credit scoring in the banking system or P2P lending platforms. Lessmann et al. (2015) have provided a comprehensive overview of recent credit scoring research development by comparing 41 machine learning algorithms implemented from 2003 to 2015. Their work aims to fill the gap of similar work conducted by Baesens et al. (2003) with four unique value-added: expanding the types of classifiers by including the ensemble algorithm, taking into consideration of the cost-sensitivity algorithm, highlighting the importance of various types of performance measurement, and introducing more proper statistical test. A systematic literature review performed by Dastile et al. (2021) focuses on the technical aspects of developed models. They investigate 76 recent models and provide various matrices of performance measurements.

Five SLRs have been conducted to study the socio-technical aspects of P2P lending. Ariza-Garzon et al. (2021) performed a bibliometric and systematic analysis to analyze the trend of P2P lending research in the last decade. They recognized that the US and China conducted more research on this topic than other countries. They discussed the rising in the use of machine learning to improve the performance of the models. Basha et al. (2021) conducted a content analysis of 198 studies and classified research topics from thematic and methodological perspectives. They discuss four types of determinants that influence funding success in P2P lending: financial, demographic, social, and macroeconomic. Suryono et al. (2019) implemented the Kitchenham SLR approach to identify the P2P lending industry challenges. Zhao et al. (2017) proposed a taxonomy of P2P lending platforms from three perspectives: application domain, reward type, and trading rule. Bachman et al. (2011) investigated hard and soft factors that determine the success of P2P lending loans by focusing on profit-oriented platforms and excluding charity-based platforms.

The recent SLRs focus on either the technical aspects of credit scoring or a variety of social issues in P2P lending. Moreover, we need to comprehensively identify the elements in the credit scoring system in P2P lending, both from technical and social aspects. The understanding of the elements is expected to assist the architects and policymakers in designing an inclusive system.

3 RESEARCH METHOD

The purpose of this study is to identify the elements making up P2P lending systems. We adopt SLR guidelines as explained in Kitchenham (2004) and Kitchenham & Charters (2007) with several considerations. First, the primary differentiating factor between SLR and the traditional narratives review is in the research protocol (Boell & Cecez-Kecmanovic, 2015). SLR aims to answer specific research questions using a particular protocol and apply predetermined selection criteria in advance. The research protocol helps the researcher to structure the search and the analysis using pre-defined steps and procedures with clear searching criteria and inclusion and exclusion criteria. Second, SLR allows analysis to be carried out in various settings and methods (Kitchenham, 2004). SLR is suitable to study research from multiple perspectives and investigate the elements that have never been addressed explicitly in previous studies. Third, unlike traditional reviews that allow researchers' judgment in advance, SLR encourages minimizing initial interpretation (Boell & Cecez-Kecmanovic, 2015).

There are three main stages of SLR: planning, conducting, and reporting the review (Kitchenham, 2004). In the planning stage, the research questions are formulated, and the review protocol is developed; in the conducting and review stage, we select the primary studies, perform the quality assessment, data extraction, and data synthesis; in the reporting stage, we provide the conclusions with the evaluation.

For this research the literature review research questions include: What type of research approach is followed? What type of algorithms are used for credit scoring? And what elements make up a P2P lending system? In this way, an overview of the dominating research approaches and deeper insight into the algorithms used for P2P lending will be obtained. We used the terms credit scoring, model*, algorithm, and machine learning to ensure the query retrieves all the technical papers. The terms inclusiveness (unbanked, prosocial, micro), trustworthiness (trust*, fair*), lenders' decision-making, and information asymmetry are added to the query due to our concern with the social aspects. Following the searching protocol, we identified 440 sources from the literature as of April 2022, as shown in Figure 1.

The overall statistics are aligned with the findings of Ariza-Garzon et al. (2021), who showed that the authors from China and the USA are conducting more research on this topic than other countries/regions. Two factors are contributed to the number of research in a particular region: the increase in the number of the P2P lending companies and the availability of data transactions. We apply backward and forward search (Webster & Watson, 2002) to include papers frequently cited in the literature yet not found in

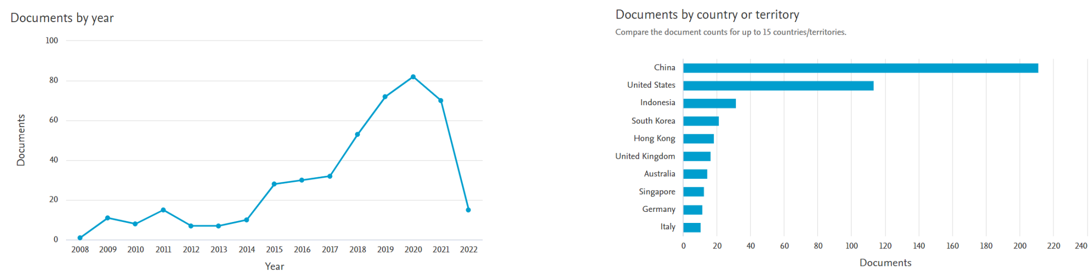

Figure 1: Searching analytics provided by Scopus retrieved in April 2022

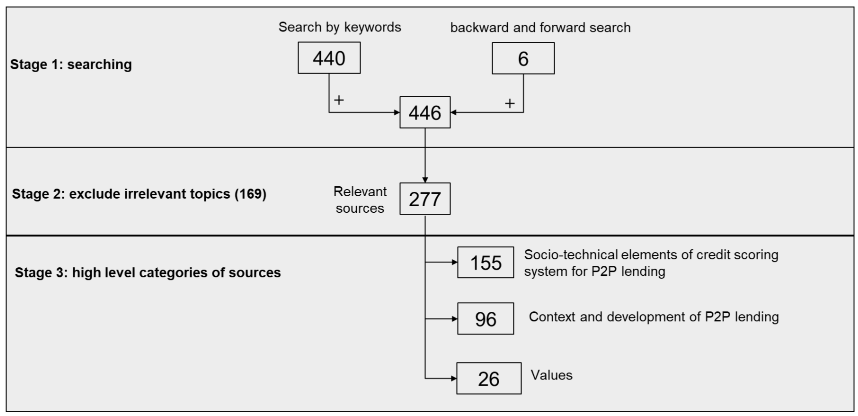

Figure 2: searching stages and the number of resulting papers

the primary searching (n=6). Furthermore, 169 papers are excluded from further reviews after screening the abstracts because the detailed explanation in those papers is not the main focus of this study, for example, technology acceptance, herding behavior, psychological assessment, and Fintech in general. It leaves us with 277 sources, which are then classified into three categories: socio-technical elements of the P2P lending system (n=155), general context and development of P2P lending (n= 96), and values of trustworthiness and inclusiveness (n=26). Figure 2 shows the visual representation of the searching steps.

4 FINDINGS AND DISCUSSION

We identified four general types of research: case study to build a theory, case study to develop statistical models, essay/theory development, and SLR. It shows that the majority of the study on P2P lending is based on case study research (n=229), which is contextual-based. The case study examines various socio-technical elements of P2P lending credit scoring based on particular business needs and contextual challenges. The findings emphasize the need for taking the context into account when designing P2P lending systems.

Figure 3 shows the types of algorithms applied in the research for modeling credit scoring and interest rate in P2P lending, retrieved from 84 studies from the year 2012 to April 2022. It reflects high attention on analytical aspects of credit scoring to create the model with the best performance indicators and produce maximum financial profits.

Furthermore, we examine socio-technical elements identified in each study. The result is presented in Figure 4. It is important to note that each source could discuss more than one element. For example, a study that proposes a model for credit scoring discusses the importance of proper regulation and offline verification (hybrid approach).

We identified five categories of elements required in designing a credit scoring system for P2P lending, namely Data and Processing (n=103), Business (n=91), Organizational (n=28), Policy and Governance (32), and Culture (7). The elements are clustered to capture the vast amount of different elements in an easy-to-understood manner. The SLR revealed that credit scoring for P2P lending is not merely about technology and software design for maximizing profits. Elements like culture, policy and governance, and organizational aspects play a key role in shaping P2P lending systems. Hereafter we discuss each of the elements as presented in table 1.

Data Processing and *Business*, are the most technical categories. The main technical challenge is designing algorithms with the best prediction accuracy and optimum profitability. Failure in addressing data issues significantly impacts accuracy and decreases profits. Several technical issues need to be addressed properly, for example, how to choose the best classifiers, how to design ensemble and hybrid algorithms to provide optimum profit, how to ensure data quality, how to deal with big data, and how to utilize data from social networks and social media efficiently. Furthermore, applicants

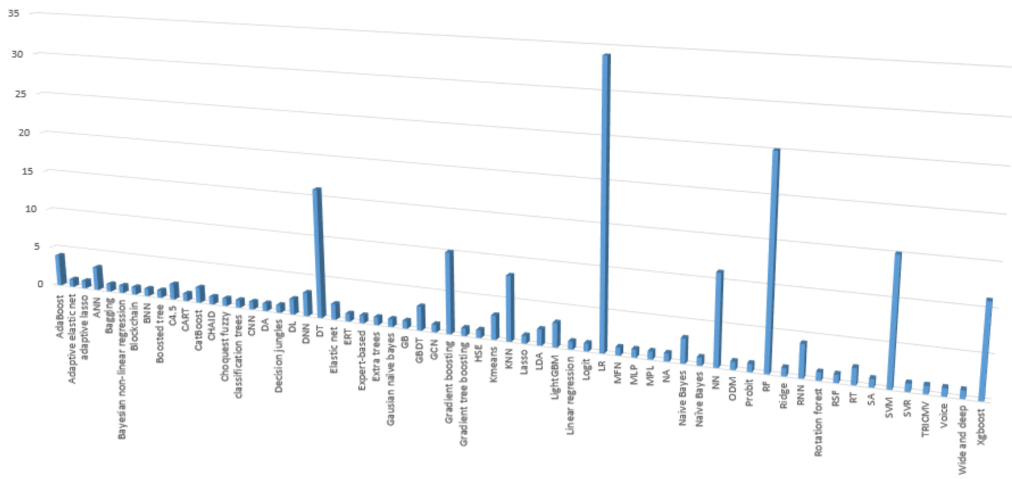

Figure 3: Algorithms used in credit scoring and rating mechanism for P2P lending

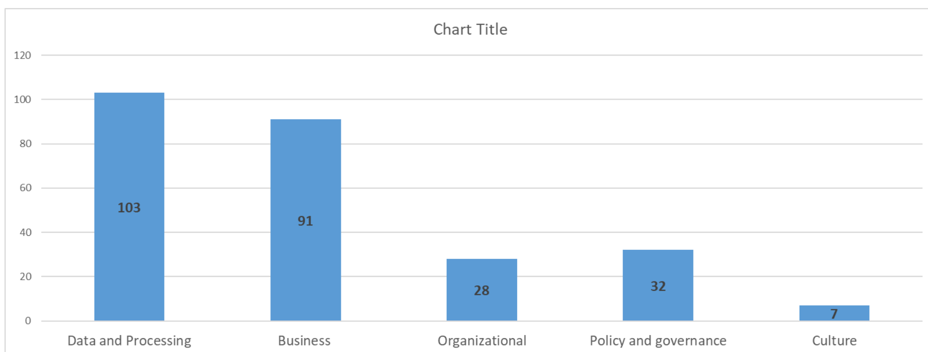

Figure 4: Socio-technical elements of credit scoring system in P2P lending

could falsify the information which impacts the system's accuracy. Therefore, there is a need to design algorithms to mitigate fraud and other fraudulent activities

Policy and governance are required to mitigate moral hazards and maintain industrial stability. Without clear regulations, supervision, and monitoring, the credit scoring system could be designed arbitrarily. Industry-standard is required to ensure sustainability and promote information sharing. The next category is *the organizational aspect*, which is strongly determined by human decisions in operational strategy. Platform policy and reputation influence the risk perceived by the lenders. The design of credit scoring is encouraged to accommodate a variety of lenders' risk appetites. Moreover, offline engagement is required in pro-social lending platforms as a strategy to improve awareness and examine the real impact of credit on society.

Culture is about beliefs, norms, and societal background. Credit scoring designed for collectivist culture could be different from the one designed for individualism culture; the schema for the micro-enterprises market is different from the market dominated by customers who borrow money for domestic needs.

In general, the elements show the type of decisions relevant for designing a P2P credit score system. The elements show that equal attention should be given to technical and social aspects, and the complex interaction among elements needs to be considered in designing a proper credit scoring system.

More explanation on each element and sub-elements are as follow.

4.1 Data and processing

4.1.1 Data quality. No literature explicitly defines data quality in P2P lending platforms, nevertheless, data quality elements are reflected in the analysis and discussions. Data quality includes the recognition of data sources and the preparation of data for the analytical process. Data from social networks and social media can be used to improve the scoring algorithm (Zhang et al.,2016; Guo, et al., 2016). However, the strategy to utilize this data efficiently remains a big challenge. Another crucial aspect is data preparation to handle redundant features which consume enormous space and impact performance (Li et al., 2018; Xia et al., 2018). Feature selection improves classification accuracy by omitting the redundant variables

Table 1: Elements of credit scoring system in P2P lending

No	Element	Sub elements (number of papers)	Definition
1	Data and Processing	Data quality (n=18)	Various parameters reflect the trust of the stakeholders towards the data, such as credibility, completeness, consistency, and accuracy.
		Data analytics (n=85)	Any mathematical or statistical modeling that is transformed into particular computer programming languages to process the data and produce the output based on the predefined logic.
2	Business aspects	Scoring and grading (n=69)	A value that represents the creditworthiness of a borrower and reflects the credit risk.
		Pricing/interest rate (n=15)	A margin of the financial transaction paid to the lenders or the platform calculated based on a particular portion of the transactions.
		Community-based system (n=8)	A platform's functionality that supports groups/communities' interaction among participants
3	Organizational	Partnership (n=5)	All kinds of collaboration and coordination between stakeholders involved in P2P lending industries.
		Business strategy (n=23)	The company's strategy to expand the coverage of the business.
4	Policy and governance	Policy and regulation (n=30)	All kinds of laws, regulations, and provisions which are issued by the government and authorized institutions to regulate the industry.
		Standards (n=2)	Rules, principles, and best practices relevant to P2P lending platforms.
5	Culture	Culture (n=7)	Beliefs, norms, and societal backgrounds influence behavior in specific geographical regions.

while keeping the crucial information; it also reduces searching costs (Li et al., 2020; Akanmu & Gilal, 2019).

4.1.2 Data analytics. Machine learning and various statistical approaches contribute to the development of the credit scoring model (Ariza-Garzon et al., 2021; Niu et al., 2020). Researchers continuously examine methodologies to improve system performance and address a variety of business requirements. We identify six clusters of research in analytical modeling:

1. Credit scoring models in general to classify good and bad borrowers and predict the probability of default (n=44). The models applied various prediction measurements, such as Kolmogorov–Smirnov, the percentage of correctly classified (PCC), and the Partial Gini Index (Lessmann et al., 2015).
2. Credit scoring models to predict the survival time (n=3). The survival time model consists of two components: the incidence component to predict default probability and the latency component to predict the time of default (Jiang et al., 2019; Wang et al., 2018).
3. Rejection inference to overcome the issue of sample bias that influences predictability by exploring the data in the rejected group (n=4) (Liu et al., 2020; Xia, 2019; Xia et al., 2018). This approach is motivated by the high number of rejected applications compared to the accepted ones, therefore, the prediction accuracy could be biased (Xia et al., 2018).
4. Network-based scoring (n=1), aims to utilize topological information in network similarity to improve credit scoring prediction . The policymaker could apply this approach for early-warning financial risk.
5. Credit scoring prediction addresses class imbalance and dimensionality issues (n=12). The imbalance dataset leads to prediction bias because the algorithms create a prediction based on the majority class and ignore the minority class (Chen et al., 2021; Niu et al., 2020; Li et al., 2020).
6. Utilizing social networks and social media to improve prediction accuracy and reduce information asymmetry (n=8).

4.2 Business

4.2.1 Scoring and grading. The design of the credit scoring model is contextually aligned with the business goal of the company and the target market. For example, the credit scoring schema for consumptive credit is different from the one for micro-enterprises; the credit scoring model for pro-social lending in areas with low digital literacy is different from the one targeted for urban areas.

We identify three types of research in modeling the credit schema, namely credit scoring, profit scoring, and a combination of both. Credit scoring develops models to improve default prediction with emphasis on various aspects, for example, the utilization of data from social media and social networking, utilizing topological information in network similarity (Giudici, Hadji-Misheva, & Spelta, 2019), and the use of more than one timestamp of features in the algorithm (Zhou, Fujita, Ding, & Ma, 2021). Profit scoring considers the potential profit from the defaulters by developing cost-sensitive algorithms (Ye, Dong, & Ma, 2018; Serrano-Cinca & Gutiérrez-Nieto, 2016; Xia et al., 2017). The mixed-method combines credit scoring and profit scoring and develops a two-stage algorithm to optimize prediction accuracy and financial profitability, such as (Bastani, Asgari, & Namavari, 2019) and (Wang & Ni, 2020).

4.2.2 Pricing/Interest rate. The most common pricing schema is risk-based pricing, in which high-risk customers imply high-interest rates (Zhao et al., 2017). Several P2P lending platforms allow the borrowers to state the desired interest rate (Syamil et al., 2020; Zhao et al., 2017; Chen et al., 2016), whereas other platforms let the system define the rate (Caldieraro et al., 2018) based on the risk adhered to participants (Kumra, Khalek, & Samanta, 2021). The credit rating mechanism is one of the factors that significantly influences credit risk (Ma & Wang, 2016). In various studies on India's pro-social P2P lending platform, the researchers suggest establishing regulations to protect the limit of an interest rate for the people at the bottom of the pyramid of the economy (Kumra, Khalek, & Samanta, 2021; Gupta, 2014). The interest rate in the Islamic P2P lending system is designed based on the profit-loss partnership which requires physical goods as the underlying transactions (Pişkin & Kuş, 2019). Interest rate is used as one of the parameters in outcome analysis, along with the probability of success and probability of default (Tao, Dong, & Lin, 2017; Qiu, Xu, & Zhang, 2010).

4.2.3 Community-based. Several platforms equipped their system with community features (Zhao et al., 2017; Yang & Lai, 2014; Yum et al., 2012; Berger & Gleisner, 2009). The community-based forum is expected to reduce information asymmetry (Niu, Ren, & Li, 2019). Studies show that individuals' scoring is affected by group performance and the trust of the lenders towards group leaders. Group leaders play a significant role in reducing information asymmetries which leads to better credit disbursement and interest rates (Berger & Gleisner, 2009). Moreover, a collective behavioral signal of community creates a positive impact, especially on low-grade rating customers (Collier & Hampshire, 2010). The active participation of members in a group/community provides the strongest signal to the platform and improves individual reputation (Collier & Hampshire, 2010). These collaborative signals reduce information asymmetry (Yang & Lai, 2014). Furthermore, data collected from the social interaction in communities can be utilized as input to improve the credit scoring model (Zhang, Diao, Hai, & Li, 2016).

4.3 Organizational

4.3.1 Partnership. Despite the initial paradigm that the P2P lending platform is a threat to the future banking business, the collaboration and partnership between P2P lending platforms and banking institutions are started to emerge. For example, banks provide loans to P2P lending platforms to be distributed to borrowers (Tambunan, Santoso, Busneti, & Batunanggar, 2021). A study by Kohardinata et al., (2020) reveals the change in the relationship between P2P lending platforms with rural banks, from substitution effect in 2018 to complementary impact in 2019 due to a more efficient partnership. P2P lending partnerships are also established with Big Data and Fintech companies to enhance risk assessment capabilities (Au & Sun, 2019). A pro-social lending platform in India launched a partnership with 39 non-government organizations which act as financial intermediaries to conduct loan management (Ravishankar, 2021).

4.3.2 Business strategy. Business strategy includes all the efforts conducted by the P2P lending companies to expand their business coverage. The strategies align with the company's vision and the target market. Research in this area includes the strategy for market expansion (Wang & Greiner, 2011), building companies' reputations (Ping et al., 2019), customers' protection (Amalia et al., 2019), the use of social media to increase competitiveness (Ke, Chen, & Du, 2016), the impact of investors' sentiment in social media (Fu et al., 2019), and hybridity – combining online validation and offline engagement.

Offline engagement is believed to play a significant role in optimizing the societal impact by maintaining a good relationship with borrowers (Ravishankar, 2021). Offline verification provides an opportunity to reduce taste-based bias (Tao et al., 2017). Rang De, a pro-social P2P lending platform in India, built a solid offline partnership with the borrowers and intermediaries by establishing intermediary relationship-building and borrower relationship-building (Ravishankar, 2021). The platform owners and the lenders visit the intermediaries and the borrowers to examine the real impact of the credit on society (Gupta, 2014). Renrendai, a P2P lending platform in China, minimized the trustworthiness issue by embedding offline verification into the online approval process (Tao et al., 2017).

4.4 Policy and Governance

4.4.1 Policy. Compared to the banking system that must comply with The Basel Committee on Banking Supervision, the regulation and supervision of P2P lending Fintech is a growing discourse with no available global standard and guidelines. Each country could have a different regulatory framework. Some countries have regulated controls, while others are not under precise regulation (Basha, Elgammal, & Abuzayed, 2021). The government is expected to address at least two issues: collaboration and infrastructure (Kohardinata et al., 2020). The P2P lending system involves many stakeholders who have different purposes and constraints and could have dependencies on each other. A coordination mechanism is required to build and maintain the interconnection among stakeholders. Coordination is also needed to manage the information flow.

Bibliometric analysis conducted by Ariza-Garzon et al. (2021) explains that the unavailability of clear regulation causes an increase in P2P lending fraud. The collapse of dozens of P2P lending platforms in China is due to internal mismanagement and the lack of a regulatory framework (Zhang & Wang, 2019). Therefore, there is an urgent need for regulation and supervision to ensure the industry's sustainability (Ariza-Garzon et al., 2021). China's government issued a law that encourages P2P lending platforms to collaborate with banking institutions in 2015. In parallel, the standardization of P2P lending is also gradually built (Ma & Wang, 2016). A study by Kumra et al. (2021) advised policymakers to pay attention to the BoP market segment by conducting programs with the goals of setting interest rate limits and improving awareness and literacy. Moreover, credit risk could be triggered by changes in the regulations or economic situations which impact individuals' repayment capability (Zhou, Fujita, Ding, & Ma, 2021). The supportive policy environment plays a significant role in minimizing credit risk (Ma & Wang, 2016).

4.4.2 Standards. Regulations and industry standards are essential to improve the industry's stability by mitigating the risk raised by low-quality or illegal platforms (Shi et al., 2019). Industrial self-regulation, including information sharing, improve platforms' quality and lenders' confidence (Wang & Hua, 2014). Industry standards could also address the imbalance distribution of the P2P lending industry (Shi et al., 2019)

5 CULTURE

A limited number of studies (n=7), explicitly discuss how culture could influence the design of P2P lending. Qiu et al. (2010) compare the role of social capital in two different cultures. They argued that the collectivist culture creates more impacts on the lending performance than the individualistic culture. Yang & Lee (2016) concluded that the culture of China with the tendency to trust and collaborate with known communities positively influences investment behavior. Moreover, cultural similarities and geographical distance influence lenders' investment decisions (Burtch, Ghose, & Wattal, 2014). A proper credit scoring system should be able to address specific and context-based cultural issues.

6 CONCLUSIONS

A credit scoring system is required to assess the creditworthiness of a customer as part of risk assessment. P2P lending credit scoring system is a relatively new phenomenon in comparison with the credit scoring implemented in banking institutions. One of the unique value propositions of the credit scoring system in P2P lending is the ability to implement artificial intelligence and various statistical approaches to design a model that utilizes data from social media, social networks, and utility providers. P2P lending platforms provide an opportunity to reach customers that have not been served by the banking system, therefore, extending the coverage of credit disbursement. However, establishing such a system remain challenging due to various issues, such as inclusiveness and complexity of stakeholders. Moreover, the elements making up such a system are not known. We need to understand the elements of P2P lending system to help us design the system properly and identify the potential challenges adhered to each element.

This study aims to identify the elements that build the complexity of the P2P lending system. Having conducted a Systematic Literature Review, we recognize five categories of elements of relevance for designing P2P lending system: Data and Processing, Business, Organizational, Policy and Governance, and Culture. The categories of elements show that the design of P2P lending system goes beyond the technical challenges to create a system with the highest accuracy and maximum profit. The system requires not only an understanding of the technical aspects but also the need to include social aspects. They have to be designed in concert.

The elements reflect the type of decisions relevant to designing an inclusive system, therefore, the understanding of each element is crucial for the policymakers and system architects. The works of the literature show that the design requirements could vary according to the societal background and risk appetite. The interconnection between elements needs to be understood to acknowledge the potential challenges caused by technological factors, decision-making in the company, and the coordination process among stakeholders. Moreover, in addition to the potential benefit to the economy, the inherent risk should be carefully addressed. Parties involved in a P2P lending system could have different goals and might misrepresent their abilities and willingness to fulfill the intended goals. If the systems do not equip themselves with a proper anticipated algorithm and business logic, there is a chance for the participants to exaggerate their capabilities. It could lead to moral hazards and create substantial risks to society and the economy.

This study provides two significant contributions. First, we specifically review credit scoring in the context of P2P lending instead of credit scoring in general. The result shows that, in addition to the general issue of credit scoring, research on P2P lending systems addresses extended issues such as survival analysis, reject inference, profit scoring, and utilization of social network data. Moreover, online P2P lending requires real-time prediction to align with the real-time dynamic of transactions. Second, we provide elements that build an end-to-end arrangement of the P2P lending system. We recommend that policymakers use the elements to assist them in identifying the challenges in designing an inclusive P2P lending system. For future research, we encourage the study of data governance and data privacy which are rarely explored.

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