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Rethinking SMEs Lending Decisions-Making: A Two-Stage Model Integrating AI and HI Approaches

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Abstract

The paper proposes a two-stage creditor decision-making model that offers a new and compre-hensive approach to use both artificial intelligence and human intelligence to predict SMEs fail-ure/Success. This model includes more relevant factors and criteria than the current models and provides a more balanced and thorough assessment of the creditworthiness of SME Financing applicants, which leads to best identification of the factors influencing the performance and sustainability of this sector. Additionally, the model proposes incorporating bank management in the decision-making process to ensure that lending decisions align with the strategic objectives of the institution. This model could benefit financial institutions and bank managers by improving their lending decisions, reducing credit risks, and supporting the growth and sustainability of SMEs in the global economy. the model can be also applied to other corporate and individuals loan applicants.

Keywords: *lending decisions; SMEs, Throughput Model, credit risk, two-stage creditor decision-making model, evaluation model, artificial intelligence, human intelligence, bank management, financial institution.*

Introduction

SMEs has been considered as a main force of global economic growth. It also constitutes an important source of employment, social stability and innovation. In developing countries, SMEs play a vital role in addressing various socio-economic challenges. However, it is unfortunate that most of these SMEs do not sustain for long as they encounter several difficulties that lead to very high failure rates.

Thus, predicting default risk of SMEs has become a great concern of the banking, in general. This has led academics, since the 1970s, to give an increased attention on the analysis of SMEs failure (Edmister 1972; Laitinen 1993). However, SMEs default prediction variables found in literature seem to be insufficient or difficult to under-stand in particular circumstances (e.g., in unstable environments). This is evident in the case of the number of variables mainly neglected by previous-related studies. For example, it has not yet taken into consideration the changes of failure inputs enforced by unavoidable risks related to overall economic climate or macroeconomic factors (e.g., the Covid-19 conditions) towards more wide employment of qualitative (soft) variables/data, related to organizational ambidexterity , intellectual and social capital, innovation skills, unstructured big data, and credit-based relational capital. Moreover, psychological factors such as time pressure, inhibitions, or anxieties have not yet ad-dressed by SEMs-related literature, despite their importance to investment and credit decision making process. This

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can broadly result in the basis of an objective risk, and might be a subject to what so called “misvaluation” of a given decision (Hirshleifer, 2001).

In contrast, the dramatic growth of artificial intelligence (AI) techniques (e.g. ma-chine learning and deep learning) is simplifying and motivating the integration of AI and human intelligence (HI) to realize technological predicting and high valuation in many businesses. Interacting AI algorithms with human abilities can help better identifying the treatment factors influencing decision-making process, which enables organizations (i.e., banks) to be more reactive to complex and uncertain situations (Dubey et al., 2022). The advantage of employing algorithms to overcome a given problem or make a specific decision is that they provide a suitable answer on a regular basis (Rodgers and Nguyen, 2022; Rodgers et al., 2022). In the banking sector, algorithms have become an integral part of decision-making processes. They help banks and other financial institutions to make faster and more objective decisions on loan approvals at lower operating costs and minimum credit risks (i.e., those incurred by business failure or fraud). They also help making stronger customer acquisition, and adding more customer lifetime value (Agarwal et al., 2021). It is, however, still not known whether AI-powered banks perceive some factors related to their individuals and corporate clients besides the available financial data to generate a highly accurate prediction of clients' capacity to pay. A limited number of prior research have examined the impact of borrowers’ behaviour on AI-driven decision-making of banks. Rodgers et. al (2023) made a significant contribution to the emerging research initiatives in this field. They used artificial neural networks technique to outperform the traditional decision making models by incorporating a more flexible approach to how creditors subjectively valuate risky projects. Despite Rodgers and his colleagues im-plied a set of perceptual factors into their model, they did not enter macro-economic factors and other considerable factors such as the borrower's background (e.g., qualifi-cations) and experience and the loan officers' human capital into the equation (see Bruns et al., 2008; Kochetkova, 2006). Such input variables enable effective lending de-cisions to be made, so that costly credit risks can be averted (Fight, 2004).

For more consideration of how SMEs-focused banks and other financial institutions should arrive at a particular credit decision, and best identification of the variables causing business success/failure, this conceptual paper suggests a two stage cred-itors’ decision-making model, derived from a Throughput Model (Rodgers and Housel, 1987), which suggests how the artificial and human intelligence can systematically be integrated by importing both information and individuals’ (i.e., loan offices and/or the bank’s management) perception towards a better identification of the variables influencing SMEs failure. This can enable the stakeholders of SMEs (e.g., SMEs’ borrowers, funders, and government) to react timely to these variables and avoid the potential consequences of them. Our model considers factors at the banking system level and others of borrower's attributes and human capital than those used by Rodgers et. al (2023), since the decision makers here are not only the banks’ lending officers, but also include other beneficiaries. The model helps these group arriving at better causal interpretation of SMEs failure/success. The paper comprises four further sections. Section 2 reviews the literature on the factors influencing SME failure, as well as the theoretical framework that has been adopted for the purpose of this paper. Section 3 dis-cusses the proposed conceptual framework (A Two-Stage creditors’ Decision-Making Model). Finally, the paper concludes in section 4.

Literature Review

Factors influencing credit risk control and lending decision making in banks: lessons learnt from prior literature

It is important to note that credit risk assessment and lending decision-making are not the same concept, but rather complementary. Credit risk assessment is a major concern for lenders and financial institutions (Mpofu and Nikolaidou 2018; Priyadi et al., 2021). It involves the evaluation of a borrower's creditworthiness and assessing the likelihood of default on loans or other financial obligations by using qualitative and quantitative data (Anderson, 2021; Muñoz-Cancino et al., 2023). It may also takes into account the analysis of macroeconomic factors, such as the state of the economy and industry trends that might affect a borrowers' ability to repay their loan (Koju et al. 2019; Rashid and Intartaglia, 2017; Priyadi et al., 2021) . The credit risk determining factors for lenders and financial institutions are multifaceted, with a comprehensive assessment often including an analysis of the borrower's personal finances as well as external economic factors. This approach allows lenders to evaluate the potential de-fault risk associated with a loan and make informed decisions about approving or denying credit applications. Moreover, lenders typically use various credit risk models and algorithms to assess the borrower's creditworthiness accurately. These models and algorithms may incorporate a mix of quantitative and qualitative methods to evaluate credit risk, such as statistical analysis, probability calculations, financial ratios, market trends, and expert judgment (Shi et al., 2022; Yang and Hasan, 2022). By analysing these credit risk determining factors, lenders can determine the likelihood of a borrower defaulting on their loan or failing to make timely payments and take necessary.

On the other hand, lending decision-making involves determining whether or not a borrower is approved for credit and how much credit they are eligible for. This involves considering the results of credit risk assessment, along with other factors such as market conditions and internal lending policies, to make a final decision. assessment provides important information for lending decision-making, other factors such as borrower's business plan and market trends cannot be fully captured by traditional credit risk assessment models alone. Therefore, both credit risk assessment and lending decision-making require a combination of expertise, data analysis, and sound judgement to be effective in minimizing risks while maximizing profits for the bank. Moreover, credit risk assessment and lending decision-making are crucial elements in the risk management process for a bank.

Under conditions of uncertainty (i.e., unpredictable risk), lending decision makers are advised to use both accounting (financial) and supplementary (non-financial) in-formation in order to help improve their judgments and decisions (Boot, 2000; TrÖnn-berg and Hemlin, 2012). For example, the Basel latest agreement (Basel III) allows banks to develop and choose their own risk prediction models based on macroeconomic environmental factors (i.e., data) besides their individual criteria (The Basel Committee on Banking Supervision, 2000). Furthermore, a number of previous studies have argued that nonfinancial information, which cannot be obtained from clients' financial records, allows loan officers to make better assessments for successful lending decisions (e.g., Grunert et al., 2005; Treacy and Carey, 2000; Ball et al., 2008). Such concern has led to widespread calls for disclosure of nonfinancial-information to which loan applicants (i.e., firms) have responded by voluntarily disclosing information about nonfinancial aspects of the business. Many corporate reporting is now accommodated non-financial information relating to future plans, intellectual capital, and customer relations (Power, 2001). Moreover, most of commercial banks adopt what so-called relationship banking or relationship lending technique (see Boot (2000) for a review) to make their lending decisions based on not only quantifiable (financial) data, but also on subjective (soft) qualitative ones. These two classes of information or data are often beyond readily available public information and can be confidentially obtained from multiple interactions with the bank's clients/borrowers (Boot, 2000). They can be summarized as 'the 5C's of bank lending' – character, capacity, capital, collateral and conditions and used by different institutions in the debit market.

In contrast, Casey (1980) demonstrate that loan officers with access to significant-ly more information could not predict bankruptcy more accurately than their counter-parts who had access to a limited information. Hwang and Lin (1999) support this conclusion by showing that using more information does not always lead to better decisions and the cornerstone of the successful decisions is the way in which the information used for decision making is presented, not the amount of it. Rodgers (1992) attributed this phenomenon to the possibility that loan officers sometimes are over-whelmed by a sea of information in arriving at a better loan decisions, so their decisions may be neither optimal nor objective. Moreover, the information needed for relationship-based lending technology is difficult to verify (Cole, 1998; Uchida et al. 2006).

With this in mind, a major concern of the guiding conceptual accounting frame-work included in Statement of Financial Accounting Concepts No. 2 (SFAC #2) (FASB, 1980) is to offer guidance to decision-makers such as creditors to develop their judgement and choice when confronted with several information sources. With increasing amount of financial and nonfinancial information available, this study seeks to demonstrate how different philosophical aspects (perception, information, judgement, and decision) might systematically be adopted by creditors towards a better loan decisions. It does so by highlighting an lending decision-making model pertinent to two stages of creditors' thinking processes. This model also represents the decision-models approach of Decision Usefulness Theory , which can be used by professional accounting standards setters and accounting participants to improve the information provided to financial reports' users. (Scott, 2003).

Theoretical Framework (Throughput Modelling)

Throughput Modelling (Rodgers, 1997; Rodgers and Housel, 1987) is a conceptual framework that helps individuals to specify useful exogenous latent variables (i.e., information and perception) in order to arrive at better decisions. The significance of this model is that it introduces four philosophical concepts: perception (P) or (i.e., categorizing previous events stored in the memories based on knowledge, experience, training, attitudes, believes, and etc.); information (I) (stems from humans' senses, and must be reliable and relevant); judgement (J) (sorting, classifying, and weighting P and I); and decision choice (D) (selecting the best alternative solution or course of action), and suggests how these interact in making a choice. This type of modelling is useful in depicting whether certain processes and information can explain how to sustain SMEs' competitive advantage, as demonstrated by the firm's RBV (Osterloh and Frey, 2000).

The traditional decision-making model, relying only on information (either quantitative or qualitative), normally involves serial processing. Throughput Modelling takes this a step further by assuming that there are several algorithmic pathways in the overall choice. These include: (1) P→D, the expedient pathway; (2) P→J→D, the ruling guide pathway; (3) I→J→D, the analytical pathway; (4) I→P→D, the revisionist pathway; (5) P→I→J→D, the value-driven pathway; and (6) I→P→J→D, the global perspective pathway (Rodgers, 2006; Rodgers and McFarlin, 2017) (see Figure 1).

Rodgers (1997) argues that the selection of pathway is affected by the level of expertise, time pressure, the stability of the environment, and the information being deficient, noisy, difficult to understand, or irrelevant.

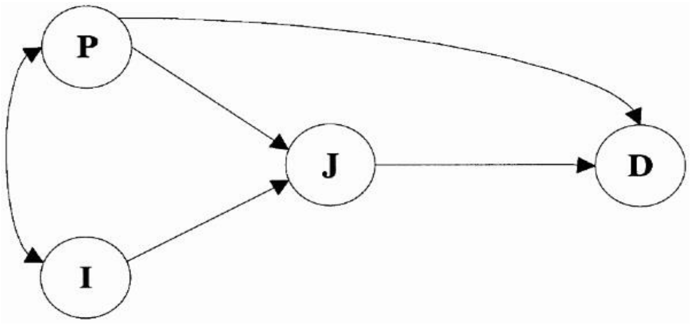


Figure 1. Throughput Model (Rodgers and Housel, 1987)

The six algorithmic pathways are described as follows:

1. P→D: Where Perception Leads Directly to a Decision Choice

This algorithmic pathway represents a decision maker who has sufficient knowledge (education) and experience to make a decision without the aid of information. The decision maker may find that the information is too noisy, incomplete, or difficult to understand, or might lack the time to consider available alternatives. It is very useful in AI applications ranging from data gathering to problem solving.

2. P→J→D: Where Perception Leads to Judgement, Then to a Decision Choice

This algorithmic pathway usually relates to circumstances, without time pressure, when the decision maker (i.e., person or organization) is confronted with a variable or unstable environment. The information being noisy, incomplete, or irrelevant may contribute to the decision maker downplaying or ignoring the currently available information.

3. I→J→D: Where Information Leads to Judgement, Then to a Decision Choice

This algorithmic pathway assumes that the information available to and used by the decision maker is relevant and reliable. Also, the decision maker who follows this algorithmic pathway usually specifies the problem, weighs all factors, identifies all available alternatives (events or objects), rates them against each factor, and finally selects the optimal alternative.

4. P→J→D: Where Information Leads to Judgement, Then to a Decision Choice

This algorithmic pathway supposes that the decision maker is influenced by an unstructured environment and that the available information may be incomplete, so it may be difficult to deal with the problem in the previous programmatic and analytical way. Alternatively, provided that they have long experience or are educated to a high level, the available information and decision maker's perceptions are sufficient to draw a conclusion about the current situation.

5. P→I→J→D: Where Perception Influences Information that Leads to Judgement, Then to a Decision Choice

In this algorithmic pathway, the decision maker's perception influences the available information. In other words, the decision maker will search for information that is appropriate to his or her perception, which in turn will impact on both the judgement and the decision.

6. I→P→J→D: Where Information Influences Perception that Leads to Judgement, Then to a Decision Choice

In this algorithmic pathway, the decision maker's perception is influenced by the information available in making a decision. In this case, it has either a positive or a negative impact on the frame (perception) of the decision maker, concerning the current situation.

Depicting AI Algorithms into the Throughput Model

AI algorithms can improve decision making, credit risk assessment, automation, fraud detection, and credit scoring in the lending industry. However, it's important to note that the use of AI algorithms also raise some concerns related to data privacy and algorithmic bias (see Sadok et al., 2022). Thus, lenders should employ AI algorithms in a responsible and transparent manner.

Fundamentally, the Throughput Model proposes the use of algorithms in order to solve problems, usually defined by someone as a sequence of steps (Rodgers, 2020; Rodgers and Al Fayi, 2019; Rodgers, Alhendi and Xie, 2019). It is best to use algorithms when there is an absolutely need to the correct or best possible decision. AI algorithms can be represented in the Throughput Model since it satisfies six algorithmic criteria of precision, uniqueness, finiteness, inputs, outputs, and generality/effectiveness Knuth (1997) see Table 1.

Table 1. The Correspondence between algorithmic criteria and Throughput Model processes

AI algorithms criterion	Definition	Throughput procedures
Precision	The steps are precisely stated (defined)	The model clearly defines various pathways (steps) in the process of making a decision (e.g., P→D, P→J, J→D, etc.). Every step and the order the steps must be taken in the process are precisely specified (see Fig 1). Details of each step and the sequence of operations for turning inputs (i.e., P and/or I) into outputs (i.e., J and D) are also be spelled out.
Uniqueness	Results of each step are distinctively defined and affected only by the inputs and results of earlier steps.	The model provides parallel routes between input and output latent variables (nodes) in two stages (i.e., I → J and P → J in the first stage and P → D and J → D in the second stage)
Finiteness	The algorithm must always terminate after a finite number of steps.	Each algorithmic pathway in the model ends with an output for any valid input (i.e., J in the first stage and D in the second stage). The model ends with the decision (D) with the highest

		anticipated value is an individual’s decision choice. This includes the selection of the best alternative solution or course of action.
Inputs	An algorithm must have a well-defined inputs.	Each algorithmic pathway in the model has a well-defined input variable (e.g., perception and/or information).
Outputs	An algorithm must describe what the output is and how it is related to the input.	Each output generated by any of the model's algorithmic pathways follows a logical sequence that leads to a conclusion, making it adaptable for future changes with ease
Generality/Effectiveness	• Generality means the algorithm can be applied to a set of inputs or problems. • Effectiveness means the steps that are required to get to output must be feasible with the available resources (i.e., don’t contain unnecessary and redundant steps).	Each algorithmic pathway starts with one or high-level of input items, which represent the model’s input latent variables (e.g., perception and/or information). Thus, the model can be applied in a variety of situations and contexts, without requiring significant modifications. Moreover, the model's inclusion of latent variables means all selected item(s) must be necessary and represent(s) the entire domain of the these variables and all of its relevant facets.

The Proposed Model (A Two-Stage Creditors’ Decision Making and Evaluating Model)

Defining Key Concepts

To avoid confusion, it is more favourably to revise the definition of each construct building the Throughput Model (i.e., perception, information, judgement, and decision choice), before the discussion of the proposed conceptual framework. In quantitative research, this is used to demonstrate construct validity as well as to provide a clear description about how they are operationalized (Lillis, 2006).

1. Perception (how lending decision makers perceive a loan application):

The Throughput Model begins with an individual's perception of the issues involved in decision-making, thorough either heuristics or mental operations. Here, perception provides the frame for the thinking process and clarifies how the decision maker (e.g., loan officer) views the issue, based on their way of using knowledge or experience, training, attitudes, believes, and etc., in order to direct and guide their search for confirmation or rejection of the incoming information necessary to decision-making (Rodgers, 2006). In the proposed model, perception includes the level of education or experience of the banks' loan officers, who primarily identify the strengths and concerns of the borrower's financial condition. In this decision-making process, the bank officers also need to consider different characteristics related to the borrower's knowledge (i.e., qualifications), general experience, business experience, reputation, and the current condition of the industry (Bruns et al., 2008; Ottavia et al., 2011). Moreover, the loan officers must employ their insight to consider other macroeconomic factors (e.g., GDP growth rate, unemployment rate, lending growth rates, inflation, crises indicators, and etc.) (see Kanapickiene et al., 2023), which would affects the creditworthiness of their loan applicants. Such data may affect the likelihood of loan approval, and banks' officers are considered to employ this perception of attributes when obtaining these borrowers-specific data. Loan officers here are assumed to rely only on their own perceptions regarding the value of their clients/ borrowers (P1).

On the other hand, a number of prior research argue that the lending decision-making process is also influenced by factors within the bank itself, such as loan officers' human capital (Dimov and Shepherd, 2005; Kochetkova, 2006; Bruns et al., 2008; Ottavia et al., 2011). Human capital can be defined as the individual's knowledge, skills, competencies, abilities, attitude, talents and experience that add value to a given organisation, contribute to achieving its goals, and support its decision-making processes (Becker, 1975; Chandler and Hanks, 1998; Davenport, 1999; Carpenter et al., 2001; Huang et al., 2002). Based on the previous definitions, human capital in a bank lending department is the capacity and know-how of the bank loan officers to assess and operationalize loan applications. These sets of factors can be employed by the loan officers' educational qualifications, their banking experience, their lending experience, and most specifically, their recent SME lending experience (Ottavia et al., 2011). Despite these self-perception factors can be considered by loan officers in the banks, Self-Perception Theory (Bem, 1972) argues that individuals do not always have clear access to their own internal states or mind, so they infer them from external cues, such as their actions, expressions, or situations. The theory suggests that individuals might change their attitude to match their behaviour, but it does not specify the conditions or mechanisms for this change. Thus, in order to obtain best determination of the risks of making a loan, the current study suggests banks' managements (i.e., the President, Board of Directors, Executive Committee, Credit Committee, CEO, Vice CEO, Headquarter Managers , Area Managers , or Branch Managers) to be involved in evaluating the lending decision-making process, especially since this process is considered as one of the main activities that ensure the continuity of their institutions (P2). The P2 construct can be act as a moderating variable in the relationship between P1 (i.e., the loan officers' perception regarding the borrowers' performance in terms of credit scores, potential profit, and attributes, and the possibility of granting them a loan.

In order to measure the items building the first pillar of perception construct (P1), the paper suggests using a widely used personality assessment questionnaire used by Rodgers (1992), which is called Myers-Briggs Types Indicator (MBTI) . The questionnaire identifies the loan officers' psychological preferences in how they make a preliminary analysis to evaluate loan applications during this perceptual stage in terms of: (1) the borrowers' characteristics; and (2) the borrowers' surrounding macroeconomic circumstances. On the other hand, the loan officers' human capital (proxied by their knowledge, skills, competencies, abilities, attitude, talents and experience) as perceived by the second group of P1 (i.e., the bank's CEOs) would be the second pillar of P (P2) that can help them in assessing the lending decision making process of the bank.

2. Information (Financial information used by lending decision makers in assessing a loan ap-plication):

In the Throughput Model, resources include all reliable and relevant information available to an individual for problem-solving purposes. Reliability relates to a resource being ac-curate, well-known or dependable. Relevance relates to it being well-timed or sufficient for the purpose. Since standardized financial information provided by firms and used mainly by creditors meets the reliability and relevancy requirements, we include it in our proposed model. This considers three groups of financial information (liquidity, income, and risk ratios) that are generally used by bankers to assess short-term loan applications. According to Rodgers et al. (2023), these three measures are sufficient since they exhibit a high level of correlation with other measures that would not yield any additional relevant information (Rodgers et al., 2013). The current ratio (current assets/current liabilities) will be used to reflect the borrowers' liquid assets. The profitability of the bank's borrowers will be deter-mined by profit net margin ratio (Net profit/total revenue). A risk of borrowing company will be measured by the debt/worth ratio.

3. Judgement (Lending decision rules):

It is now well established from a variety of studies that both financial and nonfinancial information (e.g., individuals' perception) are used by loan officers in order to form their credit risk judgments, before arriving at lending decisions (Rodgers, 1992; Guiral, 2012). Moreover, the term 'judgement' in the Throughput Model refers to the action of analysing (sorting, classifying, and weighting) perceptions and information available for problem-solving or decision-making purposes (Rodgers, 2006). In order to analyse these two variables, the lending decision makers usually use a framework called the ''five Cs of credit'' (character, capacity, capital, conditions, and collateral), where the concepts of these items are combined in order to obtain their credit judgments and lending decisions (need a reference). Character represents the loan officers or lending decision makers' approach of outlying management's declaration that is related to debt pay off (i.e., credibility judgments). This includes evaluating the borrower's integrity, stability, and honesty. Capacity here means the borrowers' ability to independently manage their financial affairs in a manner consistent with personal self-interest and values (Marson and Hebert, 2008). this includes also the non-financial ability of management (i.e., experience) to enable a business capable of meeting its financial obligations (Guiral, 2012). Capital refers to the funds available/used to operate a borrower's current/future business. Conditions refer to determining the prevailing economic circumstances in terms of unavoidable risks may encountering the borrower (e.g., recession, industry issues, and etc.), and the alternative way of mitigating those risks. Finally, collateral is defined as the valuable assets that can be used as a security for a loan. this includes the explicit pledges required when weaknesses are noticed in the other Cs.

For judgmental function, there are two groups of strategies or "decision rules" that are used in making a decision based on information and decision makers' perceptions: (1) compensatory strategy, which allows a trade-off between features (also known as conflict-confronting strategy); and non-compensatory strategy, which does not allow a trade-off between criteria or decision rules (also known as conflict-avoiding strategy) (Rodgers, 2006). Biggs et al. (1985) discovered that bank loan officers switch their judgmental strategies de-pending on the size of their tasks. When they have to handle bigger tasks, they use shortcuts that ignore important information and rely on one criterion only (i.e., non-compensatory strategy). But when they tackle similar tasks simultaneously, they use more thorough methods that consider all the relevant information (i.e., compensatory strategy).

Using the compensatory strategy of analysis, the paper propose the five Cs of credit (i.e., character, capacity, capital, conditions, and collateral), as an alternative criteria to a borrower's financial performance (i.e. Information), and the lending decision makers' perceptual and preliminary evaluation of a loan application (i.e., Perception). This seems to be a way to contrast the contribution of lending decision makers' perceptions of: (1) loan applicants' at-tributes (e.g., borrowers' credit score and history, their potential income, and their personality traits); (2) the micro and macro-economic conditions; and (3) loan officers' human capital (i.e., knowledge, skills and experience) to the overall performance of the loans granted by the bank.

4. Decision Choice (Neither approving nor not approving a loan):

Ultimately, the decision with the highest anticipated value is an individual's decision choice. This includes the selection of the best alternative solution or course of action. Yates (1990) identified three decision types: choices, evaluations, and constructions. Choices are selecting one option from a set. Evaluations are assessing the value of each option. Constructions are creating the best attainable option. For the purpose of this study, the paper suggests using the choice type of decision, as it is the most common and relevant type for loan officers who have to decide whether to approve, reject loan applications, or accept it with conditions.

The model

The Throughput Model (Rodgers, 1997; Rodgers and Housel, 1987) depicted in this proposed model includes various algorithmic pathways that may affect a creditor's decision and evaluation processes. The model proposed here merges the concepts of perception, available information, the 5 Cs of credit judgement (analysis of information or perception), and decision choice as applied to the loan applicants. Loan officers base their perception of the borrowers' performance based on factors such as credit score and history, their potential income, their personal characteristics, and macroeconomic environmental conditions. Loan officers here are assumed to rely only on their own perceptions regarding the value of such factors (P1). The (P2) variable, which pertains to how bank management views loan officers' human capital (e.g., qualifications, training, experience), could potentially moderate the relationship between P1 and the likelihood of loan approval. Information (I) includes the set of financial information provided by the borrowers (i.e., profitability, liquidity, and leverage). Information (I), together with lenders' perceptions, influences the 5 Cs of credit judgement, which analyses the creditworthiness of a borrower (i.e. J). The 5 Cs of credit involves detailed analysis of all available information and creditors' perceptions. Decision choice then follows. This final phase represents information, perception, and judgement (see Figure 2). Thus, the model includes the following steps (algorithms):

Stage 1:

(P1→J): Loan officers use their perception of the borrowers' performance based on factors such as credit score, income, personal characteristics, and macroeconomic conditions to form their credit risk judgments.

(I→J): Loan officers use financial information provided by the borrowers, such as profitability, liquidity, and leverage to go through the judgmental process.

(P1↔P2) Loan officers' perception (i.e., P1) and bank management's perception regarding the loan officers' human capital (i.e., P2) will significantly influence each other.

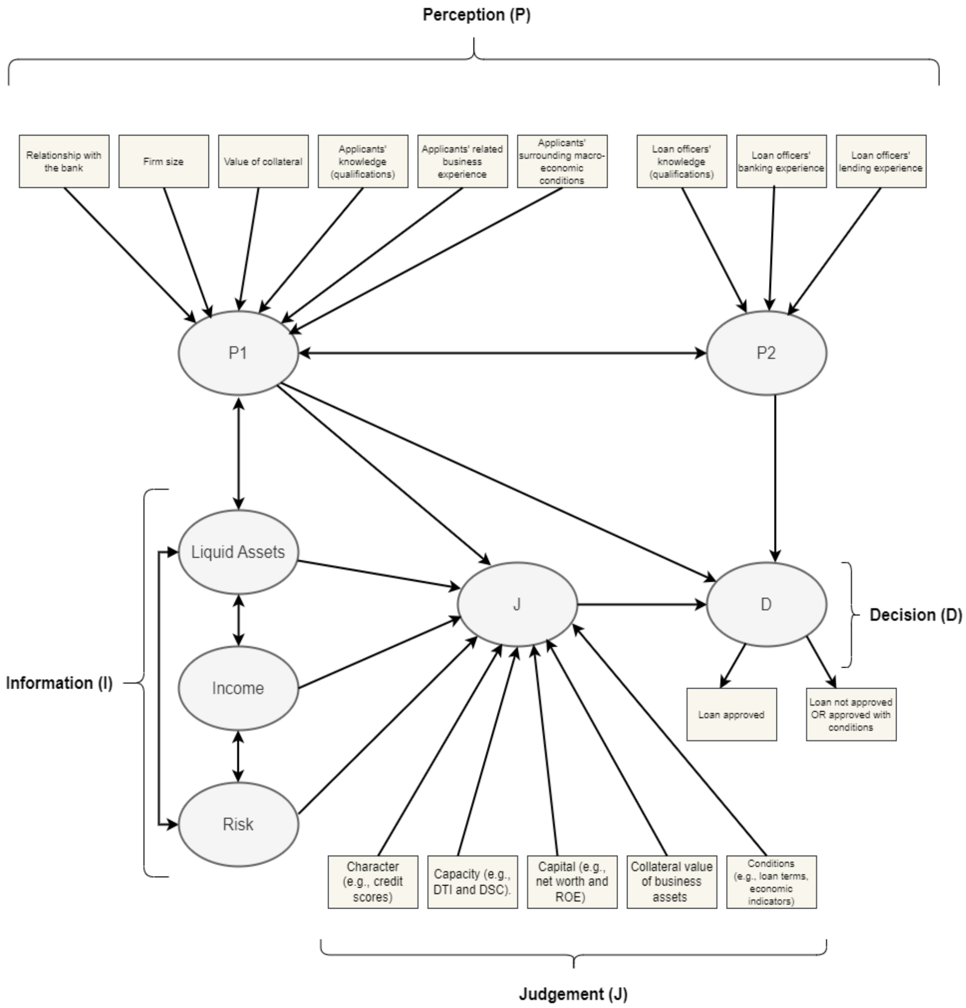
Stage 2:

(J→D): Loan officers analyse the information and their perception to decide whether to approve or reject the loan application.

(P1→D): Loan officers use their perception of the borrowers’ performance based on factors such as credit score, income, personal characteristics, and macroeconomic conditions to directly arrive at lending decision making.

(P1*P2→D) As loan officers' human capital increases, the effect of their perception regarding the borrowers’ performance on the overall lending decision choices increases.

Figure 2. A two-stage creditors’ decision-making and evaluation model



Discussion and Conclusion

Small and medium-sized enterprises (SMEs) play a crucial role in the global economy, but they face significant challenges that result in high failure rates. Financial institutions and bank managers are concerned with predicting the default risk of SMEs, but existing literature on SME failure prediction often overlooks important factors affecting business success or failure. To address this issue, artificial intelligence (AI) techniques such as machine learning and deep learning can be used to make quicker and more objective decisions with lower operating costs and reduced credit risks. However, it is unclear whether AI-powered banks use the perception of their creditors regarding the performance of the bank’s individuals and corporate clients along with relevant financial data to accurately predict clients' ability to pay.

To fill this gap, a two-stage creditor decision-making model is proposed that integrates both artificial and human intelligence to arrive at a better understanding of the factors influencing SME success or failure. The model considers factors at the bank and the banking system levels, simultaneously. This allows SME stakeholders to respond promptly to these variables and prevent potential negative consequences. The proposed model utilizes perception, information, judgement, and decision-making to assess loan applicants' creditworthiness. The perception stage involves how lenders perceive a loan application based on their knowledge, experience, and beliefs, while the information stage includes financial information provided by borrowers used to evaluate their creditworthiness. The judgement stage involves using the 5 Cs of credit criteria to analyse the information and perception to determine the borrower's creditworthiness. Finally, the decision choice stage involves selecting the best alternative based on the evaluation of the loan application using a compensatory strategy of analysis.

The proposed model also recommends involving bank management in the evaluation process to ensure the continuity of their institutions. This can be captured by controlling the effect of their loan officers' human capital on the perception-based lending decisions (i.e., $P1*P2 \rightarrow D$). Overall, this two-stage creditor decision-making model provides a comprehensive framework for lenders to evaluate loan applications and make informed decisions using a combination of micro and macro- economic factors that consider both artificial and human intelligence.

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