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Modelling credit and investment decisions based on AI algorithmic behavioral pathways☆

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ABSTRACT

This paper provides a new approach to understanding bankers' risk-taking behavior. We build upon prior studies that suggest artificial intelligence algorithms are an effective approach to obtaining this understanding. Our approach uses behavioral finance and a unique decision-making model. Although the decision-making literature is replete with descriptions and explanations of creditors and investors' perceptions and judgment, it does not provide an algorithmic model that incorporates a more flexible approach to how creditors subjectively valuate risky projects. Specifically, a model is presented where 33 corporate bankers realized ex ante that they were unable to accurately model the underlying uncertainty that characterizes a company's need for a loan. The results indicate that bankers' risk assessments result in different evaluations of financial information regarding loans. This approach depicts an integrative algorithmic modelling process, whereby limits in the amount of historical conditional information prohibit the use of more complex econometric techniques.

1. Introduction

In our modern era, machine learning and deep learning are governed by artificial intelligence (AI) algorithms, which create a process to solve a problem or make a decision choice that produces an appropriate possible solution (Rodgers, 2020). An algorithm is a group of instructions that directs to a planned objective from a reasonable initial situation. In principle, an algorithm is therefore separate from a machine learning or deep learning program, even though these programs are commonly exercised for the implementation of an algorithm. Essentially, machine learning denotes computers learning from data using algorithms to achieve a task without being explicitly programmed. On the other hand, deep learning implements an intricate structure of algorithms modeled on the human brain. This permits the processing of unstructured data such as documents, images, and text (Rodgers, 2022).

Therefore, AI is intelligence used by machines, as opposed to the intelligence used by humans. The benefit of implementing an algorithm to solve a problem or make a decision is that it yields an appropriate answer on a continual basis (Rodgers and Nguyen, 2022; Rodgers et al., 2022). Algorithms can also deal with complex and uncertain situations. In contrast, traditional economic and financial theory uses rather sweeping simplifying assumptions to enable the use of the fundamental von Neumann–Morgenstern axioms (von Neumann and Morgenstern, 1947). These are based on the idea that decision makers operate rationally to maximize some utility measure and evaluate all accessible information in making decision choices.

To further our understanding of commercial loan officers arriving at decisions choices, we propose an AI Algorithmic Throughput Model as a framework via which to analyze decision-making algorithmic pathways (Rodgers, 1997). Using AI algorithmic pathways, the Throughput Model captures the concepts of perceptions, judgments, and choices (see Fig. 1). That is, the Throughput Model approach accentuates "algorithmic decision-making" as the procedure of entering data to harvest a score or a choice that is engaged to support decisions such as prioritization, classification, association, and filtering (Diakopoulos, 2016). Moreover, machine learning and deep learning are segments of AI that

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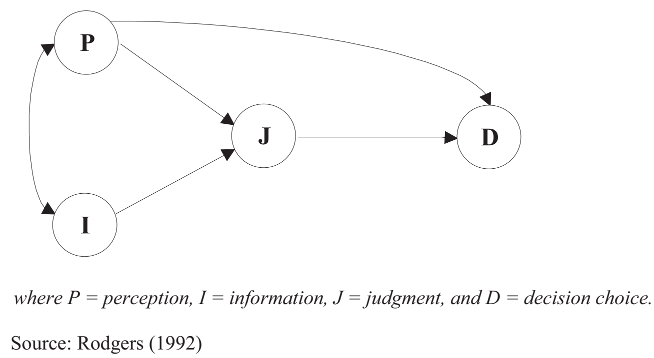

Fig. 1. Throughput model
where P = perception, I = information, J = judgment, and D = decision choice.
Source: Rodgers (1992).

deal with characterizing real-world events or objects with mathematical and statistical models, assembled on data of the Throughput Model (see Rodgers and Nguyen, 2022). The Throughput Model algorithms provide more control and transparency, which enables us to look into the black box of machine learning and deep learning tools. Traditional algorithms can range in complexity from those that just enabling simple business rules to those that make highly complex decisions and have to be constantly maintained, optimized and re-calibrated. In any event, however, they are more transparent and more controllable than AI that effectively operates in auto-pilot mode.

Approaches based purely on inference from observations have proved effective in many domains. Such approaches have also generally proved scalable. That is, machine learning outcomes can be improved in accuracy by adding more training data, and the training process can be made more rapid by increasing computing power. Thus, an important factor enabling the recent successes of deep learning is the availability of more data and faster processors. Deep learning can be viewed as a type of machine learning that is basically a neural network designed with three or more layers, attempting to simulate human brain behavior, thereby enabling learning from large amounts of data. Note that neural networks with hidden layers may have superior in optimization performance and accuracy (Rodgers, 2020).

Nonetheless, the ability to make accurate predictions in particular circumstances may not always facilitate effective solutions in decision-making in different circumstances. For instance, during the recent pandemic, several machine learning systems broke down as they were predicting based on statistical regularities in the existing, and no longer valid, data rather than using causal relationships (see: https://www.technologyreview.com/2020/05/11/1001563/covid-pandemic-broken-ai-machine-learning-amazon-retail-fraud-humans-in-the-loop/).

Causality is very important when dealing with derivations in different circumstances, under which machine learning may not work as expected. Judea Pearl, a Turing Award–winning scientist, has strongly criticised deep learning methods that do not consider causal inferences (Schölkopf et al., 2021). In our paper, we consider several concepts and approaches that are very helpful in developing machine learning models that incorporate causality. The concepts we use are “structural causal models” and “independent causal mechanisms.” Overall, the objective is that instead of relying on statistical correlations, an AI system should detect the relevant causal variables and distinguish their influence from, perhaps transitory, environmental factors.

In sum, algorithms can be designed to provide computers with the ability to learn on their own (i.e., enable machine learning). Applications for machine learning embrace data mining and pattern recognition. Today’s Internet is ruled by algorithms. These mathematical constructions regulate what you witness in your Facebook feed, what movies Netflix endorses to you, and what ads you observe in your Gmail. In the Throughput Model, algorithms are employed as parallel processing parts of the model (i.e., P → J and I → J; P → D and J → D), which is supported by the parallel work being done in the field (Gold, 2012). The process of Throughput Modelling enables the detection of different constructs and parallelism regardless of changing environments or situations. Understanding and incorporating the relevant causal relationships can make AI systems more robust and able to cope with unpredictable environmental changes. In addition, causal AI models may not require training datasets of the same size as models based on identifying statistical regularities.

The premise used in this paper is that after human knowledge and experience has been used to implement an algorithmic model, then *causal reasoning* can be used to make inferences about the effect of interventions, counterfactuals and environmental changes on potential outcomes (Schölkopf et al., 2021). Based on our reasonably sized dataset, it is illustrated that learning and implementing a causal model, requires fewer examples to adapt and can be reused without further training modules. Furthermore, causal models (i.e., Throughput Modelling) allow individuals and organizations to repurpose prior acquired knowledge for new domains. For instance, when commercial loan officers learn financing techniques for an industrial company, they can quickly apply their knowledge to other financing sectors, such as real estate and consumer loans. In contrast, transfer learning in machine learning algorithms, which do not use causality, is very problematic (Rodgers, 2022). In practice it is limited to very simple tasks, such as, detecting new kinds of objects using image classifiers. In more complex tasks, such as decisions about company finance, machine learning algorithms need to be trained on very large datasets which may not be available and are still unable to respond effectively to minor environmental changes in the environment (e.g., small changes to market conditions or regulatory changes).

Algorithms can be depicted in the Throughput Model as fulfilling six features of precision, uniqueness, finiteness, inputs, outputs, and generality/effectiveness (Table 1) see Knuth (1997):

1. *Precision:* each step of the algorithm must be precisely defined/specified. This minimizes subjectivity.
2. *Uniqueness*: an algorithm is distinctively defined and only affected by the inputs and results of earlier steps.

Table 1
Algorithms as problem solvers.

Features	Procedures	Outcomes
Precision	The procedures are precisely stated or defined (e.g., P → J; I → J, etc.).	The solution of a problem is presented step-by-step, making it easy to understand.
Uniqueness	Results of each step are distinctively defined and affected only by the inputs and results of earlier steps.	An algorithm uses a definite unique procedure.
Finiteness	An algorithm has a finite number of steps after which it terminates.	An algorithm is like a recipe (e.g., baking a pie or cake). The steps selected are finite for the outcome.
Input	An algorithm employs input.	Every input in an algorithm has its own definitions; therefore, it is easy to correct.
Output	An algorithm produces output.	Every output in an algorithm has its own logical sequence for a conclusion; therefore, it is easy to change for the future.
Generality/effectiveness	An algorithm pertains to a set of inputs.	Using an algorithm makes it possible to break down a problem into smaller pieces; therefore, it is simpler for individuals and organizations to convert into a program and/or solve a problem.

3. *Finiteness:* an algorithm has a finite number of steps after which it terminates. If a process has all the other characteristics of an algorithm except for finiteness it is a computational process.
4. *Inputs:* an algorithm generally has input(s), given either right from the start or as it runs.
5. *Outputs:* an algorithm may have one or several outputs derived from the given relationship to the inputs.
6. *Generality/Effectiveness:* an algorithm is expected to be effective, i.e., it can be computed in a finite amount of time using simple means (i.e., pencil and paper).

Using a finance model for commercial loan making purposes, this research paper illustrates that Throughput Modelling algorithms are robust when interventions change the statistical distributions of a problem. For example, when a person views an object for the first time, her/his mind will subconsciously factor out lighting from its appearance. This is the reason why, in general, people can recognize the object when they see it under new lighting conditions.

The Throughput Model is a basic conceptual quantitative model that links the phases of a purchasing process in terms of "perception" (P), "information" (I), "judgment" (J), and "decision choice" (D), where "P" or "I" (or iterations between both) lead to "J," which then leads to "D" (and/or "P" directly leads to "D"). Hence, understanding the different algorithmic pathways that lead to "D" can help to suitably design a system to uncover consumer decision models (see Fig. 1). Moreover, the algorithmic pathway that customers link to an option can vary depending on the number of alternatives, the decision maker's mood, her/his former experience with that kind of decision, and so on (Rodgers, 2020).

The Throughput Model differs from the traditional economic theory (i.e., rational model) because it is (1) a process model (i.e., opens up the black box via algorithms), (2) similar to a human neural network providing parallel routes in two stages (i.e., I → J and P → J in the first stage and P → D and J → D in the second stage) (see Fig. 1), (3) inclusive of a symbolic neural network function (i.e., P ↔ I) that imitates a Bayesian model (see Fig. 1), and (4) provides different algorithmic stages representative of human information processing (Bolstad and Curran, 2016; Rodgers et al., 2022).

Neural networks (also referred to as artificial neural networks or ANNs) are called this since they mirror, to an extent, the way biological neural networks, such as the human brain, are assembled (Cui et al., 2006). That is, neural networks are connected from layers of interconnected, neuron-like, nodes. Furthermore, they embrace an input layer, an output layer, and a variable number of intermediate 'hidden' layers. Additionally, 'deep' neural nets basically have more than one hidden layer (see Fig. 2) (Rodgers, 2020).

The Throughput Model addresses decision-making as a cognitive process that occurs in the mind of individuals prior to a decision choice (see Fig. 2). The decision-making perspective implies that a decision can be influenced by one of the model algorithms. This perspective is focused on learning the factors (i.e., perception and/or information) that bring value to the options (i.e., judgment) before a decision choice is made. The Throughput Model also provides a way to depict situations not yet viewed before and think about parallel processing. Humans do not need to drive an automobile off a cliff to know what will happen. Counterfactuals portray an essential role in diminishing the number of training examples a machine learning model requires to operate in analyzing big data.

The rest of the paper is structured as follows: Section 2 discusses AI modelling of contemporary finance theory. Section 3 lays out the foundations of algorithmic decision-making and rational behavior in the context of bank lending. Section 4 describes the Throughput Model, a decision-making model that has been successfully implemented in different areas such as auditing, ethics, trust, commercial lending, sexual harassment and executive compensation (Rodgers, 2022; Rodgers et al., 2019; Rodgers et al., 2020; Rodgers and Nguyen, 2022). Section 5 presents our analysis, subjects and model testing, while Section 6 describes the results. Finally, Section 7 concludes and provides useful insights on the bankers' AI algorithmic decision-making process.

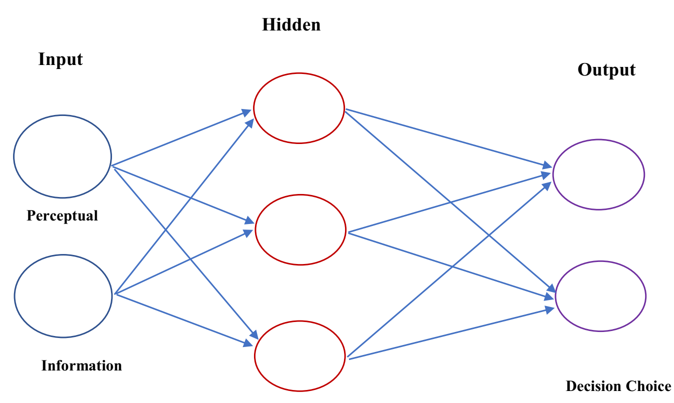

Fig. 2. Artificial single layer neural network for decision choice algorithm
Source: Rodgers, 2020.

2. AI Modelling of contemporary finance theory

A key aspect of contemporary finance theory is that risk premiums can be evaluated for known risk factors. There are some clear problems with the foregoing approach. In the real financial world, risk factors are seldom known ex-ante. In addition, many academic investigations in the area have found examples of irrational behavior and recurrent errors in judgment (see among others DeBondt and Thaler, 1990; Shiller, 1995; Thaler et al., 1997; Kahneman, 2011; Henderson, 2012; Hirshleifer, 2014). A major implication of the behavioral literature is that investments are evaluated not only on the basis of their objective risk but also may be subject to what can be broadly called "misvaluation" due to psychological factors (Hirshleifer, 2001). The financial crisis of 2007 to 2008 starkly highlighted some of the potential consequences of investment misvaluation particularly by highly leveraged banks. Such findings have put the basic finance paradigm into a vibrant evolution. This has led to the new frontier of incorporating algorithms to better explain the financial markets and the behavior of the participants in them.

An algorithm is a process or set of rules to be used in calculations. Further, machine learning is a set of algorithms that enables the software to update and "learn" from previous outcomes without the need for programmer intervention (Rodgers et al., 2017). It is fed with structured data in order to complete an assignment without being programmed how to do so.

In the financial domain algorithms can be used with various broad groups of objectives. One group of objectives aim to predict or model market movements or market states more effectively than traditional methods without necessarily emphasizing an understanding of the behavior of market participants. Various algorithmic methodologies can be used including agent-based modelling (e.g. Ehrentreich, 2007; Manahov et al., 2015), neural nets (see, Li and Ma, 2010) and a variety of other computation approaches (see, Cavalcante et al., 2016). Another group of objectives aims to model the behavior of market participants which gives the possibility of modifying, supporting or improving it. A key element of this is to use artificial intelligence to yield intelligent decision support systems (Pavlou et al., 2005). The intelligence should be exhibited by thinking, making decision choices, problem solving, and learning (Liu et al., 2018). Therefore, in our paper attention is focused on an AI algorithmic decision-making model that explains how individuals' biases can drastically influence the analysis phase en route to a decision. In broad terms, the paper advances the debate on how algorithms can assist the decisions of managers in potentially risky environments when affected by behavioral traits (see, for example, Delgado-

García et al., 2010, and Pillai, 2010).

The paper attempts to understand and explain how using a decision-making model's algorithmic portrayal of perceptual categorization and classification of information can help us better understand bankers' misjudging loan opportunities. Making appropriate loans is one of the most fundamental banking activities and inappropriate lending and credit assessments will affect bank profitability, asset quality and solvency (Basel Committee on Banking Supervision, 2006). For example, in the years from 2008 to 2011 the Corporate Division of HBOS, one of the largest banks in the UK, recognized £21.9bn of loan impairment losses, which would have been sufficient to cause the failure of the firm without further capital injection (Financial Conduct Authority and Prudential Regulatory Authority, 2015, p.94). To a considerable degree lending decisions depend on the judgment of bank executives so greater understanding of how lending decisions may be biased is potentially of great economic importance.

A limited number of previous papers have examined perceptual factors in the decision-making of banks. Somerville and Taffler (1995) examined bankers' judgment regarding country risk of less developed countries as an important part of the credit allocation process and their judgment proved to be biased. Baklouti and Baccar (2013) also documented microloan officers' behavior bias that decreases with experience, while Kaustia and Perttula (2012) pointed out the dangerous impact of bankers' overconfidence on their risk assessments. Moreover, Wilson et al. (2007) investigated the role of gender in the perceptions of bank loan officers and Bacha and Azouzi (2019) examined the impact of bank managers' emotional biases and gender on credit decision-making. In the same spirit, Jarboui and Boujelbene (2012) documented that emotions and psychological biases may cause distortions in decision-making of bank managers. As our example centres around securing the funds for a project the corporate finance literature is also relevant and a quantity of papers have shown the significance of perceptual features (see, for example, Heaton, 2002, 2019; Baker et al., 2004; Malmendier and Tate, 2005).

We incorporate a model (i.e., Throughput Model) viewed as a depiction of human and artificial intelligence, which depicts the interactions between information and the processes of decision makers at different phases of processing (Foss and Rodgers, 2011). Such a model is useful in highlighting perceptual and selective informational processes in one phase and diagnosing information in another phase. The model attempts to demonstrate the entire flow of information and the importance of bias behavior in the different phases of information processing by a risk averse decision maker, such as a banker. Unlike other behavioral finance papers that advocate the existence of risk-taking regions in the agent's utility (e.g., Kahneman and Tversky, 1979), we take the neo classical "risk averse" perspective. Further, we include the perceptual framing that may influence the data gathering and evaluation aspects of the decision process. The central idea is that since the "level" of risk lending is a crucial parameter of the commercial loan process; biases in the estimates of risk will critically affect the decision. While our approach can be located within the tradition of experimental research, with the associated advantages of enabling the testing of theoretically grounded concepts, our setting is realistic in nature and our subjects are experienced professionals as this is best practice given our intention to ensure the results are highly relevant to practice (Libby et al., 2002).

3. Algorithmic decision-making and rational behavior

Decision-making is an essential element for any kind of organization.[1] Competence in this activity differentiates the effective managers from the ineffectual ones. Financial decisions involve risk and economic agents are generally risk averse in these domains. Decision-making under risk is characterized by the inability to possess complete information regarding the outcome of our decision. Generally, three principal components of risk can be identified: the magnitude of loss, the chance of loss, and the exposure to loss (e.g., MacCrimmon and Wehrung, 1990).[2] Riskiness in a decision-making environment can be reduced if at least one of these components can be reduced without increasing the others. Traditionally, finance theory provides the necessary tools, via utility theory, to evaluate risk when important features associated with the risk are ex ante completely known to creditors and investors. More specifically the traditional framework assumes a complete knowledge of possible outcomes (i.e. states of the economy) as well as the probabilities associated with such outcomes and so does not address much of the uncertainty associated with the situation. In most cases though, uncertainty cannot be accurately estimated by historical financial data alone. This is because historical financial data of comparable projects may not be easy to obtain or may not even exist. In such cases distributional aspects of the uncertain outcome will be unknown. Even when comparable projects exist they are seldom copycats of the project at hand that are to be evaluated. Consider the typical example of evaluating the potential performance of investing in a new restaurant. Although at first glance a plethora of comparable projects exists, when all restaurant openings are included in the database, it is irrational to exclude the conditional information (e.g. specific location, type of cuisine, state of the economy, etc.) from the evaluation process. On the other hand, the inclusion of more specific conditioning information will result in an ever-declining volume of sample points for the analysis. At some point the decision maker will undoubtedly be faced with the dilemma of which projects to include in the sample and where to draw the line on what is a truly "comparable" project. Related to this is the problem of how to proceed given information which is less than ideal. Given these issues, some type of systematic decision-making, or algorithmic, approach needs to be employed to make decisions given the practical difficulties of employing the traditional theoretical methodology.

4. Throughput model

Decision-making can be depicted by four key concepts of perception, information, judgment, and choice (Hogarth, 1987; Simon, 1957). Combining these key concepts, we argue that algorithmic pathways are expected to provide a unique perspective for decision-making. Decision-making algorithms are a key component of machine learning/ deep learning in that they guide the computer how to learn to operate on its own. In turn, the device continues to gain knowledge to improve processes and run tasks more efficiently. Moreover, as highlighted in the introduction, algorithms can be depicted in the Throughput Model as fulfilling six features of precision, uniqueness, finiteness, inputs, outputs, and generality/effectiveness, which can improve AI systems (Rodgers et al., 2022) (see Table 1). Although it may be inadvisable for researchers to expend a great deal of effort devising individual or idiosyncratic decision models, due to costs versus benefit considerations, it is undoubtedly worthwhile for decision-making researchers to understand the models that best describe how individuals begin and then process the decision-making task. We believe that this model will address and aid individuals' decision-making processes in a comprehensive way. Since decision makers often spend most of their time

[1] We take the view that decision-making is continuous, occurring over time and directs and affects the nature, degree, and pace of change (see Kickert and van Gigch, 1979; Mintzberg et al., 1976; Nutt, 1984; and Simon, 1957).

[2] The magnitude of loss is the actual loss that occurs. This is generally not known for certain in advance so has to be estimated. The chance of loss is the possibility of a loss. The exposure is the maximum loss that could possibly occur. In the context of bank loans the exposure is the complete value of the loan as there is a possibility that none of it is paid back. The chance of a loss is the probability that some of the loan is not repaid (most loans are fully repaid). The magnitude of the loss is the amount of the loan that is not repaid in the event of a default.

eliciting information in attempts to find or design alternative courses of action, this Throughput Model is useful in understanding how they summarize credible evidence of the current situation. The Throughput Model also captures important elements from and relevant to other theoretical models. This meta-theoretical analysis can provide a priori predictions about which decision makers in which tasks will exhibit which processes associated with which theories. Our model explicitly recognizes relevant developments in cognitive science, information systems, and economic analysis.

In the Throughput Model, a banker desires to evaluate the feasibility of a particular risky loan using a modification of the well-known Sharpe ratio as a measure of risk adjusted return (Higgins, 2004),[3] employing the variance instead of the standard deviation in the denominator. According to the Sharpe ratio measure, excess return from a loan has to be properly normalized by the riskiness of the loan as this is measured by the variance of its net cash flows to arrive at a risk adjusted measure of performance which has to be above the banker's risk aversion (a) for the project to be undertaken. Therefore, we assume that:

- L represents the completely known required initial loan amount for undertaking the project.

The banker knows the exact amount of the initial required loan. There is also risk related to this parameter due to uncertainties. For example, in an oil exploration exercise, it may not be known how many drills have to be used before oil is discovered.

- X represents the unknown random future cash flow from the project associated with the loan.

In the oil exploration example, X is unknown because of uncertainty about the amount of barrels that can be extracted at an acceptable cost at the facility when and if exploration proves to be successful.

- $\mu = E(X)$ is the expected cash flow from financing the project.
- R is the principal and interest that must be returned to the creditors financing the project (typically a bank syndication loan) for every dollar invested in the project. Generally, interest charged will depend on the riskiness, which is discussed next.
- $\sigma = \sigma(X)$ is the standard deviation of the risky cash flow X. For example, in project financing, a bank consortium expects to be compensated by a return of the risk of the underlying project. For example, if there is a pipeline developed in a hostile area, then geo-political risk will inflate the required yield from the bank due to higher default risks. Total risk can be decomposed to risk related to the evaluation of the state of the economy (e.g., oil prices, foreign exchange risk, country risk, geo-political risk, etc.).

Let us further assume that the banker exhibits a constant degree of absolute risk aversion (α).

Under this assumption the banker maximizes the expected negative exponential of her risk aversion scaled final profits. If her profits from current operations, that is without undertaking the new project, equal W_0 her random profits after the project will equal:

$$W = W_0 + X - LR \tag{1}$$

More specifically the risk averse banker lends only in projects that increase her utility given by:

$$E\left(e^{-aW}\right) = E\left(e^{-a(W_0+X-LR)}\right) \tag{2}$$

Let us now derive the condition that results in undertaking a project when the banker behaves rationally and has correctly assessed the mean $\mu = E(X)$, and variance $\sigma^2 = E(X-\mu)^2$, of the project under consideration, and furthermore views the project cash flow realization as a random drawing from a Gaussian distribution, i.e. $X \sim N(\mu, \sigma^2)$. First, the banker considers her utility resulting from undertaking the project[4]:

$$U = E\left(e^{-a(W_0+X-LR)}\right) = e^{-a(W_0-LR)}E\left(e^{-aX}\right) = e^{-a(W_0-LR)}.exp\left(-\alpha\mu + \frac{\alpha^2\sigma^2}{2}\right) \tag{3}$$

The banker will lend only if her utility increases by financing a project. This means that her loan utility U should become greater than her no loan utility $U_0 = e^{-aW_0}$. Simple algebra leads to the following investment criterion:

$$U > U_0 : \frac{a}{2} < \frac{\mu - \mathrm{L}R}{\sigma^2} \tag{4}$$

That is, under perfectly rational decision-making the banker will only undertake a project that has a modified Sharpe ratio greater than half her risk aversion. Since the numerator of the ratio is a measure of risk premium over the life of the project, it provides a calculation of the return premium earned for each unit of risk.

The Throughput Model in Fig. 1 is a useful illustration, since it provides a structure for analyzing decision-making tendencies to accept or avoid risk. Such analysis can yield further insight into the behavioral aspects of the decision-making process (Kahneman and Lovallo, 1993). The circles in the figure represent the theoretical constructs of perception, information, judgment, and decision choice (Rodgers, 1997): In the *first phase*, perception and information affects judgment; in the *second phase*, perception and judgment affects decision choice. *Perception* involves the ***framing*** of the decision environment. This means perceiving deviations from sources of information in the decision environment that could affect decision makers' judgment and decision choice. *Information* sources (I circle in Fig. 1) represent external critical factors in analyzing a project. Judgment denoted to as the subsequent stage in the decision-making process, necessitate more analysis of the person's frame and information. Decision choice incorporates selecting the best alternative solution or course of action. The next sub-sections explain each of the major concepts in relation to risk aversion.

4.1. First phase: perception

Individuals' judgments and decisions are often affected by the "framing" of problems and irrelevant but comparable options (Rodgers, 1997). When valuing securities with sparse information, individuals are more likely to be biased (Shefrin and Statman, 1994). In one often cited example, a person is offered a fixed amount of money or a cross pen, in which case most choose the money. However, when offered the cross pen, the money, or an inferior pen, most individuals choose the cross pen. Sales people, as a rule, attempt to benefit from this type of behavior by offering inferior options with the aim of making the primary option appear more attractive. Decision makers' use of the Sharpe ratio, or other utility maximising decision rules, depends heavily on the completeness/incompleteness of their information and their experiences/biases. How decision makers frame their problem set can immensely influence the distributional parameters (i.e., mean and variance) they select. Since most decisions are unstructured, a process-pathway oriented approach provides a comprehensive framework in assessing options, exploring possibilities, testing assumptions and learning (Nutt, 1984). Finally, in considering the psychology of decision-making the willingness to accept risk is influenced by the perception of

[3] The Sharpe ratio is frequently used in practical financial decision-making and is a special case of a utility maximising decision rule. The Throughput model could be used with general utility maximising decision rules.

[4] We have framed the decision in terms of maximising utility as is conventional in economics but it could equally be framed as an NPV maximising decision as would be more common in corporate finance literature.

the variables in the situation, as well as by the outcome that is likely to result from a choice.

Another issue related to project evaluation is that the time to evaluate a project and limited cognitive resources may restrict the optimal analysis of environmental data. For example, narrow framing (Kahneman and Lovallo, 1993), as a result of limited resources, may be analyzed in isolation from its environment. These framing issues in large are influenced immensely by (1) a decision maker's level of expertise, (2) time pressures related to task completion, (3) ill-structured information, and (4) unstable environment (Klein et al., 1993). Specifically, individuals' expertise may bias or influence selection of projects due to specialized knowledge and may also result in overconfidence. Second, as a result of time pressures an individual may not analyze all the data the environment provides optimally. Third, information may be difficult to interpret based upon its limitations, noise level, or errors inherent within. Finally, the environment in which the project is under consideration may change rapidly. Each of these four components regulates how well individuals frame information on route to making a decision.

Eventually the loan analysis revolves around "heuristics" (Tversky and Kahneman, 1974), "self-deception" (Trivers, 1991), and "emotions" (Ellsberg, 1961), which selectively weight only a subset of the data.[5] First, limits on attention, processing abilities and memory can contribute to how information is selected (Tversky and Kahneman, 1981). Second, individuals who believe they are already competent may have considerable inertia in adjusting their cognitive processes (Einhorn and Hogarth, 1978). Third, emotions like anxiety and fear may act as mechanisms that overcome reason (Frank, 1988). Thus, the decision is an ultimately subjective one since there is no theory that can guide it. The desire to find a completely analogous situation will mathematically result in an empty set since in real life every project is a unique endeavor. In a sense the dilemma faced by a rational real-life creditor or investor is "how much conditioning information is enough"? The theory of probability and statistics can be deployed only after this question has been resolved. In this paper we focus on this pre-processing stage and more specifically on how individual framing of this pre-processing stage can influence the analytical stage.

This part of our analysis is related to research that studies decision-making under so-called "model uncertainty" (Edwards, 1968). Under this strand of research, the rational banker who understands that she does not know the exact distributional aspects of her project (i.e., the model) takes a conservative stance by minimizing the potential loss under any distribution (model) that she deems to be plausible. This process results in a worst-case scenario analysis. Despite its theoretical attractiveness this approach may be too conservative for real life applications. Unless the banker can somehow narrow the model universe quite drastically her conservative min-max approach will in most cases result in inaction. The magnitude of the observed entrepreneurial activity and the willingness of bankers to lend funds in unknown environments are evidence that in most cases bankers do not take such a conservative approach.

Where perception influences judgment is in the banker's beliefs about the profitability, liquidity and risk of a loan project. These beliefs have been formed without looking at any information, and represent the banker's "gut feeling" about the project. In a sense, the banker has decided to entertain the idea of pursuing such a project because she feels that the risk premium compensates her for the risk of the project. Therefore, without performing any analysis, a banker has a belief that the project's risk adjusted performance will be equal to S_i where subscript *i* represents individual belief. This is especially related to the well documented phenomenon of overconfidence with experts (Griffin and Tversky, 1992; Miller and Ross, 1975). For example, there is a substantial literature on calibration that illustrates that people tend to underestimate the risk of their assessments due to self-deception (Nel et al., 1969; Steele and Liu, 1983; Odean, 1998). If they expect a project to provide a cash flow μ_i they will tend to underplay the variance of "their" correct assessment $\sigma_i^2$and thus reach a high initial S_i perceived project performance. This will then bias them towards accepting the project that they set their eyes on in the first place. This leads to the first hypothesis:

H1. : Bankers' perceptual processes will significantly influence their judgments when dealing with a first time borrower (i.e., P → J).

The double-ended arrow linking perception and information (Fig. 1) is important in identifying frame of mind or biases in subjective judgments and/or decisions. That is, much support indicates that a person mental process associating perception and information relies on numerous cognitive bypasses that frequently cause biases (Bem, 1972; Kahneman and Tversky, 1979).

Moreover, the TP model pathway depicting perception ↔ information simulates an *artificial* neural network attempt to simplify and represent decision-making behavior in that bankers' experience is matched with the input of information. In other words, the bankers are searching for similarities between their knowledge and incoming information (Rodgers, 1997). In addition, updated information will influence bankers' experience and will guide them to the selection of information sources.

Information-processing limitations, complexity, and coherence are at least three reasons why this may happen (Kleindorfer et al., 1993). First, *information-processing limitations* occur, because most individuals have difficulties dealing with a large amount of data (Thaler and Shefrin, 1981). In addition, *complexity* is owed to the setting that the problem is offered and the kind of assignment (Grether and Plott, 1979; Lichtenstein and Slovic, 1971; Tversky et al., 1990). Finally, *coherence* evolves from a person's thinking process to comprehend experiences in his/her environment (Langer, 1975; Rodgers, 1992; Kruschke and Johansen, 1999). A characteristic of coherence is a person attempting to offer causal explanations whereby none exists, or to make uncertain situations more assured through the implementation of heuristics (Kleindorfer et al., 1993). In a quantitative framework, as the one presented here, perception manifests as a **selectivity** bias where the banker chooses what constitutes the universe of "similar" projects that will be used in the assessment. By exhibiting such selectivity essentially, the banker controls and defines the historical sample and thus eventually the estimates for the performance parameters μ and σ^2. Here selectivity will directly impact the estimates from the correct values that would be achieved if the entire historical sample were used, $\mu_e$and σ_e^2 to the selected estimates $\mu_0$and σ_0^2.

The second hypothesis follows:

H2. : Bankers' perceptions and financial information used in loan making will covary significantly (i.e., P ↔ I).

4.2. First phase: information

Working memory captures accommodating financial and nonfinancial inputs for subsequent recovery. It also comprises the accommodation of partial outcomes in multifaceted serial calculations, such as ratio, cash flow, and trend analysis understanding. The accommodation conditions at the processing level during understanding are instinctively understandable. A user of financial information must be able to retrieve some depiction of dissimilar fragments of the financial information to associate them to, for example, the notes of the financial statements later on. Moreover, storage demands ensue at numerous other processing stages. A person must also deposit the premise of the financial information, the depiction of the setting to which it refers, the timing of the information, and the environmental context of the company.

Historical performance data from similar projects can provide some information as to the potential profitability as well as to the risk of the

[5] Some argue that natural evolution has enhanced the capability to focus on "rules of thumb" (see Simon, 1956).

project at hand. That is, a banker can estimate the mean return μ and deviation σ with some degree of accuracy (standard error). For example, if one is willing to assume that project returns (r) can be modeled as drawn from a Normal distribution with mean μ and variance σ^2 : $r \sim N(\mu, \sigma^2)$, using returns from similar projects she can find the maximum likelihood estimates μ_0 and σ_0. Then the risk-adjusted performance supported by the data is:

$$S_0 = \frac{\mu_0 - LR}{\sigma_0^2} \tag{5}$$

The third hypothesis concludes that:

H3. : Financial information used by bankers in assessing a loan application will significantly influence their judgments (i.e., I → J).

4.3. Second phase: judgment

A key feature of the judgmental phase is the assumption of interrelating knowledge structures, which is referred to as schemata. Rumelhart and Ortony (1977) argued that schemata are data structures for indicating the common concepts deposited in memory. They subsist for widespread concepts underlying financial, economic, and management information used in individuals' judgments. For example, Gilboa and Schmeidler (1995) illustrate a case-based decision theory that is not grounded on evaluating outcomes and their probabilities.

Representations like schemata (Rumelhart, 1975; Rodgers, 1992; Rodgers, 1997) are helpful structures for encoding knowledge in making important decisions. Intuitively, these tasks seem to require the strength of information and perceptual processing simultaneously influencing judgmental processing. Griffin and Tversky (1992) argued that base-rate underweighting and conservatism result from too much reliance on the strength of information signals and too little reliance on the weight of those signals. In this phase, the information is evaluated, and weights are placed on essential information items in order to assess options or the criteria across the options. This enables the banker, for example, during the second phase to make or to refuse the loan. The banker should employ inspection and reasoned guidelines to detect the source of the problem. Both deductive and inductive reasoning are required for effective diagnosis and direct data gathering as shown by the direct arrow leading from information to judgment in Fig. 1. This phase also comprises the enhancement of alternative explanations or courses of action. Decision makers should retrieve ideas and suggestions from their knowledge bases, examine concepts and pertinent information, and employ ingenuity and creativity. For example, Shiller and Pound (1989) noted that nearly all investors who had recently bought a stock had it brought to their attention by direct interpersonal communication. The evaluation of alternatives may use a single criterion or methodology, or a combination of objective criteria or methodologies including compensatory or non-compensatory weighting schemes (Payne et al., 1992).

An illustration earlier indicated that under perfectly rational financial decision-making a risk averse banker will undertake a risky project only if this risk-adjusted measure of performance meets or exceeds her degree of risk aversion $a/2$. Here we are interested in enhancing this rational framework whereby the decision maker may deviate from the completely rational choice because of her personal biases (Shiller, 2014). Camerer (1995, 1998) and Kahneman and Tversky (1979) address this issue by considering choice mechanisms that involve functional forms incorporating probability weightings and utility functions. In some cases, these functional forms are explicitly based on modified axioms of choice. For example, a banker who is biased in favor of undertaking a project may decide, before looking at any historical data, that the project provides a risk-adjusted performance S_i. This is similar but not the same to the Bayesian concept of a prior distribution, in that a banker is neither endowed with a prior distribution nor will she employ Bayes rule to combine her prior distribution with historical data to reach a posterior distribution. A true Bayesian approach would be dictated by pure rationality. Instead, the banker somewhat arbitrarily produces her performance measure as a convex combination of her subjective performance belief and the one supported by the historical data (of course this data have also been screened and selected again according to her personal judgment). This leads to the fourth hypothesis:

H4. : Irrationally and selectively chosen information chosen by bankers' analysis of a potential loan will significantly influence their decisions (i.e., J → D).

4.4. Third phase: decision choice

The third phase incorporates the selection of the best alternative answer or plan of engagement (see decision choice in Fig. 1). During this phase, the decision maker should implement her managerial capabilities to ensure that the choice is followed corresponding to instructions. Moreover, Yates (1990) purported three kinds of decisions: these are choices, evaluations, and constructions. In a choice condition a person is challenged with a well-defined set of alternatives and the typical chore is to select one of them. Evaluations, on the other hand, represent indications of worth for an individual's alternatives. Finally, constructions are decisions whereby a person attempts to amass the most adequate alternative that is achievable.

Decision choices are influenced by the project structure beyond the overall probability distribution of consumption outcomes that it provides. Ellsberg (1961) suggested that individuals are averse to ambiguity which can cause irrational choices. Further, Camerer (1995) suggested that aversion to ambiguity may unduly increase risk premia with the introduction of new financial markets due to the combination of uncertainty about both the structure of the economic environment and the resulting outcomes. In addition, mood and emotions affect individuals' choices with respect to risk (Mann, 1992). Individuals in good moods have been shown to be more optimistic in their choices than those in bad moods (Wright and Bower, 1992). Decision choice is achieved here by a biasing of the historical Sharpe ratio towards the personal opinion of the individual. For example, the simplest way to do this is to form a weighted sum of the historical and the judgmental performance where the weights used for each represent the strength of the bias or alternatively the objectivity of a banker. More specifically say:

$$S = w_i S_i + (1 - w_i) S_0 \tag{6}$$

where w_i represents the strength of the personal bias or conservatism. The phenomenon of conservatism identified by Edwards (1968) implies that under specific situations individuals do not update their beliefs as fast as an optimal Bayesian update would imply. In a sense a high value of conservatism w_i implies a tendency to dismiss and underweight new evidence. That is the higher the w_i weight the less willing the decision maker is to use the evidence supplied by the historical data. A low w_i on the other hand signifies a more objective and less judgmental banker who is willing to abandon (or undertake) a project mainly based on historical performance data even if such action contradicts her initial personal assessment of the project. A possible explanation for conservatism is the costs involved in processing new information and updating beliefs. Actually there exists evidence that new patterns that are more costly to process from a cognitive viewpoint get underweighted.

Before we describe the distributions underlying the model major concepts, an example of a banker's decision is discussed below. A bank manager has information (**I**) presented to her for analyzing a prospective company to include in the company's portfolio. The banker could or could not generate a perception (**P**) of the subject entity grounded on the information collected. The banker at this point can use judgment (**J**) and then proceed to making a decision (**D**) or not use any judgment and jump to a decision, or use information, perception, and judgment simultaneously to reach a decision (see Fig. 1). When a banker frames a company's financial information to evaluate its credit worthiness, her under-or over-estimation of the risks can affect the company's expected profitability. This hypothesis is tested by a direct link from perception to decision choice:

H5: Bankers' perceptual processes will significantly influence their decision choices when dealing with a first time borrower (i.e., P → D).

5. Subjects and model testing

5.1. Subjects

Thirty-three bankers, from commercial banks in the southern California area, agreed to participate in this study.[6] The average capitalization value of the banks was 69 billion in U.S. dollars. The average lending experience of the participants was seven years and all were college graduates. Subjects were provided with financial and other information on 10 companies, five of which were classified by Moody's classification of bonds and stocks as "good" credit risks (B = companies classified as "good") and five of which were classified as "bad" credit risks (C = companies classified as "bad"). The companies were presented in random order across subjects. Subjects' average time of completion was one hour. The company data provided were obtained from the Compustat database and comprised ratios, income statement, balance sheet, and statement of cash flow. The ratios used were sufficient for our investigation as they are highly correlated with other ratios in the same classification and so using other ratios will not yield any more significant information (Pedhazur, 1982).

The total sample size (number of responses) based on repeated measures across the ten cases was 330. That is, each subject received 10 cases (i.e., 5 good and 5 bad performing company cases). The cases and the measurement instruments were delivered to the bankers at their place of employment. The instructions given to the subjects told them to evaluate the significance of many information items in establishing their choices regarding whether an entity ought to obtain an unsecured one-million-dollar line of credit for one year. The amount of one million dollars was selected in order to hold constant the loan amount across cases. In this way, research results were not subject to possible interpretation of changing loan amounts across cases. Subjects' responses were recorded on an interval scale (i.e., excellent, satisfactory, substandard, and doubtful) based on the system used by the Office of the Comptroller of the Currency (2017). The scale went from 0 to 30 for excellent, 31–60 for satisfactory, 61–90 for substandard, and 91–120 for doubtful (measured in centimeters). The subjects were instructed to treat this scale as continuous (i.e., from 0 to 120). The scale properties followed the assumption of normality as follows: equal intervals where the distances between the numbers are of a known constant size. The scales showed good internal consistency reliability (ranging from 0.80 to 0.90) and predictive validity with measures of subsequent performance variables in other studies (Rodgers, 1997, 1999).

Subjects were requested to put a tick-mark along the scale for three sets of questions that revealed their:

(1) perceptual processes (classification and categorization of information),

(2) judgmental processes (analysis of information), and

(3) decision choices.

These questions were selected based on bank procedures for analyzing business loan applications and empirical results supporting these questions at two large banks (Cohen et al., 1966; Rodgers, 1997). We use the questionnaire employed by Rodgers (1992).

5.2. Model testing

This section describes in detail the questionnaire items used as indicators for each of the latent concepts of perception, judgment and decision choice (see Rodgers, 1992). A one-way repeated measure analysis of variance design was employed to determine whether significant differences in the decision choice question of loan approval existed in the ten cases. This repeated measure design affords the researcher to control for individual differences among subjects as well as depicting that the ten cases are unique (Cohen and Cohen, 1975: pp. 410–412). Next, a covariance structural model was implemented to capture bankers' perceptions, use of information, judgments and decision choices. Fig. 3 consists of four latent exogenous variables ($\xi_1, \xi_2, \xi_3, \xi_4$) and two latent endogenous variables (η_1, η_2).

ξ_1 represents subjects' perceptual processes. The following four indicators measure this latent variable:

XPCR$_1$, as a credit risk,

XPREG$_2$, as a regular bank customer,

XPBUS$_3$, increasing bank deposit accounts and other bank business, and

XPBPROF$_4$, in terms of the bank's potential profitability.

The variables ξ_2, ξ_3, and ξ_4 represent financial information in terms of liquid assets, income, and risk of a company, respectively:

ξ CR is measured by X_5, which is current ratio,

ξ NM is measured by X_6, which is the net margin ratio, and.

ξ DE is measured by X_7, which is the debt/worth ratio.

The current ratio, net margin, and debt/equity ratios were used in the model because decision makers generally use these ratios to evaluate a short-term credit request (Rodgers, 1992). As discussed above adding other measures would not yield any more significant information due to their high correlation with the three we have employed.

Moreover, η_1 represents subjects' judgmental processes, a latent variable measured by five indicators, which represent loan officers' analysis of a company's information as well as their evaluation of the loan in terms of:

YJRISK$_1$, their bank's share of risk,

YJLIQ$_2$, the liquid assets of this company,

YJFPROF$_3$, this company's profitability

YJCRED$_4$, this company's credit rating, and

YJCLASS$_5$, their bank's classification system of the loan.

Finally, η_2 represents subject's decision choices. The following two indicators measure this latent variable:

YDC1, whether the loan should be approved, and

YDC2, conditions on the loan.

According to the model depicted in Fig. 3, perceptual processes affect (γ_{21}) judgmental processes and decision choice directly. Perceptual processes and financial information are correlated. That is, φ_{21} =perception ↔ liquid assets, φ_{31}=perception ↔ income, φ_{41} = perception ↔ risk, φ_{32}=liquid assets ↔ income, φ_{42}=liquid assets ↔ risk, and φ_{43}=income ↔ risk.

Financial information (i.e., liquid assets, income and risk) affects judgment directly ($\gamma_{12}, \gamma_{13}, \gamma_{14}$), and judgment affects decision choice directly (β_{21}).

Following is the structural model equations of η_1 (judgmental processing) and η_2 (decision choice) for Fig. 3. The structural equations are:

$$\eta_1 = \gamma_{11}\xi_1 + \gamma_{12}\xi_2 + \gamma_{13}\xi_3 + \gamma_{14}\xi_4 + \zeta_1 \tag{7}$$

$$\eta_2 = \beta_{21}\eta_1 + \gamma_{21}\xi_1 + \zeta_2 \tag{8}$$

In the context of a multiple regression equation, Eq. (7) indicates that γ_{11} value for the effect of perceptual processing on η_1, is the effect of perceptual processing after having controlled for γ_{12} (liquid assets), γ_{13} (income), and γ_{14} (risk) variables in the equation. Eq. (8) shows the γ_{21}value for the effect of perceptual processing on η_2 after having controlled for β_{21} (judgmental processing). The perceptual processing effects in the two equations can be seen as effects over and above the

[6] The study was given ethical approval by the Hull University Business School Ethics Committee reference date 05 Oct 2015 and the participants gave consent before completing the exercises for the study.

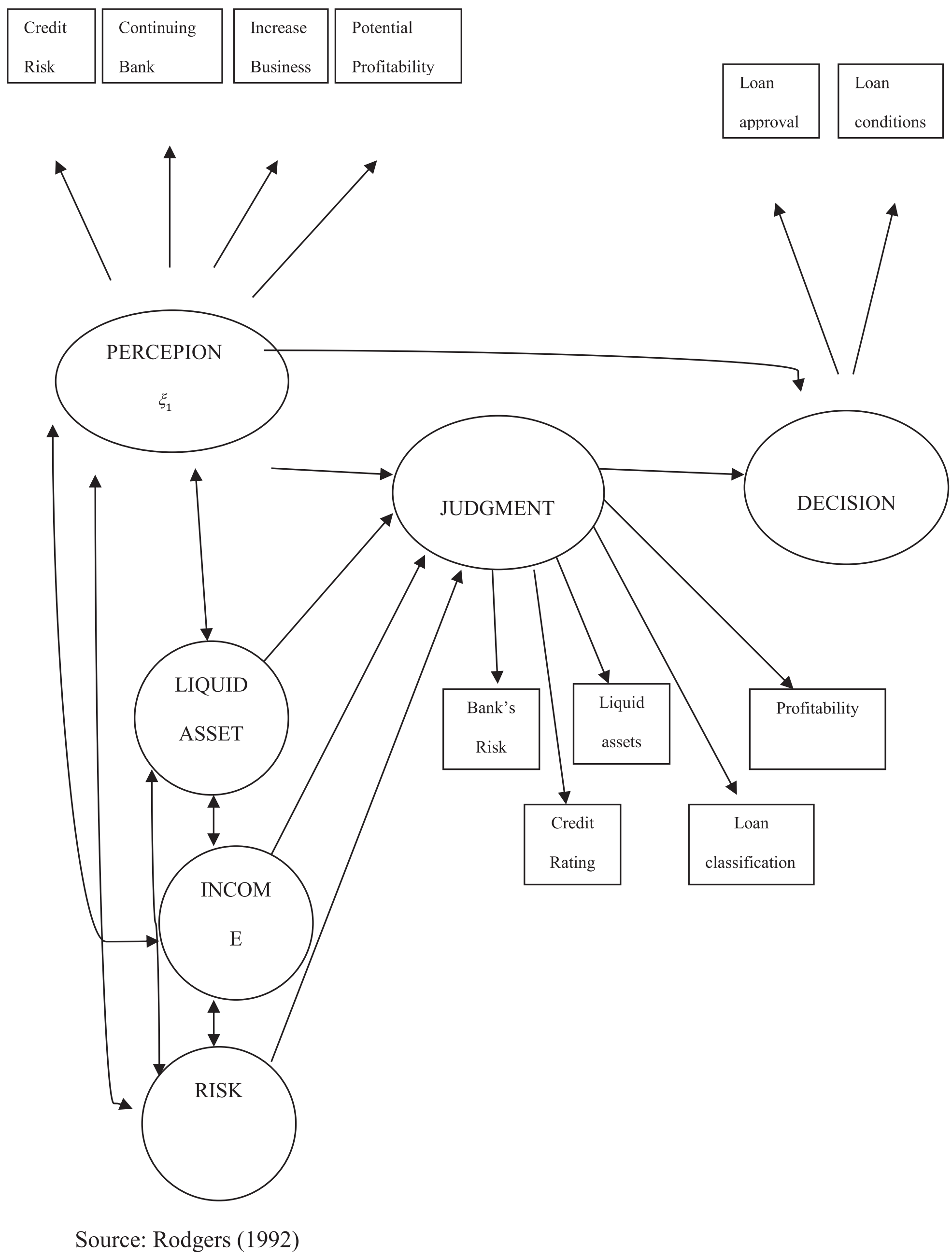

Fig. 3. Bankers' decision-making processes
Source: Rodgers (1992).

direct effects of the other variables.

6. Results

The repeated measure analysis of variance design indicated that significant differences exist in the mean decision choices for companies.[7] The greatest advantage of using this repeated measure design is that the loan officers' treated the companies differently (Cohen and Cohen, 1975). That is, each case company was treated independently thus supporting the "validity" that the companies were unrelated and treated as such by the loan officers. Maximum likelihood (MLH) was used to estimate the conceptual and measurement systems implemented by the program LISREL (Joreskog and Sorbom, 1993). A major strength of LISREL is its latent-variables approach to covariance structural model testing, whereby multiple indicators of each factor are obtained. Multiple indicators improve construct validity of measurements and reduce measurement errors (Rodgers, 1997).

The chi-square test showed modest discrepancies between the observed correlation matrix and that implied by the bankers' model.[8] Yet, the normed fit index (NFI), the incremental fit index (IFI), and the comparative fit index (CFI) values surpassed the threshold of 0.95 for acceptable fit (Bentler and Bonett, 1980). Bentler's (1990) study acknowledged the CFI to have less sampling variability than the NFI or IFI. Unlike the IFI, the CFI never exceeds 1 and avoids the NFI's small

[7] $F(9{,}298) = 53.364$, $p < .001$.

[8] $(\chi^2_{df=68} = 291.0)$

sample under-estimation of model fit. Typically, fit indices less than 0.80 indicate that a particular model may be a poor fit to the data and/or does not capture the tested theory well. These three fit indices are nonetheless asymptotically equivalent (Bentler, 1990). Further, the root mean square residual (RMR = 0.03), goodness of fit index (GFI = 0.89), and adjusted goodness of fit index (AGFI = 0.83) had reasonable fits.

The RMR is a good indication of the model to the data. The GFI offers a nonstatistical evaluation of the suitability of the model fit to data that can be employed to conclude whether, on feasible grounds, the model has value in depicting the data (Bentler, 1990). However, when there are a large number of degrees of freedom relative to sample size, the GFI has a downward bias (Sharma et al., 2005). In addition, it has also been found that the GFI increases as the number of parameters increases (MacCallum et al., 1996); and, has an upward bias with large samples. Therefore, the adjusted goodness-of-fit index (AGFI) was used to correct for the degrees of freedom in the model. Although, the AGFI tends to increase with sample size. Individual parameter estimates further corroborated this theory.

The factor loadings are the standardized regression weights for calculating observed elements from latent concepts. To recognize the variance of the latent concepts, the first indicator loading was fixed on its latent concept equal to one. In addition, the factor loadings are high and consistent for each of the latent concepts under inquiry. Hence, it can be determined that the model evaluated the theoretical concepts conjectured to occur at the plane of latent factors with an acceptable degree of precision and that the observed variables are satisfactory indicators of these factors. That is, the perception, information, judgment and decision choice concepts relate well to the supporting questionnaire items. Table 2 reports the correlation matrix, means and standard deviations of the model. Table 3 repeated analysis of variance design reports that firms analyzed by the bankers were significantly different from one another. Finally, as a test of validity of the firm types, "good loans" types were significantly different from "bad loan" types of firms.

Hypothesis 1 was supported in that the effect of perception (ξ_1) on judgment (η_1) was 0.81 (γ_{11}) at $p < .01$. It seems that bankers pursued lending activities because the risk premium compensates them for the risk of the project. For example, bankers may be more willing to loan money if the client deposit large sums of money and bring other relationships to the bank. Therefore, without performing any analysis, the bankers' belief suggested that projects' *risk adjusted performance* will be equal to S_i (i.e., perceived project performance). Thus, our results show that, in this respect, bankers' behavior is in accordance with basic finance theory.

Hypothesis 2 was confirmed in that the correlation of liquid assets, income, and risk with decision makers' perception (i.e., φ_{21}, φ_{31}, *and* φ_{41}) was statistically significant at the p-value < .01 level. This suggests that covariation perception and its resultant effect on judgment are determined jointly by situational information (liquid assets, income, and risk) and the individual's previous outlooks or viewpoints (perception) about the information. Apparently, the bankers controlled and defined the historical financial information thereby influencing the estimates for the performance parameters μ and σ^2. That is, bankers' selectivity impacted the estimates from the financial information that would be achieved if the entire historical sample were used, μ_e and σ_e^2 to the selected estimates μ_o and σ_o^2. To underscore hypotheses 1 and 2, bankers

Table 3
Non-parametric chi-square goodness-of-fit test.

Types	Total observed decisions f_0	Total expected decisions f_e	$f_0 - f_0$	$(f_0 - f_0)^2$	$\frac{(f_0 - f_e)^2}{f_e}$
"Good loans"	152	165	13	169	1.02
"Bad loans"	134	165	31	961	5.82
χ^2					6.84[c]

[c] Significant at $p < .001$.

Table 2
Descriptive statistics of variables. In this table we provide descriptive statistics of the variables used in our study. The perception variables are based on the bank manager's perception of the customer as: a credit risk P_{CR}; a regular bank customer P_{REG}; in terms of increasing bank deposit accounts and other business P_{BUS}; in terms of the bank's potential profitability P_{BPROF}. The judgment variables are based on the bank manager's evaluation of the company in terms of: your bank's share of risk J_{RISK}; the liquid assets of the firm J_{LIQ}; the profitability of the firm J_{FPROF}; the credit rating of the firm J_{CRED}; the bank's classification system of the loan J_{CLASS}. The decision choice variables are: loan approval DC_1; which conditions would you approve the loan DC_2. The financial variables are: current ratio CR; net margin NM; debt/equity DE.

Correlation matrix	Perception variables				Judgment variables					Decision choice variables		Financial variables		
	P_{CR}	P_{REG}	P_{BUS}	P_{BPROF}	J_{RISK}	J_{LIQ}	J_{FPROF}	J_{CRED}	J_{CLASS}	DC_1	DC_2	CR	NM	DE
P_{CR}	1.00													
P_{REG}	0.92	1.00												
P_{BUS}	0.86	0.93	1.00											
P_{BPROF}	0.85	0.88	0.90	1.00										
J_{RISK}	0.84	0.80	0.76	0.79	1.00									
J_{LIQ}	0.81	0.76	0.74	0.75	0.74	1.00								
J_{FPROF}	0.86	0.80	0.80	0.79	0.80	0.75	1.00							
J_{CRED}	0.90	0.87	0.85	0.84	0.82	0.82	0.89	1.00						
J_{CLASS}	0.92	0.87	0.86	0.86	0.84	0.79	0.88	0.93	1.00					
DC_1	0.71	0.71	0.73	0.72	0.64	0.66	0.71	0.75	0.75	1.00				
DC_2	0.78	0.76	0.75	0.72	0.68	0.69	0.76	0.79	0.79	0.80	1.00			
CR	−0.45	−0.42	−0.39	−0.40	−0.40	−0.50	−0.46	−0.47	−0.46	−0.36	−0.41	1.00		
NM	−0.62	−0.58	−0.57	−0.54	−0.57	−0.46	−0.67	−0.61	−0.62	−0.52	−0.59	0.34	1.00	
DE	0.61	0.59	0.62	0.60	0.55	0.47	0.82	0.59	0.60	0.55	0.60	−0.52	−0.71	1.00
Means														
	P_{CR}	P_{REG}	P_{BUS}	P_{BPROF}	J_{RISK}	J_{LIQ}	J_{FPROF}	J_{CRED}	J_{CLASS}	DC_1	DC_2	CR	NM	DE
	56.89	53.90	54.97	54.99	59.19	54.77	61.32	57.23	58.87	29.51	66.69	0.0	0.0	0.0
Standard deviations														
	P_{CR}	P_{REG}	P_{BUS}	P_{BPROF}	J_{RISK}	J_{LIQ}	J_{FPROF}	J_{CRED}	J_{CLASS}	DC_1	DC_2	CR	NM	DE
	30.75	30.75	31.61	30.51	31.11	31.16	32.00	29.60	29.74	16.85	41.87	1.0	1.0	1.0

utilizing their perceptions rejected 8 % of the loans classified by Moody's as "good." Also, the bankers accepted 19 % of the loans classified as "bad."

Hypothesis 3 was partially supported. The use of financial information was significant at $p < .01$ for both liquid assets (γ_{12}) and income (γ_{13}). This information is typically modeled based upon bankers' guidelines for lending to companies and is drawn from a Normal distribution with a mean μ and variance σ^2. Although, correlations do not imply causality, our results are supported by the notion that we are operationalizing a theory (i.e., Throughput Model) to assist in explaining the data. Risk information (γ_{14}) was not statistically significant due to the short duration (i.e., one year) of the proposed loan. In other words, risk information was not as meaningful as the liquidity and income information of the company for payment of the proposed loan.

Hypothesis 4 was supported in that the effects of judgment (η_1) on decision choice (η_2) was 0.70 (β_{21}) at $p < .01$. Apparently, bankers somewhat arbitrarily produced their performance measure as a convex combination of their subjective performance belief and the one supported by the historical financial information. This data was screened (see hypothesis 1) and selected (hypothesis 3) according to their personal judgments.

Hypothesis 5 was rejected in that the 0.19 (γ_{21}) effect of perception on decision choice was not significant. However, the indirect effect of perception still had a considerable impact (0.56) on decision choice. That is, the indirect effect is accounted for because perception affects judgment, which in turn affects decision choice. Elements of knowledge apparently become increasingly interconnected so that perceptual processes influence the analysis and selection of financial information. Although, financial crisis or boon time may influence portfolio selections, decision-making on a banker level typically is confined to its operating procedures as depicted by the U.S. Comptroller of the Currency as reported by Rodgers (1992). For example, our scale reflects the notion of boundedness in the commercial lending theatre (Simon, 1957). It appears that financial information analyzed was influenced by perception in the judgmental stage. Thus, perceptual influence on structuredness of information may partially explain the choices made by decision makers. Namely, decision choice was achieved by a biased historical Sharpe ratio in the direction of bankers' perceptions. More specifically: $S = w_i S_i + (1 - w_i) S_0$, where w_i represents the strength of the personal bias.

7. Conclusions

This paper provides ideas for AI systems that incorporate causality. The advantage of this approach is that, instead of relying on statistical correlations, the systems will be able to identify the relevant causal variables. This will allow them to better deal with, perhaps transitory, environmental factors. The concepts we use are "structural causal models" and "independent causal mechanisms."

We illustrate the utility of our approach with a specific case study drawn from banking. By doing this we contribute to artificial intelligence and finance research by explaining how emotions and cognitive errors influence bankers and the decision-making process in a way that potentially can lead to incorrect valuations. Without fully understanding and identifying these processes, these models can only hope to capture a portion of the decision processes of individuals. It is also key to recognize how individuals' prior beliefs may override their other processes and influence their judgments and choices. This is not to say that decision makers' prior beliefs are totally erroneous when they affect their judgments and choices, but their prior beliefs should be used to support their other processes.

Due to bankers' limited processing ability only a limited amount of information is considered for further detailed analysis. Therefore, risk is introduced given that a complete set of information cannot be analyzed due to incompleteness of information, time pressures, expertise level, and an unstable environment. Since the "risk level" of a loan (i.e., "good" versus "bad" according to Moody's classification) is crucial in the loan analysis process, biases in the estimates of risk influences the decision (i.e., misclassifications of the loan as depicted in Table 3). It should be mentioned that, especially during periods of crisis and liquidity shortage, our results have important implications since biased bankers' decisions may have a significant impact on financing the real economy.

The result also demonstrates an advantage of using an algorithmic Throughput Model (via path analysis) when trying to uncover the indirect effects of one parameter or another because it shows both the ***direct*** and ***indirect*** effects. It is very important to consider both direct and indirect effects in a model, since together they equal the total accounting information-processing effect of an independent variable on a dependent variable. Also, indirect effects rest on a stronger theoretical foundation than do direct effects because indirect effects act through other modeled variables. Direct effects act through unmodeled variables, and hence unknown forces.

It is worth noting, however, that the ideas presented in the paper are at the conceptual, experimental design, and structural equation modelling levels. Implementing these ideas presents a number of challenges as set out in general terms in Schölkopf et al. (2021): (a) We need to infer potentially abstract causal variables from the available input features; (b) there is a need to address the fact that there is no overall consensus on which characteristics of the data reveal causal relations; (c) the usual experimental protocol using training and test sets may be insufficient for inferring and evaluating causal relations on existing data sets; (d) we often lack appropriately scalable and numerically correct algorithms.

In summary, the AI algorithmic Throughput Model attempts to demonstrate the entire flow of information and the importance of biased behavior in the different phases of information processing by a decision maker. Given the lack of theoretical analysis of decision-making from a holistic viewpoint in the behavioral finance literature, we believe this paper makes a significant contribution to an exponentially emerging stream of research.

CRediT authorship contribution statement

Waymond Rodgers: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing. **Robert Hudson:** Formal analysis, Writing – original draft, Writing – review & editing. **Fotini Economou:** Formal analysis, Writing – original draft, Writing – review & editing.

Data availability

The data that has been used is confidential.

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