



The Role of Professional Judgment in Financial Risk Management: Limitations of Formal Models and Decision-Making Under Uncertainty

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Abstract

This article examines the role of professional judgment in financial risk management when quantitative models provide incomplete, unstable, or contextually ambiguous decision support. The study integrates a structured review of recent research on model risk, credit-risk assessment, probabilistic forecasting, explainable machine learning, and behavioral finance with a comparative analysis of two organizational settings: receivables management during Air Liquide's disengagement from Russia and scholarship-program financial administration at UCF Global. The analysis demonstrates that model outputs remain conditional on the quality and relevance of input data, the validity of underlying assumptions, the selected specification, and the correspondence between the model's operating boundaries and the decision environment. Credit-risk scholarship further indicates that financial variables may be productively supplemented by behavioral, situational, and alternative information, provided that the resulting assessment remains transparent, explainable, and subject to effective governance. On this basis, the article develops an Integrated Professional Judgment Framework comprising quantitative assessment, discrepancy detection, qualitative enrichment, documented authorization, and outcome-based recalibration. The findings provide conceptual support for a hybrid approach in which professional judgment does not substitute for formal analysis but performs a disciplined interpretive and governance function when model applicability is uncertain. The framework is relevant to financial analysts, credit-risk managers, and institutional decision-makers operating in complex, data-constrained, and rapidly changing environments.

Keywords: Professional Judgment, Financial Risk Management, Credit Risk, Accounts Receivable, Value at Risk, Altman Z-Score, Decision-Making Under Uncertainty, Behavioral Finance, Qualitative Risk Factors, Hybrid Decision Model.

INTRODUCTION

The growing reliance of financial institutions on quantitative methods has transformed model risk from a technical concern into an independent component of organizational risk governance. The Prudential Regulation Authority defines model outputs as inherently uncertain because they represent simplified approximations of complex real-world processes and are constructed from necessarily limited observations [1]. Consequently, the relevance of a model cannot be inferred solely from its statistical sophistication: its applicability to the decision under consideration and the validity of its assumptions within the prevailing business environment must be assessed explicitly [1]. Model risk therefore arises not only from errors in construction or implementation but also from the inappropriate interpretation of otherwise correctly calculated outputs, particularly when data quality

deteriorates, structural relationships change, or the model is applied beyond its operating boundaries [1]. The Basel Committee's review of supervisory effectiveness reaches a complementary conclusion, emphasizing that early-warning systems, benchmarking, high-quality data, and technological tools generate reliable supervisory value only when combined with consistent expert judgment, effective challenge, and institutional accountability [2]. These principles establish the central premise of the present study: quantitative models are indispensable instruments of financial analysis, but their practical reliability depends on validation, contextual interpretation, and formally governed professional oversight.

The scientific gap addressed in this study arises from the limited integration of three established but largely parallel research traditions. The first examines model risk and

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demonstrates that analytical outputs are contingent on assumptions, data quality, implementation integrity, and the conditions under which a model remains valid [1]. The second concerns credit-risk and default assessment, where recent research has expanded beyond conventional accounting variables toward behavioral, situational, socioeconomic, and alternative data capable of capturing dimensions of borrower risk that are not fully represented in financial statements [5, 15, 19]. The third is behavioral finance, which documents the systematic influence of anchoring, overconfidence, loss aversion, herding, availability effects, and risk perception on financial choices [3, 18]. Organizational research adds a further dimension: Grant and Nilsson [4] show that strategic and financial rationales in capital-investment decisions may be generated through intuitive expertise even when the final decision record is expressed in predominantly analytical terms. Kaye et al. [6] similarly demonstrate that decisions under uncertainty require explicit treatment of assumptions, ranges of possible outcomes, alternative interpretations, and the consequences of error. Taken together, these literatures explain why neither automated scoring nor unaided intuition provides a sufficient account of high-quality financial decision-making. What remains insufficiently developed is a structured mechanism through which model output, contextual evidence, expert interpretation, and retrospective learning can be integrated within a single auditable decision process.

The present article addresses this gap through the following research **objective**: to identify the conditions under which formal financial risk models fall short of adequate decision support, and to characterize the structure and mechanisms of professional judgment that fills the resulting gaps in practice. **The scientific novelty** of the study consists in the construction of an Integrated Professional Judgment Framework (IPJF) for accounts receivable and program financial risk, grounded simultaneously in systematic literature review and in the documented operational experience of financial analysts working within internationally recognized organizations. **The working hypothesis** of the study holds that non-schematic, context-sensitive financial decisions informed by qualitative expertise are expected to support more resilient outcomes in ambiguous environments than algorithmic recommendations applied without expert mediation.

The study carries practical significance for at least three audiences. For financial analysts operating in credit and receivables management, it provides a structured model for articulating and legitimizing the qualitative reasoning that already shapes daily decisions. For scholarship program administrators and educational finance professionals, it demonstrates how the same decision logic applies to non-commercial financial sustainability challenges. For US-based organizations developing international financial talent pipelines, the article illustrates how cross-functional specialists who bridge analytical rigor with organizational

awareness contribute to institutional stability and competitiveness, consistent with broader workforce development priorities in the financial services and higher education sectors.

The limitations of the present study should be acknowledged. The case analysis draws on a relatively bounded set of organizational contexts (one industrial multinational operating in the Russian market during a period of geopolitical disruption, and one US university scholarship program), which limits the generalizability of specific numerical thresholds proposed in the framework. The literature review, while systematic in scope, is constrained to sources published between 2019 and 2026 and available through peer-reviewed channels, meaning that some practitioner knowledge embedded in internal organizational procedures may not be fully captured. Additionally, the behavioral dimensions of professional judgment explored here draw on documented patterns from the broader literature rather than from primary psychometric measurement, which future empirical work should address.

MATERIALS AND METHODS

The methodological design of the study rests on three complementary approaches, each selected to address a distinct layer of the research problem.

A structured targeted review was undertaken using the 20 publications included in the reference list. The source base covers the period 2019–2025 and combines peer-reviewed journal research [3–7, 9, 10, 13, 14, 18, 19], two research preprints [8, 15], supervisory and policy publications [1, 2, 17], a rating report [16], and official corporate disclosures [11, 12, 20]. The review was organized around six analytical domains: model risk and governance; decision-making under uncertainty; behavioral influences on financial judgment; credit-risk assessment and default prediction; Value at Risk and probabilistic forecasting; and explainability in machine-learning applications. Each source was examined for its contribution to one or more components of the proposed framework, including the conditions of model applicability, the role of qualitative information, the governance of overrides and post-model adjustments, and the use of feedback for recalibration. Corporate disclosures were used exclusively to establish company-specific financial facts and the temporal context of the Air Liquide case, whereas supervisory and policy documents informed the governance, validation, and explainability dimensions of the analysis.

For analytical purposes, the source base was divided into four functional groups. The first comprises studies of professional judgment, behavioral finance, and decision-making under uncertainty [3, 4, 6, 18]. These publications provide the conceptual basis for examining intuition, risk perception, cognitive bias, and disciplined choice under incomplete information. The second group includes research on credit-

risk assessment, default prediction, accounts receivable management, probabilistic forecasting, and explainable machine learning [5, 7–10; 14, 15, 19]. These sources define the methodological possibilities and limitations of contemporary quantitative assessment. The third group consists of case-study methodology [13], which informs the comparative interpretation of the two organizational settings. The fourth group contains supervisory, policy, rating, and corporate materials [1, 2, 11, 12, 16, 17, 20]. These publications provide standards for model governance and explainability and establish the documented financial context of Air Liquide. The synthesis gives greatest theoretical weight to peer-reviewed research, while official and supervisory sources are used to substantiate institutional requirements and company-specific facts.

Two organizational cases were selected for in-depth qualitative analysis based on their complementarity in terms of sector, scale, and type of financial uncertainty involved. The first case covers financial receivables management at Air Liquide Russia during the period July 2022 to September 2023, a context characterized by geopolitical disruption, currency volatility, and the organizational challenge of maintaining client relationships while controlling escalating credit exposure. The second case covers scholarship program financial administration at UCF Global (University of Central Florida) during 2025, a context characterized by multi-stakeholder coordination across students, donors, and program administrators, with financial sustainability directly linked to the quality of data management and decision support.

The analytical protocol for each case followed a structured template: identification of the formal instruments in use, identification of conditions under which formal instruments produced ambiguous or contradictory signals, documentation of the qualitative factors that informed the actual decision taken, and assessment of the outcome. The evidence in the case was taken on the basis of the author's work experience. This approach is consistent with case study methodology as applied in management research [13], where depth of contextual analysis is prioritized over breadth of sample.

The Integrated Professional Judgment Framework (IPJF) proposed in the Results and Discussion section was developed through an iterative synthesis process combining the theoretical insights from the literature review with the pattern of observed decision-making across the two cases. The synthesis followed a template analysis approach: key decision points were coded from the case narratives and mapped against theoretical decision nodes identified in the literature, and the resulting structure was refined until it achieved internal consistency and coverage of all documented decision types. The framework was not subjected to empirical validation in the present study, which represents

a direction for future research. Visual representations of the framework and source-based statistical evidence were developed using Python (matplotlib library, version 3.10) to ensure reproducibility. For Figure 3, the 1–5 values are author-assigned ordinal ratings used solely to visualize the qualitative synthesis of the cited literature across seven operational dimensions. A score of 1 denotes comparatively limited suitability and a score of 5 comparatively strong suitability within a given dimension; the values were not generated through statistical estimation, empirical measurement, or formal weighting, and no composite score or hypothesis test was calculated from them.

RESULTS AND DISCUSSION

A primary output of the systematic literature review is a consolidated picture of where and why formal quantitative models fail as sole decision support tools in financial risk management. Three model types merit specific analysis given their prevalence in the organizations examined: Value at Risk (VaR), credit scoring under the Five Cs framework, and the Altman Z-score model.

Value at Risk remains widely used in portfolio risk assessment, but its effectiveness depends on model specification and the conditions of the estimation sample. Al Mamun et al. [8] compare out-of-sample exceedance rates across DLM, GARCH, and LSTM models for S&P 500 returns, while Wang et al. [9] evaluate several VaR specifications for the Shanghai Composite. Their findings vary by model and testing design and therefore do not justify a universal claim that every VaR specification systematically understates risk. In conjunction with the PRA model-risk principles [1], these findings imply that VaR should be interpreted as a specification-dependent estimate rather than as a complete representation of loss exposure. Its responsible use therefore requires comparative specification analysis, backtesting, sensitivity testing, explicit documentation of assumptions, and reassessment whenever the market environment moves beyond the conditions represented in the calibration sample.

For one-day 95% VaR, the nominal unconditional exceedance rate is 5%. Figure 1 reports observed exceedance rates from two independently conducted backtesting exercises: the S&P 500 study (1,257 test observations [8]) and the Shanghai Composite study (1,038 forecast observations [9]). Values are reproduced from the reported failure counts or rates, with calculations rounded to two decimal places. Because the studies use different assets, observation periods, estimation methods, and model sets, their percentages should be interpreted within each study rather than treated as a pooled sample or a directly comparable ranking of models. A separate narrative passage in [8] gives an approximate DLM rate of 4.8%; Figure 1 consistently uses the explicit counts ($75/1,257 \approx 5.97\%$).

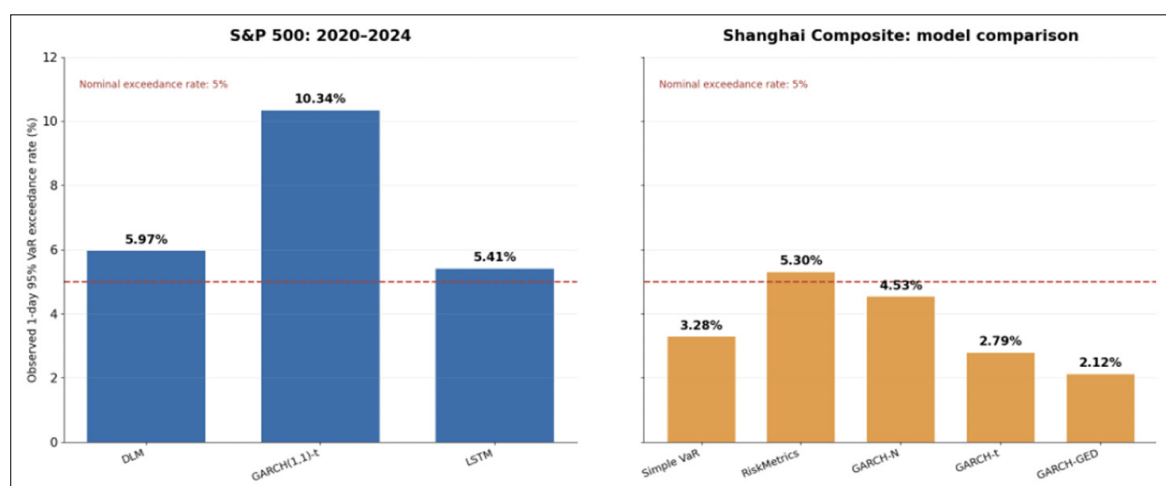


Figure 1. Observed exceedance rates in two separate one-day 95% VaR backtests: S&P 500 ([8]) and Shanghai Composite ([9]). Panels are based on distinct samples and model specifications; the nominal rate is 5%.

The Altman Z-score presents a different limitation: it is a bankruptcy or financial-distress indicator calculated for an individual reporting company from that entity's financial-statement variables. It is not a score for a portfolio of receivables, nor can it be inferred directly from the payment status of individual invoices. Its applicability to a particular counterparty depends on the availability of suitable entity-level accounting data, the variant of the model used, and the relevance of the calibration population [5, 14, 19]. Changes in the collectibility of receivables can affect a company's accounting indicators, but this does not make a portfolio-level Altman score a valid measure of credit exposure. This distinction reinforces the need to combine appropriate firm-level distress signals with receivables aging, payment behavior, and contextual assessment.

Table 1. Key Limitations of Standard Financial Risk Models in Practice (compiled by the author based on systematic literature review ([5, 6, 7, 8, 9, 10, 14])).

Model	Primary use case	Key limitation
Value at Risk (VaR)	Market risk quantification; regulatory capital (Basel III)	specification-dependent tail-risk and coverage errors; backtesting outcomes vary with the assumed distribution, market regime, and calibration data
Altman Z-score	Bankruptcy prediction; financial distress assessment	Calibrated on manufacturing firms; low accuracy for service and technology sectors; ignores qualitative factors
Five Cs credit scoring	Credit approval; accounts receivable risk classification	Judgmental approach requires subjective inputs; automation reduces contextual sensitivity; high false-negative rate in complex cases
GARCH / variance models	Volatility forecasting; short-term risk estimation	Regime-switching behavior not captured; underperformance during structural breaks (geopolitical events, pandemics)
Neural network scoring	Credit default prediction; behavioral scoring	Black-box interpretability problem; data quality dependency; high computational cost; explainability constraints under regulation

The Air Liquide case illustrates financial decision-making under a pronounced change in the operating environment. Air Liquide reported Group revenue of EUR 29,934 million for 2022 [12]. In the same reporting period, the Group's Russian activities were deconsolidated from September 1, 2022 as part of the announced disengagement process [12]. Air Liquide Finance subsequently reported that loans and receivables granted to Russian entities and outstanding at December 31, 2022 had been fully impaired in the amount of EUR 56 million, representing less than 0.5% of total loans and receivables [11]. The financial statements also recognized a EUR 6.7 million loss associated with the unwinding of hedging transactions and a EUR 6.1 million provision for foreign-exchange risk [11]. These disclosures demonstrate that geopolitical and organizational change

affected both the recoverability assessment of financial claims and the treatment of related market exposures. The case therefore provides an appropriate setting for examining how historically grounded indicators must be reconsidered when the legal, strategic, and operational assumptions underlying their interpretation change materially.

The financial analyst role in this environment involved monitoring client accounts across Moscow-based and foreign-contract portfolios, analyzing payment behavior, assessing credit risk per client, and recommending whether to continue or restrict deliveries. The standard automated approach in industrial gas supply is clear: if a client's account reaches a defined overdue threshold, shipments are automatically blocked pending payment. In practice, however,

this rule created systematic tension between two legitimate organizational objectives: financial risk control and the preservation of strategically important client relationships during a commercially sensitive period.

The professional judgment applied in this context differed from the algorithmic default in three documented respects. First, the analyst applied a differentiated risk classification rather than a binary block-or-deliver decision: clients were assessed along dimensions including payment history over at least the preceding 12 months, strategic importance to the remaining business, size and age structure of the outstanding balance, and likelihood of dispute versus liquidity-driven delay. Second, the analyst engaged in active monitoring rather than reactive control: when early signals of payment deterioration appeared, the assessment was escalated before the automated threshold was reached, enabling earlier dialogue with the client and greater flexibility in outcome. Third, for clients exhibiting elevated but manageable risk, supply continuation was maintained with enhanced monitoring cadence, reflecting an understanding that abrupt

supply termination can damage long-term relationships and trigger the very defaults it was designed to prevent.

This approach directly affected the quality of financial data flowing into the organization's budgeting process. The analyst's receivables classifications informed key financial ratios used in reporting to stakeholders, including liquidity and leverage measures and return on investment. The Altman Z-score, by contrast, is a separate financial-distress metric that can be calculated only for an individual reporting company (such as the Russian subsidiary) when suitable entity-level financial statements and a valid model specification are available; it cannot be calculated for its receivables portfolio. The accuracy of these indicators depended on the quality of the underlying receivables assessment, which the formal model alone could not assure. By ensuring that the ERP system reflected both the legal status of debts and their realistic collectibility probability, the analyst contributed to data integrity that no scoring algorithm could independently maintain. Table 2 presents the differentiated classification of accounts receivable risks applied in the Air Liquide case.

Table 2. Differentiated Receivables Risk Classification Applied in the Air Liquide Case (compiled by the author based on documented operational practice at Air Liquide Russia (2022-2023) and credit risk literature [5, 10]).

Risk tier	Trigger criteria	Professional judgment layer	Recommended action
Low	Overdue < 30 days; clean payment history; strategic key account	Verify: operational delay vs. structural risk	Continue supply; standard monitoring cadence (monthly)
Moderate	Overdue 30-60 days; partial payment history; mid-tier client	Assess: payment capacity vs. willingness; relationship value	Continued supply with enhanced monitoring (weekly); direct client communication
Elevated	Overdue 60-90 days; irregular history; significant balance	Full qualitative review: dispute probability, legal status of contract, geopolitical exposure	Conditional supply (pre-payment or collateral); formal escalation to management
Critical	Overdue > 90 days; non-responsive; no clear recovery path	Document judgment rationale for audit; legal department notification	Supply restriction; initiate formal recovery; prepare documentation for judicial proceedings

The second case introduces a substantially different institutional context in which professional financial judgment operates: scholarship program administration at the University of Central Florida (UCF) Global office, specifically the Lewis Foundation Scholarship program. While this case does not involve commercial credit risk in the traditional sense, it shares the fundamental structure of the problem: a set of formal eligibility criteria and administrative procedures operates alongside a complex relational and operational reality that those criteria do not fully capture, and the quality of financial continuity for program beneficiaries depends significantly on the judgment of the coordinating professional.

The Lewis Foundation Scholarship program at UCF supports international students, primarily from the Bahamas, throughout their academic enrollment. Its financial sustainability depends on three parallel streams: maintaining a sufficient pipeline of qualified applicants, ensuring that enrolled scholarship recipients maintain academic eligibility

(thus avoiding mid-cycle funding disruptions), and providing donors with reporting materials accurate enough to sustain their ongoing commitment. Each of these streams creates a distinct financial risk if mismanaged.

The scholarship coordinator role in this environment involved tasks that formal administrative procedures do not fully encompass. Application verification required not merely checking whether required documents were present but assessing whether errors in submitted materials were clerical or reflected deeper misunderstandings of program requirements. Students who submitted incomplete applications were contacted directly, guided through specific corrections, and supported in resubmission, a process that reduced the rate of disqualification for preventable administrative reasons. This function corresponds structurally to what credit analysts do when they assess whether a payment delay reflects a client's operational issue or a deeper solvency problem: the data on its face does not answer the question, but contextual judgment and direct inquiry can.

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A particularly instructive instance of financial judgment under uncertainty involved the question of summer funding for enrolled students. A segment of UCF academic programs requires continuous enrollment through summer terms, but donor-funded scholarship structures did not originally account for this requirement, creating a gap in financial coverage during the summer period. The operational resolution required direct engagement with donors to discuss the possibility of extending funding coverage to summer semesters and making the case for why program continuity for the student was inseparable from the donor's investment in educational outcomes. This is not a situation reducible to formal financial modeling: it required an understanding of donor motivation, the student's academic trajectory, and the program's long-term sustainability in a way that combined financial logic with organizational relationship management.

The reporting function of the role further illustrates the

judgment dimension: statistical reports on applicant numbers, recipient progress, and program outcomes were prepared not as passive data aggregations but as persuasive financial documents intended to demonstrate program impact to donors. The selection of which metrics to present, how to contextualize them, and how to frame the relationship between program inputs and student outcomes all required professional judgment about what information was material to the donor's decision to continue funding. This is analogous to the financial analyst's task of deciding which receivables data to highlight in a management report and how to frame the risk exposure it represents.

The decision logic common to both cases can be formalized into a structured framework. The Integrated Professional Judgment Framework (IPJF) presented in Figure 2 synthesizes the documented decision patterns from both organizational contexts and grounds them in the theoretical framework established by the literature review.

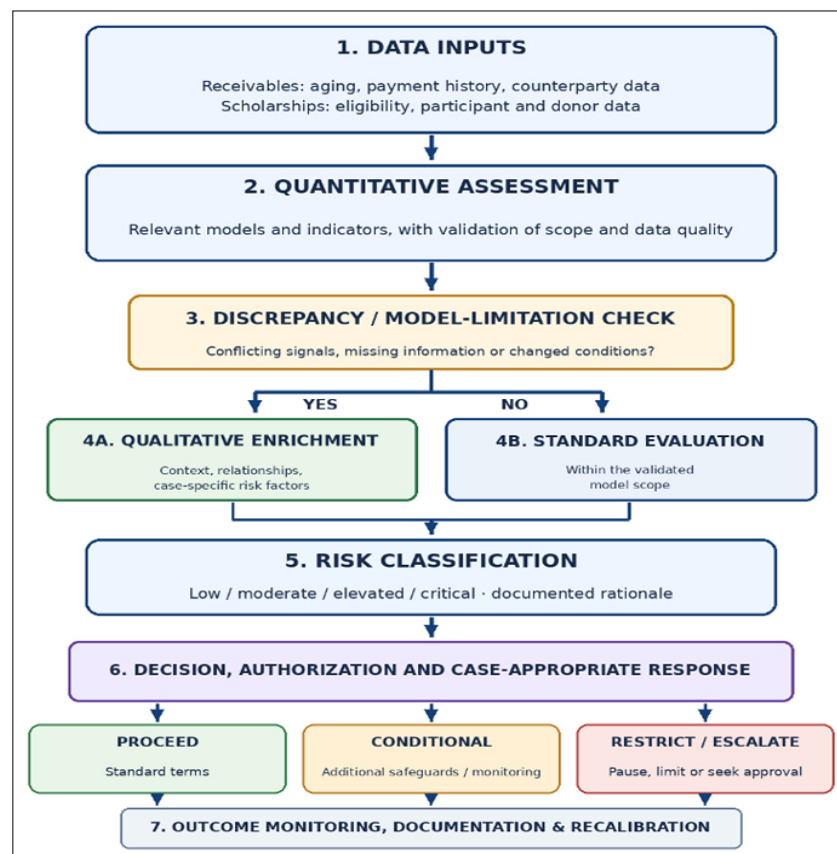


Figure 2. Integrated Professional Judgment Framework (IPJF) for Receivables Credit Risk and Scholarship-Program Financial Management: generalized decision options applicable to both settings (author's development).

The IPJF presented in Figure 2 operationalizes five interrelated functions—quantitative assessment, discrepancy detection, contextual enrichment, documented decisions, and outcome-based feedback—through a staged workflow. The input layer aggregates all available quantitative data: for accounts receivable, this includes aging reports, payment history records, counterparty-level Altman Z-scores where suitable financial statements and model specifications are available, liquidity and leverage ratios, and ERP-recorded

transaction histories. For scholarship administration, this includes applicant data, academic performance records, donor commitment schedules, and program budget tracking. Formal assessment is followed by discrepancy checking, qualitative enrichment where warranted, risk classification, a documented decision, and outcome monitoring. The decision options in Figure 2 are deliberately general: proceeding, proceeding conditionally with safeguards, or restricting or escalating the case as context requires. In Air Liquide these

options may concern supply and credit terms; in scholarship administration they may concern disbursement, participant support, or donor escalation.

The critical design feature of the IPJF is the discrepancy detection gate at the third layer. This gate is triggered when the formal model produces ambiguous or contradictory signals, when the data environment does not match the model's calibration assumptions (for example, a client with no prior history, or a student from a non-standard academic pathway), or when contextual information available to the practitioner but not captured in the data suggests that the model output is misleading. When the gate triggers, the process enters the qualitative enrichment layer, where the practitioner incorporates judgment about factors that the formal system does not encode: strategic client value, relationship history, organizational commitment signals, and behavioral indicators of payment willingness versus capacity in the receivables case, or academic trajectory, support need,

and donor engagement in the scholarship case.

The framework's feedback layer introduces a monitoring mechanism that is absent from purely algorithmic risk systems. Each decision taken is documented with its reasoning rationale, and the outcomes are tracked over time. When actual outcomes diverge systematically from model predictions, the divergence is used to recalibrate risk thresholds and refine qualitative assessment criteria. This feedback loop prevents the judgment layer from drifting into unsupported intuition while also preventing the formal model layer from calcifying around assumptions that no longer fit the environment.

The conceptual comparison across seven assessment dimensions presented in Figure 3 below illustrates the relative positioning of the three main approaches: pure quantitative models, unaided professional judgment, and the hybrid approach embodied in the IPJF.

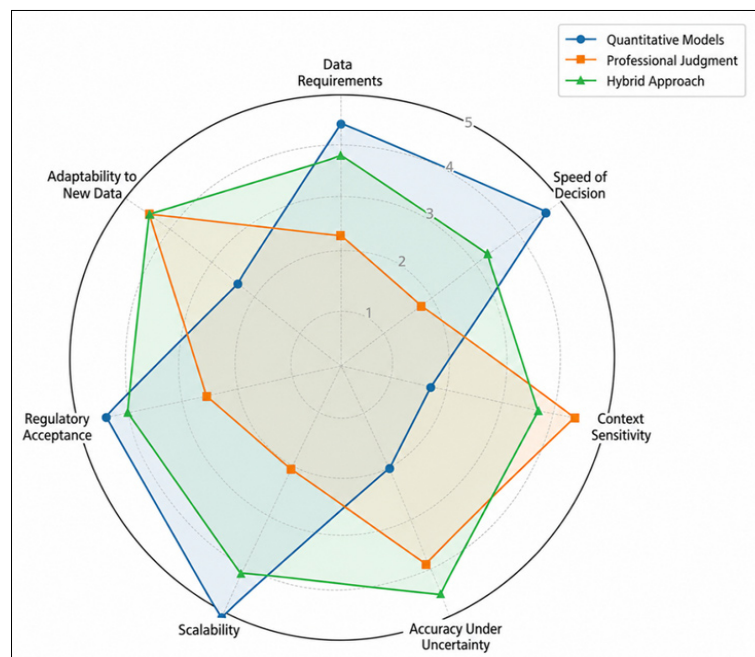


Figure 3. Conceptual Comparison of Risk Evaluation Approaches by Key Operational Dimensions (author's qualitative synthesis of [3, 4, 5, 6, 8, 10]; 1–5 values are heuristic ordinal ratings rather than empirical performance estimates).

Figure 3 should be interpreted as a conceptual visualization of the literature synthesis rather than as the result of a quantitative performance test. Within this heuristic coding, quantitative models are positioned relatively higher on data-processing speed, regulatory acceptance, and scalability, whereas professional judgment is positioned relatively higher on context sensitivity, adaptability to novel data, and decision support under genuine uncertainty. The hybrid IPJF is represented as comparatively balanced across the seven dimensions, suggesting a theoretical trade-off in which structured expert oversight may complement the strengths and limitations of formal models. The ordinal differences shown in the figure are illustrative and should not be read as statistically estimated effect sizes or measured performance gaps.

The integration of professional judgment into a structured framework requires explicit attention to the documented behavioral risks that expert judgment introduces. The literature on behavioral finance identifies several cognitive patterns that systematically distort financial decision-making when judgment operates without accountability structures: availability bias, anchoring on recent payment behavior, loss aversion in relationship management decisions, and herding in peer-group comparisons [3]. These biases are not eliminated by professional expertise; research suggests that experienced practitioners can exhibit them as strongly as novices in certain decision contexts [6].

The IPJF addresses this vulnerability through two structural features. First, the qualitative enrichment layer requires the

practitioner to explicitly document the factors considered and the weight assigned to each, rather than producing a single undifferentiated recommendation. This requirement does not eliminate cognitive bias but creates an accountability trail that enables supervisory review and retrospective evaluation. Second, the feedback loop compares actual outcomes against documented reasoning, which over time provides empirically grounded calibration of which qualitative factors have been predictive and which have introduced noise.

An additional behavioral risk documented by Grant and Nilsson [4] in their study of expert fund managers is what

they term “decision paralysis under high uncertainty,” the tendency to defer decisions indefinitely rather than commit under ambiguity. In the receivables management context, this corresponds to a reluctance to escalate a client relationship to restricted supply status even when risk indicators clearly warrant it, out of concern for commercial consequences. The IPJF’s Risk Tier classification (Table 3) serves as an explicit countermeasure: by mapping specific observable trigger criteria to recommended actions, it reduces the space of discretion in a way that maintains flexibility while anchoring the decision calculus.

Table 3. Behavioral Risk Factors in Professional Financial Judgment and IPJF Mitigation Mechanisms (compiled by the author based on [3, 4, 6]).

Behavioral bias	Mechanism of distortion	Manifestation in financial practice	IPJF mitigation feature
Availability bias	Overweighting of recent or salient events	Overestimating client risk after one missed payment; underestimating after a long clean period	Structured payment history review across minimum 12-month window (Tier classification)
Anchoring	Over-reliance on initial estimate or reference point	Locking credit limit to historical balance without reassessing current risk	Periodic recalibration requirement in feedback loop layer
Loss aversion	Asymmetric weighting of losses vs. equivalent gains	Reluctance to restrict supply to important client despite elevated risk signal	Explicit escalation triggers (overdue > 60 days) that require action documentation
Overconfidence	Excessive certainty in own assessment relative to evidence	Underweighting model signals when personal relationship with client is strong	Mandatory model output review before qualitative enrichment layer activates
Decision paralysis	Deferral under high uncertainty to avoid commitment	Delayed escalation of deteriorating client; delayed donor communication on scholarship gap	Time-bound decision gates and supervisor notification requirements
Herding	Conforming to peer or industry practice without individual assessment	Applying uniform overdue thresholds without account-specific adjustment	Differentiated tier structure replacing binary block/deliver rule

The findings of this study lead to a set of recommendations for organizations seeking to improve their financial risk management practice by better integrating professional judgment with formal modeling.

The first recommendation concerns documentation architecture. Organizations that rely on expert judgment in credit and program financial decisions should institute a standardized reasoning record for all non-routine decisions, meaning decisions that deviate from the formal model recommendation or involve qualitative factors not captured in the quantitative signal. Such records serve three functions: they make the reasoning process auditable and supervisable, they create a longitudinal dataset for retrospective calibration, and they protect the practitioner from the accusation of arbitrary decision-making when outcomes are unfavorable.

The second recommendation concerns role design. The evidence from both cases suggests that the most valuable financial risk function is not purely analytical (running models) or purely relational (managing clients and stakeholders), but occupies the interface between the two.

Organizations that structurally separate these functions, assigning quantitative analysis to one team and relationship management to another, lose the integration benefit that contextual judgment provides. The practitioner who understands both the Altman Z-score calculation and the client’s supply chain pressures is in a position that neither a pure data analyst nor a pure account manager can occupy. This cross-functional profile should be explicitly recognized in role design, performance evaluation, and professional development programs.

The third recommendation addresses the feedback loop specifically. Neither of the two organizations studied had a formalized mechanism for tracking how judgment-based decisions performed relative to model predictions over time. In the absence of such tracking, practitioners lack empirically grounded calibration of their own judgment quality, and organizations lack the ability to identify whether their risk assessment culture is drifting toward excessive permissiveness or excessive conservatism. A simple quarterly review protocol, comparing actual client payment outcomes against their prior risk tier classifications, would provide

the data needed for ongoing calibration without creating prohibitive administrative burden.

The fourth recommendation concerns the scholarship program financial management domain specifically. The Lewis Foundation Scholarship case illustrates that donor relations, student support, and program financial sustainability are operationally inseparable, yet they are frequently assigned to different functional areas in university administration. The recommendation is to recognize scholarship program coordination as a financial risk management function in its own right, with explicit metrics for program sustainability (application pipeline adequacy, eligibility retention rate, donor renewal rate, funding gap incidence), and to staff these roles with professionals who combine data management competence with stakeholder communication skills and financial awareness.

CONCLUSION

This study has addressed the role of professional managerial judgment in financial risk management under conditions where formal quantitative models provide insufficient or ambiguous decision support. The research objective was to identify the conditions under which formal models fall short and to characterize the structure of professional judgment that fills the resulting gaps. Both objectives have been met.

The systematic literature review established that Value at Risk, the Altman Z-score, and credit scoring systems each carry documented structural limitations that become operationally significant during periods of market disruption, regime change, or in data environments that deviate from the models' calibration assumptions. In the S&P 500 backtest reported in [8], the observed one-day 95% VaR exceedance rate varied by specification: approximately 6.0% for DLM, 10.3% for GARCH(1,1)-t, and 5.4% for LSTM. These are exceedance frequencies, not percentages of peak-loss underestimation, and they cannot be generalized to all crises or all VaR models. The Altman Z-score shows reduced accuracy for service-sector and non-manufacturing firms, and neural network scoring models face regulatory resistance due to interpretability constraints [10].

The comparative case analysis of Air Liquide Russia (2022-2023) and UCF Global's Lewis Foundation Scholarship program (2025) documented the practical decision mechanisms through which professional judgment supplements formal models in two structurally parallel but institutionally distinct contexts. In both cases, the practitioner applied differentiated risk assessment incorporating payment or performance history, contextual factors not captured in formal data systems, strategic and relational dimensions of the counterparty, and proactive monitoring rather than reactive threshold-based response. These practices may have contributed to the quality of financial data flowing into organizational reporting and may have supported the continuity of operationally critical processes.

The Integrated Professional Judgment Framework proposed in this study offers a structured model for organizing the interface between formal quantitative assessment and expert contextual judgment. Its five-layer design, combining data input, quantitative assessment, discrepancy detection, qualitative enrichment, and feedback-driven recalibration, provides a practical architecture that can be adapted to both commercial credit management and institutional program financial administration. The conceptual comparison across seven assessment dimensions suggests that the hybrid approach may combine complementary strengths of quantitative assessment and structured expert judgment while mitigating some of the limitations associated with either approach used in isolation; this comparison is illustrative rather than an empirical performance test.

The findings of the literature review and comparative case analysis provide conceptual and case-based support for the hypothesis that non-schematic, context-sensitive financial decisions grounded in expertise and behavioral awareness may support more resilient outcomes in complex organizational environments than formal models applied in isolation. The practical significance of this finding extends to organizations operating in international, cross-functional, or institutionally complex financial environments, where the capacity to make sound non-schematic decisions under genuine uncertainty is a competency that analytical infrastructure alone cannot replicate.

Future research should address three areas left open by this study. First, empirical validation of the IPJF through prospective application in a controlled organizational setting, with quantitative tracking of decision quality metrics over time. Second, psychometric measurement of the specific cognitive competencies that make professional judgment effective in these contexts, moving beyond the behavioral bias framework to a positive account of what good judgment looks like. Third, examination of how organizational design, including role structure, documentation requirements, and performance incentive systems, shapes the quality of the judgment-model interface in practice.

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