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DISTRESS AND RESTRUCTURING RISK IN POLISH COOPERATIVE BANKS: RESEARCH GAPS AND A FRAMEWORK FOR EARLY-WARNING MODELLING

Abstract

The purpose of the article. The article identifies the research gap caused by the lack of empirically validated early-warning models for distress and restructuring risk in Polish cooperative banks. It argues that models developed for commercial banks or non-financial enterprises cannot be transferred mechanically to cooperative banks because of Poland-specific institutional, regulatory and data constraints, including institutional protection scheme (IPS) membership and local-market exposure.

Methodology. The study applies a scoping review approach (PRISMA-ScR), critical literature analysis, document analysis and regulatory-institutional mapping. The review covers bank failure, distress and restructuring models from 1970 to 2025 and was supplemented by a targeted screening of review studies and empirical comparisons on logit, discriminant analysis, tree-based methods, machine learning and systemic early-warning systems. Evidence from corporate-bankruptcy and general financial-distress literature is used only for method taxonomy and validation criteria, not as direct evidence for bank-specific predictors. The article is exploratory: it does not estimate a final predictive model but defines the data architecture, candidate predictors and validation path required for future empirical research.

Results of the research. The study provides a publishable research agenda for Poland by: (1) updating the description of the cooperative banking sector; (2) distinguishing bank-distress modelling from corporate-bankruptcy prediction; (3) explaining why prudential regulation is not a substitute for statistical prediction; (4) proposing a Poland-specific variable set for an early-warning system; (5) defining a two-layer data blueprint for a bank-year panel combining public and supervisory/IPS data; and (6) translating the verified review literature into method-selection and validation rules, including interpretability, calibration, class imbalance and false-negative costs.

Keywords: cooperative banks; early-warning models; institutional protection schemes; restructuring risk

JEL Class: C53, G01, G21, G38



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Introduction

Bank distress prediction represents one of the key challenges in financial risk management, particularly in a dynamically changing economic and regulatory environment. Bank failures and forced restructuring events have consequences not only for individual institutions but also for depositors, local borrowers, supervisory authorities and the wider financial system (Grossman, 1993; Xu, 2022). Over recent decades, numerous statistical and machine-learning models have been developed to identify deterioration in banks' financial condition before formal insolvency or resolution occurs (Citterio, 2024). However, models developed for large commercial banks cannot be applied mechanically to Polish cooperative banks, because the latter operate under a distinct institutional architecture, different data-access constraints and strong local-market exposure.

In Poland, the banking sector, particularly cooperative banks, plays a significant role in ensuring economic stability, especially in local communities (Pluskota, 2018, pp. 249–261). Co-operative banks have unique characteristics, differing from larger commercial banks in terms of organisational structure and strategic goals. Their operations focus on local communities, with social capital playing a critical role in their functioning, influencing customer relationships and financial stability. Therefore, there is a need to develop dedicated failure prediction models that consider the specific attributes of these institutions.

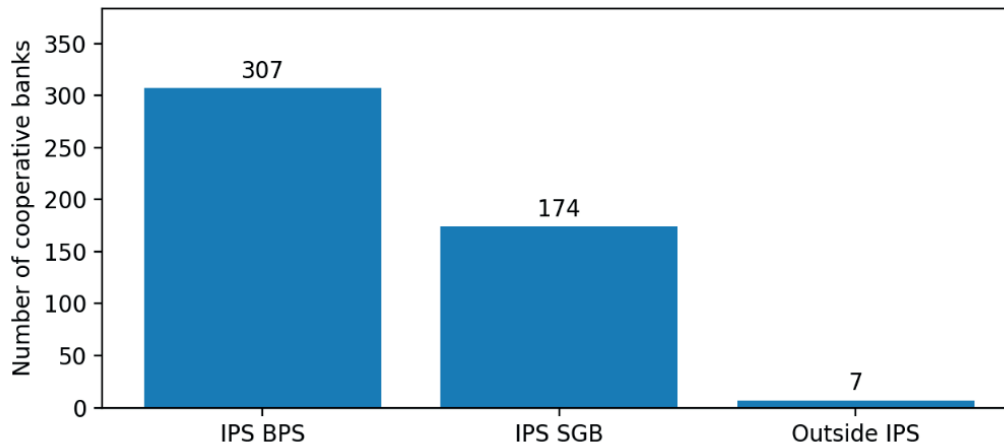
One of the most significant challenges in developing predictive models for Polish cooperative banks is the collection of harmonised bank-level and supervisory data. Compared with commercial banks, cooperative banks are smaller, locally embedded and more dependent on internal capital generation and relationship banking. Publicly available data is useful for a baseline prototype but are insufficient for a supervisory-grade model without confidential COREP/FINREP, SREP, recovery-plan and IPS support information. This constraint is central to the research agenda proposed in the article.

The Polish cooperative banking sector operates within two associating banks: Bank Polskiej Spółdzielczości S.A. (BPS) and SGB-Bank S.A.; and two recognised institutional protection schemes (IPS): IPS BPS and IPS SGB. As of 31 December 2025, 488 cooperative banks and two associating banks operated in Poland. Among cooperative banks, 307 were members of IPS BPS, 174 were members of IPS SGB and seven operated outside an IPS (KNF, 2026).

The current structure explains why a Polish early-warning model cannot be reduced to a generic commercial-bank model. IPS membership affects monitoring, liquidity management and potential support mechanisms; at the same time, it does not eliminate bank-level heterogeneity. KNF data for 2025 shows that cooperative banks remained well capitalised, with a total capital ratio of 29.51% at year-end 2025, while still differing in credit-risk profiles, local exposure and IPS status (KNF, 2026).

Figure 1.

Structure of the Polish cooperative banking sector by IPS membership (December 31, 2025)



Source: Own elaboration based on KNF (2026).

Consequently, adapting existing models or developing new early-warning models for cooperative banks in Poland requires a sector-specific approach: the model must combine bank-level financial ratios, IPS status, supervisory/legal events and local macroeconomic conditions. The research gap is therefore not merely the absence of a model, but the absence of a transparent, empirically testable architecture for such a model.

The aim of this article is to identify this research gap and propose a structured blueprint for future empirical modelling of cooperative-bank distress and restructuring risk in Poland. The article specifies data sources, candidate variables and methodological requirements for a model that could be validated in subsequent quantitative research.

Research Methodology

In line with the article's objective, the following research stages were conducted:

- review of existing bank failure prediction models described in the literature: this phase utilised information on various predictive models (e.g., global bank failure prediction models such as logit, decision trees, and random forests) that have been studied and validated in different countries, with the results published in academic literature. Alongside presenting the characteristics of each model, a preliminary attempt was made to evaluate their applicability to Polish conditions, with a particular focus on cooperative banks in Poland;
- literature analysis to highlight the lack of studies on adapting global predictive models: this stage aimed to demonstrate the absence of research analysing the potential adaptation of global models, such as logit, decision trees, or random forests, to the specific conditions

of the Polish market. It included an assessment of the rationale for applying existing models to the Polish cooperative banking sector, considering both the operational characteristics of these banks and the features of the analysed models;

- demonstrating the need to develop dedicated bank failure prediction models for cooperative banks: this stage focused on emphasising the need for models specifically tailored to cooperative banks due to their unique operational scope compared to commercial banks. The analysis explored various aspects of cooperative banks' operations, such as their operational characteristics, risk specificity, capital resources, organisational structure, and data accessibility. It also highlighted the lack of predictive models for cooperative banks, in contrast to the availability of such models for commercial banks;
- identifying key research needs for developing predictive models: at this stage, specific areas and conditions enabling the adaptation of models to the evolving operational context of cooperative banks in Poland were identified. Additionally, quantitative and qualitative variables (and their accessibility) necessary for constructing failure prediction models for these banks were recognised.

The study is of exploratory nature and therefore, it does not formulate causal hypotheses. It applies critical literature analysis, document analysis (Bowen, 2009), comparative analysis and regulatory-institutional mapping. The exploratory character is treated as a limitation and a research-design choice: the paper builds the architecture of a future model rather than estimating the model itself.

The literature review was designed as a scoping review in line with PRISMA-ScR (Tricco et al., 2018). The review covered bank failure, distress and restructuring models published between 1970 and 2025, with particular attention to logit/panel-logit, decision trees, random forests, survival/hazard models and systemic early-warning systems. Inclusion criteria were: empirical banking samples, transparent predictor reporting and reported diagnostic measures or validation logic. Exclusion criteria were: purely conceptual papers without model specification, studies limited to non-financial firms without banking adaptation, and single-case descriptions without model validation. A supplementary screening of review literature was used to classify sources into three evidence tiers: (1) bank-failure and banking-crisis EWS studies; (2) broader bankruptcy or financial-distress reviews useful for method taxonomy and validation criteria; and (3) lower-transferability material, such as theses or generic data-mining texts, used only to orient the search and not as core evidence. The scoping review is not a meta-analysis; it maps the field and translates the literature into a model-design blueprint for Polish cooperative banks.

This distinction is important because not every bankruptcy-prediction source is bank-specific. Reviews of corporate bankruptcy and AI-based financial distress prediction help iden-

tify method families, sampling issues and validation metrics (Alaka et al., 2018; Qu et al., 2019; Kuiziniene et al., 2022; Shetty et al., 2022), whereas bank-failure studies define the relevant failure channels and predictors (Kumar & Ravi, 2007; Liu et al., 2021; Citterio, 2024).

Global Predictive Models for Bank Failure or Restructuring

The screened literature can be organised into four strands: classical statistical models (discriminant analysis, logit/probit), bank-specific probability-of-default and failure models, tree-based or ensemble machine-learning models, and systemic banking-crisis early-warning systems. This distinction matters because individual cooperative-bank distress, corporate bankruptcy and systemic banking crises are related but not identical outcomes.

Logit Model

The logit model, also known as logistic regression, is one of the classical tools for predicting bank failures. It estimates the probability of a binary event, such as distress, failure or supervisory intervention, using explanatory variables. In bank applications, logit models rely on financial indicators such as asset quality, liquidity, profitability and capital adequacy. Meyer and Pifer (1970) and Martin (1977) established the usefulness of early-warning logit approaches for bank supervision. Later research comparing logit with data-mining methods shows that logit remains valuable as a transparent benchmark, even when machine-learning models improve classification in some settings (Jing & Fang, 2018; Citterio, 2024).

In banking applications, logistic regression remains a transparent baseline, but cooperative-bank data requires careful specification. Class imbalance, time-varying covariates and nested structures (bank-year observations within IPS structures) call for panel-logit, Firth-penalised logit or survival/hazard extensions. For the Polish IPS context, validation should be stratified by IPS membership, year and bank size.

Studies of bank probability-of-default models confirm that logit/probit specifications can be strengthened by grouping heterogeneous banks and adding macroeconomic variables (Peretsky et al., 2004). However, cut-off selection, misclassification costs and out-of-sample validation are decisive, especially because missed failures are more costly than false alarms from a supervisory perspective (Davis & Karim, 2008; Affes & Hentati-Kaffel, 2019).

Decision Trees

Decision trees are another bankruptcy prediction method widely applied in banking risk analysis. This data analysis technique involves step-by-step decision-making based on the values of individual variables. It is particularly useful in cases where data is diverse and difficult to interpret using traditional statistical methods. Research by Citterio (2024) indicates that decision

trees are flexible, allowing for adaptation to the specific characteristics of the banking market, where financial variables are often complex and multidimensional. Internationally, decision trees have been widely applied in the banking sector. For example, in the U.S. banking sector, they are used to analyse both financial and operational data. A key advantage of this method is its intuitive output, which enables managers to make informed decisions. However, in Poland, there is a lack of research on the application of decision trees in banking, including cooperative banks, representing a gap that future studies should address.

Random Forests

Random forest algorithms represent an advanced predictive method based on ensembles of decision trees. They are useful when predictors interact non-linearly and when variable importance must be explored across many financial and non-financial indicators. In banking applications, however, random forests should be treated as complements rather than substitutes for transparent statistical models, because supervisory usefulness depends not only on accuracy but also on calibration, interpretability and false-negative costs (Jing & Fang, 2018; Citterio, 2024). In Poland, this method could be valuable for analysing cooperative banks operating in diverse local markets, provided that data standardisation problems are solved.

The additional review evidence supports using tree-based ensembles as robustness tools rather than as a default black-box solution. ML models may deliver predictive gains in default classification, but their use in regulated finance creates supervisory costs related to explainability, governance and validation (Alonso & Carbó, 2020). On tabular datasets, tree-based models often remain strong benchmarks (Grinsztajn et al., 2022), which justifies testing random forest or gradient boosting against transparent logit/Firth-logit baselines.

Application of Predictive Models in the Polish Market

Although global bank failure prediction models, such as logit, decision trees, and random forests, have been successfully applied in various countries, Poland lacks dedicated predictive solutions tailored to the specific conditions of cooperative banks. Research conducted by Prusak (2005, pp. 1–207) suggests that adapting these tools to the Polish market, where cooperative banks often operate under different conditions than commercial banks, is essential. Prusak (2005, pp. 1–207) also emphasises that the operational specificity of businesses (and by analogy, cooperative banks) necessitates the inclusion of non-financial variables, such as local relationships or levels of social trust, which are critical to the stability of these institutions.

Polish cooperative banks have unique financial structures, and their operations are closely tied to local market conditions. As such, predictive models must incorporate these unique factors, including local economic conditions, customer relationship specifics, and diverse funding

sources. While models like logit could provide a solid foundation, adapting them to local conditions requires further research.

In the context of economic and regulatory changes, the stability of Polish cooperative banks is closely linked to the overall stability of the European financial sector. Gasz (2014, pp. 45–60) highlights that European stability conditions are crucial to the functioning of financial institutions at the national level.

Bank Failure Prediction Versus Bankruptcy Prediction for Non-Financial Enterprises

Predicting bank failure differs materially from predicting bankruptcy of non-financial enterprises. Banks perform maturity transformation, are vulnerable to liquidity shocks and deposit withdrawals, and operate under capital, liquidity, recovery and resolution regimes. Therefore, distress can materialise through channels that are not captured by corporate leverage/profitability models alone.

A bank-specific model should include asset quality (NPL ratio, coverage ratio, cost of risk), liquidity and funding metrics (LCR, NSFR, loan-to-deposit ratio and deposit concentration), solvency indicators (CET1/Tier I and total capital ratio), profitability and efficiency ratios (ROAA, ROAE and C/I), as well as institutional variables such as IPS membership, support availability and supervisory-intervention signals. Corporate bankruptcy models can inspire methodology, but they are not sufficient for cooperative-bank distress modelling.

Broader financial-distress and corporate-bankruptcy reviews therefore serve only a limited role in this paper. They justify a wider methodological menu (e.g., ensemble models, support vector machines, neural networks and resampling approaches), but they do not justify transferring corporate predictors directly to cooperative banks. The proposed Polish EWS must remain bank-specific and institution-specific.

Polish Cooperative Banking Sector: Institutional Specificity, Data Access and Research Gap

Despite the development of the Polish banking sector and the growing literature on bank distress, dedicated early-warning models for cooperative banks in Poland remain scarce. General bank-failure models can provide methodological families, but they do not solve the Poland-specific problem of IPS architecture, local exposure, data fragmentation and legal access to supervisory variables.

In Poland, cooperative banks operate within a legally and institutionally specific architecture: two associating banks (BPS and SGB-Bank) and two IPS arrangements (IPS BPS and IPS SGB). This structure affects liquidity management, risk monitoring, support mechanisms and the interpretation of bank-level ratios.

As of December 31, 2025, 488 cooperative banks operated in Poland; 307 belonged to IPS BPS, 174 to IPS SGB and seven remained outside an IPS. Two associating banks — BPS and SGB-Bank — also operated in the sector (KNF, 2026). This data directly addresses the need to analyse the whole cooperative-banking sector rather than a single associating group.

IPS arrangements should not be treated as consolidated banking groups, but they may influence prudential treatment and risk transmission. The ECB guide defines an IPS as an arrangement that protects member institutions and ensures their liquidity and solvency where necessary; it also indicates that IPS eligibility may affect risk weights, large-exposure treatment and liquidity waivers under the CRR framework (ECB, 2016).

The structure of Polish cooperative banks therefore requires predictors that go beyond standard financial ratios: IPS membership, availability or use of support funds, local credit concentration, exposure to farmers and SMEs, regional macroeconomic indicators, supervisory measures and recovery-plan status should be analysed together with classical ratios such as NPL, coverage, C/I, ROAA, capital adequacy and loan-to-deposit ratio.

The cooperative business model still matters: cooperative banks are not driven solely by profit maximisation but also by the needs of members and local communities (Hesse & Čihák, 2007; Pluskota, 2018). In modelling terms, local relationships, concentration of borrowers and community-level shocks are potential explanatory variables rather than narrative ornaments.

Polish cooperative banks are highly exposed to local economic and social conditions, which may strengthen client loyalty but also creates correlated regional risk. For this reason, public macro data at the poviát or voivodeship level should be linked with bank-level indicators wherever legally and technically feasible.

The literature therefore supports a hybrid research approach combining financial ratios, institutional variables and local socio-economic indicators (Groeneveld & De Vries, 2009; Ayadi et al., 2010). For Poland, IPS variables are the missing hinge in this hybrid architecture.

Concise Comparative Note: IPS-Based Cooperative Systems in Germany and Italy

A concise international comparison confirms that IPS-based cooperative banking systems can support risk monitoring but cannot be copied mechanically. Germany's BVR protection systems and Italy's cooperative banking groups illustrate how network-level monitoring, support mechanisms and more standardised data can strengthen early-warning capacity (ECB, 2016; European Parliament, 2022).

The lesson for Poland is therefore cautious: foreign IPS architectures justify including network-level variables in an EWS model, but Polish model design must reflect the domestic legal framework, the two associating banks, the two IPS structures and local data-access limitations.

This comparison supports the article's central thesis: the research problem is not only methodological but institutional. A model for Polish cooperative banks should combine bank-level indicators with IPS-level and local-economy variables.

Challenges with Data Access in Poland

One of the greatest challenges in predicting cooperative-bank distress in Poland is limited access to harmonised bank-level and supervisory data. Public aggregate data is available from KNF, GUS and NBP; individual banks publish financial statements to varying degrees; and IPS reports provide selected group-level information. However, granular COREP/FINREP, SREP, recovery-plan and supervisory-intervention data are generally not publicly available.

The problem is therefore not the total absence of data, but fragmentation, uneven standardisation and restricted access to the most informative supervisory and IPS variables. A credible research design should explicitly distinguish between a public prototype and an enhanced supervisory/IPS model.

A reasonable database should therefore be built in two layers. The baseline public layer would contain bank-year observations based on annual financial statements, Pillar 3 disclosures, KNF/GUS/NBP sector data and local macroeconomic indicators from Statistics Poland. The enhanced supervisory/IPS layer would add confidential variables such as SREP measures, recovery-plan status, IPS support intensity and granular liquidity/capital reporting.

This two-layer architecture explains why existing public data is insufficient for a fully validated supervisory-grade model but sufficient for a transparent prototype. The prototype can identify candidate predictors, test baseline logit/ML specifications and indicate which confidential variables materially improve calibration and early-warning usefulness.

The data problem also has a governance dimension: cooperation among cooperative banks, IPS institutions, researchers and supervisors would be necessary to define anonymisation rules, data dictionaries, validation windows and access protocols.

Local macroeconomic variables should be linked to cooperative banks using defensible service-area proxies, such as registered seat, branch network or disclosed credit concentration. This is necessary because regional shocks affecting farmers, SMEs and local governments may affect cooperative banks more strongly than large diversified commercial banks.

Legal and Regulatory Framework: Boundary Conditions and Predictors

Legal regulations are essential for the functioning of cooperative banks, but they should be treated as boundary conditions and sources of predictors rather than as substitutes for statistical prediction. In Poland, the relevant framework includes the Banking Law Act of August 29,

1997, the Act December 7, 2000 on cooperative banks, their associating and associating banks, and the Act of June 10, 2016 on the Bank Guarantee Fund, deposit guarantee scheme and resolution. At the EU level, the CRR framework, including CRR3 (Regulation 2024/1623), defines capital and risk requirements relevant to model variables.

Strict regulation reduces the probability and social cost of bank distress, but it does not predict failure by itself. Regulatory ratios are usually threshold-based and point-in-time; they may not capture local borrower concentration, deterioration in loan quality, profitability erosion, deposit concentration or the timing of IPS support. Prediction requires dynamic statistical modelling of leading indicators.

Accordingly, legal and supervisory variables should be operationalised in the model as observable signals: breach or proximity to capital/liquidity thresholds, recovery-plan status, early-intervention measures, IPS support events, resolution-planning indicators and changes in regulatory buffers. This interpretation answers the regulatory question without treating regulation as a substitute for dynamic prediction.

Specificity of Cooperative Bank Operations and the Need for Dedicated Early-Warning Models

Cooperative banks differ from commercial banks because their operating model is based on member ownership, relationship banking and local-community service. This divergence in governance, objectives and customer relations means that failure prediction models developed for large diversified commercial banks are insufficient for this banking segment without adaptation.

A dedicated model for cooperative banks should therefore include both financial and non-financial variables: local labour-market dynamics, borrower concentration, relationship banking, local government exposure, branch-network changes, operational efficiency and IPS membership. These variables are not decorative; they affect how risk accumulates and how quickly it can be mitigated.

Organisational Structure and Management of Cooperative Banks

One fundamental distinction between cooperative and commercial banks lies in their ownership and organisational structures, rooted in cooperative principles of solidarity and member-based governance. In cooperative banks, the governance model is shaped by member participation and local representation (Act of December 7, 2000; Fonteyne, 2007). This structure fosters long-term relationships with customers and the local community.

This governance structure can support relationship banking, but it may also affect the speed and formality of decision-making. In an EWS model, governance and organisational variables

should therefore be treated as potential contextual predictors rather than as anecdotal background. The key modelling implication is not that cooperative governance is risky per se, but that it changes how risks are monitored, escalated and mitigated.

The Role of Social Capital and Local Relationships

Social capital and local relationships are foundational to the financial stability of cooperative banks. Citterio (2024: 101818) argues that integrating social aspects into predictive models can significantly enhance their effectiveness, especially amid shifting market conditions. Unlike commercial banks, which operate on a broader scale, cooperative banks rely on the trust and long-term relationships of local clients.

In Poland, cooperative banks are deeply integrated into local communities, meaning their financial stability is strongly linked to regional economic health. As noted in the literature (Martin, 1977, pp. 249–276), traditional financial models like logit do not always account for such variables, potentially underestimating risks for cooperative banks. Czechowska and Kuśmierka (2022, pp. 8–27) highlight the importance of social capital and ties in financial decisions made by younger clients, suggesting that incorporating these variables into bankruptcy prediction models could enhance forecast accuracy and stakeholder satisfaction.

Limited Capital Resources and Their Impact on Financial Stability

Compared to large commercial banks, cooperative banks have significantly smaller capital resources. Limited access to capital markets means they rely mainly on member contributions and retained earnings. This reliance makes smaller cooperative banks less able to respond to sudden macroeconomic shocks, increasing the risk of restructuring or, in extreme cases, failure.

Institutional protection schemes provide an important defence mechanism, but they also require predictive risk tools to support timely decisions. In Poland, where cooperative banks play a key role in serving local communities, capital accumulation depends largely on retained earnings and member-related mechanisms. Predictive models should therefore reflect capital buffers, capital erosion, profitability and IPS support capacity when forecasting distress or restructuring risk.

Operational Specificity and Operational Risk

Understanding the impact of technology on risk management is vital when examining the operational specifics of cooperative banks. As digitalisation becomes increasingly widespread, cooperative banks must adapt their strategies to the new market realities, requiring investments in modern information systems. Citterio's (2024) findings indicate that implementing innovative technological solutions, such as artificial intelligence, can enhance these institutions' ability to monitor risks and forecast financial problems.

Furthermore, integrating local data into predictive algorithms could improve crisis forecasting, which is crucial for the stability of banks operating in a volatile economic environment. Analyses by Boos et al. (2024, pp. 497–533) suggest that predictive models must account for operational specifics to accurately forecast failure risks.

The Need to Adapt Models to Cooperative Bank Specifics

In addressing the need to adapt models to cooperative-bank specifics, the key issue is not financial education as a stand-alone topic, but the operationalisation of local and institutional signals. Customer loyalty, member participation, local borrower concentration and branch-network dependence may all affect distress dynamics, but they must be translated into measurable variables before they can enter an EWS model.

Developing educational programmes for members may support long-term financial literacy and trust; however, model design should focus on variables that can be observed, harmonised and validated. This distinction helps maintain empirical testability and model parsimony.

In the Polish context, early warning indicators should be developed for cooperative banks — preferably within existing institutional protection schemes — to more effectively forecast restructuring or bankruptcy risks. Łupiński (2019, pp. 99–113) emphasises the importance of tailoring predictive models to the specifics of this sector.

Creating effective failure prediction models for cooperative banks requires consideration of factors that are not relevant, or are less relevant, for large, diversified institutions. Traditional predictive models based primarily on financial data may fail to account for variables related to local relationships, social capital and operational specificity (Prusak, 2005). International evidence on bank failure prediction shows that advanced models can improve classification, but they must be interpreted with attention to false-negative costs and calibration (Jing & Fang, 2018; Citterio, 2024).

Research Needs: Data, Variables and Model Design

When analysing research needs, it is essential to connect global modelling approaches with the local structure of cooperative banking. Digitalisation, regulatory change and financial-market integration increase the need for advanced risk monitoring, but the empirical specification must still reflect domestic IPS architecture, local exposures and data availability (Citterio, 2024; NBP, 2025).

Collaboration among cooperative banks, IPS institutions, supervisors and research institutions could improve data quality and support anonymised research datasets. Such cooperation is critical for transforming the proposed model architecture into a validated early-warning system.

The review is used to specify a minimum model architecture rather than to rank methods mechanically. Table 1 translates the literature and the Polish institutional setting into a candidate variable dictionary; Table 2 identifies feasible data sources and remaining access gaps.

The literature does not support a simple ranking such as ‘machine learning is better than logit’. Some studies report higher discrimination for data-mining or ensemble models, while others stress the value of transparent logit models and the danger of false negatives. Therefore, model choice should be driven by validation design, decision costs and interpretability rather than headline accuracy (Jing & Fang, 2018; Alonso & Carbó, 2020; Liu et al., 2021).

Table 1.

Proposed Poland-specific variable set for a cooperative-bank early-warning system

Variable block	Examples of predictors	Expected role in an EWS
Capital / solvency	CET1/Tier I, total capital ratio, buffer above regulatory minimum, own funds and member-share fund dynamics	Lower buffers and rapid erosion increase distress risk
Asset quality	NPL ratio, coverage ratio, cost of risk, restructuring flow, exposures to farmers/SMEs	Deterioration signals credit-risk stress
Liquidity / funding	LCR, NSFR, loan-to-deposit ratio, non-sticky deposit concentration, IPS versus solo liquidity treatment	Funding stress and liquidity deterioration are leading bank-failure channels
Profitability / efficiency	ROAA, ROAE, net interest margin, C/I, net result dynamics	Weak profitability reduces internal capital generation and shock absorption
Institutional / IPS	IPS membership (BPS/SGB/ outside), IPS support intensity, support-fund use, group monitoring score	Network support may reduce failure probability but can signal hidden distress
Supervisory / legal	Recovery-plan status, early-intervention measures, resolution-planning flags, proximity to regulatory thresholds	Regulatory signals become predictors, not a substitute for prediction
Local macro / market	Powiat unemployment, income, demographic change, agricultural/ SME conditions	Local shocks may affect cooperative banks more strongly than large commercial banks

Source: Own elaboration based on the literature review and institutional/regulatory sources discussed in the article.

Table 2.*Data sources and availability for building a cooperative-bank panel*

Data layer	Potential sources	Availability / limitation
Public sector aggregates	KNF quarterly cooperative-bank reports; GUS financial results of banks; NBP Financial Stability Report	Useful for sector context, benchmark ratios and macro-financial environment; not sufficient for bank-level calibration
Bank-level public data	Annual financial statements, Pillar 3 disclosures, commercial registers, bank websites	Feasible for a public prototype; standardisation and missing data are the main obstacles
IPS-level data	IPS BPS and IPS SGB reports, support-fund disclosures, group risk summaries	Important for membership/support variables; detailed support events may require access agreements
Supervisory / confidential data	COREP/FINREP, SREP, recovery plans, early-intervention and resolution data	Needed for enhanced model calibration; requires supervisory or IPS cooperation and strict data governance
Local macro data	GUS Local Data Bank: unemployment, income, demographics, business activity	Public and linkable to bank territories, but geographic mapping of bank exposures is required

Source: Own elaboration based on publicly available institutional data sources and supervisory-reporting frameworks discussed in the article.

Developing effective distress and restructuring-risk models for cooperative banks in Poland requires detailed data and a disciplined variable dictionary. The following subsection identifies the minimum financial, institutional, supervisory and local-macro variables needed for a base-line model.

Detailed Financial and Balance-Sheet Data

Data availability and scope consistently form the foundation of any distress or restructuring-risk model. For banks, including the cooperative ones, access to granular data remains limited, presenting a significant challenge for researchers and financial institutions in Poland. Meyer and

Pifer (1970) and Martin (1977) show that bank-level financial indicators are central to early-warning modelling, but the Polish cooperative-banking context also requires institutional, supervisory and local-macro variables.

In Poland, the problem is therefore not only legal access but also standardisation: bank-level data must be harmonised across reporting formats, mergers and IPS status changes. Legislative or sectoral data-sharing arrangements would improve research quality, but a baseline prototype can already be built from public data combined with local macroeconomic indicators.

Identification of Significant Variables in Distress and Restructuring-Risk Prediction

Identifying variables relevant to the prediction of cooperative-bank distress is a key task, because these institutions operate under local conditions that are not fully captured by traditional models. Socio-economic factors such as unemployment, local business activity and agricultural-sector conditions may influence credit quality and funding stability.

Beyond traditional financial indicators such as liquidity, profitability, capital adequacy and asset quality, non-financial and institutional variables may prove crucial. These include IPS membership, support-fund availability, recovery-plan status, branch-network intensity, local borrower concentration and deposit concentration.

Many of these variables are not typically included in corporate bankruptcy models, which limits their usefulness for cooperative banks. Research into Poland-specific predictors is therefore essential, particularly under changing regulatory, competitive and interest-rate conditions.

This article sets out an operational research agenda for a Polish cooperative-bank early-warning system. Its key contribution is the specification of the institutional, regulatory and data conditions that such a model must satisfy.

The analysis shows that a valid model for Poland must include IPS architecture (BPS/SGB/ outside IPS), bank-level financial ratios, supervisory and legal events, and local macroeconomic indicators. Foreign models can provide methodological families — logit, panel-logit, decision trees, random forests or survival/hazard models — but not a ready-to-use Polish specification.

The exploratory character of the article is a limitation: it does not estimate and validate a final model. Its practical value lies in defining a publishable empirical next step: a bank-year panel, a transparent variable set and validation metrics such as AUC, Brier score, calibration curves and class-imbalance handling.

The proposed model architecture can support the following practical applications:

- supporting risk-management decisions in cooperative banks by identifying early deterioration in solvency, asset quality, liquidity and profitability;
- prioritising remedial actions and IPS support by distinguishing temporary liquidity pressure from deeper solvency or asset-quality stress;

- strengthening supervisory early-warning systems by combining financial indicators with recovery-plan, IPS and local-macro variables;
- informing regulatory policy by showing which indicators are leading signals and which are merely minimum compliance thresholds;
- expanding future research through comparative validation of panel-logit, Firth-logit, random forest and gradient boosting specifications on the same Polish dataset.

Data Availability and Governance

Challenges related to data availability require stronger cooperation among cooperative banks, IPS institutions, supervisors and research organisations. The aim should be to develop standardised data dictionaries, anonymised access protocols and validation samples that can be used without breaching prudential secrecy or competition-sensitive information.

Local universities and research institutes could support this process by developing prototypes, testing variable definitions and evaluating the predictive usefulness of public data. The broader bankruptcy-prediction literature confirms that access to reliable data is crucial for effective modelling (Shi & Li, 2019), but bank-specific EWS development also requires supervisory and institutional variables.

In Poland, cooperative banks publish financial statements, but they are not required to disclose the full set of granular supervisory variables necessary for a calibrated EWS. Legislative or sectoral data-sharing arrangements would therefore improve research quality and supervisory usefulness.

Model-Selection and Validation Protocol

The proposed empirical stage should compare model families on the same harmonised bank-year panel. A defensible protocol would include: (1) an interpretable baseline (logit/Firth-logit/panel-logit); (2) a time-to-event model; (3) a tree-based ensemble; and (4) sensitivity analysis across IPS strata, bank size and time windows. The aim is not to crown a universal winner, because review evidence shows that no bankruptcy/distress tool dominates all criteria and datasets (Kumar & Ravi, 2007; Alaka et al., 2018).

Validation should use out-of-time tests and report AUC/ROC, precision-recall measures for imbalanced samples, Brier score, calibration curves, false-negative rates and cost-sensitive thresholds. This approach is consistent with bank EWS studies that emphasise the costs of missed distress events and the need for supervisory usefulness rather than accuracy alone (Davis & Karim, 2008; Affes & Hentati-Kaffel, 2019; Wang et al., 2021).

Because cooperative-bank failures or restructuring events are rare, the final model should also document class-imbalance handling, temporal stability and explainability. For machine-learning

specifications, variable-importance and SHAP-type explanations may support interpretability, but they should not replace calibration and economic plausibility checks.

Conclusions

The article identifies a specific and still underdeveloped research gap: the absence of empirically validated early-warning models for distress and restructuring risk in Polish cooperative banks. The gap is not merely technical. It reflects the institutional architecture of the sector, data fragmentation, IPS membership, local-market exposure and limited public access to supervisory variables.

The proposed research contribution is therefore a framework rather than a finished predictive model. It defines: the relevant institutional context; a candidate variable set; a two-layer data architecture; and validation requirements for future empirical work. This is a necessary step before model estimation because importing foreign models without adapting them to IPS status, local exposures and Polish data constraints would lead to model misspecification.

For future empirical research, three model families should be tested on the same bank-year panel: a baseline panel-logit or Firth-logit model, a survival/hazard model for time-to-distress events, and an interpretable tree-based machine-learning model such as random forest or gradient boosting. Model evaluation should report AUC/ROC, precision-recall measures, Brier score, calibration curves, false-negative rates, class-imbalance treatment and cost-sensitive thresholds. This design follows the review literature: predictive accuracy must be assessed together with interpretability and supervisory usefulness.

The practical relevance of the framework lies in its possible use by cooperative banks, IPS institutions and supervisory bodies. A validated EWS could support earlier identification of deteriorating asset quality, liquidity pressure, capital erosion and local macroeconomic stress. Regulations and IPS arrangements provide safeguards, but they do not replace a dynamic prediction.

The main limitation of the article is that it does not estimate a final model. This limitation is deliberate: the article first establishes the data, institutional and methodological preconditions for credible modelling. The next research step should therefore be the construction of a harmonised panel dataset for 2010–2025 and the out-of-sample validation of the proposed model families.

Further research should also test whether IPS membership and IPS support intensity reduce the hazard of distress after controlling for bank size, capital buffers, asset quality, liquidity, profitability and local macroeconomic conditions. This would transform the current research-needs analysis into a directly testable empirical contribution.

Disclosure Statement

The authors report no conflicts of interest.

References

- Affes, Z., & Hentati-Kaffel, R. (2019). Predicting US banks bankruptcy: Logit versus canonical discriminant analysis. *Computational Economics*, 54(1), pp. 199–244. <https://doi.org/10.1007/s10614-017-9698-0>.
- Alaka, H. A., Oyedele, L. O., Owolabi, H. A., Kumar, V., Ajayi, S. O., Akinade, O. O., & Bilal, M. (2018). Systematic review of bankruptcy prediction models: Towards a framework for tool selection. *Expert Systems with Applications*, 94, pp. 164–184. <https://doi.org/10.1016/j.eswa.2017.10.040>.
- Alonso, A., & Carbó, J. M. (2020). *Machine learning in credit risk: Measuring the dilemma between prediction and supervisory cost*. Banco de España Working Paper. www.bde.es/f/webbde/SES/Secciones/Publicaciones/PublicacionesSeriadas/DocumentosTrabajo/20/Files/dt2032e.pdf.
- Ayadi, R., Llewellyn, D. T., Schmidt, R. H., Arbak, E., & De Groen, W. P. (2010). *Investigating diversity in the banking sector in Europe: Key developments, performance and role of co-operative banks*. Brussels: Centre for European Policy Studies.
- Boos, D., Karampatsas, N., Garn, W., & Stergioulas, L. K. (2024). Predicting corporate restructuring and financial distress in banks: The case of the Swiss banking industry. *Journal of Financial Research*, 47(2), pp. 497–533. <https://doi.org/10.1111/jfir.12375>.
- Bowen, G. A. (2009). Document analysis as a qualitative research method. *Qualitative Research Journal*, 9(2), pp. 27–40. <https://doi.org/10.3316/QRJ0902027>.
- Citterio, A. (2024). Bank failure prediction models: Review and outlook. *Socio-Economic Planning Sciences*, 92, 101818. <https://doi.org/10.1016/j.seps.2024.101818>.
- Czechowska, I. D., & Kuśmierska, W. (2023). Uwarunkowania decyzji młodych klientów na rynku usług finansowych na przykładzie rachunków bankowych. *Internetowy Kwartalnik Antymonopolowy i Regulacyjny*, 11(7), pp. 8–27. <https://doi.org/10.7172/2299-5749.IKAR.7.11.1>.
- Davis, E. P., & Karim, D. (2008). Comparing early warning systems for banking crises. *Journal of Financial Stability*, 4(2), pp. 89–120. <https://doi.org/10.1016/j.jfs.2007.12.004>.
- [ECB] European Central Bank. (2016). *Guide on the approach for the recognition of institutional protection schemes (IPS) for prudential purposes*. www.bankingsupervision.europa.eu/ecb/pub/pdf/institutional_protection_guide.en.pdf.
- Fonteyne, W. (2007). Cooperative banks in Europe: Policy issues. *IMF Working Paper*, 159. <https://doi.org/10.5089/9781451867237.001>.
- Gasz, M. (2014). Uwarunkowania stabilności europejskiego sektora finansowego. *Acta Universitatis Lodzensis. Folia Oeconomica*, 2(301), pp. 67–77. <http://hdl.handle.net/11089/14852>.

- [GUS] Główny Urząd Statystyczny. (2026). *Wyniki finansowe banków w 2025 r.* <https://stat.gov.pl/obszary-tematyczne/podmioty-gospodarcze-wyniki-finansowe/przedsiębiorstwa-finansowe/wyniki-finansowe-bankow-w-2025-r-,5,30.html>.
- Groeneveld, H., & De Vries, B. (2009). European co-operative banks: First lessons of the sub-prime crisis. *International Journal of Cooperative Management*, 4(2), pp. 8–21.
- Grossman, R. S. (1993). The macroeconomic consequences of bank failures under the National Banking System. *Explorations in Economic History*, 30(3), pp. 294–320. <https://doi.org/10.1006/exeh.1993.1012>.
- Grinsztajn, L., Oyallon, E., & Varoquaux, G. (2022). Why do tree-based models still outperform deep learning on typical tabular data? *Advances in Neural Information Processing Systems*, 35, pp. 507–520. https://proceedings.neurips.cc/paper_files/paper/2022/hash/0378c7692da36807bdec87ab043cdadc-Abstract-Datasets_and_Benchmarks.html.
- Hesse, H., & Čihák, M. (2007). Cooperative banks and financial stability. IMF Working Paper No. WP/07/2. <https://doi.org/10.5089/9781451865660.001>.
- Ippolito, F., Hope, P., & Van Dijk, R. (2022). *Institutional Protection Schemes in the Banking Union*. European Parliament. [www.europarl.europa.eu/RegData/etudes/STUD/2022/699514/IPOL_STU\(2022\)699514_EN.pdf](http://www.europarl.europa.eu/RegData/etudes/STUD/2022/699514/IPOL_STU(2022)699514_EN.pdf).
- Jing, Z., & Fang, Y. (2018). Predicting US bank failures: A comparison of logit and data mining models. *Journal of Forecasting*, 37(2), pp. 235–256. <https://doi.org/10.1002/for.2487>.
- [KNF] Komisja Nadzoru Finansowego. (2026). *Sytuacja banków spółdzielczych i zrzeszających po IV kwartale 2025 roku*. www.knf.gov.pl/knf/pl/komponenty/img/Sytuacja_bankow_spoldzielczych_i_zrzeszajacych_IV_kwartal_2025_97783.pdf.
- Kuiziniene, D., Krilavičius, T., Damaševičius, R., & Maskeliūnas, R. (2022). Systematic review of financial distress identification using artificial intelligence methods. *Applied Artificial Intelligence*, 36(1), e2138124. <https://doi.org/10.1080/08839514.2022.2138124>.
- Kumar, P. R., & Ravi, V. (2007). Bankruptcy prediction in banks and firms via statistical and intelligent techniques: A review. *European Journal of Operational Research*, 180(1), pp. 1–28. <https://doi.org/10.1016/j.ejor.2006.08.043>.
- Liu, L. X., Liu, S., & Sathye, M. (2021). Predicting bank failures: A synthesis of literature and directions for future research. *Journal of Risk and Financial Management*, 14(10), 474. <https://doi.org/10.3390/jrfm14100474>.
- Łupiński, M. (2019). Wskaźniki wczesnego ostrzegania przed niestabilnością finansową polskiego sektora bankowego. *Roczniki Kolegium Analiz Ekonomicznych*, 55, pp. 99–113. <https://EconPapers.repec.org/RePEc:sgl:annals:i:55:y:2019:p:99-113>.
- Martin, D. (1977). Early warning of bank failure: A logit regression approach. *Journal of Banking & Finance*, 1(3), pp. 249–276. [https://doi.org/10.1016/0378-4266\(77\)90022-X](https://doi.org/10.1016/0378-4266(77)90022-X).

- Meyer, P. A., & Pifer, H. W. (1970). Prediction of bank failures. *Journal of Finance*, 25(4), pp. 853–868. <https://doi.org/10.1111/j.1540-6261.1970.tb00558.x>.
- [NBP] Narodowy Bank Polski. (2025). *Financial Stability Report. December 2025*. <https://nbp.pl/en/financial-stability-report-december-2025>.
- Peresetsky, A., Karminsky, A., & Golovan, S. (2004). *Probability of default models of Russian banks* (BOFIT Discussion Papers No. 21/2004). Bank of Finland, Institute for Economies in Transition. www.econstor.eu/bitstream/10419/212551/1/bofit-dp2004-021.pdf.
- Pluskota, P. (2018). Współpraca banków spółdzielczych z samorządem lokalnym. *Ekonomiczne Problemy Usług*, 4(133/1), pp. 249–261. <https://doi.org/10.18276/epu.2018.133/1-20>.
- Prusak, B. (2005). *Nowoczesne metody prognozowania zagrożenia finansowego przedsiębiorstw*. Warszawa: Difin.
- Qu, Y., Quan, P., Lei, M., & Shi, Y. (2019). Review of bankruptcy prediction using machine learning and deep learning techniques. *Procedia Computer Science*, 162, pp. 895–899. <https://doi.org/10.1016/j.procs.2019.12.065>.
- Regulation 2024/1623 of the European Parliament and of the Council of 31 May 2024 amending Regulation (EU) No 575/2013 as regards requirements for credit risk, credit valuation adjustment risk, operational risk, market risk and the output floor. <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32024R1623>.
- Rozporządzenie Ministra Finansów z dnia 1 października 2010 r. w sprawie szczególnych zasad rachunkowości banków. Dz.U. 2010 nr 191 poz. 957. (2010). <https://isap.sejm.gov.pl/isap.nsf/download.xsp/WDU20101911279/O/D20101279.pdf>.
- Shetty, S., Musa, M., & Brédart, X. (2022). Bankruptcy prediction using machine learning techniques. *Journal of Risk and Financial Management*, 15(1), 35. <https://doi.org/10.3390/jrfm15010035>.
- Shi, Y., & Li, X. (2019). A bibliometric study on intelligent techniques of bankruptcy prediction for corporate firms. *Heliyon*, 5(12), e02997. <https://doi.org/10.1016/j.heliyon.2019.e02997>.
- Tricco, A. C., Lillie, E., Zarin, W., O'Brien, K. K., Colquhoun, H., Levac, D. et al. (2018). PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and explanation. *Annals of Internal Medicine*, 169(7), pp. 467–473. <https://doi.org/10.7326/M18-0850>.
- Ustawa z dnia 10 czerwca 2016 r. o Bankowym Funduszu Gwarancyjnym, systemie gwarantowania depozytów oraz przymusowej restrukturyzacji. Dz.U. 2026 poz. 620. <https://isap.sejm.gov.pl/isap.nsf/download.xsp/WDU20260000620/T/D20260620L.pdf>.
- Ustawa z dnia 29 sierpnia 1997 r. – Prawo bankowe. Dz.U. 2026 poz. 38. <https://isap.sejm.gov.pl/isap.nsf/download.xsp/WDU20260000038/T/D20260038L.pdf>.

- Ustawa z dnia 7 grudnia 2000 r. o funkcjonowaniu banków spółdzielczych, ich zrzeszaniu się i bankach zrzeszających. Dz.U. 2025 poz. 265. <https://isap.sejm.gov.pl/isap.nsf/download.xsp/WDU20250000265/T/D20250265L.pdf>.
- Wang, T., Zhao, S., Zhu, G., & Zheng, H. (2021). A machine learning-based early warning system for systemic banking crises. *Applied Economics*, 53(26), pp. 2974–2992. <https://doi.org/10.1080/00036846.2020.1870657>.
- Xu, C. (2022). *Reshaping global trade: The immediate and long-term effects of bank failures*. CEPR Discussion Paper No. DP17163. <https://doi.org/10.1093/qje/qjac016>.