Design Science Research: A Practical Methodology for Enhancing Qualitative Liquidity Risk Management

Hamed Mirashk[1], Amir Albadvi[1], Mehrdad Kargari[1], Mohammad Ali Rastegar[1] and Mohammad Talebi[2]

[1]Faculty of Industrial and Systems Engineering, Tarbiat Modares University, Tehran, Iran
[2]Imam Sadiq University, Iran

h.mirashk@modares.ac.ir
albadvi@modares.ac.ir (corresponding author)
m_kargari@modares.ac.ir
ma_rastegar@modares.ac.ir
mtalebi@isu.ac.ir

https://doi.org/10.34190/ejbrm.23.1.3544

Abstract: In the banking sector, managing liquidity risk is paramount to ensure financial stability and resilience. This study is motivated by a quest to determine the appropriate research methodology that satisfies both theoretical and practical aspects of designing and developing a system that integrates qualitative factors, specifically news sentiment, into liquidity risk forecasting for risk managers to rely on and use the predicted results. Previous works reveal a significant theoretical gap in liquidity risk prediction, highlighting the necessity for a methodology that bridges theoretical advancements and practical applications. The primary questions focus on evaluating how well Design Science Research (DSR) handles short-term liquidity risk prediction and the influence of qualitative factors on these predictions. The DSR approach in this study involved iterative phases of problem identification, artifact creation, and rigorous evaluation. A predictive model was developed, intertwining news sentiment analysis with quantitative liquidity ratios derived from Basel III principles. The results demonstrate that the model achieves an 86% accuracy rate in theoretical evaluations and an impressive 95.5% in real-world scenarios, outperforming traditional methods. This integration of qualitative factors into the predictive model enhances accuracy, providing a more comprehensive understanding of liquidity risk dynamics. By meeting its objectives, this study answers the posed questions that DSR can be used as a research methodology that validates not only the theoretical aspect of the problem but also the practical application of the framework. The study contributes to advancing risk management practices and suggests future work directions, reinforcing the importance of DSR methodology and similar methods considering qualitative dimensions in banking liquidity risk assessment. This advancement paves the way for more proactive and informed decision-making processes in banking institutions.

Keywords: Design science research (DSR), Proactive liquidity risk management, Liquidity risk scenarios, News sentiment, Predictive model

1. Introduction

Design Science Research (DSR) is a methodological approach that focuses on identifying problems and creating innovative artifacts to enhance technological and scientific knowledge. This study employs DSR to address the complexities associated with measuring liquidity risk in banking systems. Traditional methods of liquidity risk measurement are fraught with challenges, including complexity, time consumption, high costs, and susceptibility to errors. To overcome these issues, this research leverages DSR methodologies to develop practical solutions and innovative artifacts for liquidity risk assessment.

DSR is a top-down strategy that emphasizes problem identification and artifact creation. It aims to generate new knowledge through the development of innovative solutions that not only solve specific problems but also enhance their respective fields of application. In this study, DSR methodologies are used to create a framework for predicting liquidity risk positions in the upcoming months and scenarios. The framework draws from the Basel III model's principles of liquidity risk management, with a particular focus on short-term liquidity resilience in acute stress scenarios. The primary objective is to evaluate the real-world impact of this predictive model on liquidity risk assessment across diverse scenarios.

This research aims to identify a suitable methodology for risk prediction that incorporates qualitative factors. The objective is to develop an effective methods for assessing liquidity risk, which will assist managers in forecasting potential scenarios and taking appropriate actions. The research questions are designed to evaluate

Cite this article: Mirashk, H. et al. 2025. "Design Science Research: A Practical Methodology for Enhancing Qualitative Liquidity Risk Management", *Electronic Journal of Business Research Methods 23(1)*, pp.01-19, https://doi.org/10.34190/ejbrm.23.1.3544

how well the selected methodology handle the prediction of short-term liquidity risk levels and the influence of qualitative factors, such as news sentiment, on these predictions. The ultimate goal is to bridge the gap between theoretical approaches and practical application, ensuring that the chosen methodology provides a robust and scientifically validated solution for real-world scenarios.

The DSR methodology encompasses distinct phases—Problem Identification, Design, Instantiation, and Use—each incorporating an evaluation step. This iterative process progresses from problem identification through solution provision, aiming to develop artifacts that enrich knowledge and ascertain their real-world applicability through continual interaction.

In the subsequent sections, the paper delves into a literature review (Section 2) and an in-depth discussion of the DSR methodology (Section 3), including its phases and their execution within this study. The evaluation of each DSR phase (Section 4) in this context is also elucidated. The objective and research questions in this study serve to justify the suitability of DSR as the best methodology to solve the problem of liquidity risk assessment in banking systems.

2. Literature Review

Design Science Research (DSR) constitutes a pragmatic paradigm aiming to address real-world challenges by crafting innovative solutions. Simon (1996) underscores DSR's focus on the IT artifact's applicability within specific domains. However, comprehensive investigations into the practical viability and effectiveness of these methods often remain limited to small-scale demonstrations, contributing to a gap in understanding method development and application in real-world settings (Hassel, 2012; Eden & Ackermann, 2018).

Within domains like risk science, publications providing insights into practical method development and application are notably scarce (Cedergren, 2019; Rae et al., 2020). Few studies have employed DSR in risk management, as shown in Table 1. Effiong et al. (2020) explored liquidity risk management's impact on consumer goods companies' financial performance through regression analysis. Arias (2015) proposed a software architectural design for liquidity risk management, utilizing the DSR approach in solution design and implementation.

In digital forensics, the DSR paradigm guided the development of an integrated digital forensic framework (Zhang, 2021). Similarly, Montenegro (2016) employed DSR to assess and reduce information security risks in telecommunication operators. Tavana (2018) introduced a new model employing Artificial Neural Network and Bayesian Networks to assess liquidity risk measurement through a real-world case study. Guerra (2022) utilized machine learning techniques for liquidity risk modeling in the Supervisory Review and Evaluation Process (SREP), providing stress-testing scenarios.

An (2017) proposed a model predicting financial liquidity risk using various models and statistical tests to discern variables affecting firms' liquidity statuses. Cedergren (2022) employed Action Design Research (ADR) to merge Risk Management and Business Continuity Management, focusing on theoretical advancement and practical solutions within a public sector organization.

Despite real-life constraints, ongoing research aiming to bridge the gap between method development and practical implementation remains limited. Swankie (2019) highlighted the gap in using AI to predict liquidity risk, emphasizing AI's potential to streamline risk calculation and factor identification. Nobili et al. (2021) developed an early warning system using predictive algorithms, outperforming traditional procedures. Guerra et al. (2022) investigated AI techniques in liquidity risk modeling, showcasing superior results with the XGBOOST algorithm.

Table 1: Indication of area and problem domains of recent researches –with DSR or Liquidity RM approach

RESEARCH AREA	Problem	Uses DSR	Considers Liquidity Risk Management
SUPPLY CHAIN MANAGEMENT	Lack of specification can affect coordination (Vosooghidizaji, 2020)	✓	
	Consideration of supply chain data analytic approaches (Kakhki, 2019)	✓	

RESEARCH AREA	Problem	Uses DSR	Considers Liquidity Risk Management
RESEARCH AREA	Problem	Uses DSR	Considers Liquidity Risk Management
INDUSTRY 4.0	Lack of a digital strategy (Cavata, 2020)	✓	
	Integration and digitalization of the quality management system (Kakhki, 2019)	✓	
	Supporting the production strategy using data processing aspects (Campos, 2020)	✓	
	Optimizing resources and reducing hospital stay in intelligent hospitals (Flórez, 2020)	✓	
	Decentralization of productive system control using autonomous devices (Guirro, 2020)	✓	
	Lack of internal firm capabilities for implementing Industry 4.0 (Raj, 2020)	✓	
LIQUIDITY RISK & MANAGEMENT	Information System Architecture for Liquidity Risk (Arias, 2015)		✓
	Investigating how top managers stimulate debates without generating conflict (Pereira, 2019)		✓
	Using AI techniques for liquidity risk measurement (Tavana, 2018)		✓
	Investigating whether AI techniques can model liquidity risk (Guerra, 2022)		✓
	Early warning system for liquidity risk identification (Nobili, 2021)		✓
	Prediction of firm health in liquidity (An, 2017)		✓
	Understanding the effects of liquidity risk management on financial performance (Effiong, 2020)		✓
	Predicting liquidity risk using machine learning techniques (Swankie, 2019)		✓
CONSUMERS INTENTIONS	Factors influencing behavior & measuring actual usage (Wu, 2023)	✓	

Table 1 encapsulates diverse research domains, outlining prevalent problems within each sector and the incorporation of Design Science Research (DSR) alongside the consideration of liquidity risk management. In the realm of supply chain management, challenges encompass issues like specification deficiency affecting coordination and the integration of data analytics for improved processes. Industry 4.0 confronts barriers such as the absence of digital strategies and the need for enhanced integration in quality management systems. Liquidity risk and management explore the utilization of AI techniques for risk measurement and early warning systems. Additionally, it delves into predicting firm health regarding liquidity and studying the impact of risk management on various sectors. Consumer intentions studies the influence of factors on behavior and the implications of liquidity risk management on consumer goods companies. Lastly, within business model innovation, research examines the necessity for profound customer understanding and the role of DSR in developing innovative models, specifically focusing on liquidity risk within these models.

In reviewing Table 1, it's evident that some research within the domain of liquidity risk and management does not actively incorporate Design Science Research (DSR) methodologies. Specifically, several studies within this field focus primarily on exploring liquidity risk, its measurement, and management strategies without explicitly employing the DSR framework. This absence of DSR integration signifies a gap where traditional research methods might prevail over the systematic and iterative approach offered by DSR in addressing liquidity risk within these studies.

The Design Science Research (DSR) paradigm emerges as a promising avenue to address liquidity risk challenges. However, despite its potential, the literature reveals a substantial gap in understanding the practical viability and effectiveness of such methods, often limited to small-scale demonstrations. Publications addressing the development and application of methods, particularly in risk science domains, remain scarce.

However, the literature review exposes a critical gap: the simultaneous exploration of liquidity risk prediction and DSR methodology. This gap forms the cornerstone of this study's novelty, aiming to integrate quantitative approaches, news sentiment analysis, and the application of liquidity risk positions as artifacts derived from established procedures like BASEL liquidity standards. Such an approach not only enhances predictive accuracy but also empowers risk managers to make informed decisions based on anticipated scenarios, ensuring preparedness through tailored plans for various contingencies.

In conclusion, while DSR holds promise in addressing liquidity risk challenges, there's an urgent need for comprehensive studies bridging the gap between theoretical advancements and practical implementations. This study seeks to fill this void by integrating DSR methodology with liquidity risk prediction, aiming to offer a holistic and practical solution in the banking sector's risk management landscape.

2.1 Liquidity Coverage Ratio (LCR)

The Liquidity Coverage Ratio (LCR) stands as one of the two conventional methods outlined by the Basel Supervisory Committee to assess a bank's capability to cover its net cash flow in the upcoming 30 days through its high-quality asset reserves. This ratio is formulated as LCR equals the quotient of quality cash assets over net outflows in the subsequent 30 days, expressed as a percentage, and it should not fall below 100%. Eq.1 delineates this criterion (BCBS, 2008). The net outflows over this period signify the discrepancy between inflows and outflows within the same duration.

(Eq. 1) $$LCR = \frac{\text{Quality cash assests}}{Net\ outflows\ over\ the\ next\ 30\ days} \geq 100\%$$

Net outflows over the next 30 days=Inflows over the next 30 days – Outflows over the next 30 days

The computation of the Liquidity Coverage Ratio involves three critical factors: firstly, the valuation of cash assets, constituting the numerator, emphasizing assets with high liquidity. Secondly, the recognition of the surplus rate between the liabilities and assets categories. Thirdly, the segmentation of requested deposits into short-term and long-term, with the application of specific coefficients for each deposit category (Tavana, 2018). However, the intricate nature of these calculations and parameter estimations makes the utilization of this ratio challenging and cumbersome in practice.

2.2 Assessment of Liquidity Risk Using Sentiment Analysis

Calculating liquidity risk based on different scenarios is a relatively complex and time-consuming task. Therefore, using traditional methods is inefficient and tedious. In these situations, machine learning and artificial intelligence methods can greatly control computational complexity. Machine learning systems have the capability to adapt to environmental changes, eliminating the need to design and write code for a variety of situations. Instead, the system can intelligently learn behaviors and events in similar situations, delivering the same behavior or an appropriate response.

With the development of artificial intelligence, Natural Language Processing (NLP) has strongly supported machine translation, spam detection, information extraction, summarization, Q&A tasks, and sentiment analysis (Jiang, 2020; Khurana, 2022). Overall, it is expected that liquidity risk can be predicted using sentiment analysis methods to estimate or predict its affecting factors.

3. Research Methodology

The research adopted the Design Science Research (DSR) methodology, a problem-solving approach aimed at advancing human knowledge through the creation of inventive artifacts. These artifacts serve to augment the technological and scientific knowledge domains by addressing problems and refining the settings in which they operate. DSR's outcomes encompass newly devised artifacts and design knowledge (DK) that undergo continuous refinement through design theories, thereby enhancing the relevance of these artifacts in various application contexts (vom Brocke et al., 2020). DSR's primary objective lies in broadening the horizons of human and organizational capabilities through the development of innovative artifacts, evident in constructs, models, methods, and instances. The knowledge pertaining to crafting such artifacts within DSR is termed Design Knowledge (DK) (Gregor et al., 2013).

This section outlines the research steps according to the DSR methodology. Various stages of DSR encompass every aspect, ranging from the problem domain linked to liquidity risk prediction to the solution domain connected with real liquidity scenarios. Therefore, DSR validates that the generated artifact is not only novel but also pragmatically applicable. It iterates between the realms of scientific exploration and real-world applicability to refine the artifact and ensure that the results are useful and interact effectively within the environment. In fact, in each of the six phases of Design Science Research (DSR), we develop an artifact relevant to that specific phase.

In this study, during the problem identification phase, we developed an artifact that describes the problem domain by looking forward to liquidity risk and aiming to reduce the complexity of its calculation. Subsequently, we proceeded to the second phase, defining the objectives and boundaries of the solution domain based on theories, models, and algorithms demonstrated in the literature. This involved the consideration of qualitative parameters and related data analysis techniques to simplify the calculation of liquidity risk, aligning with the artifact's relevance. Moving on to the design phase, a solution was devised utilizing a news sentiment approach to extract qualitative and environmental parameters influencing liquidity positions. This phase involved developing a theoretical solution with rigor, incorporating news data and selecting various AI algorithms to assess the impact of these parameters on liquidity risk within a nonlinear space for predictive purposes.

The theoretical solution was then practically demonstrated, taking the theory into real circumstances. The prediction artifact was utilized in actual liquidity scenarios to outline appropriate contingencies and plans. Subsequently, in the evaluation phase, the effectiveness and efficiency of the practical solution were assessed. If successful, the design science and real artifacts were communicated and published. Therefore, all artifacts generated in each phase underwent evaluation to ensure they met environmental requirements and achieved satisfactory results.

3.1 DSR Methodology

Figure 1 illustrates a conceptual framework for comprehending, executing, and appraising the design science research methodology. The environment delineates the problem space housing the focal phenomena, encompassing people, organizations, and existing or planned technologies. Within this space lie challenges and opportunities that articulate the stakeholders' organizational needs, collectively forming the 'research problem.' Aligning research pursuits with these stakeholders' needs ensures innovative research solutions. The knowledge base serves as the primary resource for driving DSR, comprising foundational theories and methodologies. Previous research outcomes and established reference procedures offer theories, frameworks, tools, models, and examples that guide the research's design phase. In the evaluation stage, methodologies dictate the processes to be employed. The research's rigor is established by drawing upon existing foundations and methodologies (Hevner et al., 2004; vom Brocke et al., 2020).

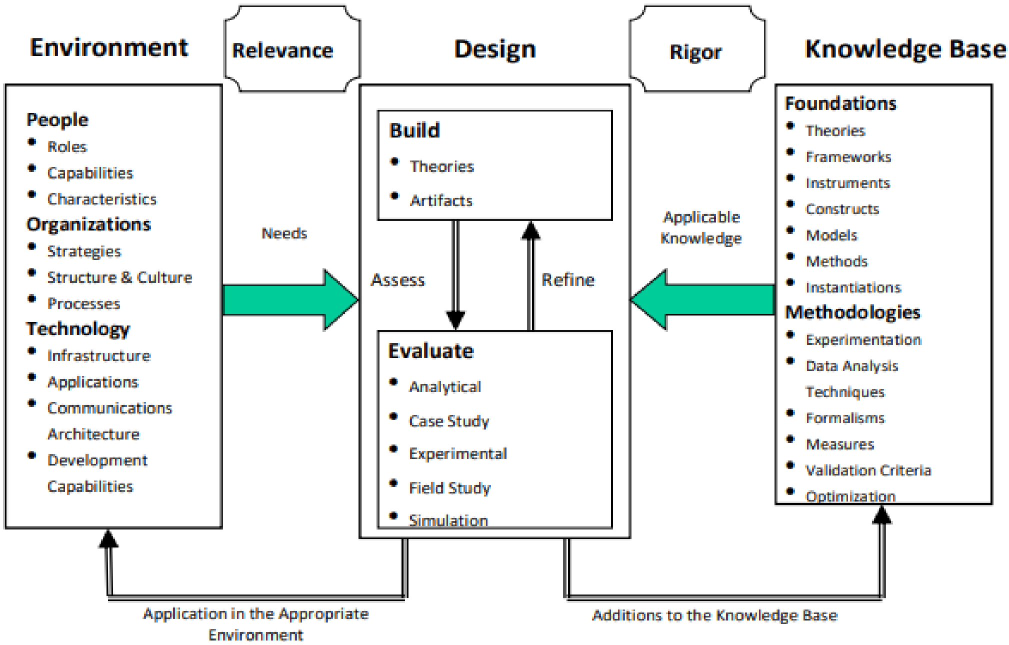

Figure 1: DSR Framework (Jan vom Brocke, 2020)

Being aware of the possibility of stress scenarios or crises, banks can be prepared and make appropriate plans to manage them. Therefore, each scenario is subjected to a certain action plan. According to the European Banking Authority (EBA), there are different plans for each risk level. A business continuity plan is appropriate when no significant risk has been identified. A business contingency plan is needed when the risk level enters the prudential range. Finally, the recovery plan is used in stress scenarios (EBA, 2021; Financial Stability Board, 2022).

The design science research method consists of six steps. Each step has its own characteristics, which are explained for this study:

1. State Problem: Identifying the problem and motivating
2. Define Objectives: Defining objectives of a solution
3. Design and Development: Designing and developing an artifact
4. Demonstration: Finding a suitable context and using the artifact to solve the problem
5. Evaluation: Observing the effectiveness and efficiency of the solution
6. Communication: Scholarly publications and professional publications

Based on the above procedure, the following sections discuss the research method.

3.2 Problem Evaluation

The identified issue has been a focal point in numerous studies. In 2018, Tavana et al. underscored that computing LCR and similar liquidity risk measures is time-consuming, challenging, and sometimes infeasible due to limited information access (Tavana et al., 2018). Additionally, Swankie et al., in a review article, pinpointed a research gap in predicting liquidity risk using artificial intelligence methods (Swankie et al., 2019).

3.3 Design and Instantiation of a Solution

This phase involved the design and instantiation of an artifact. In the context of DSR, an artifact embodies a research innovation, encompassing the definition of desired functionalities, architectural framework, and the actual creation of the artifact. In this study, the targeted artifact was a model predicting the bank liquidity risk for upcoming months. Given the problem's non-deterministic nature and the influential impact of environmental factors like news on liquidity risk, artificial intelligence methods such as text mining and sentiment analysis were applied. These methods aimed to approximate liquidity risk levels, facilitating the anticipation of potential scenarios. The researchers demonstrated a proposed model capable of approximating liquidity levels for the upcoming month.

3.3.1 Proposed model (figure 2 overview)

The proposed model encompasses several phases outlined in Figure 2, addressing various tasks delineated in the preceding section's research questions. Specifically, deep learning and machine learning techniques were utilized to estimate liquidity risk levels and identify the most influential factors derived from feature extraction. Textual news data underwent sentiment analysis to extract key qualitative features crucial for predicting LCR levels.

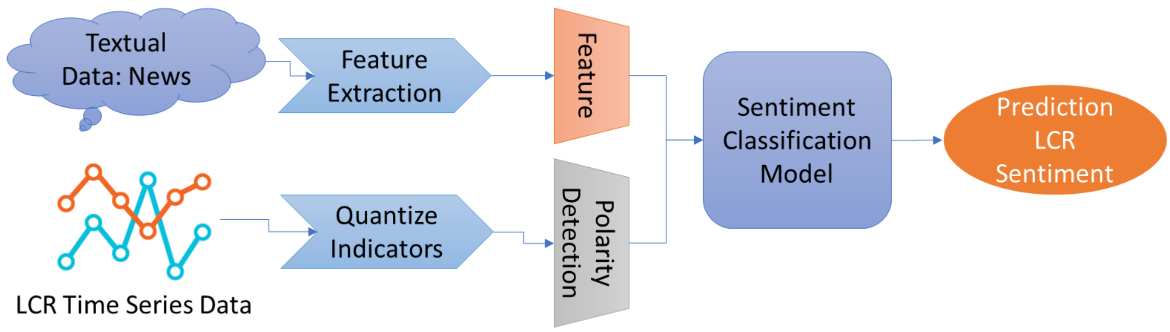

Figure 2: Overview of the research

Input sources encompass news data and computed bank LCR values. Features were extracted from textual data, focusing on feature extraction methods within text mining to identify key qualitative aspects for subsequent use. The subsequent section involved preprocessing and data preparation for subsequent steps. Additionally, the quantitative LCR data obtained from a sample bank over time required classification for use in the sentiment predictive model. The time series' quantitative data (LCR) was used to identify the polarity or sentiment of the news—acting as a monthly news indicator—in the area of interest, i.e., the liquidity risk level.

As depicted in Figure 2, machine learning algorithms utilized the selected features to predict the expected output or LCR level. In the case of artificial neural networks, well-predicting features are selected (activating neurons), while those exerting no influence or a counteractive effect have minimal or no impact on the network structure. Despite being a black-box method, the artificial neural network's effectiveness in nonlinear prediction and classification has been established. The evolution of natural language processing methods has transitioned from statistical and linear methods to machine learning, culminating in deep learning techniques and generative AI, notably large language models. Thus, the black-box nature of these methods doesn't imply unpredictability; scientific evaluation criteria, along with data division into evaluation, test, and training sets, ensure result accuracy and generalizability, as employed in this research. Subsequently, the model trained with validation data exhibiting acceptable accuracy underwent testing using previously unseen test data, enabling prediction comparisons with actual values. Moreover, these predictions for the current month could integrate into the liquidity risk time series data, informing future predictions.

The procedural steps are as follows:

- Collect quantitative and qualitative data from pertinent sources (banks and news agencies).
- Preprocess and normalize textual data, along with preparing (labeling) quantitative liquidity risk data.
- Identify and extract qualitative features from news utilizing text representation techniques.
- Develop a sentiment analysis model using machine learning, conventional neural networks, and deep learning methods, constituting the core focus of this project. Various algorithms were employed, parameters fine-tuned for each, and the most optimal one selected based on their comparative outcomes.
- Predict liquidity risk and evaluate the chosen model. Evaluation criteria for classification problems include accuracy, F1-score, recall, specificity, and AUC.

3.3.2 Research variables

This study involved two types of data: dependent and independent variables. The dependent variable comprised features extracted from news, while the independent variable was the liquidity risk ratio used as a predictive variable. Both qualitative and quantitative variables are detailed in Table 2.

Table 2: Research Data Sources

Variable name	Variable type	Type of data	Data time	Source of data
Liquidity Coverage Ratio	Quantitative variable	Bank liquidity risk data	April 2004 – November 2020	**A semi-private sector bank in Iran**
News quality index	Qualitative variable	News	April 2004- November 2020	**Fars News agencies**

3.3.3 Quantitative data

The bank's risk index, indicative of historical and backward-facing trends within the bank's status, was sourced from a semi-private bank as previously referenced (Nopp, 2015). Figure 3 illustrates the liquidity risk index trends of this bank from 2004 to 2020, displaying noticeable shifts in the bank's liquidity risk.

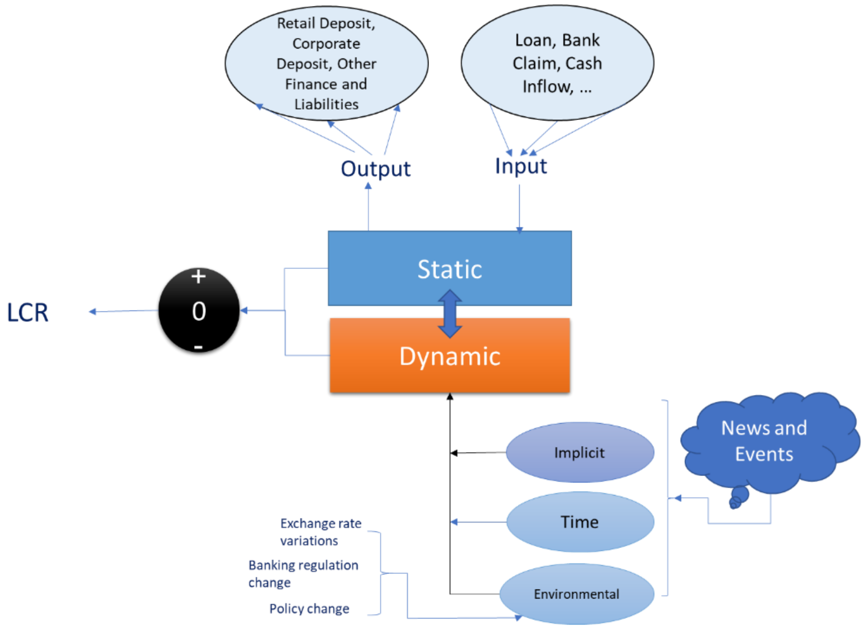

Figure 3: Trend chart depicting the liquidity risk index of the bank under validation throughout the study duration

3.3.4 *Collection and preprocessing of qualitative data*

In this study, news data were gathered and scraped from the reputable website of Fars News Agency. Extracted from https://www.farsnews.ir/archive between April 2004 and November 2020, these details were consolidated into a table that included news summaries, types, bodies, titles, and dates. For keyword extraction, the summary, title, and body of each news item were combined into a full-text input for subsequent feature extraction. As asserted by Töws (2018), news, being forward-looking, impact the future; hence, the data collection period should match that of liquidity risk data.

3.3.5 *Design and instantiation of the solution*

In this section, we evaluated the outcomes of the design and instantiation model applied to the bank's liquidity risk data and the gathered news. As previously outlined, the news data were consolidated into sets of 300 and 500 items, and the model was trained utilizing the features matrix, with labels denoting the bank's liquidity risk level. These labels were constructed in both triple-class and quintuple-class formats. Consequently, the input data (refer to Table 3) comprised four cases that were fed into two classifiers: the Feedforward Neural Network and the Convolutional Neural Network. Varied hyperparameters were established for each algorithm. The dense units were indicative of the number of neurons in dense layers. Specific details including activation functions, optimizer methods, input quantities as batch sizes, and the number of training epochs were specified for each evaluation case.

Table 3: Input data modes presents the input data options to the learning model

N	Number of samples	No of Train Samples	No of Test Samples	No of Validation	Type of combination	Number of classes
1	14169	9918	2125	2126	300	3
2	14169	9918	2125	2126	300	5
3	1000	5978	1281	1281	500	3
4	1000	5978	1281	1281	500	5

Feedforward Neural Networks:

In feedforward neural networks, a sequential model composed of standard Dense layers is employed. In these layers, all nodes in one layer are connected to all nodes in the next layer. Before utilizing Dense layers, the number of neurons in each layer must be specified, known as a hyperparameter or Unit, and its suitable value is obtained through experience. Another important point is that before passing outputs from one layer to another, they must pass through a non-linear activation function, such as RELU, which is commonly used. This activation function is determined by the activation hyperparameter and maps weighted inputs to neuron outputs. Lastly, for classification problems, the Softmax activation function is typically used in the final layer. The Loss hyperparameter in neural networks represents the loss function, measuring the distance between predicted outputs by the network and the desired outputs. The Optimizer hyperparameter indicates the optimization algorithm that adjusts the weights to minimize error. This algorithm is executed iteratively until an optimal solution is reached.

Convolutional Neural Networks:

In convolutional neural networks (CNNs), one-dimensional convolutional layers, one-dimensional Max Pooling layers, and dense layers are utilized. This research employs a multi-layer CNN for predicting bank liquidity risk. The primary core of the CNN is the convolutional layer, responsible for the majority of computations within the network. Each convolutional layer in a CNN comprises a set of filters, constructing the output by convolving these filters with the input layer. Hyperparameters like Filters in the Conv1D layer represent the number of detected features (output space dimensions), while Kernel_size defines the length of the convolution window in the Conv1D layer.

The objective of the Max Pooling layer is to reduce the spatial size of the feature matrix obtained from the convolutional layer. Unlike the convolutional layer, the Max Pooling layer doesn’t possess trainable parameters; it conducts simple yet effective subsampling. The Pool_size hyperparameter in the MaxPooling1D layer determines the size of the Max Pooling window. Typically, the final layers of a CNN serve as dense layers for classification purposes, transforming the extracted feature set into a vector and passing it through a dense classification layer to identify the corresponding class.

3.3.6 Evaluation of the Design and Instantiation Phase

Next, the results pertaining to validation accuracy, test accuracy, precision, recall, and F1-Score for both algorithms are presented in Tables 4 and 5. Additionally, other metrics such as imbalanced accuracy, Cohen's kappa, and ROC AUC are utilized. Several studies have attempted to address the challenge of learning multiclass scoring functions using AUC metrics (Gimeno, 2021).

Table 4: Results of evaluation criteria obtained from the Deep Learning Network

Feedforward Neural Network													
Triple													
Bin size	**Dens e units**	**Activation**	**Optimizer**	**Batch size**	**Epochs**	**val_acc**	**test_acc**	**Precis ion**	**Recall**	**F1 score**	**Balance Accuracy**	**Cohens kappa**	**ROC AUC**
300	512-256-128-64	relu	adam	8	29	83.11	84.1	83.56	84.07	84.1	84.07	75.88	95.44
500	512-256256	relu	rms	64	43	88.91	88.6	88.5	88.63	88.6	88.56	82.75	97.56
Quintuple													
300	1024-512-256128	relu	rms	64	19	84.85	88.29	88.23	88.5	88.29	88.31	85.31	98.53
500	512-256128	relu	rms	64	42	87.35	82.51	82.19	83.42	82.51	82.3	78.04	97.22

In terms of test accuracy, one of the key evaluation criteria for the models, the highest results were observed in the feedforward neural network, achieving approximately 88.6% accuracy with a combination of 500 and triple-class, slightly decreasing to 88.29% with the quintuple-class and a combination of 300. Moreover, the feedforward neural network algorithm exhibited the highest precision, recall, and F1-Score of 88.5%, 88.63%, and 88.6%, respectively, for the combination mode of 300 in the 5-class setup. Another critical metric, ROC-AUC, also favored the feedforward neural network algorithm, reaching approximately 98.53% with the combination model of 300 in the quintuple-class configuration, closely followed by the feedforward neural network with the combination model of 500 in the triple-class configuration.

Table 5: Results of validation criteria obtained from the Convolutional Neural Network

Convolutional Neural Network															
Triple															
Bin size	**Filter s**	**Kern el size**	**Pool size**	**Dens e units**	**Activation**	**Optimize r**	**Batch size**	**Epochs**	**Balance Accuracy**	**test_acc**	**Precision**	**Recall**	**F1 score**	**Cohens kappa**	**ROC AUC**
300	64128256	3	2	256	relu	adam	8	25	82.07	81.7	81.73	82.02	81.7	81.78	72.38
500	64-128	3	2	128	relu	adam	32	21	84.07	**83.29**	82.74	83.32	83.29	83.26	74.63
Quintuple															
300	128-256512	3	2	512	relu	rms	16	16	80.24	81.19	80.9	81.41	81.19	81.22	76.39
500	64128256	3	2	256	relu	adam	64	30	80.95	82.28	82.15	82.33	82.28	82.28	77.78

Considering the outcomes across all criteria, the deep neural network algorithm emerges as a promising model for predicting bank liquidity risks based on qualitative news data.

3.4 Demonstration and Evaluation of the Solution in Practice

Following the Design Science Research (DSR) approach, this section examines the practical application of the proposed model. Initially, the results from the prior step were readied for use. Subsequently, potential scenarios were delineated based on specified ranges derived from the liquidity risk levels of banks. These scenarios were compared with predicted scenarios generated from the instantiation phase to ascertain prediction accuracy. As presented in Table 6, the test data from earlier steps were classified into monthly news. Employing the combination mode (explained in the instantiation phase), each month's news was segmented into several samples (each containing 'm' news pieces). Each sample was fed into the model to predict the subsequent month's liquidity level. As shown in Figure 4, to standardize the labels for each month derived from the risk level of each sample, a voting method was adopted. For instance, if the first month had 20 samples and the labels were predicted 10, 7, and 3 times respectively, the most frequently predicted label was considered the selected label for that month.

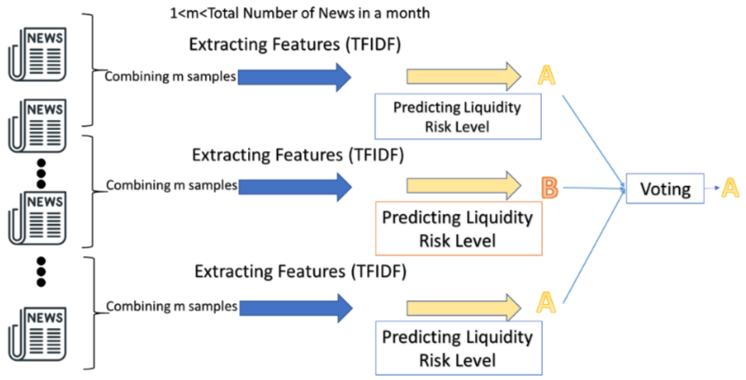

Figure 4: Predicting monthly liquidity level using voting method

The possible liquidity risk scenarios were derived from the risk range defined in Basel. Particularly, the Liquidity Coverage Ratio (LCR), introduced as a liquidity risk measurement index on January 1, 2015, was initially set at a minimum requirement of 60%, gradually increasing by 10% annually to reach 100% by January 1, 2019. This incremental approach aimed to ensure LCR adoption without significantly disrupting banking systems or ongoing economic financing (Basel III: The Liquidity Coverage Ratio and Liquidity Risk Monitoring Tools, 2013). This Basel approach defined two ranges:

- A safe range: above the permissible LCR limit.
- An unsafe range: below the permissible LCR limit.

The European Central Banking Supervision defined four different LCR ranges, establishing three primary thresholds: a recovery indicator, a warning indicator, and a critical indicator. Hence, four main ranges were identified using three thresholds set by the European Banking Authority (EBA). Each range had distinct action plans: a recovery plan for the critical range, a contingency plan for the warning range, and a business continuity plan for the safe range. These ranges were vital in characterizing the investigated scenarios. The following table (Table 6) illustrates the diverse LCR ranges based on the Basel Committee guidelines and EBA Risk Assessment procedures. Furthermore, these ranges were cross-validated with the risk departments of the assessed banks to verify their efficiency and effectiveness (RISK ASSESSMENT OF THE EUROPEAN BANKING SYSTEM, 2021).

Table 6: LCR ranges extracted from BASEL and EBA

YEAR / LCR Risk Range	Before 2016	2016-2017	2017-2018	2018-2019	After 2019
Completely Safe Range	>65	>75	>85	>95	>105
Safe Range	60-65	70-75	80-85	90-95	100-105
Warning Range	20-60	30-70	40-80	50-90	60-100
Critical Range	<20	<30	<40	<50	<60

In this context, the Liquidity Coverage Ratio's (LCR) potential scenarios in banks were categorized into twelve distinct scenarios, each outlined in the EBA report, with specific importance for the bank, necessitating appropriate action plans. Therefore, the identification and anticipation of potential scenarios based on the bank's current situation for the upcoming month were crucial, allowing the bank to proactively mitigate or hedge risks before they materialize (RISK ASSESSMENT OF THE EUROPEAN BANKING SYSTEM, 2021).

Table 7: Scenarios extracted from 4 ranges of LCR

Scenario No	Source range	Destination range	Risk Type	Action from perspective of regulatory	Action from perspective of shareholder
1	Safe Range	Completely Safe Range	Decrease Risk	No action needed	Invest in cases with less liquidity and more profit
2	Completely Safe Range	Safe Range	Increase Risk	No action needed	No action needed

Scenario No	Source range	Destination range	Risk Type	Action from perspective of regulatory	Action from perspective of shareholder
3	Safe Range	Safe Range	Constant Risk	No action needed	No action needed
4	Safe Range	Warning Range	Increase Risk	Invest in cases with more liquidity	Invest in cases with more liquidity
5	Warning Range	Safe Range	Decrease Risk	No action needed	No action needed
6	Warning Range	Warning Range	Constant Risk	Invest in cases with more liquidity	Invest in cases with more liquidity
7	Warning Range	Critical Range	Increase Risk	Low liquidity assets should be sold	Low liquidity assets should be sold
8	Critical Range	Warning Range	Decrease Risk	Invest in cases with more liquidity	Invest in cases with more liquidity
9	Critical Range	Critical Range	Constant Risk	Low liquidity assets should be sold	Low liquidity assets should be sold
10	Critical Range	Safe or Completely Safe Range	Decrease Risk	No action needed	Invest in cases with less liquidity and more profit
11	Safe or Completely Safe Range	Critical Range	Increase Risk	Low liquidity assets should be sold	Low liquidity assets should be sold
12	Completely Safe Range	Completely Safe Range	Constant Risk	No action needed	Invest in cases with less liquidity and more profit

The table above (Table 7) delineates potential scenarios derived from the LCR ranges, approved by the bank's liquidity risk management experts. Moreover, corresponding actions for each scenario should refer to the financial report of the EBA, outlining actions or improvement programs (Supervision, 2018). Subsequently, discussions revolve around scenarios observed within the bank's actual data, utilizing liquidity risk predictions derived from the preceding phase, converted into monthly predictions using the voting method in the prior segment.

Identifying the scenarios in the target bank based on possible scenarios and matching these with the monthly predictions. To evaluate the occurred scenarios and compare them with the monthly predictions from the previous step, these scenarios were identified using available LCR data. They were then compared with the predictions made, assessing the association between the predicted risk levels of the triple and quintuple classes calculated monthly. Figure 5 depicts the scenarios observed in 2019 and 2020, showcasing liquidity risk across the completely safe, warning, and critical ranges, totaling scenarios 6, 7, 8, 9, 11, and 12.

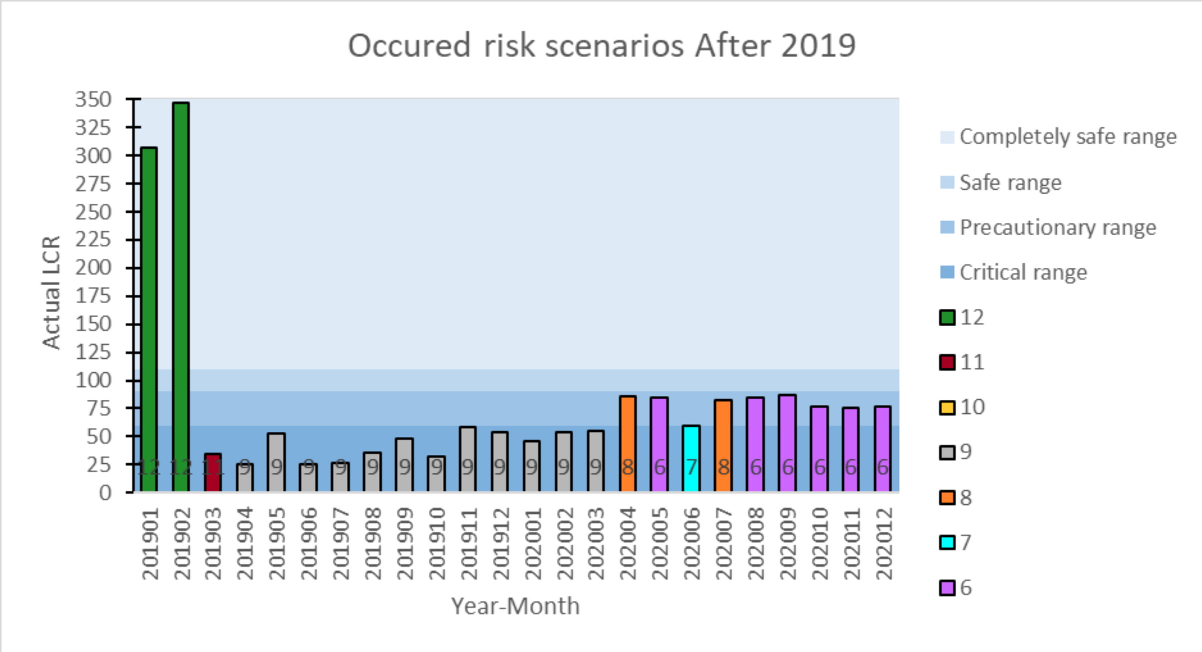

Figure 5: Scenarios that occurred after in the different ranges of liquidity risk

Figure 6 illustrates liquidity risk and its predicted levels, showcasing changes in green (increase), red (decrease), and gray (constant) colors for the combination of 300 and Quintuple class using the deep learning method. The consistency between predicted liquidity levels and LCR value changes across different months is evident. It also displays the labeling of five classes using the deep learning method, depicting trends of increase and decrease, well-aligned with LCR changes. Other prediction modes based on the deep learning algorithm corroborated these findings. These diagrams effectively cover the transitions between safe and unsafe ranges as per the wing committee's instructions in various cases.

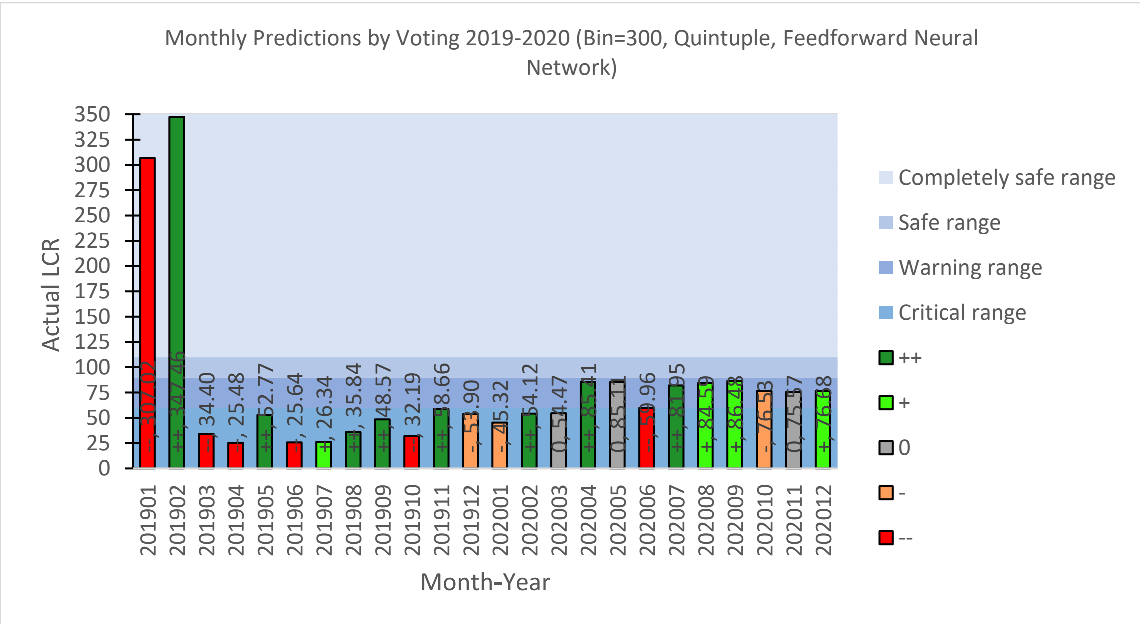

Figure 6: Sentiment prediction with deep learning method, combining 300 and Quintuple tags in months post-2019, depicting actual liquidity changes (++ high increase, + increase, 0 no change, and – low or high decrease compared to the previous month)

Tables 8, 9 compares the liquidity risk level results from occurred scenarios and predicted scenarios via triple-class and quintuple-class methods. In 2019, approximately 64% of the scenarios were accurately predicted.

Similarly, in 2020, around 83% of the triple-class mode and approximately 92% of the quintuple-class mode were correctly recognized.

Table 8: Comparison between risk levels in occurred scenarios and the prediction of risk sentiment each month in the year 2019

Predicted sentiment of monthly risk - Quintuple Mode	Predicted sentiment of monthly risk – Triple Mode	Risk level based on occurred scenarios	Type of occurred scenarios	Date
No change	No change	No change	Scenario 12	02-2019
Significant Increase Risk	Increase Risk	Significant Increase Risk	Scenario 11	03-2019
No change	No change	No change	Scenario 9	04-2019
Significant Decrease Risk	Decrease Risk	No change	Scenario 9	05-2019
No change	No change	No change	Scenario 9	06-2019
No change	No change	No change	Scenario 9	07-2019
Significant Decrease Risk	Decrease Risk	No change	Scenario 9	08-2019
Significant Decrease Risk	Decrease Risk	No change	Scenario 9	09-2019
No change	No change	No change	Scenario 9	10-2019
Significant Decrease Risk	Decrease Risk	No change	Scenario 9	11-2019
No change	No change	No change	Scenario 9	12-2019

Table 9: Comparison between risk levels in occurred scenarios and the prediction of risk sentiment each month in the year 2020

Predicted sentiment of monthly risk - Quintuple Mode	Predicted sentiment of monthly risk – Triple Mode	Risk level based on occurred scenarios	Type of occurred scenarios	Date
No change	No change	No change	Scenario 12	01-2020
Significant Decrease Risk	Decrease Risk	No change	Scenario 12	02-2020
No change	No change	No change	Scenario 11	03-2020
Significant Decrease Risk	Decrease Risk	Decrease Risk	Scenario 9	04-2020
No change	No change	No change	Scenario 9	05-2020
Significant Increase Risk	Increase Risk	Increase Risk	Scenario 9	06-2020

Predicted sentiment of monthly risk - Quintuple Mode	Predicted sentiment of monthly risk – Triple Mode	Risk level based on occurred scenarios	Type of occurred scenarios	Date
Significant Decrease Risk	Decrease Risk	Decrease Risk	Scenario 9	07-2020
No change	No change	No change	Scenario 9	08-2020
No change	No change	No change	Scenario 9	09-2020
No change	Increase Risk	No change	Scenario 9	10-2020
No change	No change	No change	Scenario 9	11-2020
No change	No change	No change	Scenario 9	12-2020

4. Evaluation and Finalization of the DSR Cycle

This assessment analyzed various scenarios occurring between 2019 and 2020, comparing the outcomes (scenarios) with the predictions from the instantiation phase. Ultimately, it assessed the practical solution's accuracy. The Table 10 illustrates the practical model's accuracy, considering scenarios across different years, reflecting BASEL's perspectives on safe and unsafe ranges, and referencing EBA's four mentioned ranges (completely safe, safe, precautionary, critical). Subsequently, it evaluated whether the DSR cycle was concluded based on the obtained results.

Table 10: Evaluation of Prediction accuracy of risk level in occurred scenarios

Year under assessment		**Accuracy of Predicted Scenarios**		
		2019	**2020**	**Average**
Accuracy of Prediction In Basel Range	*Triple Class*	91%	100%	95.5%
	Quintuple Class	91%	83%	87%
Accuracy of Prediction in EBA	*Triple Class*	83%	64%	73%
	Quintuple Class	92%	64%	75%

Using the DSR approach enables the enhancement of liquidity risk prediction in the bank by considering qualitative factors. As depicted in Table 9, integrating qualitative factors into the prediction model through sentiment analysis techniques achieves a high accuracy rate, approximately 95.5% with the best-selected parameters. This outcome underscores the strong performance of the proposed model. Hence, the DSR cycle is concluded and does not require further continuation.

4.1 Ex Ante and Ex Post Evaluation Results

This section assesses the outcomes derived from the practical solution of the research, adhering to the DSR evaluation framework introduced by Pries-Heje et al. (Pries-Heje, 2008). The framework encompasses four aspects of DSR evaluation, mapping criteria to Ex Ante vs Ex Post and artificial vs naturalistic evaluations, as illustrated in the table below.

Table 11: DSR Evaluation Strategy Selection Framework for this study

DSR Evaluation Strategy Selection Framework		**Ex Ante** Formative Lower Build Cost Evaluate Design Artifacts Less Risk To participants	**Ex Post** Summative Slower Evaluate Instantiation Higher Risk To Participants
Naturalistic	Socio-technical Artifacts Higher Cost Organizational Access needed Artifact Effectiveness Evaluation Higher Risk Participants		Real User/Real System and Real Problem Highest Risk to Participants Best Evaluation of Effectiveness Identification of side effects
Artificial	Purely Technical Artifacts Desired Rigor: Control of variable Artifact Efficacy Evaluation Less Risk During Evaluation	Unreal User/ Unreal System Lowest Cost Fastest Lowest Risk To participants	

Table 11 indicates that in Ex Ante evaluation, DSR Research was mapped to artificial evaluation methods (designing purely technical artifacts), while for Ex Post evaluation, it was mapped to naturalistic evaluation methods (real technical artifacts or case studies). Artificial evaluations involve activities like experimentation and observation. The dominance of the scientific/rational paradigm in artificial DSR evaluation provides benefits like stronger scientific reliability, better repeatability, and falsifiability. This study utilized criteria-based analysis (data analysis) to validate the Ex Ante phase.

Conversely, naturalistic evaluation involves assessments in real environments (involving real people, real systems, and real settings), which are empirical and may be interpretive, positive, or critical. This study applied empirical evaluation in the Ex Post phase of DSR, employing scenario analysis within a case study to identify and evaluate the application of solutions in a real situation. Table 12 presents the evaluation method and corresponding results for Ex Ante and Ex Post phases, along with the outcome of each phase.

Table 12: DSR Evaluation Method Selection Framework for this study

DSR Evaluation Method Selection Framework	**Ex Ante**	**Ex Post**
Naturalistic		Scenario Analysis Case Study Accuracy = 95.5%
Artificial	Data Analysis Criteria Based evaluation Accuracy=88.6%	

5. Conclusion

This study set out to identify a suitable methodology for risk prediction in the principles of the Basel III model, with a focus on short-term liquidity resilience in acute stress scenarios. Through iterative phases (DSR) of problem identification, design, instantiation, and use, we sought to bridge the gap between theoretical evaluations and practical implementation, providing a scientifically validated solution applicable in real-world scenarios. The DSR method evaluated the real-world instantiation to assess its applicability and validity. Initially, the results underwent assessment within an instance, followed by testing the instantiation stage outcomes in real-case scenarios.

The practical findings shows the method's accuracy in predicting occurrence scenarios, approximately 75% within four EBA ranges and 95.5% across two Basel ranges in the ex post naturalistic evaluation phase. Considering the accuracy in predicting scenarios and aligning with the evaluation criteria within the DSR methodology across four steps—identification, design, instantiation, and use—the study indicated the methodology in similar design instances (Ex Ante Artificial Evaluation) and its practical application in real scenarios (Ex Post Naturalistic Evaluation).

The research questions guiding this study were designed to assess the efficiency and efficacy of our methodology. The results demonstrated that DSR is a highly effective methodology for addressing complex and time-consuming calculations in financial and risk management problems. While this research focused on the initial iteration due to satisfactory results, future research could incorporate action research to further enhance artifact development and address issues simultaneously.

In conclusion, this study highlights the importance of using a structured research methodology like DSR to develop effective solutions for complex financial problems. The framework and insights generated contribute significantly to liquidity risk management, providing practical tools and knowledge to help banks navigate financial challenges. The proposed DSR approach has shown high accuracy and generalizability in predicting liquidity risk, validating its applicability and establishing a strong foundation for future research and improvements.

Ethical statements: This article does not contain any studies with human participants performed by any of the authors.

Competing interests: Hamed Mirashk as first author and other authors declare no competing interests.

Availability of data/materials: The data that support the findings of this study are available from here and news from here but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data are however available from the authors upon reasonable request and with permission of Central Bank of Iran.

Source code as supplementary material is also provided here. The source code contains all the custom computer code used to generate results that are reported in this paper and central to its main claims.

Informed consent: This article does not contain any studies with human participants performed by any of the authors.

Author Declaration on AI Tools and Services: The authors affirm that no artificial intelligence (AI) tools or services were used in the creation, analysis, writing, or editing of this manuscript. All content, including text, analysis, and figures, is the result of the authors' independent efforts and original work.

References

Alan R. Hevner Ram, S. T., 2004. Design science in information systems research. MIS Quarterly, 28(1), pp.75-105.

Alexander Cedergren, H. H., 2022. Using action design research for developing and implementing a method for risk assessment and continuity management. Safety Science, 151, p.105727.

Alok Raj, G. D., 2020. Barriers to the adoption of industry 4.0 technologies in the manufacturing sector: An inter-country comparative perspective. International Journal of Production Economics, p.107546.

An, C.-H., 2017. A study on estimation of financial liquidity risk prediction model using financial analysis. International Journal of Applied Engineering Research, 12(20), pp.9919-9923.

Antônio Marcos Holanda de Sousa, J. d., 2020. Is it possible to implement ERP in the production function of civil construction. Artigo Original, 27, p.4445.

Arias, J. A., 2015. Design of information system for the liquidity risk management in financial institutions. In: 2015 10th Iberian Conference on Information Systems and Technologies (CISTI). IEEE, pp.1-6.

Basel Committee on Banking Supervision, 2013. Basel III: The liquidity coverage ratio and liquidity risk monitoring tools.

Basel Committee on Banking Supervision, 2008. Principles for sound liquidity risk management and supervision.

Basel Committee on Banking Supervision, 2018. Report on recovery plans. European Central Bank.

Bayer, C., 2019. Recent advancements in sentiment analysis in finance.

Boguth, O. & Carlson, M., 2016. Horizon effects in average returns: the role of slow information diffusion. The Review of Financial Studies, 29(8), pp.2241-2281.

Brendan Juba, H. S., 2019. Precision-recall versus accuracy and the role of large data sets. Proceedings of the AAAI Conference on Artificial Intelligence, 33(9), p.19.

Calabrese, R., Girardone, C. & Vennari, P., 2015. Estimating bank default with generalised extreme value regression models. The Journal of the Operational Research Society, 66(11), pp.1783-1792.

Camilo Andrés Cáceres Flórez, J. M., 2020. Application of automation and manufacture techniques oriented to a service-based business using the Internet of Things (IoT) and Industry 4.0 concepts. Case study: Smart Hospital. Gestão & Produção, 27(3).

Carlos Montenegro, M. M., 2016. DSR approach to assessment and reduction of information security risk in TELCO. IEEE Latin America Transactions, 14(5), pp.2402-2410.Cedergren, A., Hedtjärn Swaling, V., Hassel, H., Denward, C., Mossberg Sonnek, K., & Albinsson, P.-A. (2018).

Cavata, J. T. & Araújo, A. A., 2020. Highlighting the benefits of Industry 4.0 for production: an agent-based simulation approach. Gestão & Produção, 27.

Central Bank of Trinidad and Tobago, 2022. Recovery planning guideline for financial institution.

Clemens Nopp, A. H., 2015. Detecting risks in the banking system by sentiment analysis. EMNLP.

Daneshvar Kakhki, M. & Baradaran Vahdat, V., 2019. Information systems for supply chain management: a systematic literature analysis. International Journal of Production Research, 57(15-16), pp.5318-5339.

Diksha Khurana, A. K., 2022. Natural language processing: state of the art, current trends and challenges. Multimedia Tools and Applications.

Eden, C. & Ackermann, F., 2018. Theory into practice, practice to theory: Action research in method development. European Journal of Operational Research, 271(3), pp.1145-1155. DOI: 10.1016/j.ejor.2018.05.061.

Effiong, S. A., 2020. Liquidity risk management and financial performance: are consumer goods companies involved. International Journal of Recent Technology and Engineering, 9(1), pp.580-589.

Eric Ghysels, R. G., 2020. Improving portfolio selection by balancing liquidity-risk-return: Evidence from stock markets. Econometrics: Econometric & Statistical Methods - General eJournal.

European Banking Authority, 2021. Risk assessment of the European banking system.

Fernando Celso de Campos, A. G., 2020. Proposal for a framework for production strategy utilizing big data: illustrative case in public service. Gestão & Produção, 27(3).

George Daniel Brown Swankie, D. B., 2019. Examining the impact of artificial intelligence on the evaluation of banking risk. Center for Financial Regulation and Innovation.

Giancarlo Pereira, N. T., 2019. Top managers' role in key account management. Journal of Business & Industrial Marketing, 34(5), pp.977-993.

Gimeno, P., Mingote, V., Ortega, A., Miguel, A., & Lleida, E., 2021. Generalizing AUC optimization to multiclass classification for audio segmentation with limited training data. IEEE Signal Processing Letters, 28, pp.1135-1139. DOI: 10.1109/LSP.2021.3084501.

Gregor, S. & Hevner, A. R., 2013. Positioning and presenting design science research for maximum impact. MIS Quarterly, 37, pp.337-356.

Guerra, P., Conlisk-Rodriguez, M., Samandari, H. & Unger, R., 2022. Machine learning for liquidity risk modelling: a supervisory perspective. Economic Analysis and Policy, 74, pp.175-187.

Guidelines on recovery plan indicators, 2021. European Banking Authority.

Guirro, D. N., 2020. Manufacturing operational management modeling using interpreted Petri nets. Gestão & Produção, 27(2).

Hevner, A. & Chatterjee, S., 2010. Design Research in Information Systems: Theory and Practice (Volume 22). Integrated Series in Information Systems. ISSN 1571-0270. DOI: 10.1007/978-1-4419-5653-8. Springer New York Dordrecht Heidelberg London.

Hanley, J. A. & McNeil, B. J., 1982. The meaning and use of the area under a receiver operating characteristic (ROC) curve. Radiology, 143(1), pp.29-36. DOI: 10.1148/radiology.143.1.7063747.

Jiang, K. & Liu, X., 2020. Natural language processing and its applications in machine translation: a diachronic review. Natural Language Processing and Its Applications in Machine Translation.

Nam, K. & Suk, N., 2019. Financial news-based stock movement prediction using causality analysis of influence in the Korean stock market. Decision Support Systems, 117, pp.100-112.

Nobili, S. & Laviola, M., 2021. A liquidity risk early warning indicator for Italian banks: a machine learning approach. ERN: Banking & Monetary Policy, 1337.

Pham, X. & Ho, H., 2021. Using boosting algorithms to predict bank failure: an untold story. International Review of Economics & Finance, 76, pp.40-54.

Pries-Heje, J. & Baskerville, R., 2008. Strategies for design science research evaluation. 16th European Conference on Information Systems, ECIS 2008, pp.255-266.

Rae, A., Provan, D., Aboelssaad, H. & Alexander, R., 2020. A manifesto for reality-based safety science. Safety Science, 126, 104654. DOI: 10.1016/j.ssci.2020.104654.

Simon, H. A., 1988. The Sciences of the Artificial. 2nd ed. Cambridge, MA: MIT Press.

Shapiro, A. P., 2022. Credit ratings and market information. The Review of Financial Studies, 35(10), pp.4425-4473.

Solangi, Y., Shah, A. & Abro, A., 2018. Review on natural language processing (NLP) and its toolkits for opinion mining and sentiment analysis. IEEE 5th International Conference on Engineering Technologies and Applied Sciences, pp.1-4.

Gomes, T. & Kihato, N., 2011. Strengthening bank management of liquidity risk: The Basel III liquidity standards. Financial System Review, pp.35-42.

Tavana, M. & Abolhasani-Rahmati, A., 2018. An artificial neural network and Bayesian network model for liquidity risk assessment in banking. Neurocomputing, 275, pp.2525-2554.Metz, C. E. (1978). Basic principles of ROC analysis. Semin Nucl Med, 8(4), 283-98. doi: 10.1016/s0001-2998(78)80014-2

Tòws, D. M., 2018. Text mining and reporting quality in German banks: A co-occurrence and sentiment analysis. Journal of Accounting and Finance, 6, pp.54-81.

Vom Brocke, J. & Hevner, A., 2020. Introduction to design science research. Springer International Publishing, pp.1-13.

Vosooghidizaji, M., Taleizadeh, A. & Govindan, K., 2020. Supply chain coordination under information asymmetry: a review. International Journal of Production Research, 58(20), pp.6246-6270.

Wu, J. & Ma, J.-Y., 2023. MC 2.0: testing an apparel co-design experience model. Journal of Fashion Marketing and Management, 19(1), pp.69-86.

Zhang, X. & Zheng, C., 2021. A design science approach to developing an integrated mobile app forensic framework. Computers & Security, 105, p.102226.

Zweig, M. H. & Campbell, G., 1993. Receiver-operating characteristic (ROC) plots: a fundamental evaluation tool in clinical medicine. Clinical Chemistry, 39(4), pp.561-577. DOI: https://doi.org/10.1093/clinchem/39.4.561.