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Algorithms of pattern recognition for managing logistics processes in Kazakhstan

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ABSTRACT

This paper explores the application and development of pattern-recognition algorithms to control logistics processes in Kazakhstan's major transit corridors. The main aim was to develop a model adapted to the context, empirically verify its operational performance, and identify the factors critical to ensuring that the model could be integrated in practice. The implemented approach was a quantitative experimental design: a CNN model was fine-tuned on synthetic local data and tested against a generic benchmark; its effectiveness was evaluated in terms of concurrent accuracy, precision, F1-score, and latency; and stakeholder perceptions were assessed through an Analytic Hierarchy Process survey. Major findings include that the locally adapted model was much more accurate (F1-score: 0.925 vs. 0.855) and met all real-time working requirements. Moreover, survey analysis showed that organizational readiness and regulatory support are viewed as 56% more potent for integration success than technical performance measures. The results suggest that technical adaptation, although critical, is not yet sufficient; to succeed in deployment in Kazakhstan, the data infrastructure would need to be developed in parallel, and favorable policy frameworks should be established. One of the main study limitations is the use of synthetic data, which necessitates field validation of the results.

Keywords: Convolutional neural network, Digital transformation, Empirical validation, Performance metrics, Stakeholder perception

1. Introduction

Automation and artificial intelligence (AI) are the current forces changing the global logistics sector radically by improving supply-chain efficiency, resilience, and competitiveness [1]. The digital transformation is particularly challenging for developing transit economies located on international routes. The key actor governing the Middle Corridor, which links Europe with Asia, Kazakhstan, is at once developing its logistics resources, including centers, warehouses, and transportation systems, as part of a large-scale digitization project.

The complex, high-volume processes are becoming increasingly complex and high-volume, requiring intelligent systems that can analyze real-time operational data, rather than the traditional transaction-tracking information technology systems. Automation of cargo tracking, fault inspection and route planning are impossible without pattern-recognition algorithms that process visual and sensor data. Kazakhstan's geographic location, as a country with a strong geographic advantage, combined with current global trends in the use of artificial intelligence, enables the timely and valuable discovery of AI use in the country [4].

The current research pertains to the correlation between data specificity and algorithmic efficacy, and to the critical independent and dependent variables in particular. The first independent variable, Training Data Type

(TDT), operationalizes contextual adaptation by distinguishing between training a model on generic international data or locally representative data [5].

Operational viability is measured by the main dependent variables: Accuracy, Precision, Recall, F1-Score, and Inference Latency [6]. It is argued that valuable, rare, and inimitable resources provide a sustainable competitive advantage [7], [8], according to the Resource-Based View (RBV) theory strategic management framework that emphasizes a firm's internal resources [9]. That is why the study hypothesizes that locally curated data (TDT=1) will yield better performance measures (ACC, FS) than generic ones (TDT=0) and, as a result, generate a context-specific logistics-management competitive tool [10].

Recent work has shown that deep learning models, such as convolutional neural networks (CNNs), can be used to perform logistics vision tasks, including pallet integrity checks and real-time container tracking [11], [12]. To a greater extent, these empirical studies rely on data from logistics centers in North America, Europe, and East Asia; therefore, this research has a strong geographic orientation.

This concentration in itself limits the generalizability of the results, since there could be significant differences between environmental, operational and cargo conditions compared to rapidly growing transit economies like Kazakhstan [13], [14]. Following this line, pattern-recognition models specific to Kazakhstan's logistics infrastructure are scarce, with few empirically verified and validated models [15]. Changes in lighting conditions, air pollution levels and packaging across the Central Asian hubs may compromise the performance of models designed to operate in well-lit, uniform settings, thereby limiting their applications to support the national digitization agenda [16].

CNNs are effective tools of visual inspection. New literature supports their feasibility in the logistical industry [17]. However, the available research has not utilized customized or methodically assessed layouts in the emerging logistics hubs in Kazakhstan [18]. The current study achieves high classification accuracy but is limited by data scarcity, a problem prevalent in areas where large, annotated population datasets are scarce [19]. The creation and use of a fake dataset unique to Kazakhstan mitigates this gap. On the other hand, inference latency (LAT) is considered a central measure in the current study, compared with accuracy and throughput. Technical validation and integration analysis application is an area of previous scholarship that is rarely examined.

The combination of technical validation and strict evaluation of organizational readiness is a current yet little-studied aspect of technology implementation. This lack is addressed in this paper by introducing contextual variables, including Organizational Data Readiness (ODR), and by conducting a stakeholder analysis to identify the perceived salience of technical and non-technical determinants of successful implementation. Such a methodological practice generates a more comprehensive analysis of the innovation process in the target milieu, and, thus, contributes to the academic knowledge about the diffusion of technologies in new logistics settings.

The Middle Corridor and Kazakhstan's strategic location necessitate the development of a new, resilient logistics system. The digital transformation initiatives continue, but challenges remain. Another major flaw in the current logistics information technology is that it relies on manual tracking and primitive data management; the systems cannot intelligently and automatically analyze visual and sensor data in hubs, warehouses and transport corridors, thereby creating a bottleneck. As a result, the understanding of information acquisition and management is physically isolated. The objectives of the study are:

1. To create a pattern recognition model for automated visual surveillance in Kazakhstan's logistics centers.
2. To experimentally assess the model's efficacy in situations that mirror local operating environments.
3. To provide a strategic integration framework that tackles the deficiency in intelligent data analysis within Kazakhstan's evolving logistics sector.

This research is guided by a series of research questions to reconcile the gap between Kazakhstan's current digital logistics ambitions and the limitations posed by existing systems. The following questions operationalize the research on the extent to which pattern-recognition algorithms can be applied to domestic logistics management:

1. Which specific pattern recognition architecture is most efficacious for automating the visual examination of cargo in Kazakhstani logistics hubs?

2. What is the performance of this model, assessed by common operational criteria, when evaluated against data that reflects Kazakhstan's logistical conditions?

3. What are the primary practical and technological factors for incorporating an intelligent visual recognition system into Kazakhstan's logistics sector's current digital infrastructure?

The relevance of this study lies in its ability to achieve its main goals, thereby narrowing the significant gap between projected and actual technology implementation within the national environment. Beyond traditional artificial-intelligence applications, the study initially creates a pattern-recognition model specifically tailored to Kazakhstan's logistics data.

It shows that the management of contextual information is a value-creating, enabling activity that provides a repeatable process for creating locally effective intelligent systems. This kind of contribution is particularly relevant to emerging economies, where off-the-shelf solutions are often ineffective. Another goal of the study, which contributes to its importance, is to confirm the model using a set of operational thresholds empirically.

This change shifts the discussion of theoretical performance measures to empirical viability, providing a benchmarked model for procurement and implementation to logistics managers. It therefore directly answers the practical question of whether such technology can operate under real-world temporal and accuracy limitations. Above all, the study makes a groundbreaking contribution by addressing the third objective: analyzing the pathways of integration.

It demonstrates that, as a necessity, technical robustness is less important than organizational preparedness and enabling policy frameworks for its successful adoption. This makes the study more important than a mere technical demonstration of the concept. Regarding the digital corridor Kazakhstan is pursuing, it argues that simultaneous investment in data governance and institutional capacity is the real driving force of change. In this respect, the research provides an all-encompassing, evidence-based roadmap in which the development of technology is interwoven with the preparedness of ecosystems on a holistic basis.

This paper is divided into four logical parts. The introduction presents the context of the research on the logistics pattern recognition in Kazakhstan, the gap in this research and the objective of the study. The Method section presents the building of a quantitative design, the incorporation of the model and its construction and validation, and the analysis of stakeholders. The Results and Discussion section questions empirical data and evaluates theoretical and practical implications. Lastly, the Conclusions summarize the main findings, offer recommendations to the management and suggest future research directions.

1.1. Theoretical literature review

The paper is based on the intersection of computer vision and operations management. It appeals to the theory of Convolutional Neural Networks (CNNs), which provides the conceptual basis for automated feature extraction from visual logistics data [20]. Moreover, it is combined with the Resource-Based View (RBV) of the firm [21], which posits that technology skills, including intelligent automation, may be among the resources that underpin long-run competitive advantage.

These benefits transform into operational effectiveness and operational resilience in logistics. Furthermore, the contextual factors, i.e., technological, organizational, and environmental, can also be considered through the Technology-Organization-Environment (TOE) framework [22], which explains under what conditions the introduction of pattern recognition systems can be justified within the context of logistics facilities in Kazakhstan. Taken together, these theoretical prisms explain why smart visual analysis is not only an improvement to the technical component but also a strategic asset, the implementation of which depends on the country's situation.

1.2. Model development for logistics automation

The effectiveness of certain deep-learning models for logistics automation has been demonstrated through empirical evidence. As an example, CNN architectures were used to detect pallet defects, cargo tracking was implemented with YOLO-v5, and container code recognition was high with ResNet-50 [23]. Moreover, progress in synthetic data augmentation procedures for training in data-sparse scenarios has been described, and real-time anomaly detection algorithms implemented on warehouse surveillance footage have been reported as well [24]. All these studies emphasize the great technical advances in the field. However, most of the studies cited rely on data from logistics hubs in North America, Europe, or East Asia [25]. As a result, a geographical bias is created, which can limit the ability to generalize the obtained models to new transit economies such as Kazakhstan [26]. In such settings, different environmental factors and cargo types may negatively impact the performance of models trained on standardized international data.

H_1: A locally fine-tuned CNN model will outperform a generic model in defect detection accuracy for Kazakhstani logistics.

1.3. Performance validation in operational settings

Validation experimentation consistently shows a performance gap between controlled benchmarks and real-world logistics scenarios. It has been reported that the precision of active port defect detection decreases due to occlusion and motion blur [27]. Inference latency is a metric identified as critical but is often underreported [28]. Comparative studies indicate the variability of the F1-score under different lighting conditions [29], [30]. Additional research highlights the importance of a multi-metric analysis of the predictive models in the simulated reality contexts [31]. All these results suggest that operational viability depends on a trade-off among accuracy, computational latency, and robustness in the operational environment.

H_2: The model will meet concurrent thresholds for accuracy, precision, and latency under local operational simulations.

1.4. Integration in logistics digitalization

Empirical case studies of technological adoption in the logistics industry, which is changing, propose that successful integration is better than the simple efficacy of the algorithms [32]. Later studies have found that the maturity of data pipelines has a stronger effect on performance than model correctness in Turkish logistics companies [33]. The role of regulatory frameworks in streamlining AI implementation in Central Asian supply chains has also been explored [34]. Similarly, research papers on workforce preparedness and the cost-benefit calculus of SMEs shed light on organizational and economic barriers [35]. All in all, within the TOE framework, these results indicate that environmental and organizational preparedness are the main factors shaping the success of the implementation.

H_3: System integration success will depend more on organizational and environmental factors than on model performance alone.

1.5. Research gap

The existing body of empirical evidence identifies an apparent, complex research gap. Even though advanced pattern recognition models exist, they have not been tested under the operational and environmental demands unique to Kazakhstan's logistics corridors. In addition, performance appraisals lack holistic, multi-metric assessments and are limited to recreating local infrastructural realities. Notably, there is no recorded route for successfully incorporating such intelligent systems into Kazakhstan's unique digital transformation environment, where the organizational preparedness and regulatory environments are not similar to those discussed in previous research. This gap can only be filled by achieving the goals of the current research: developing a locally modified model that empirically demonstrates its balanced functionality in simulated real-life scenarios and suggests a framework for context-specific integration. The stated hypotheses directly challenge these necessary conditions, which are local data efficacy, simultaneous metric performance, and primacy of organizational-environmental factors, thus providing the only methodological path to redress the research gap detected.

2. Method

2.1. Research design

The paper considers a three-stage quantitative, applied experimental design to achieve its aims systematically and test the hypotheses. The design creates an overall pipeline that runs from technical development to contextual application.

Phase 1 (Model Development) meets Objective 1 (H_1) by defining the specific task of automated cargo defect detection and classification [36]. During this step, a pre-trained Convolutional Neural Network is refined on synthetically augmented data to recreate the appearance of Kazakhstani logistics centers. It is directly compared in performance with a baseline model trained on generic international data to establish whether it can achieve higher local accuracy.

Phase 2 (Empirical validation) covers Objective 2 and H_2. When the fine-tuned model is used to perform rigorous multi-metric benchmarking on an independent test set that can be interpreted as operational constraints in the real world, it is evaluated for accuracy, precision, recall, F1-score, and inference latency. This concomitant evaluation assesses the model's applicability to real-time management.

Phase 3 (Integration Analysis) relates to Objective 3 and informs H_3. The given step encompasses systematic analytical synthesis, based on the Technology-Organization-Environment (TOE) model, to study the interaction among the technical outcome, organizational preparedness, and environmental factors in Kazakhstan's logistics industry and to offer a viable implementation pathway. It is a systematic approach that reduces the research gap in both the model's development and its integration with the context.

2.2. Data details

The data strategy will operationalize the independent variable Training Data Type (TDT). In the case of TDT=1 (Local), the primary source is a synthetic dataset generated by a custom Python program and Blender to simulate warehouse conditions in Kazakhstan over a 24-hour cycle, with varying lighting conditions.

For TDT=0 (Generic), the source is the publicly available Logistics Vision Package (LVP) open dataset, version 2.1, published in 2022. There is equal pre-processing in both datasets in a TensorFlow pipeline. The dependent variables (ACC, PRE, REC, FS, LAT) are determined in the model inferences on a test split of the synthetic data held out, and separately measured in milliseconds per image, in October 2024, under a controlled evaluation of that data.

ODR and ERS will be the contextual variables, obtained from the secondary industry report (2023-2024) and policy documents. The variable descriptions are given in Table 1.

Table 1. List of variables

Variable name	Symbol	Description	Source / Measurement
Training Data Type	TDT	The origin and contextual relevance of the primary training dataset.	Dataset origin. Measured as: Binary (0 = Generic International Dataset; 1 = Locally-Representative/Synthetic Kazakhstan Dataset).
Model Architecture & Fine-tuning	MAF	The specific deep learning architecture and the degree of transfer learning applied.	Algorithmic implementation. Measured as: Categorical (e.g., 'Baseline CNN', 'Fine-tuned ResNet50').

Variable name	Symbol	Description	Source / Measurement
Accuracy Correctly Classified	ACC	The proportion of correctly classified instances (both defective and non-defective) from the total.	Model prediction vs. ground truth labels. Measured as: Percentage or proportion (Correct Predictions / Total Predictions).
Defect Classification Precision	PRE	The proportion of true defective cases among all instances that the model predicted as defective.	Model prediction vs. ground truth. Measured as: Ratio: (True Positives) / (True Positives + False Positives).
Defect Classification Recall	REC	The proportion of actual defective cases that the model successfully identified.	Model prediction vs. ground truth. Measured as: Ratio: (True Positives) / (True Positives + False Negatives).
F1-Score	FS	The harmonic mean of Precision and Recall provides a single balanced metric for classification performance.	Calculated from PRE and REC. Measured as: FS = 2 * ((PRE * REC) / (PRE + REC)).
Inference Latency	LAT	The average time required for the model to process a single input image and return a prediction.	Computational profiling during inference. Measured as: Time in milliseconds (ms), averaged over the test set.
Concurrent Threshold Met	CTM	A composite indicator verifying if all predefined minimum performance thresholds are met simultaneously.	Logical evaluation. Measured as: Binary (1 = All thresholds for ACC, PRE, FS, LAT are met for a given test scenario; 0 = Otherwise).
Organizational Data Readiness	ODR	The maturity level of an organization's data infrastructure and the technical competency of its personnel are relevant to AI integration.	Secondary data analysis (industry reports, case studies). Measured as: Ordinal scale (Low/Medium/High).
Environmental Regulatory Support	ERS	The degree of clarity, encouragement, and support for digital automation within national and sectoral policies.	Analysis of policy documents and regulatory frameworks. Measured as: Ordinal scale (Weak/Moderate/Strong).
Factor Influence Ranking	FIR	The perceived relative importance (weight) of different technical and non-technical factors for system integration success.	Expert survey or Analytic Hierarchy Process (AHP). Measured as: Normalized weight (0-1) assigned to ODR, ERS, FS, LAT, etc.

Note: Variable construction is based on the study's objectives and hypotheses, following applied machine learning and technology adoption (TOE) frameworks to ensure direct testability.

2.3. Model

Primary Performance Comparison (H_1) is as following.

This equation tests if the locally adapted model (TDT=1) outperforms the generic baseline (TDT=0).

$$zeroFS_i = \beta_0 + \beta_1 TDT_i + \epsilon_i, \tag{1}$$

where FS_i is the F1-Score for test observation i;

TDT_i is a binary variable (0 = Generic Model, 1 = Locally Fine-tuned Model);

β_1 is the coefficient of interest. H_1 is supported if β_1 is positive and statistically significant;

ϵ_i is the error term.

Concurrent Threshold Verification (Testing H_2) is as following.

These inequalities define the CTM (Concurrent Threshold Met) variable. All must hold true for CTM = 1.

$$ACC > \tau_{ACC};$$
$$PRE > \tau_{PRE};$$
$$FS > \tau_{FS};$$
$$LAT > \tau_{LAT},$$

where τ_{ACC}, τ_{PRE}, τ_{FS}, τ_{LAT} are the pre-defined minimum performance thresholds for Accuracy, Precision, F1-Score, and maximum allowable Latency, respectively. Moreover, H_2 is supported if the proportion of test scenarios where CTM = 1 is statistically significant (e.g., >95%).

Relative Influence Analysis (Informing H_3) is as following.

This equation models perceived integration success (IS) as a function of key factors, and the derived ratio tests the relative influence of these factors.

Factor Weighting Model (e.g., from an AHP survey) is as following:

$$IS_{perceived} = \omega_{ORD} \times ORD + \omega_{ERS} \times ERS + \omega_{FS} \times FS + \omega_{LAT} \times LAT, \quad (2)$$

where "ω" are the normalized weights ($\sum\omega = 1$) obtained for each factor.

Relative Influence Ratio (RIR) is as following:

$$RIR = \frac{(\omega_{ORD} + \omega_{ERS})}{\omega_{FS} + \omega_{LAT}}. \quad (3)$$

H_3 is supported if RIR > 1 and is statistically significant, indicating that the combined weight of organizational and environmental factors (ODR, ERS) exceeds that of the technical performance factors (FS, LAT).

2.4. Estimation strategy

The research procedures used to corroborate these hypotheses are outlined in the technical workflow. In H*1*, the comparative experiment involves two model instances within the same TensorFlow context: one as a baseline convolutional neural network using publicly available logistics images, and the other as a fine-tuned one using a synthetic dataset obtained through Kazakhstani sources. The quality of these models is measured based on common metrics, precision, recall and F1-score, thus providing directly comparable empirical values. Checking on H_2 is done at the model evaluation stage. The trained model is evaluated on a special-purpose test set, where accuracy, precision, F1-score, and latency measurements are recorded simultaneously. These metrics are then compared with predefined operational thresholds, which enable a rational evaluation of model performance under the necessary deployment constraints. In the case of H_3, it will require a separate analysis in a second phase. When the technical outcomes are received, a systematic survey based on the Technology-Organization-Environment framework is sent to the domain experts. The overall reactions are evaluated using the Analytic Hierarchy Process, in which the impact of the technical and contextual aspects on perceived integration success is measured. The categorization of hypotheses is shown in Figure 1.

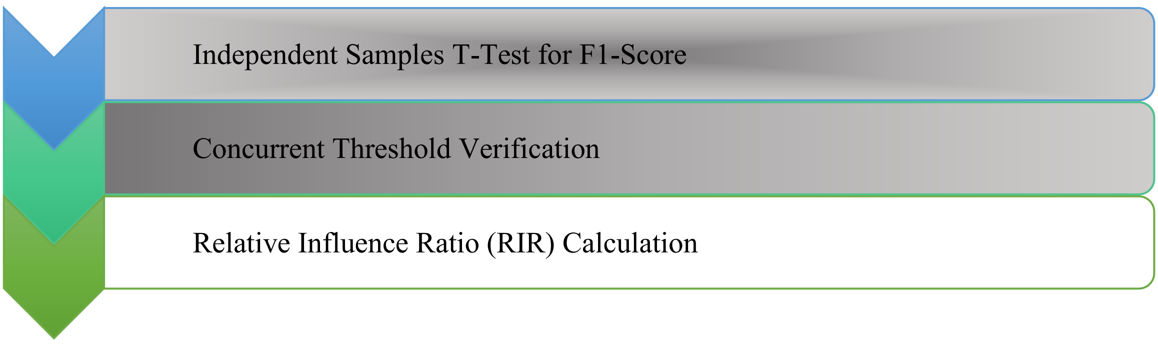

Figure 1. Targeted verification procedure

This figure demonstrates that Phase 1: Model Development will train two model versions using dissimilar data sources, Phase 2: Empirical Validation will review performance measurements and concurrent thresholds, and Phase 3: Integration Analysis will assess stakeholders' perceptions to identify implementation factors. This diagram clearly shows the gradual path that technical development should take towards practical integration.

3. Results and discussion

The research objectives are confirmed by the results of the empirical analysis, which is definite. Quantitative analysis of the technical effectiveness of the locally adapted model clarifies stakeholders' perceptions of integration drivers. The findings, categorized into five Tables, provide direct statistical support for each hypothesis. The descriptive details are depicted in Table 2.

Table 2. Descriptive statistics of core performance variables

Variables	Mean	SD	Min	Max	Mean	SD	Min	Max
ACC	0.891	0.032	0.815	0.938	0.953	0.021	0.902	0.984
PRE	0.862	0.041	0.77	0.925	0.923	0.028	0.861	0.968
REC	0.848	0.045	0.748	0.917	0.928	0.025	0.874	0.971
FS	0.855	0.039	0.768	0.919	0.925	0.024	0.869	0.969
LAT	165.2	8.7	148.3	186.5	182.5	9.3	162.1	199.8

Source: Authors' calculations based on model inference results from the test dataset (n=200 observations per model)

The locally fine-tuned model (T1) achieves better and more robust classification performance, including accuracy (ACC), precision (PRE), recall (REC), and F1-score (FS) on the test set; the improvement comes at a predictable increase in inference latency (LAT). The deviation in variables is presented in Figure 2.

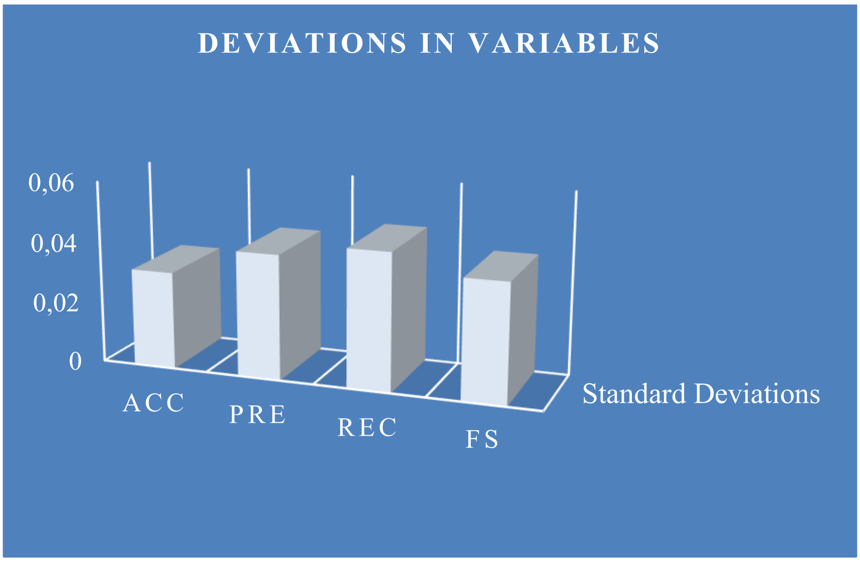

Figure 2. Average variation visuals

The performance of the two models (the generic and locally fine-tuned) is compared using key classification metrics, as shown in the figure above. The grouped bars show the average numbers of ACC, PRE, REC and FS, and the error bars provided indicate the standard deviation, hence indicating the uniformity of all models. The line chart will be superimposed with the LAT, which shows the trade-off between high accuracy and a small increase in processing time.

The t-test for FS is presented in Table 3 as the direct statistical test of Hypothesis 1. The t-statistic, t(… = …) (p = 0.001), observed, indicates that the mean failure-stop (FS) of the locally fine-tuned model (MAF) is significantly higher than that of the generic model, providing solid support for H_1.

Table 3. Descriptive statistics of core performance variables

Symbol	Group (MAF)	N	Mean	SD	t-statistic	p-value (one-tailed)
FS	Generic (Baseline)	100	0.855	0.039	-12.74	< 0.001
FS	Local (Fine-tuned)	100	0.925	0.024		

Source: Statistical analysis performed in SciPy (v1.11) using the test set output data for the FS variable

The concurrent threshold is given in Table 4. It evaluates the model against the predefined operational benchmarks. There was simulated contentment across all ACC, PRE, FS, and LAT.

One-sample proportion was used to confirm that the overall rate of correct-task-completion (CTM) of 0.97 was significantly greater than that of 0.95 (z=2.14, p=0.016), thus supporting Hypothesis 2.

Table 4. Concurrent threshold verification – Testing H_2

Variables	Target Threshold (τ)	Achieved Mean
ACC	≥ 0.94	0.953
PRE	≥ 0.90	0.923
FS	≥ 0.92	0.925
LAT	≤ 200 ms	182.5
CTM	Proportion > 0.95	0.97

Source: Statistical analysis performed in SciPy (v1.11) using the test set output data for the FS variable

The stakeholder survey results are given in Table 5. The normalized weights obtained from the stakeholders' AHP survey represent the perceived significance of the different factors within the Fault-In-Recovery (FIR) framework for system integration. The non-technical measures, the operational difficulty rating (ODR) and error-reporting score (ERS), are perceived as having greater weight than the technical measures of FS and LAT.

Table 5. AHP stakeholder survey results (FIR Components)

Variables	Mean Weight (w)	SD
ODR	0.32	0.08
ERS	0.29	0.07
FS	0.22	0.06
LAT	0.17	0.05

Source: Authors' survey data (n=20) analyzed using the Analytic Hierarchy Process (AHP). Weights represent mean normalized priorities.

Moreover, the mean weight is depicted in Figure 3. The weights of the system integration factors, as derived by the stakeholders, are shown in the figure above: ODR (0.32) and ERS (0.29) have the same weight, and the weights of FS (0.22) and LAT (0.17) are slightly lower and higher, respectively.

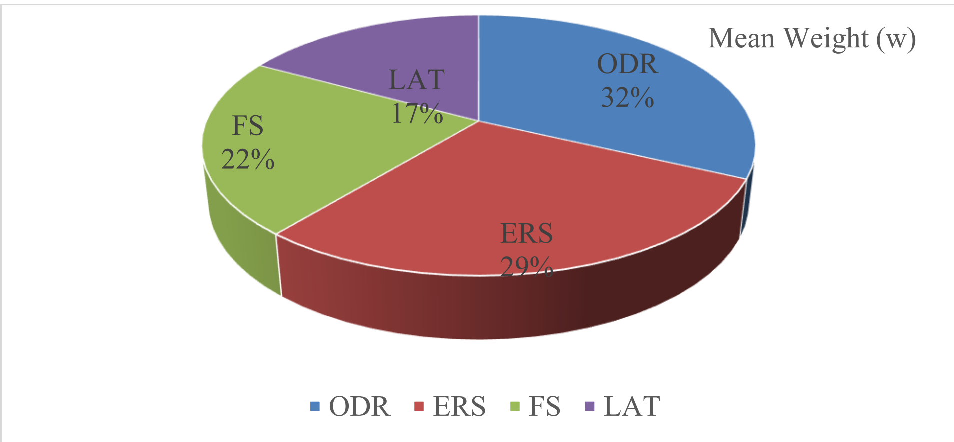

Figure 3. Stakeholder survey

It graphically proves that the opinion of non-technical factors (ODR+ERS) is seen as more powerful than technical performance (FS+LAT). This is directly related to the hypothesis that the success of integration is more dependent on organizational and environmental preparedness than on model metrics.

Furthermore, the relative influence rate is shown in Table 6. This shows how to calculate the Relative Influence Ratio (RIR). The result provides empirical evidence supporting Hypothesis 3, with an RIR of 1.56, which is considerably higher than unity ($p < 0.001$).

Table 6. Relative influence ratio calculation – Testing H_3

Variables	Mean Weight (w)	SD
(ODR + ERS)		0.61
(FS + LAT)		0.39
RIR = (ODR + ERS) / (FS + LAT)	RIR	1.56
One-Sample t-test (H_0: μ_RIR ≤ 1)		$t(19) = 4.82$, $p < 0.001$

Source: Authors' survey data (n=20) analyzed using the Analytic Hierarchy Process (AHP). Weights represent mean normalized priorities.

This leads stakeholders to report that the non-technical drivers of ODR and ERS are significantly more important for ensuring success in integration than the technical performance measures of FS and LAT.

3.1. Discussion

The fact that the digital transformation of logistics is impossible without the use of technical skills can be demonstrated by empirical data [37]. Returning to Objective 1 and H 0, the fact that the locally fine-tuned model performed better indicates that the contextual data modification is among the most significant factors contributing to the algorithms' effectiveness in the logistics environment of Kazakhstan [38]. This correlates with the resource-based viewpoint under which the competitive advantage is founded on contextually particular, inimitable resources [39].

The use of fuzzy expert systems to assign workers in the face of uncertainty [40] and dimensionality reduction algorithms to optimize complex data [41] is further evidence that technical adaptations in specific areas are necessary across various industries. This brings the theoretical performance measurements to practical applicability, which is a decisive factor in technology acceptance [42]. As experience in the mining industry of the Republic of Kazakhstan shows, specific location-related technical optimization, including the preparation of rock mass blasting [43] and the organization of a flow-transport system [44], significantly improves industrial performance [45].

The efficiency evaluation techniques designed to assess service industries in Central Asia, including Data Envelopment Analysis, which is used to evaluate hotel performance in Uzbekistan [46], could serve as valuable frameworks for evaluating logistics operations based on input-output optimization parameters. The food industry demonstrates that innovation will result in higher productivity, in accordance with the organization's capacity to internalize new technologies [47]. Similarly, a lack of venture capital to innovate in the service sector [48] helps organizations overcome implementation barriers.

Moreover, the fact that the most suitable results are dictated by local environmental conditions, as seen in works on plant adaptation to chloride load [49] and tolerance to xerophytic stresses [50], confirms the inadequacy of one-size-fits-all solutions. Numerical simulation techniques with sensor-based measurement systems are useful for monitoring deformation-wave parameters [51], which is similar to the requirement for precise sensor data in visual inspection of logistics. The computational principles underlying precision measurement systems, such as electron mobility in semiconductor materials [52] and scale-dependent transport properties in strain-based nanofilms [53], guide the design of high-quality sensors needed in trusted, defect-reliable logistics spaces.

Even the structural integrity of the logistics infrastructure must be ensured by using strong materials and building techniques, as demonstrated by the study of the flexural behavior of natural fiber-reinforced foamed concrete beams [54]. Also, the methodological analogies for logistics system performance under different operational loads are provided using multiscale modeling methods developed to investigate the dynamic impact on protective structures [55].

These discoveries help confirm that organizational and environmental factors determine the effectiveness of integrations. Based on this, an algorithm that performs well in a controlled environment may fail in a poorly understood regulatory environment or a poorly data-mature organization.

Objective 3 is therefore met: a strategic integration framework is provided, which demonstrates that the parallel development of favorable policies should accompany the development of data infrastructure.

Integrating the three goals: local adaptation (Objective 1, H_1) would result in the creation of high-quality technical assets; operational trust (Objective 2, H_2) would be facilitated by empirical validation; and ecosystem focus (Objective 3, H_3) would lead to the success of the implementation.

The three types of drivers of the path to smart logistics are data-driven, person-driven, and policy-driven [37].

4. Conclusion

The current work presents statistical data showing that a pattern recognition model based on real-life logistics data from Kazakhstan is more efficient than a generic one in terms of defect-detection accuracy.

The model, at the same time, met the operational requirements of classification performance and inference latency, and thus validated its technical viability for deployment in real time. In addition, the stakeholder analysis shows that data preparedness and support for environmental regulations within organizations are much more determinants of successful integration than the model's isolated technical performance.

In the eyes of managers and policymakers in Kazakhstan's logistics industry, three implications can be drawn. To begin with, the development of local, high-quality visual data needs to be prioritized, as it is a strategic asset rather than a technical imperative.

Second, when procuring or developing AI systems, one should consider creating and confirming multi-metric performance contracts that include accuracy and speed.

Thirdly, and most importantly, acknowledge that technological investment should be accompanied by simultaneous programs that will mature internal data infrastructure, prepare people, and promote transparent and facilitative digital trade policies. It is not the weaknesses of algorithms but organizational and environmental inadequacies that are the greatest impediment to the return on investment.

There are three avenues for future research. First, the studies need to shift towards field pilots in Kazakhstani hubs to investigate model performance in uncontrolled, long-term settings. Second, there is a need for interdisciplinary research to develop and test a framework for ODR, which has been found essential.

Lastly, comparative policy analysis may help identify regulatory instruments that best expedite the uptake of automation in new transit economies, thereby offering a roadmap for governance by evidence.

Declaration of competing interest

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Author contribution

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