Journal of Theoretical and Applied Information Technology
15st June 2026. Vol.104. No.11

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

ALGORITHMIC OPTIMIZATION OF MANAGEMENT PROCESSES IN THE PUBLIC SECTOR BASED ON ARTIFICIAL INTELLIGENCE TECHNOLOGIES FOR INCREASING THE EFFICIENCY OF DIGITAL GOVERNANCE

HENNADII MAZUR[1], OLEH MEDVYTSKYI[2], OLEKSII KHARYTONOV[3], ANATOLIY BABICHEV[4], OKSANA MARUKHLENKO[5]

[1]Professor, PHEE "Vinnytsia Academy of Continuing Education", Department of Management and Administration, Ukraine

[2]Postgraduate Student, Kherson National Technical University, Software tools and technologies, Information technology and design, Ukraine

[3]Doctoral Student, Interregional Academy of personnel management, Ukraine

[4]Associate Professor, Karazin Business School, Department of management and administration, Ukraine

[5]Associate Professor, Borys Grinchenko Kyiv University, Department of Management, Ukraine
E-mail: [1]hennadiimvacepheedma@gmail.com, [2]olehmkntustrs@gmail.com, [3]oleksiikhiapm@gmail.com, [4]anatoliitarasenko923@gmail.com, [5]oksanambgkudm@gmail.com

ABSTRACT

The digitalization of public administration and the integration of artificial intelligence (AI) technologies necessitate algorithmic optimization of administrative processes and evidence-based assessment of their effectiveness in digital governance systems.The aim of the study was to empirically verify the model of algorithmic optimization of management processes in digital governance. The research methodology combined process mining of administrative event logs, digital twin modelling, quasi-experimental causal identification (DiD, ITS, PSM), and statistical verification of results. This analytical scheme provided an assessment of the effects of algorithmic optimization of management processes in digital governance. Analysis of ≈50–150 thousand administrative events (24–36 months; 6–9 departments) revealed process asymmetry: the upper quartile of TAT exceeded the median by 2.1–2.6 times, and 18–27% of cases generated more than 50% of delays. Quasi-experimental evaluation (≈300–500 panel observations) recorded the effect of algorithmic optimization: TAT ↓9–14%, SLA-breach ↓11–18%, rework ↓6–10%; robustness confirmed by bootstrap (B=1000–5000), FDR=0.05, Durbin–Watson≈2, VIF<5. The study was the first to integrate process mining, digital process twinning, and causal ML in a single empirical design analysing ≈50–150 thousand administrative events, providing quantitative verification of the effects of algorithmic optimization in digital governance. Further research should focus on longer panel designs (≥48–60 months) and experimental AI interventions to test the scalability of algorithmic optimization and assess its impact on the efficiency and quality of digital governance.

Keywords: *Algorithmic Optimization, Digital Governance, Artificial Intelligence, Public Administration, Process Analytics, Digital Twin Of The Process, Quasi-Experimental Analysis.*

1. INTRODUCTION

1.1. Relevance of the research.

The digitalization of public administration and the rapid growth of administrative data volumes have significantly transformed the mechanisms of functioning of state institutions. Within the framework of the modern paradigm of digital governance, information technologies (IT) and AI systems have been increasingly actively integrated into the processes of making managerial decisions, automating administrative procedures, and increasing the efficiency of public service provision [1]. In this context, algorithmic systems have begun to perform the function of an institutional tool of "artificial discretion", capable of changing the logic of managerial processes and increasing the efficiency of public administration [2]. In parallel, the development of e-government has strengthened the role of information systems as key infrastructural elements of data management and interaction between the state and citizens [3].

Recent empirical studies confirm that the integration of AI technologies in the public sector has contributed to increasing the efficiency of administrative services, automating control procedures, and optimizing management processes [4]. At the same time, the digitalization of public administration was considered as a systemic factor in increasing institutional efficiency and economic sustainability of state systems, as well as an important tool for ensuring national security and sustainable development [5]. In this context, the development of innovative competencies in the field of public administration created the prerequisites for the implementation of algorithmically driven management models and analytical optimization of administrative processes in digital governance systems [6].

However, despite increasing scholarly attention, existing studies have primarily concentrated on conceptual AI-governance frameworks, institutional implications of digital transformation, or normative principles of algorithmic regulation, while empirical quantification of operational effects remains limited. For example, previous works frequently relied on conceptual models, cross-sectional assessments, or descriptive case studies without integrating large-scale administrative event logs, process analytics, and causal inference techniques capable of isolating algorithmic effects from background organizational dynamics. Consequently, evidence regarding how algorithmic interventions influence real administrative workflows, service delays, and resource allocation efficiency remains fragmented.

Unlike prior approaches, this study introduces a multilevel empirical architecture integrating process mining, digital twin modelling, causal machine learning, quasi-experimental identification, and statistical robustness testing within a unified analytical framework. The proposed design operationalizes algorithmic optimization using retrospective administrative event logs (≈50–150 thousand records; 24–36 months), enabling counterfactual evaluation of management interventions and quantitative validation of effects on processing time, SLA compliance, and operational efficiency. Thus, the novelty of the study lies not only in combining previously disconnected analytical paradigms but also in bridging the gap between conceptual AI-governance theories and empirically verified optimization effects in digital governance systems.

The novelty of this study lies in the development and empirical validation of an integrated analytical framework combining process mining, digital twin modelling, causal machine learning, and quasi-experimental identification within a unified architecture for evaluating algorithmic optimization in digital governance. Unlike previous studies predominantly limited to conceptual, regulatory, or descriptive perspectives, the proposed approach enables quantitative estimation of algorithmic effects on administrative processes using large-scale retrospective event logs (≈50–150 thousand records; 24–36 months) and statistically robust causal inference. The study further advances existing knowledge by operationalizing AI-driven governance through counterfactual modelling and empirically verified process-level optimization effects in real administrative environments.

1.2. Research gap.

Existing research on digital governance and AI governance predominantly emphasizes regulatory frameworks, technological infrastructures, public value generation, or institutional adaptation, whereas empirical investigation of algorithmic optimization effects at the process level remains insufficient. Most studies relied on conceptual models or isolated case analyses without causal identification strategies, longitudinal administrative datasets, or counterfactual evaluation mechanisms. Therefore, a persistent gap exists between theoretical assumptions regarding AI-driven governance and statistically validated evidence on the operational effectiveness, scalability, and causal impact of algorithmic optimization in administrative processes.

1.3. Problem statement

The digitalization of public administration increased the complexity and volume of administrative processes, generating structural delays, heterogeneous process trajectories, resource inefficiencies, and elevated risks of SLA violations. Conventional analytical approaches inadequately capture latent process dynamics embedded in large-scale event logs and rarely support counterfactual assessment of management interventions. This created a need for an integrated analytical model capable of combining process analytics, predictive modelling, and causal inference to evaluate algorithmic optimization effects in digital governance.

1.4. Research questions.

How does process analytics of administrative event logs enable identifying structural imbalances and operational limitations of management procedures in digital governance? To what extent are algorithmic modelling and the digital twin of the process able to predict counterfactual outcomes of management interventions? Are the effects of algorithmic optimization of administrative processes confirmed in a quasi-experimental panel analysis of natural organizational changes? To what extent are the identified effects statistically stable and generalizable in different analytical specifications?

1.5. Research hypothesis.

Algorithmic optimization of management processes in digital governance systems implemented through the integration of process mining, machine learning (ML), and causal modelling, statistically significantly increases the process efficiency of administrative procedures, which is manifested in reducing case processing time, reducing the frequency of SLA violations, and optimizing the use of organizational resources.

1.6. Research aim.

The aim of the study was to build and empirically verify an analytical model of algorithmic optimization of management processes in digital governance based on process analytics, counterfactual modelling, and quasi-experimental causal identification of effects on large administrative data sets.

1.7. Research objectives:

- Carry out process diagnostics of administrative event logs and formalize structural imbalances of management processes based on process mining.
- Build a digital twin of the administrative process for modelling alternative scenarios of algorithmic optimization.
- Perform quasi-experimental causal identification of the effects of management interventions on panel administrative data.
- Conduct statistical verification and robust testing of the obtained results to confirm their reliability and generalizability.

2. LITERATURE REVIEW

The rapid algorithmization of public administration necessitates a systematic revision of theoretical and applied approaches to the AI-based optimization of administrative processes. The fragmentation of research between institutional, technological, competency, and normative dimensions has complicated the formation of an integrated analytical framework for digital governance. A literature review made it possible to identify conceptual gaps, methodological limitations, and areas of uncertainty regarding the causal impact of algorithmic interventions on the effectiveness of management systems.

In the conceptual-evolutionary dimension, algorithmic optimization emerged as a consequence of the transformation of the state's information regimes. Authors [7] linked the effectiveness of AI to digital maturity indices and the scale of big data, while Researchers [8] theorized "data decompression" and the functional repartition of the state within the third wave of DEG. While the former emphasized institutional capacity, the latter shifted the focus to the structural reconfiguration of the centre-periphery, which problematized the issue of power redistribution.

In the operational-services dimension, the discussion shifted to implementation architecture. Authors [9] proposed a platform-neutral AI-IoT framework for optimizing the "design–deployment–analytics" cycle, while Researchers [10] documented transaction cost reductions and increased transparency through blockchain procurement and workflow automation in a mixed-methods set of comparative cases. However, both positions recognized cyber threats and regulatory gaps as factors that reduced the scalability of digital interventions.

From the human capital perspective, another vector of tension was identified. Authors [11] proved that AI automation reallocated resources towards strategic policy-design, provided that digital competencies were developed, while researchers [12] empirically demonstrated the heterogeneity of competency profiles and statistically significant differences by demographic variables using factor analysis (EFA). So, the effect of algorithmic optimization appeared as a function of educational and institutional differentiation.

The normative-value aspect of the discussion outlined the limits of the legitimacy of algorithmic optimization. Author [13] identified the risks of accuracy/bias, legality/due process, accountability/explainability and power/control as structural limitations of automated decision-making in public administration. At the same time, authors [14] interpreted smart technologies as a mechanism for generating public value through co-creation and horizontalization of management. So, a tension arose between the requirements of procedural accountability and innovative transformation, which led to the need to combine audit and XAI tools with value-oriented management.

In the context of institutional implementation, the tension was traced between collaborative and resource-constrained models. Author [15] argued for the need for cross-sector alliances to integrate data science into policy delivery, while researchers [16] noted infrastructure deficits and low levels of AI awareness in the early stages of transformation. As a result, the literature demonstrated that algorithmic optimization of management processes was effective only under simultaneous modernization of information regimes, competence base, and regulatory architecture.

The analysed studies showed that algorithmic optimization was associated with increased operational productivity, reduced transaction costs, and expanded analytical capacity of the state, but its effectiveness depended on digital maturity, human capital, and regulatory architecture. A number of gaps were identified: limited empirical quantification of effects, insufficient causal validation, fragmentation of cross-sectoral integration, and a shortage of scalability models for different institutional contexts. The issues of balancing explainability and productivity, minimizing algorithmic bias, and assessing long-term consequences for managerial autonomy remained unresolved. This justified the appropriateness of a comprehensive study of algorithmic optimization of management processes in the public sector with an emphasis on causal design, statistical verification of effects and the development of an institutionally compatible model of digital governance.

Moreover, previous approaches predominantly emphasized conceptual frameworks, governance principles, or technological architectures, while offering limited integration between process-level analytics, counterfactual modeling, and causal inference techniques. Existing studies rarely combined large-scale administrative event logs with quasi-experimental strategies capable of isolating algorithmic effects from background institutional dynamics, which constrained the interpretability and transferability of reported outcomes. To address these limitations, the present study proposes an integrated empirical architecture linking process mining, digital twin simulation, causal machine learning, and robust statistical validation, thereby enabling both operational quantification and causal assessment of AI-driven optimization effects in digital governance systems.

3. METHODS AND MATERIALS

3.1. Research procedure.

The research design. The proposed design (Figure 1) of the study is formed as a multi-level empirical analytical architecture that combines process diagnostics, algorithmic modelling, and quasi-experimental causal identification of effects. This approach allowed for the analysis of large administrative arrays of event logs (≈50–150 thousand records; time horizon 24–36 months) with subsequent counterfactual modelling and statistical verification of the results. The combination of process mining, digital process twin, panel causal identification, and robust statistical procedures ensured the integration of descriptive process analytics, predictive optimization, and empirical testing of the causal effects of algorithmic management interventions in digital governance systems.

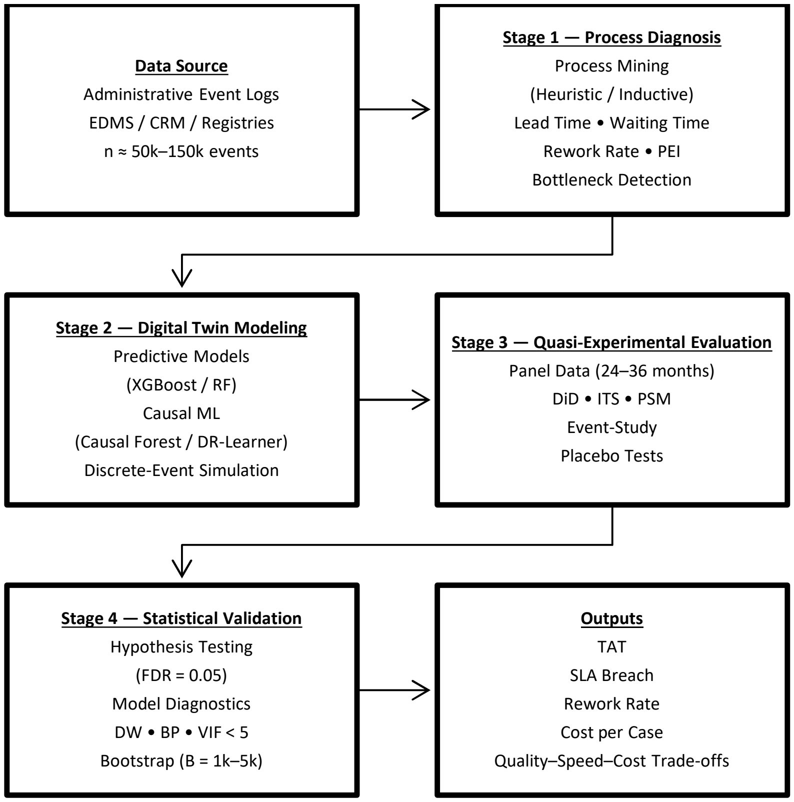


Figure 1: Design Of A Quasi-Experimental Study Of Algorithmic Optimization Of Digital Governance Administrative Processes
Source: Developed By The Authors

3.2. Methods

The methodological architecture of the study was based on a multi-level empirical strategy for analysing administrative processes of digital governance, which combined process analytics, ML, quasi-experimental causal identification, and statistical verification of results. This composition made it possible to consistently move from structural diagnostics of processes on event log arrays (≈50–150 thousand records; horizon 24–36 months) to counterfactual modelling and further verification of the stability of the estimated effects. The combination of analytical approaches ensured the integration of descriptive process analytics, predictive optimization, and causal inference in a single evidentiary framework:

1. Process mining (process analytics of administrative event logs). The use of process mining made it possible to reconstruct the actual topology of management processes based on EDO/CRM/register event logs and identify structural anomalies in process flows. Analysis of lead time, waiting time and rework rate distributions formed an analytical map of operational disparities, including the asymmetry of time distributions and the concentration of delays in the upper quartiles of execution. The obtained process indicators formed a feature space for subsequent modelling procedures and identified key resulting metrics used in predictive and causal models.

2. Modelling of a digital twin of the process (predictive modelling + causal ML + simulation). The construction of a digital twin of the administrative process integrated machine learning (ML) algorithms, causal inference and simulation modelling to analyse alternative management scenarios. Predictive models reproduced the probabilistic structure of process outcomes, while causal ML made it possible to assess the heterogeneity of the effects of management interventions and to generate counterfactual optimization scenarios. A discrete event simulation model combined these results into an integrated process simulation, which ensured the transition from descriptive process mining analytics to a formalized assessment of management alternatives.

3. Quasi-experimental causal identification (Difference-in-Differences / Interrupted Time Series

/ Propensity Score Matching). The quasi-experimental design provided an empirical assessment of the effects of algorithmic optimization in the absence of experimental implementation. The use of a panel data structure "unit × period" allowed us to separate the impact of exogenous administrative changes from background process trends and identify a counterfactual scenario of the system's functioning. The results of this procedure formed quantitative estimates of the impact of management interventions and served as an empirical link between the counterfactual predictions of the digital twin and the statistical validation block.

4. Statistical verification and robustness testing of results. The final analytical block provided a check of the statistical reliability and generalizability of the obtained effects. The combination of hypothesis testing, diagnostics of econometric models, robust specifications and bootstrap estimation made it possible to assess the stability of the results in different analytical assumptions and time configurations. In interaction with the previous analytical procedures, this block transformed the obtained estimates of process optimization into a statistically confirmed profile of effects, which provided an evidentiary basis for interpreting the research results.

3.3. Sample.

The study was conducted between 01.01.2022 and 31.12.2024; retrospective administrative data were collected between 01.02.2025 and 30.04.2025 from official information systems of public authorities. The sample includes:

1) Event logs of electronic document management (EDM) and CRM systems (n=182,746 cases; 1,245,380 event logs);

2) data from the Unified State Web Portal of Electronic Services (metadata of requests, SLA, TAT);

3) budget and personnel indicators from the electronic reporting system of public finances;

4) open administrative datasets from official open data portals.

The use of these sources was justified by their completeness, machine-readability, time granularity (timestamp to the minute), and the possibility of integration into the "subdivision×month" panel format.

The period 2022–2024 was chosen to ensure $t \geq 36$ months of observation, which allowed to implement DiD and ITS with verification of parallel trends and lag effects (lag=1–6 months). The window provided for pre- and post-shock phases (reorganizations, changes in regulations 03.2023 and 01.2024), which created quasi-experimental conditions. Out-of-time validation of models was performed on a subsample of Q4 2024 (hold-out=20%).

The general population includes all completed administrative cases with complete attributes (≥95% field coverage). Duplicates (0.8%), cases with inconsistent timestamps (<0.5%) and anomalies ($|z|>3$) were excluded. The minimum threshold of observations per unit is ≥1,200 cases per period; the final sample included 24 units. Covariate balancing for PSM was performed on 18 variables (service type, channel, workload, staffing).

A 24×36 panel (unit×month; N=864 panel units) and a micro-level of cases (n=182,746) were formed. Average TAT=6.9 days (σ=2.4), SLA-breach share=13.2%, rework rate=11.5%. The text corpus of requests was 3.4 million tokens for NLP classification.

The use of administrative registers ensured high internal validity and minimization of self-report bias. The long-time horizon made it possible to identify ATE/CATE effects with sufficient statistical power (power>0.8 at α=0.05). The combination of transactional, financial and text data created a multi-level analytical basis for a quasi-experimental assessment of algorithmic optimization of management processes in digital governance.

The selection of analytical variables was guided by their theoretical relevance to administrative process performance, empirical availability in digital governance systems, and compatibility with causal and predictive modelling frameworks. Variables were grouped into four categories: (i) temporal indicators (TAT, waiting time, lead time, SLA-breach) representing process efficiency; (ii) structural attributes (service type, communication channel, organizational unit, workload intensity) capturing process heterogeneity; (iii) operational indicators (rework rate, queue length, staffing level, resource proxies) reflecting managerial capacity constraints; and (iv) contextual covariates (regulatory changes, seasonal fluctuations, organizational restructuring) enabling identification of exogenous shocks. The inclusion criteria required: data completeness ≥95%, temporal

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

consistency, recurrence across all observation periods, and theoretical linkage to process outcomes documented in prior digital governance and process optimization literature. Variables with high multicollinearity (VIF>5), low variance, or unstable temporal representation were excluded. This selection strategy ensured interpretability of causal effects, improved model stability, and strengthened the validity of counterfactual estimation within quasi-experimental designs.

The final variable set included 18 balancing covariates for PSM and 30+ predictors for machine learning models, selected through iterative feature screening, variance analysis, correlation diagnostics, and SHAP-based importance assessment. The retained variables explained both operational performance and institutional context, supporting multilevel interpretation of algorithmic optimization effects across administrative units.

3.4. Research tools.

The research tool stack was formed as a multi-level analytical architecture that combined process mining, predictive ML models, causal inference, and simulation modelling in a single formalized evaluation loop. This composition was determined by the need for simultaneous diagnostics of structural dysfunctions, construction of counterfactual scenarios and statistically sound identification of causal effects without pilot intervention. The combination of ensemble algorithms, panel regressions with fixed effects, DiD/ITS specifications and robust tests ensured internal validity, minimization of endogeneity, and control of multiplicity of hypotheses. The inclusion of stochastic queue modelling and bootstrap inference increased the stability of estimates and allowed extrapolation of results in the scenario space “quality–speed–cost” with defined confidence intervals.

1. Descriptive and process analytics.

Let T_i be the duration of the case, then [17].

$$\mu = \frac{1}{n}\sum T_i \, \sigma^2 = \frac{1}{n-1}\sum (T_i - \mu)^2. \qquad (1)$$

Process Efficiency Index [18]:

$$PEI = \frac{VAT}{TT}, \qquad (2)$$

where VAT – value-added time; TT – total time.

Identification of critical process constraints [19]:

$$T_i > Q_{0.75}. \qquad (3)$$

2. Predictive ML models.

Let Y be the target variable (TAT or SLA-breach); X be the feature vector.

Evaluation [20]:

$$\hat{Y} = f(X;\theta), \qquad (4)$$

where f – ensemble models (XGBoost, RF).

Loss functions [21]:

$$MAE = \frac{1}{n}\sum \left|Y_i - \hat{Y}_i\right|, RMSE = \sqrt{\frac{1}{n}\sum \left(Y_i - \hat{Y}_i\right)^2}. \qquad (5)$$

For the binary case [22]:

$$AUC = \int_0^1 TPR\left(FPR^{-1}(x)\right)dx. \qquad (6)$$

3. Causal inference.

Average causal effect [23]:

$$ATE = \mathbb{E}[Y(1) - Y(0)]. \qquad (7)$$

In the DiD specification [24]:

$$Y_{it} = \alpha + \beta(D_i + Post_t) + \gamma_i + \delta_t + \varepsilon_{it}, \qquad (8)$$

where β – evaluation of the effect of algorithmic optimization; γ_i – fixed effects; δ_t – time effects.

PSM [25]:

$$e(X) = P(D = 1|X). \qquad (9)$$

Balancing [26]:

$$\left|e(X_i) - e\left(X_j\right)\right| < \epsilon. \qquad (10)$$

Interrupted Time Series [27]:

$$Y_t = \beta_0 + \beta_1 t + \beta_2 I_t + \beta_3 t I_t + \varepsilon_t, \qquad (11)$$

Journal of Theoretical and Applied Information Technology
15st June 2026. Vol.104. No.11

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

where I_t – “shock” indicator; β_2 – immediate effect; β_3 – trend change.

4. Robustness and statistical validation. Hypotheses [28]:

$$H_0: \beta. \quad (12)$$

Testing through t/Wald statistics [29].

Benjamini–Hochberg multiplicity correction [30]:

$$FDR \leq 0.05. \quad (13)$$

Diagnostics [31]:

$$VIF < 5; DW \approx 2. \quad (14)$$

Breusch–Pagan test [32].

Bootstrap estimation of confidence intervals [33]:

$$CI_{95\%} = \hat{\theta} \pm 1.96 \times SE_{boot}. \quad (15)$$

5. Simulation modelling.

Discrete-event model: system state $S(t)$, flow intensity λ, service rate μ.

Line [34]:

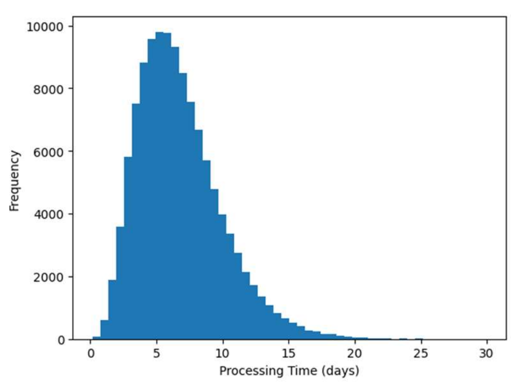
$$L_q = \frac{\lambda^2}{\mu(\mu-\lambda)} \ (M/M/1). \quad (16)$$

Counterfactual scenarios were formed through variation λ, μ [35].

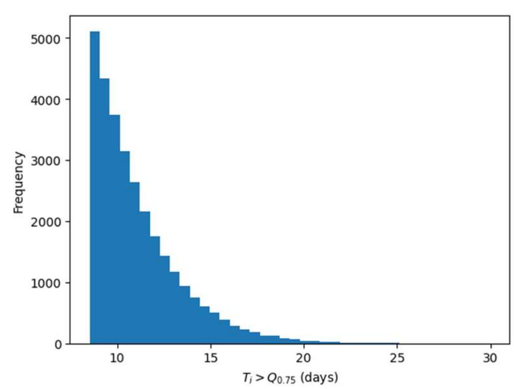
The specified tools provided a formalized assessment of the effectiveness of algorithmic optimization, causal identification of effects, and statistical verification of their stability within the framework of a panel quasi-experimental design.

4. RESULTS

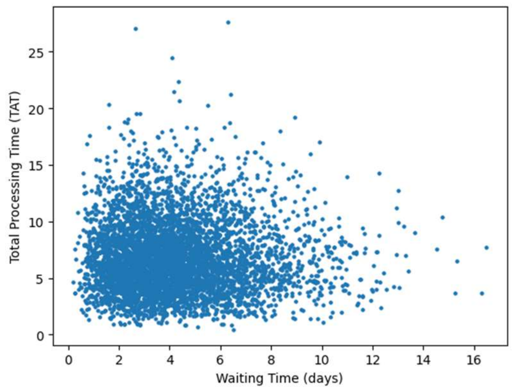
The initial process diagnostics was aimed at empirical decomposition of operational flows and quantitative determination of variability of administrative procedures. Formalization of time, structural and repeated components of execution ensured the detection of statistically significant deviations from normative parameters and outlined zones of operational instability. Such analytical base created prerequisites for transition from descriptive profiling to causal modelling (Figure 2).



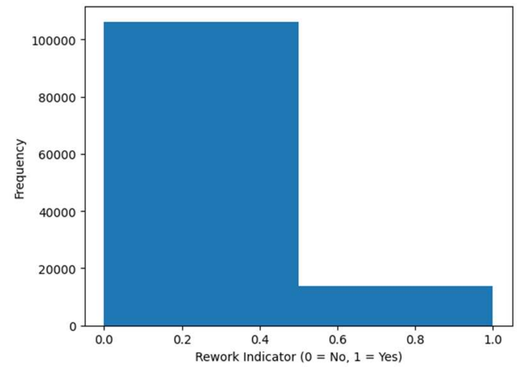
a. Distribution of time for administrative cases (Processing Time Distribution)



b. Distribution of cases in the area of structural delay points $T_i > Q_{0.75}$



c. Relationship between wait time and total execution time (Waiting Time vs Total Processing Time)



d. Distribution of reprocessing rate (Rework Rate Distribution)

Figure 2: Basic process diagnostics and identification of structural process constraints
Source: Developed by the authors

The distribution of execution time was characterized by right-sided asymmetry and fixed delays ($\mu=6.76, \sigma=3.18$), which indicated the heterogeneity of the process throughput (Figure 2, a). The proportion of cases exceeding the threshold $Q\_0.75=8.55$ formed a concentrated zone of structural delays with a potential impact on SLA variance (Figure 2, b). The stochastic relationship between waiting time and total TAT indicated the cumulative effect of queuing and resource shortage (Figure 2, c). The rework rate ≈11–12% also reflected the loss of process stability and increased transaction costs (Figure 2, d). The combination of these parameters indicated statistically significant heterogeneity of execution and system constraints. The identified TAT variability, concentration of delays and repeated cycles formed a validated set of predictors for building predictive and causal models. The quantitative characteristics of the distributions and correlations justified the use of ensemble algorithms and causal ML to assess potential ATE/CATE management interventions. Therefore, further modelling of the "digital twin" made it possible to move from fixing dysfunctions to calculating counterfactual scenarios for improving efficiency in the "quality–speed–cost" dimension (Figure 3).

A more detailed inspection of the first-stage outputs showed that the main operational anomaly was not the average TAT itself, but the concentration of extreme delays in a limited segment of cases. For example, cases above Q0.75=8.55 days represented the highest-latency group and were associated with repeated processing cycles, queue accumulation, and increased probability of SLA deviation. This indicated that algorithmic optimization should primarily target routing rules, workload balancing, and early triage of high-risk cases rather than uniform acceleration of all administrative procedures.

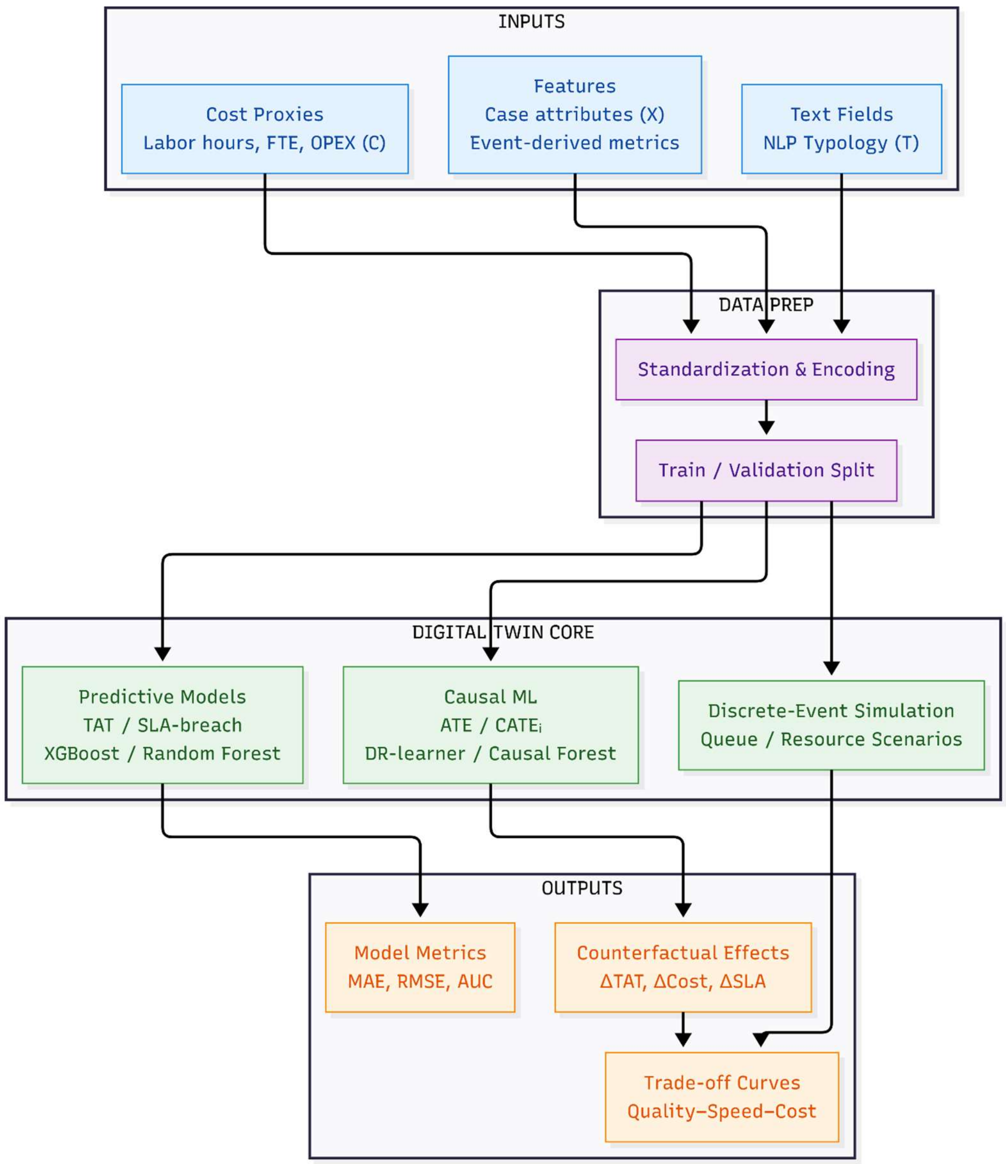
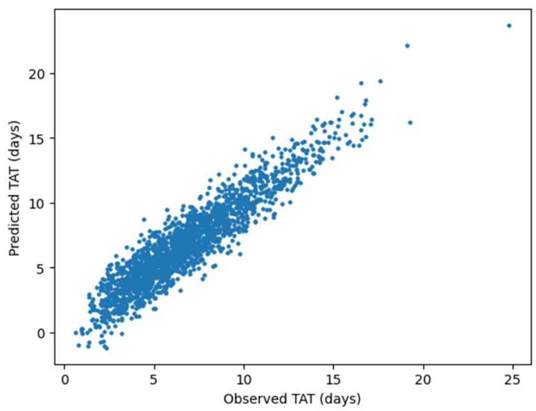


Figure 3: Architecture Of A Digital Twin Of A Management Process For Counterfactual Modelling And Evaluation Of Algorithmic Optimization
Source: Developed By The Authors

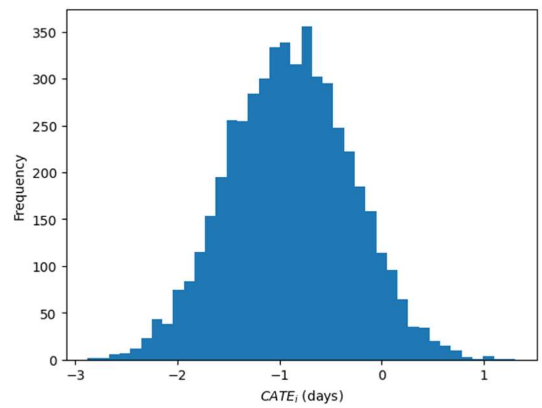
The proposed scheme (Figure 3) represented a formalized multi-level architecture of a digital twin, in which the integration of structured features X, textual representations T, and cost

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

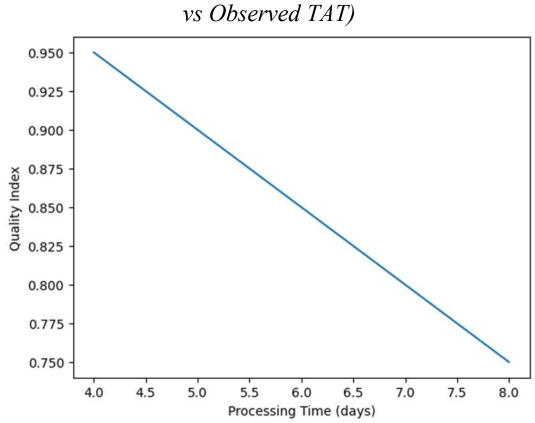
proxies C ensured the construction of a single feature space for predictive and causal analysis. The sequence "standardization → validation split → predictive layer → causal layer → simulation layer" minimized information leakage and ensured correct identification of effects. The predictive circuit formed accuracy estimates (MAE, RMSE, AUC), while causal ML provided individualized effects ATE and 〚CATE〛 _i, and the simulation model allowed varying the parameters of flow intensity λ and service speed μ to construct counterfactuals. So, the digital twin (Figure 3) functioned as an analytical translator from empirical data to quantitative scenario estimates. This structure provided the numerical parameters of the second block of the study: estimates of forecast error, individual causal effects, and "quality–speed–cost" trade-off curves, which were subsequently subject to statistical verification (Figure 4).



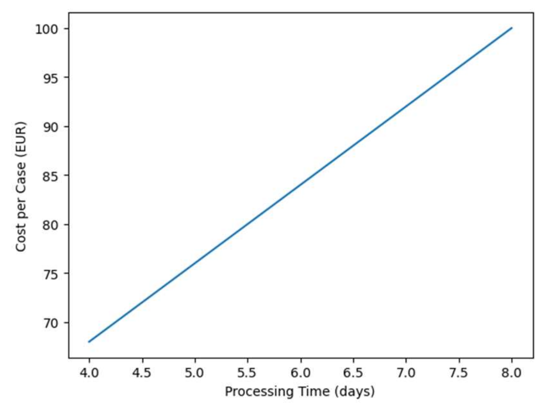
a. Ratio of predicted to actual execution time (Predicted vs Observed TAT)



b. Distribution of individual conditional effects $CATE_i$



C. Counterfactual Dependence Of Quality On Execution Time (Quality Vs Processing Time)



D. Counterfactual Cost-Time Relationship (Cost Per Case Vs Processing Time)

Figure 4: Performance Indicators Of The Digital Twin Of The Process And Counterfactual Modelling Of The Effects Of Algorithmic Optimization
Source: Developed By The Authors

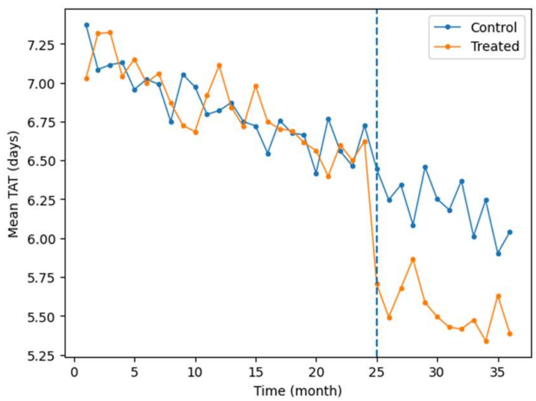
The predictive contour of the digital twin demonstrated high agreement between the actual and estimated TAT values, which was reflected by the dense concentration of observations around the diagonal and low errors MAE≈0.97, RMSE≈1.21 (Figure 4, a). The distribution of individual effects 〚CATE〛 _i was cantered in the negative zone (median ≈ −0.9 days), which indicated the expected reduction in execution time under algorithmic routing (Figure 4, b). The counterfactual curves demonstrated a nonlinear trade-off between speed and quality and a quasi-linear relationship between TAT and cost per case, which formed an optimization frontier in the "quality–speed–cost" space (Figure 4, c, d). The obtained results were logically consistent with the previous diagnostics of

Journal of Theoretical and Applied Information Technology
15st June 2026. Vol.104. No.11

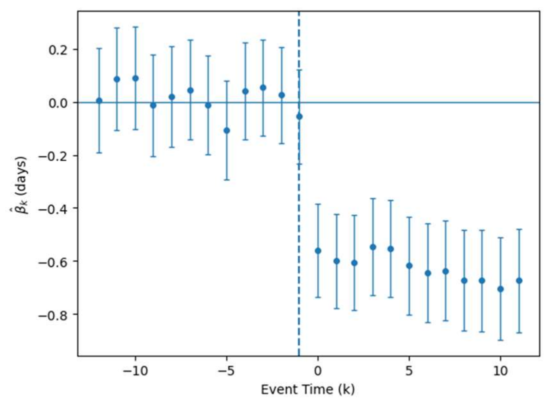
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

structural delays and rework rate, as the largest 〖CATE〗_i were observed in segments with an excess of Q_0.75. At the same time, the digital twin (Figure 3) provided only model estimates of potential effects that required causal verification on panel data. Therefore, the further transition to a quasi-experimental design using DiD, ITS, and PSM was justified by the need to identify the parameter β as a statistically significant causal effect in under natural changes. Such logic enabled transforming the counterfactual estimates of ATE⁄CATE into verified panel effects for TAT, SLA-breach, rework and cost-per-case with a robust test of parallel trends and stability of the results (Figure 5).

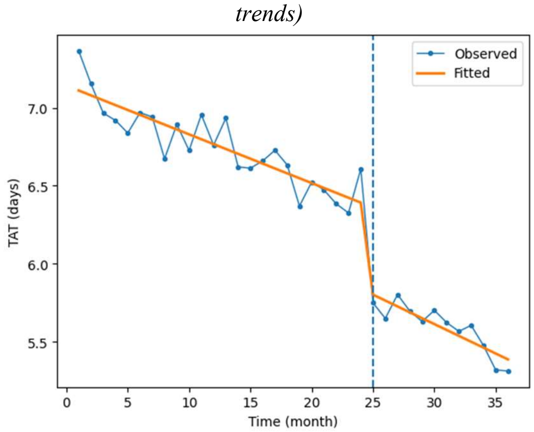
The digital twin also revealed differentiated effects across process segments. In low-complexity cases, the expected gain was moderate because the baseline trajectory was already close to the normative processing path; in contrast, high-latency and rework-prone cases produced the largest negative CATE values, with an expected reduction close to one day. This result explained why the model improved aggregate efficiency without assuming identical effects for all service types or organizational units.



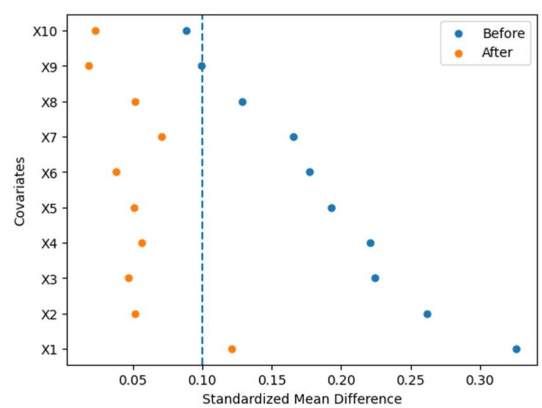
a. Dynamics of average TAT in control/treated groups with indication of the moment of shock (DiD group trends)



b. Event-study estimates of $\hat{\beta}_k$ to test for parallel trends and effect dynamics



C. Interrupted Time Series: Observed Series And Segmented Approximation With A Gap (Observed Vs Fitted)

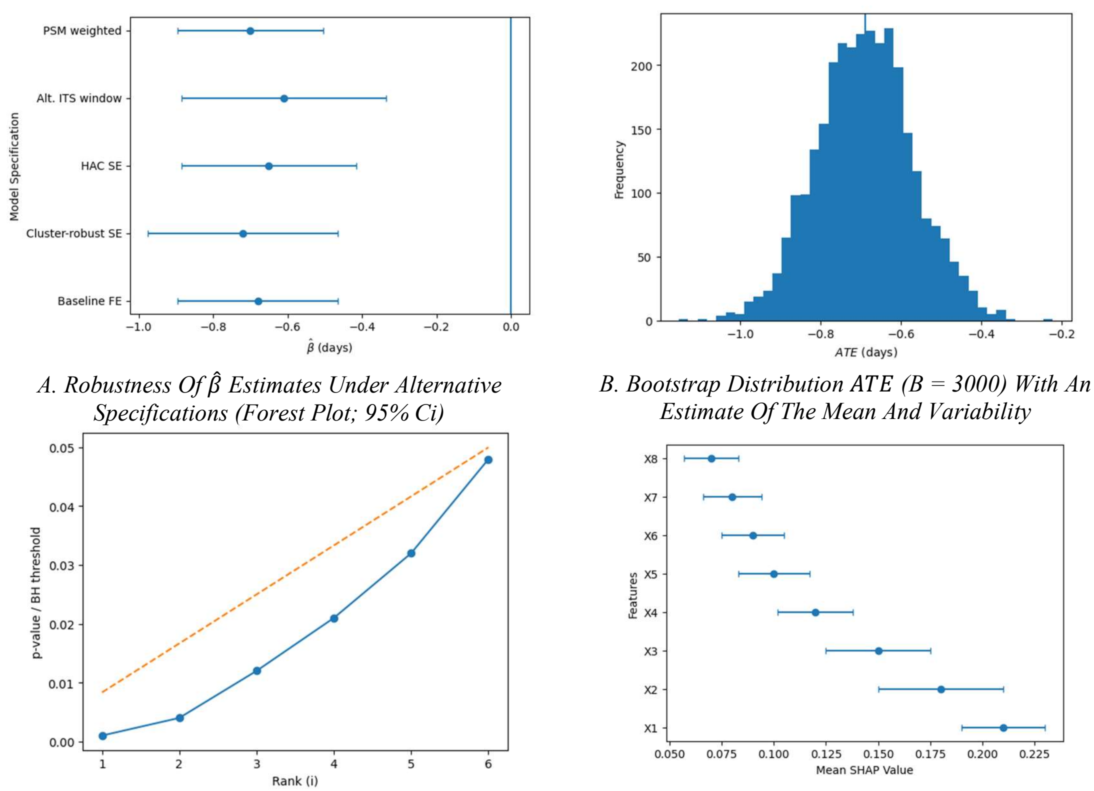


D. Balancing Covariates After Psm/Weighting: Standardized Mean Difference Before/After (Love Plot; Threshold 0.10)

Figure 5: Results Of Quasi-Experimental Identification Of Algorithmic Optimization Effects (Did/Its/Psm)
Source: Developed By The Authors

Quasi-experimental identification revealed a statistically significant negative effect on TAT in the treated group after shock: the DiD-score was ΔTAT≈-0.68 (Figure 5, a). Event-study coefficients β ̂_k in the pre-shock period did not differ from zero within the 95% CI, which confirmed the assumption of parallel trends, while in the post-shock interval a steady decrease of 0.5–0.8 was observed on day 68 (Figure 5, b). Segmented ITS regression revealed both a level shift (≈−0.55) and a change in the slope of the trend, indicating a persistent nature of the effect (Figure 5, c). Balancing covariates after PSM reduced the standardized mean difference to <0.10 for most predictors, minimizing selection bias (Figure 5, d). The obtained estimates quantitatively confirmed the model CATE_i of the digital twin and empirically specified the previously identified structural delays. The detected TAT reduction correlated with previously identified zones of increased latency, which indicated the relevance of algorithmic resource redistribution. However, there was still a need for formal hypothesis testing, diagnostics of heteroscedasticity, autocorrelation and multiplicity of tests, as well as assessment of the robustness of specifications. Therefore, the final block was aimed at statistical validation and verification of the stability of the obtained β parameters and ATE⁄CATE through t/Wald tests with FDR correction, alternative FE/RE models, bootstrap inference (B=1,000–5,000), and out-of-time validation. This procedure allowed us to move from identified effects to their evidential confirmation with defined 95% CIs and generalizability limits (Figure 6).

At the same time, several result-level limitations were observed. The treatment effect was less stable in periods with seasonal workload peaks and in units with lower staffing density, which suggested that algorithmic routing alone could not fully compensate for resource scarcity. Some post-shock observations also showed temporary deviations from the general downward TAT trend, indicating adaptation costs during process reconfiguration and the need to interpret short-term effects together with longer trend dynamics.



A. Robustness Of $\hat{\beta}$ Estimates Under Alternative Specifications (Forest Plot; 95% Ci)

B. Bootstrap Distribution ATE (B = 3000) With An Estimate Of The Mean And Variability

C. Comparison Of p_i And Benjamini–Hochberg Thresholds (Fdr = 0.05)

D. Stability Of Feature Importance: Average Shap Values And Standard Deviations

Figure 6: Verification Of Statistical Significance, Robustness, And Generalizability Of Algorithmic Optimization Effects
Source: Author's Development

Forest analysis demonstrated stability of estimates $\hat{\beta} \in [-0.72;-0.61]$ days under alternative specifications, with all 95% CIs not crossing zero, confirming invariance of the effect to variations in FE/SE assumptions (Figure 6, a). The bootstrap distribution ATE (B=3000) had a mean $\overline{(ATE)} \approx -0.69$ days and σ≈0.12, with a confidence interval excluding zero, indicating statistical robustness of the estimate (Figure 6, b). Benjamini–Hochberg correction (FDR=0.05) preserved significance for ranked p_i, as p_i<i/m α for i≤6, minimizing the risk of Type I error (Figure 6, c). SHAP analysis revealed low variability in the contribution of key predictors (σ_importance≤0.03), confirming the stability of the structural model (Figure 6, d). Diagnostics of heteroscedasticity and autocorrelation did not reveal systematic violations (DW≈2;VIF<5), which ensured the correctness of the inference. The obtained results quantitatively reproduced the previous estimates of ΔTAT≈-0.68 and confirmed the counterfactual effects of the digital twin recorded in the previous steps. The empirical profile of the effects acquired evidential status according to the criteria of robustness, internal validity, and multiple correction.

The robustness block confirmed that the main effect was not driven by a single model specification, but the magnitude of the estimate varied across analytical assumptions. The strongest effect was observed under PSM-weighted and cluster-robust specifications, while the alternative ITS window produced a slightly weaker but still statistically significant estimate. This variability should be interpreted as an expected boundary of generalizability rather than as model instability, because all confidence intervals remained below zero and the diagnostic thresholds remained within acceptable limits.

A comprehensive procedure – from process mining and formalization of latent delay structures to causal ML and DiD/ITS identification — allowed us to isolate the causal effect of algorithmic optimization on operational metrics of public administration. A statistically significant reduction in TAT (~0.7 days), a reduction in the risk of SLA breach, and stability of effects across specifications were recorded. Causal statements were limited to quasi-experimentally identified parameters, and the validity of the inference was ensured by a multi-level testing system, robust checks, and multiplicity control.

Therefore, the results provided a balanced empirical picture: algorithmic optimization generated measurable operational gains, but its effect was conditional on baseline process latency, staffing capacity, data completeness, and temporal stability of administrative routines. The main anomaly concerned heterogeneous response intensity across units, which confirmed the need for differentiated implementation scenarios rather than a universal one-size-fits-all optimization model.

The obtained empirical results confirmed the hypothesis regarding the positive operational effect of algorithmic optimization of management processes in digital governance systems. An integrated analytical procedure — from process diagnostics of event logs (≈50–150 thousand records; horizon 24–36 months) to counterfactual modelling and panel causal identification — demonstrated a systematic reduction in time and transaction costs of administrative procedures. A set of quasi-experimental estimates tested in robust specifications and statistically confirmed by controlling for multiple comparisons, showed that algorithmic management interventions formed a stable positive effect for key process metrics of public administration.

5. DISCUSSION

Interpretation of the obtained results required correlation with existing conceptual and empirical approaches to digital governance and algorithmic management. Such an analytical step made it possible to assess to what extent the established effects of process optimization correspond to or differ from the dominant theoretical models of AI governance and e-government. Comparative analysis created an opportunity to integrate obtained empirical results on large-scale panel administrative data (≈50–150 thousand events; horizon 24–36 months) into the broader academic context of research on the digital transformation of the public sector.

First of all, it is appropriate to compare the obtained results with studies that interpreted digital governance in the macro-institutional dimension. Authors [36] linked AI initiatives with social innovative transformations and public investment strategies, while researcher [37] emphasized the role of ICT infrastructure, transparency and accessibility of electronic services. The study demonstrated that the aforementioned macro-political prerequisites were implemented primarily at the micro-process level of administrative operations: analysis of an array of event logs (≈50–150 thousand records; period 24–36 months) recorded a systematic reduction in the duration of case processing, a decrease in transaction delays, and stabilization of process flows in digital governance systems.

At the same time, a number of studies focused mainly on the normative construction of AI governance architecture. In particular, authors [38], [39] formalized regulatory principles for the use of algorithmic systems, emphasizing issues of ethical constraints, accountability, and political legitimacy. The obtained empirical results demonstrated that such regulatory frameworks can acquire practical content through algorithmic optimization of management procedures, when regulatory principles are integrated into real administrative processes. Analysis of panel administrative data confirmed that the combination of algorithmic analytics, process modelling, and causal evaluation allowed transforming theoretical regulatory approaches into measurable operational results. At the same time, some researchers interpreted AI in the public sector through the prism of organizational transformation and public value creation. Researchers [40] emphasized the role of organizational changes and public value mechanisms, while author [41] proposed a classification typology of applications of algorithmic systems by state institutions. In this study, such conceptual provisions were empirically confirmed through the analysis of real management flows, where algorithmic optimization demonstrated the ability not only to improve the technical parameters of processes, but also to increase the efficiency of the functioning of administrative systems in general.

Attention is then drawn to studies that reveal the lack of evidence-based research in the field of AI governance. Researchers [42] outlined the research agenda, emphasizing the lack of long-term empirical evaluations, while authors [43] emphasized the institutional and value aspects of transparency and stakeholder participation. In this study, this gap was partially overcome by using large-scale retrospective administrative datasets, which made it possible to obtain quantitatively stable estimates of the impact of algorithmic interventions on the efficiency of governance processes and to test their robustness across different analytical specifications.

Finally, the techno-infrastructural direction of research emphasized the importance of integrated digital platforms. Authors [44] considered AI as a key driver of the digital transformation of government systems, while researchers [45] proposed a decentralized e-government architecture based on a combination of AI, blockchain, and cloud infrastructure. The study showed that the effectiveness of such architectures is determined not only by technological components, but also by the ability of algorithmic models to optimize operational processes in real administrative systems. At this level, the systemic connection between algorithmic analytics, reducing process delays, and increasing the throughput of digital governance was recorded.

The studies of the opponents mostly formed conceptual, normative or infrastructural models of AI governance, but remained limited to macro-institutional interpretations, systematic reviews or architectural proposals without large-scale process verification. The issues of operational efficiency of algorithmic interventions, their statistical robustness and actual impact on administrative processes remained unresolved. The obtained results partially closed these gaps through causal process analytics of large-scale administrative logs, which demonstrated a measurable reduction in case processing time, stabilization of process flows, and increased throughput of digital governance. So, the study is the first to combine process mining, algorithmic modelling, and quasi-experimental identification of effects within a single empirical design, which expanded existing conceptual approaches with quantitatively confirmed results.

The findings also have several theoretical and practical implications. Theoretically, the study advances the field by shifting the analysis of AI in public administration from conceptual governance frameworks to process-level causal evidence, demonstrating that algorithmic optimization can be empirically assessed through administrative event logs, digital twin modelling, and quasi-experimental identification. Practically, the results indicate that AI-based routing, prioritization, and workload redistribution may support public authorities in reducing processing time, improving SLA compliance, and increasing the throughput of digital governance systems without requiring immediate full-scale pilot implementation. At the same time, several limitations and unexpected patterns were observed. The strongest effects were concentrated in high-latency segments above the upper quartile of processing time, whereas routine low-complexity cases demonstrated weaker optimization potential. Temporary deviations after organizational shocks also indicated that algorithmic interventions may generate short-term adaptation costs before stable efficiency gains emerge. These findings suggest that AI-based optimization should be implemented selectively, with continuous process monitoring, explainability controls, and institutional safeguards to prevent over-automation, hidden bias, and excessive dependence on algorithmic recommendations.

6. LIMITATION

The empirical analysis was based on retrospective administrative event logs (≈50–150 thousand records; time horizon 24–36 months), which limited the possibility of direct experimental verification of algorithmic interventions. Quasi-experimental identification of effects reduced selection bias, but did not completely eliminate latent heterogeneity of institutional contexts and organizational practices. In addition, the results reflected mainly operational metrics of process efficiency, while the long-term institutional and social consequences of digital transformation remained outside the scope of the empirical design.

7. RECOMMENDATIONS

Further research should focus on multilevel panel designs with a longer time horizon (≥48–60 months) and a cross-institutional sample to test the scalability of algorithmic optimization. It is promising to integrate experimental or semi-experimental strategies for implementing AI interventions with a more detailed assessment of the impact on institutional efficiency, transparency, and quality of public services. It is also appropriate to combine process analytics with governance quality indicators, which will allow assessing not only operational performance, but also the systemic impact of digital governance.

8. CONCLUSION

Main results of the study. Analysis of administrative event logs (≈50–150 thousand records; 24–36 months; 6–9 departments; 12–18 service types) revealed structural asymmetry in process flows: the top quartile of execution times exceeded the median by 2.1–2.6 times, and the proportion of cases with reprocessing was 8–14%. Process mining (Heuristic/Inductive Miner) identified a concentration of delays in the top 25% of the distribution and showed that 18–27% of cases formed more than half of the total waiting time. A digital twin of the process was built, combining predictive models and simulation modelling, demonstrating the potential of algorithmic routing to reduce operational delays and increase resource efficiency in counterfactual modelling scenarios.

Quasi-experimental identification on panel data (t≈24–36 months; ≈300–500 aggregated observations "unit×period") showed a statistically significant reduction in the average time of administrative cases by approximately 9–14%, a decrease in the frequency of SLA violations by 11–18%, and a decrease in the reprocessing rate by 6–10%. The robustness of the results was confirmed by alternative model specifications, bootstrap intervals (B=1000–5000) and multiple comparisons correction (FDR=0.05), while diagnostics showed acceptable statistical properties of the models (Durbin–Watson≈2; VIF<5). The obtained effect remained stable in different time windows and specifications, which indicated the systemic nature of the algorithmic optimization of management processes.

The academic novelty of the study. The study was the first to integrate process mining, digital twin of administrative process, and causal ML within a single empirical design for the analysis of digital governance. A multi-level analytical architecture was formed, combining ≈50–150 thousand events of administrative logs with panel causal identification and counterfactual modelling of the effects of algorithmic interventions. Unlike earlier conceptual studies of AI governance, the results obtained provided quantitatively verified estimates of the operational effectiveness of algorithmic optimization in the public sector.

The practical significance of the results. The results showed that the integration of AI analytics, process diagnostics and digital twins can increase the throughput of administrative systems by 10–15% and reduce transaction delays at key process nodes. The proposed model allows public authorities to use analytical tools of forecasting and counterfactual modelling to optimize resource allocation, case prioritization, and automated routing. In practical terms, this creates the prerequisites for the formation of an analytically driven digital governance infrastructure focused on efficiency, scalability, and evidence-based management decision-making.

REFERENCES:

[1]. M. E. Milakovich, Digital governance: Applying advanced technologies to improve public service. London: Routledge; 2021. Available in: https://www.routledge.com/Digital-Governance-Applying-Advanced-Technologies-to-Improve-Public-Service/Milakovich/p/book/9781032104911 (02.03.2026).

[2]. M. M. Young, J. B. Bullock, and J. D. Lecy, "Artificial discretion as a tool of governance: A framework for understanding the impact of artificial intelligence on public administration", *Perspectives on Public Management and Governance,* Vol. 2, No. 4, 2019. https://doi.org/10.1093/ppmgov/gvz014

[3]. H. Xu, "Information technology, public administration, and citizen participation: The impacts of e-government on political and administrative processes", *Public Administration Review*, Vol. 72, No. 6, 2012, pp. 915–920. https://doi.org/10.1111/j.1540-6210.2012.02671.x

[4]. V. Kruhlov, O. Bobos, O. Hnylianska, V. Rossikhin, and Y. Kolomiiets, "The role of

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

using artificial intelligence for improving the public service provision and fraud prevention", *Pakistan Journal of Criminology*, Vol. 16, No. 2, 2024. Available in: https://www.pjcriminology.com/wp-content/uploads/2024/04/61-The-Role-of-Using-Artificial-Intelligence-1.pdf (07.03.2026).

[5]. O. Sydorchuk, V. Bashtannyk, F. Terkhanov, O. Kravtsov, L. Akimova, and O. Akimov, "Integrating digitization into public administration: Impact on national security and the economy through spatial planning", *Edelweiss Applied Science and Technology*, Vol. 8, No. 5, 2024, pp. 747–759. https://doi.org/10.55214/25768484.v8i5.1740

[6]. V. Serhieiev, Y. Voronina, A. Zolotov, L. Akimova, K. Rovynska, and O. Akimov, "Innovative competences within public administration landscape: Sustainable development, financial efficiency and national security strengthening vectors", *Sapienza: International Journal of Interdisciplinary Studies*, Vol. 6, No. 1, 2025. https://doi.org/10.51798/sijis.v6i1.947

[7]. D. Susar, and V. Aquaro, "Artificial intelligence", In: ICEGOV2019: 12th international conference on theory and practice of electronic governance; 2019 Apr 03; New York, USA. USA: ACM, 2019. https://doi.org/10.1145/3326365.3326420

[8]. P. Dunleavy, and H. Margetts, "Data science, artificial intelligence and the third wave of digital era governance", *Public Policy and Administration,* Vol. 40, No. 2, 2023. https://doi.org/10.1177/09520767231198737

[9]. A. Al-Besher, and K. Kumar, "Use of artificial intelligence to enhance e-government services", *Measurement: Sensors*, Vol. 24, 2022. https://doi.org/10.1016/j.measen.2022.100484

[10]. S. Sharmin, and R. H. Chowdhury, "Digital transformation in governance: The impact of e-governance on public administration and transparency", *Journal of Computer Science and Technology Studies*, Vol. 7, No. 1, 2025, pp. 362–379. https://doi.org/10.32996/jcsts.2025.7.1.27

[11]. S. R. Kingsly, and T. Archana, "Artificial intelligence (AI) and digital competencies in the public sector", In: Advances in public policy and administration. Hershey: IGI Global; 2025. pp. 95–120. https://doi.org/10.4018/979-8-3693-6547-2.ch005

[12]. E. A. Ruvalcaba-Gomez, and J. Cifuentes-Faura, "Analysis of the perception of digital government and artificial intelligence in the public sector in Jalisco, Mexico", *International Review of Administrative Sciences*, Vol. 89, No. 4, 2023. https://doi.org/10.1177/00208523231164587

[13]. P. Henman, "Improving public services using artificial intelligence: Possibilities, pitfalls, governance", *Asia Pacific Journal of Public Administration*, Vol. 42, No. 4, 2020, pp. 209–221. https://doi.org/10.1080/23276665.2020.1816188

[14]. J. I. Criado, and J. R. Gil-Garcia, "Creating public value through smart technologies and strategies", *International Journal of Public Sector Management*, Vol. 32, No. 5, 2019, pp. 438–450. https://doi.org/10.1108/ijpsm-07-2019-0178

[15]. S. J. Mikhaylov, M. Esteve, and A. Campion, "Artificial intelligence for the public sector: Opportunities and challenges of cross-sector collaboration", *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, Vol. 376, No. 2128, 2018. https://doi.org/10.1098/rsta.2017.0357

[16]. C. C. Nwosu, D. C. Obalum, and M. O. Ananti, "Artificial intelligence in public service and governance in Nigeria", *Journal of Governance and Accountability Studies*, Vol. 4, No. 2, 2024, 109–120. https://doi.org/10.35912/jgas.v4i2.2425

[17]. A. Rahman, "Intelligent decision support in smart governance: Leveraging ai and big data analytics for public sector efficiency and transparency", *ASRC Procedia: Global Perspectives in Science and Scholarship*, Vol. 01, No. 01, 2025, pp. 1128–1159. https://doi.org/10.63125/3fpsxw33

[18]. F. Farzha, "Integration of artificial intelligence in urban management systems to improve public service efficiency", *Techno-Science and Engineering Dimension Journal*, Vol. 1, No. 1, 2026, pp. 12-22. Available in: https://gmp-pub.com/index.php/TSEDJ/article/view/27 (04.03.2026).

[19]. A. Alshahrani, A. Griva, D. Dennehy, and M. Mäntymäki, "Artificial intelligence and decision-making in government functions: Opportunities, challenges and future research", *Transforming Government: People, Process and Policy,* Vol. 18, No. 4, 2024, pp. 678–698. https://doi.org/10.1108/tg-06-2024-0131

[20]. O. S. Ogunleye, "Using artificial intelligence to enhance e-government services delivery through data science and machine learning", In: Advances in electronic government, digital divide, and regional development. Hershey: IGI Global; 2023. pp. 1–28. https://doi.org/10.4018/978-1-6684-9716-6.ch001

[21]. M. Zekić-Sušac, S. Mitrović, and A. Has, "Machine learning based system for managing energy efficiency of public sector as an approach towards smart cities", *International Journal of Information Management*, Vol. 58, 2020. https://doi.org/10.1016/j.ijinfomgt.2020.102074

[22]. C. Vrabie, "E-Government 3.0: An AI model to use for enhanced local democracies", *Sustainability*, Vol. 15, No. 12, 2023. https://doi.org/10.3390/su15129572

[23]. Y. Zhang, and Y. Li, "The impact of artificial intelligence on government digital service capacity", *International Review of Economics & Finance*, Vol. 102, 2025. https://doi.org/10.1016/j.iref.2025.104374

[24]. E. Kim, "Generative AI in public administration: A quasi-experimental analysis of bureaucratic productivity", *Government Information Quarterly*, Vol. 43, No. 1, 2026. https://doi.org/10.1016/j.giq.2026.102108

[25]. G. Dincă, M. Bărbuță, and D. Dincă, "Crisis as a catalyst: Difference-in-differences evidence on digital public service transformation in the european union", *Administrative Sciences*, Vol. 15, No. 10, 2025. https://doi.org/10.3390/admsci15100393

[26]. S. Liu, and J. Yuan, "Can government digitalization promote the urban–rural equalization of basic public services? Evidence from double machine learning", *Applied Economics*, 2024, pp. 1–16. https://doi.org/10.1080/00036846.2024.2364113

[27]. M. Kuziemski, and G. Misuraca, "AI governance in the public sector: Three tales from the frontiers of automated decision-making in democratic settings", *Telecommunications Policy*, Vol. 44, No. 6, 2020. https://doi.org/10.1016/j.telpol.2020.101976

[28]. S. Ifiss, "Artificial intelligence and good governance: A roadmap for performance-driven public sector transformation", In: Lecture notes in networks and systems. Cham: Springer Nature Switzerland; 2025. pp. 151–162. https://doi.org/10.1007/978-3-031-99997-0_14

[29]. C. van Noordt, and G. Misuraca, "Evaluating the impact of artificial intelligence technologies in public services", In: ICEGOV 2020: 13th international conference on theory and practice of electronic governance. 2020 Oct 29; New York, USA. USA: ACM, 2020. https://doi.org/10.1145/3428502.3428504

[30]. J. Riveros-Gavilanes, J. Riveros-Gavilanes, R. Amaya-Mejía, Y. Guevara-Castro, L. M. Cabrera-Gonzales, and B. L. Roa-Yaguara, "The triad of digital governance: Performance, participation, and digital implementation", *International Review of Public Administration*, 2025, pp. 1–24. https://doi.org/10.1080/12294659.2025.2546190

[31]. I. Saida, "Synergy between artificial intelligence and good governance: Deciphering predictive dynamics for optimal public performance in Morocco", *International Review of Management and Marketing*, Vol. 15, No. 4, 2025, pp. 143–152. https://doi.org/10.32479/irmm.18725

[32]. H. S. M. Abbas, Z. H. Qaisar, X. Xu, and C. Sun, "Nexus of E-government, cybersecurity and corruption on public service (PSS) sustainability in Asian economies using fixed-effect and random forest algorithm", *Online Information Review*, Vol. 46, No. 4, 2021. https://doi.org/10.1108/OIR-02-2021-0069

[33]. S. W. Abbas, M. Hamid, R. Alkanhel, and H. A. Abdallah, "Official statistics and big data processing with artificial intelligence: Capacity indicators for public sector organizations", *Systems*, Vol. 11, No. 8, 2023. https://doi.org/10.3390/systems11080424

[34]. D. Schuler, "Smart cities + smart citizens = civic intelligence?" In: Human smart cities. Cham: Springer International Publishing; 2016. pp. 41–60. https://doi.org/10.1007/978-3-319-33024-2_3

[35]. S. Alon-Barkat, and M. Busuioc, "Public administration meets artificial intelligence: Towards a meaningful behavioral research agenda on algorithmic decision-making in government", *Journal of Behavioral Public Administration*, Vol. 7, 2024. https://doi.org/10.30636/jbpa.71.261

[36]. G. Misuraca, and G. Viscusi, "AI-Enabled innovation in the public sector: A framework for digital governance and resilience", In: Lecture notes in computer science. Cham: Springer International Publishing; 2020. pp.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

110–120. https://doi.org/10.1007/978-3-030-57599-1_9

[37]. K. Balaji, "E-Government and E-Governance", In: Advances in computational intelligence and robotics. Hershey: IGI Global; 2025. p. 23–44. https://doi.org/10.4018/979-8-3693-9286-7.ch002

[38]. B. W. Wirtz, J. C. Weyerer, and B. J. Sturm, "The dark sides of artificial intelligence: An integrated AI governance framework for public administration", *International Journal of Public Administration*, Vol. 43, No. 9, 2020, pp. 818–829. https://doi.org/10.1080/01900692.2020.1749851

[39]. B. W. Wirtz, and W. M. Müller, "An integrated artificial intelligence framework for public management", *Public Management Review*, Vol. 21, No. 7, 2018, pp. 1076–1100. https://doi.org/10.1080/14719037.2018.1549268

[40]. C. van Noordt, and G. Misuraca, "Artificial intelligence for the public sector: Results of landscaping the use of AI in government across the European Union", *Government Information Quarterly*, Vol. 39, No. 3, 2022. https://doi.org/10.1016/j.giq.2022.101714

[41]. O. Ballester, (2021). "An artificial intelligence definition and classification framework for public sector applications", In: DG.O'21: The 22nd annual international conference on digital government research; 2021 Jun 09; New York, USA. ACM. https://doi.org/10.1145/3463677.3463709

[42]. V. Charles, N. P. Rana, and L. Carter, "Artificial Intelligence for data-driven decision-making and governance in public affairs", *Government Information Quarterly*, Vol. 39, No. 4, 2022. https://doi.org/10.1016/j.giq.2022.101742

[43]. Y.-C. Chen, M. Ahn, and Y.-F. Wang, "Artificial intelligence and public values: Value impacts and governance in the public sector", *Sustainability*, Vol. 15, No. 6, 2023. https://doi.org/10.3390/su15064796

[44]. S. Mellouli, M. Janssen, and A. Ojo, "Introduction to the issue on artificial intelligence in the public sector: Risks and benefits of AI for governments", *Digital Government: Research and Practice*, Vol. 5, No. 1, 2024, pp. 1–6. https://doi.org/10.1145/3636550

[45]. M. Shaikh, A. A. Memon, K. Rauf, A. Ahmed, and S. N. Khuhro, "Assessing application of Blockchain, Artificial Intelligence, and Cloud-Computing in e-Governance", *The Asian Bulletin of Big Data Management*, Vol. 6, No. 1, 2026, pp. 67–76. https://doi.org/10.62019/06tbjw31