ISSN: 3023 - 8943

VOLUME 3, ISSUE 1, JANUARY 2026

AN INTERDISCIPLINARY JOURNAL OF ECONOMICS AND BUSINESS

INFORMATION TECHNOLOGY IN ECONOMICS AND BUSINESS

ADBA

https://journals.adbascientific.com/iteb

ISSN: 3023-8943

Information Technology in Economics and Business
Volume: 3 – Issue No: 1 (Januray 2026)

EDITORIAL BOARD

ISSN: 3023-8943

Information Technology in Economics and Business
Volume: 3 – Issue No: 1 (January 2026)

CONTENTS

https://journals.adbascientific.com/iteb/issue/view/17

ADBA
Information Technology in Economics and Business
Cutting-Edge Scientific Solutions

e-ISSN: 3023-8943
RESEARCH ARTICLE
Vol.3 / No.1 / 2026 / pp.1-8
https://doi.org/10.69882/adba.iteb.2026011

Mapping Economic Considerations in Clinical Artificial Intelligence Research

Hakan Özcan [*,1]
[*] Department of Computer Technology, Design Vocational School, Amasya University, Amasya, 05100, Türkiye.

ABSTRACT Artificial intelligence (AI) has been rapidly adopted in clinical research over the past decade, yet the extent to which economic considerations are integrated into this literature remains unclear. This study presents a large-scale bibliometric analysis of clinical AI research indexed in the Web of Science. Temporal analyses span 2000–2024 (54,219 clinical AI studies), while network mapping, citation overlay, and density analyses focus on the 2024 snapshot (N = 14,995). A ratio-based indicator was used to track the relative prominence of economic considerations over time. The results show a sharp acceleration in clinical AI publications after 2015, while studies explicitly addressing cost, cost-effectiveness, or economic burden remained persistently rare, accounting for less than 1% of annual output in most years. Structural analyses indicate that economic terms are closely linked to modeling and decision-oriented keywords but do not form independent thematic clusters. Although economics-focused studies achieve moderate normalized citation impact when present, their low frequency limits structural influence. The findings reveal a persistent imbalance between rapid methodological innovation and limited economic evaluation in clinical AI research, highlighting the need for more systematic integration of economic perspectives to support sustainable clinical deployment.

KEYWORDS
Clinical artificial intelligence
Temporal trends
Bibliometrics
Network mapping
Health economics
Economic evaluation

INTRODUCTION

Clinical applications of artificial intelligence (AI) have expanded substantially over the past decade. This expansion has been supported by advances in machine learning, larger digital datasets, and improved computational capacity. AI systems now demonstrate competitive performance across clinical tasks such as image-based classification and computer-aided diagnosis, with several studies reporting specialist-level results in narrow, well-defined settings (Cai *et al.* 2024; Esteva *et al.* 2017; Kremer *et al.* 2025; Wu *et al.* 2020). Alongside technical progress, AI is increasingly positioned as a system-level enabler for healthcare, with proposed benefits that include improved efficiency, decision support, and service delivery at scale (Davenport and Kalakota 2019).

As clinical AI models proliferate, greater attention has been directed toward how model performance is evaluated and communicated (Andersen *et al.* 2024). In practice, performance reporting in the clinical AI literature remains strongly centered on accuracy-based metrics and closely related measures (Kocak *et al.* 2025; Nagendran *et al.* 2020). These metrics provide convenient summaries of predictive behavior and are commonly used to demonstrate technical feasibility in controlled evaluation settings (Rajpurkar *et al.* 2022).

However, an emphasis on accuracy alone offers limited insight into how models operate within real clinical environments (Wiens *et al.* 2019). Important considerations such as robustness, workflow integration, reliability under data shift, and operational constraints are often discussed only briefly or omitted altogether (Rajkomar *et al.* 2019; Sendak *et al.* 2020b). As a result, performance evidence may appear compelling from a technical standpoint while remaining limited in its ability to inform deployment decisions and system-level planning in routine care (Adnan *et al.* 2025; Kelly *et al.* 2019).

Despite rapid technical progress, the economic implications of clinical AI remain insufficiently examined. Many studies focus on predictive performance and technical feasibility, while costs and resource requirements receive comparatively less attention (Kelly *et al.* 2019; Rajkomar *et al.* 2019). Reviews that focus on economic outcomes report that formal cost-effectiveness and budget impact evidence is still limited in volume and uneven across clinical domains (El Arab and Al Moosa 2025; Leigh *et al.* 2025;

Manuscript received: 23 December 2025,
Revised: 15 January 2026,
Accepted: 15 January 2026.

[1]hozcan@amasya.edu.tr (**Corresponding author**)

Wolff *et al.* 2020). When economic evaluations are conducted, they are typically concentrated in specific applications and often rely on modeled assumptions and context-specific parameters rather than broad real-world implementation (Areia *et al.* 2022; Xiao *et al.* 2021). This pattern is illustrated by application-specific analyses that integrate clinical, technical, and financial dimensions within narrowly defined use cases (Gomez Rossi *et al.* 2022). For instance, one study examined local cost structures, staffing models, and institutional priorities in relation to the economic viability of AI tools (Davis *et al.* 2023).

In several cases, economic value is discussed indirectly, for example through expected efficiency gains, without being quantified through explicit cost and outcome comparisons (Khanna *et al.* 2022; Pagallo *et al.* 2024; Teo and Ting 2023). Taken together, these findings indicate that economic considerations are not yet consistently integrated into clinical AI research, complicating efforts to plan and justify sustainable adoption. More recent work emphasizes that economic considerations are inseparable from organizational readiness, governance structures, and delivery models when planning sustainable clinical AI deployment (Hasan *et al.* 2025).

Against this background, and despite growing case-level economic analyses, a structured, literature-wide understanding of how economic considerations intersect with clinical AI research remains limited. Existing reviews predominantly focus on individual applications or summarize reported cost outcomes, but rarely examine how economic language, thematic organization, and citation patterns are distributed across the broader clinical AI corpus. Consequently, it remains unclear whether economic reasoning is becoming systematically embedded within clinical AI research or continues to appear primarily in isolated, application-specific studies.

To address this gap, the present study adopts a bibliometric perspective. Clinical AI publications are organized into analytically defined corpora and examined using network-based mappings, citation overlays, and density visualizations to characterize structural and thematic patterns. A complementary ratio-based indicator is used to capture temporal patterns in economic focus. These elements provide a coherent framework for analyzing how economic discourse is situated within the broader clinical AI landscape.

MATERIALS AND METHODS

This section describes the data sources, corpus construction, bibliometric analyses (network, citation, and density), index formulation and experimental setup used in the study.

Data Retrieval

The data were retrieved from the Web of Science (WoS) Core Collection (Clarivate Analytics). The search targeted peer-reviewed journal articles indexed under topic fields (TS; WoS Topic Search). Structured queries combined clinical terminology with AI–related terms. Only articles written in English were included, and no subject category restrictions were applied. Records were collected in a single search session to ensure consistency. Full records and cited references were exported in plain-text format for subsequent bibliometric analysis. The overall study design is summarized in Figure 1.

Corpus Definition

The study corpus was organized into two analytical groups using topic-level query logic reflecting different scopes of clinical AI research. Group 1 represents the broad clinical AI literature and includes publications in which clinical contexts are explicitly linked with AI–related concepts such as "artificial intelligence," "machine learning," or "deep learning." Group 2 captures a nested subset of this corpus in which clinical AI studies additionally engage with economic or cost-related considerations. In this group, clinical and AI-related terms co-occur with concepts, such as healthcare cost, medical or hospital expenditure, reimbursement, cost-effectiveness, and economic burden. Two complementary analytical components were applied using these groups. Temporal analysis examined year-by-year publication trends over the period 2000–2024, capturing the emergence and expansion of clinical AI research and its economics-focused subset. Bibliometric mapping of the 2024 literature snapshot was performed to characterize the contemporary thematic structure of the field. This separation avoided temporal mixing effects and ensured structural comparability.

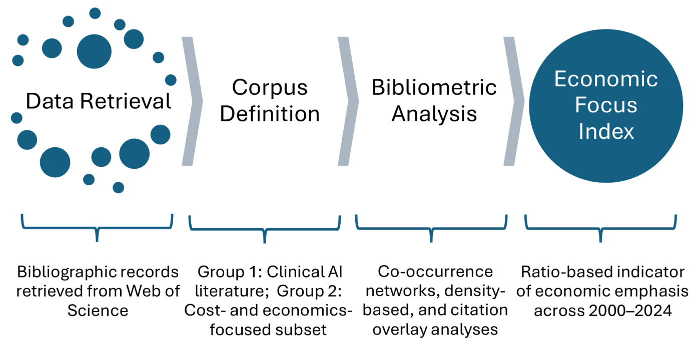


Figure 1 Overview of the study design. The records were retrieved from the Web of Science database and organized into two corpora: (i) clinical AI literature and (ii) an economics-focused subset. The analyses were conducted using co-occurrence networks, density maps, and citation overlays. An Economic Focus Index was then computed as a ratio-based indicator of economic emphasis across the period 2000–2024.

Bibliometric Analysis

Bibliometric analysis was conducted following established bibliometric mapping practices (Donthu *et al.* 2021) and implemented using VOSviewer (Van Eck and Waltman 2010). The analysis comprised three complementary visualizations: keyword co-occurrence networks, citation overlay visualizations, and density maps. Co-occurrence networks were used to represent thematic relationships based on the frequency and strength of shared keywords within each corpus. Citation overlays were derived from average normalized citation scores to assess relative influence across topics. Density maps highlighted regions of thematic concentration by emphasizing areas with high keyword occurrence and connectivity. Collectively, these bibliometric visualizations provide a structured overview of thematic organization, citation prominence, and concentration patterns within and between the two corpora.

Economic Focus Index

An Economic Focus Index (EFI) was defined to quantify the emphasis on economic considerations in the clinical AI literature. The index enables comparison across the defined corpora. It does not measure research quality or impact; rather, it aims to capture the relative strength of the economic signal within clinical AI research.

The formal definition is given in Equation (1).

$$\mathrm{EFI}_y = \frac{|G_{2,y}|}{\max(1,\ |G_{1,y} \setminus G_{2,y}|)} \tag{1}$$

Here, $G_{1,y}$ denotes the set of all clinical AI publications in year y, and $G_{2,y}$ denotes the subset of publications in the same year that explicitly address economic aspects. The numerator represents the volume of economically focused clinical AI studies, while the denominator represents the remaining clinical AI literature in that year without explicit economic focus and is lower-bounded by 1 for numerical stability.

Experimental Setup and Parameter Configuration

Key text-mining, bibliometric, and index computation settings are summarized in Table 1. Corpus definitions, keyword dictionaries, and inclusion rules were specified a priori and applied consistently across analyses. Identical preprocessing, normalization, and clustering procedures were used for both corpora; thresholds differed only for corpus size. All analyses were conducted in December 2025. Temporal trends and subfield distributions were computed in Python (v3.12) and visualized using Matplotlib (Hunter 2007). Subfield assignment (Imaging, Screening, Decision support) was implemented via rule-based keyword matching applied to titles, abstracts, and normalized keywords, using hierarchical dominance rules after thesaurus normalization. Bibliometric network construction and visualization were performed in VOSviewer (v 1.6.20) (Van Eck and Waltman 2010), using association-strength normalization and modularity-based clustering on the full keyword set.

RESULTS

This section reports the main empirical findings of the study, organized around temporal trends, bibliometric structure, functional subfield distribution, and comparative patterns between the general clinical AI literature and its economics-focused subset.

Clinical AI Growth and Economic Focus

The temporal evolution of clinical AI research and its economic focus is examined across the study period. Across 2000–2024, the clinical AI corpus comprises 54,219 articles, while the economics-focused subset comprises 659 articles. Figure 2 summarizes the corresponding publication trends and index values.

In the upper panel, the total volume of clinical AI publications shows strong and sustained growth. Annual counts increase from 18 publications in 2000 to 14,995 in 2024, with particularly rapid expansion after 2017. In contrast, economically focused studies remain scarce over time despite a cumulative total of 659 studies across the full period. Several early years report zero publications, and many others include only one study per year. Even in recent years, Group 2 counts remain modest, rising to 81 publications in 2022 and reaching 137 in 2024.

The lower panel shows the EFI values computed on a yearly basis. The values are zero or near zero throughout the early period and remain consistently low across the full time span. For example, EFI is approximately 0.010 in 2018, 0.0097 in 2020, and 0.0092 in 2024. The smoothed trend indicates gradual stabilization rather than rapid increase.

The two panels show that the sharp rise in clinical AI research volume is not matched by a comparable increase in economic focus. Despite large absolute growth, economically focused studies consistently represent less than 1% of the non-economic clinical AI literature throughout the study period.

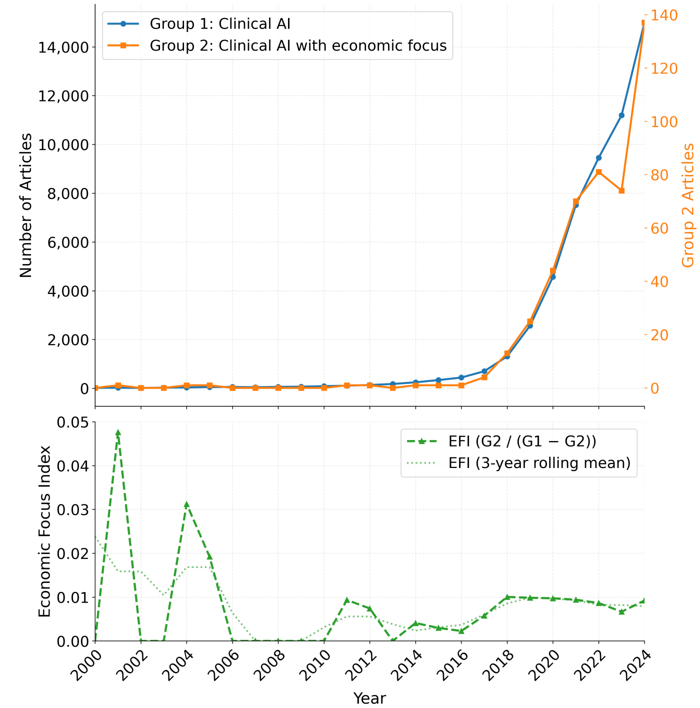


Figure 2 Temporal trends in clinical AI research and economic focus from 2000 to 2024. The upper panel shows annual publication counts for the overall clinical AI literature (Group 1, left axis) and the economically focused subset (Group 2, right axis). The lower panel shows the Economic Focus Index (EFI), with a smoothed rolling mean to highlight longer-term trends.

All subsequent bibliometric network, citation overlay, and density analyses are based on the 2024 snapshot, comprising 14,995 publications from Group 1 and 137 from Group 2, as defined in the Methods section.

Clinical AI Bibliometric Structure

The bibliometric structure of the clinical AI corpus is characterized by a small number of high-frequency concepts that organize most of the research activity. The following visualizations summarize how dominant keywords co-occur, how their citation influence varies, and where thematic concentrations form within Group 1.

Figure 3 presents the keyword co-occurrence network. A compact core is formed around general AI and modeling terms, led by “machine learning” (4,257 occurrences), “artificial intelligence” (3,298), and “deep learning” (2,752). Clinical-task terms also sit close to this core, such as “diagnosis” (1,103) and “classification” (975), indicating that methodological keywords and clinical objectives are tightly coupled in the literature. Link strengths reinforce this structure, with strong ties between “machine learning” and “artificial intelligence” (733), “deep learning” and “artificial intelligence” (510), and “diagnosis” and “artificial intelligence” (295), consistent with a consolidated methodological backbone.

Figure 4 overlays normalized citation impact on the same keyword space, highlighting where relative influence concentrates within the network. The highest average normalized citation impact is observed for “health care” (2.80), indicating strong citation attention at the interface of clinical AI and healthcare systems research. Closely following are recent language-model–related terms, including “llm” (2.22) and “chatgpt” (2.21), reflecting the

Table 1 Text-mining and bibliometric analysis setup

Component	Description
Data source	Web of Science Core Collection (full records and cited references)
Text fields analyzed	Title (TI), Abstract (AB), Author Keywords (DE), Keywords Plus (ID)
Language filter	English only
Corpus definition (Group 1)	TS = (clinical AND ("artificial intelligence" OR "machine learning" OR "deep learning"))
Corpus definition (Group 2)	TS = (clinical AND ("artificial intelligence" OR "machine learning" OR "deep learning") AND (cost OR expense* OR economic OR expenditure* OR reimburs* OR "cost-effectiveness"))
Keyword normalization	Thesaurus-based harmonization (lowercasing, spelling and plural normalization, synonym merging)
Thesaurus construction	Manually curated term lists informed by prior reviews, mapping lexical variants and synonyms to canonical forms; generic non-informative terms excluded
Minimum occurrence threshold	Group 1: t = 100; Group 2: t = 3 (size-adjusted)
Clustering method	VOSviewer association-strength normalization with modularity-based clustering
Visualization outputs	Co-occurrence network, citation overlay, density map
Citation metric	Average normalized citation score (field- and year-normalized)
Ratio metric	Economic Focus Index (EFI)
Temporal scope	Yearly analysis (2000–2024); structural snapshot focused on 2024

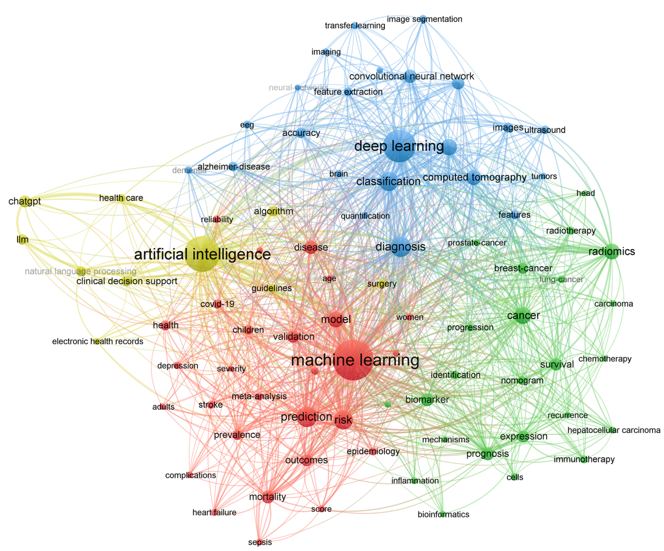


Figure 3 Keyword co-occurrence network of clinical AI literature (Group 1). The network visualizes high-frequency keywords using a minimum occurrence threshold (t = 100) after thesaurus-based harmonization. Node size reflects keyword frequency, while links indicate co-occurrence strength.

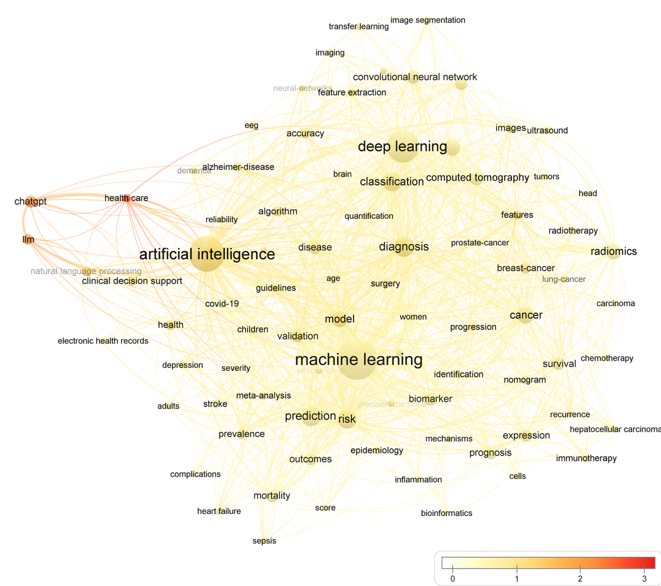


Figure 4 Citation overlay visualization of clinical AI literature (Group 1). Keywords are colored according to average normalized citation impact, with warmer colors indicating higher relative citation influence. Node size reflects keyword occurrence frequency.

rapid uptake and high visibility of generative AI topics. Elevated influence is also evident for "features" (1.45) and "natural language processing" (1.38), while core methodological terms such as "artificial intelligence" (1.26), and broader domain terms such as "health" (1.25), maintain above-average normalized citation levels. Together, these patterns indicate that both emerging AI paradigms and established clinical modeling concepts attract disproportionate citation attention within the 2024 clinical AI literature.

Figure 5 provides a density view of keyword occurrences, emphasizing dominant concentrations rather than individual links. The highest-density regions align with the same methodological and diagnostic core, with sustained prominence for "machine learning" (4,257 occurrences), "artificial intelligence" (3,298), "deep learning" (2,752), and clinical framing terms such as "diagnosis" (1,103) and "classification" (975). Imaging-related terms also contribute to dense thematic areas, including "computed tomography" (583 occurrences), "magnetic resonance imaging" (697; spatially overlapping with "deep learning" and therefore unlabeled), and “radiomics” (686), indicating that a substantial portion of the corpus concentrates around imaging-driven clinical AI workflows.

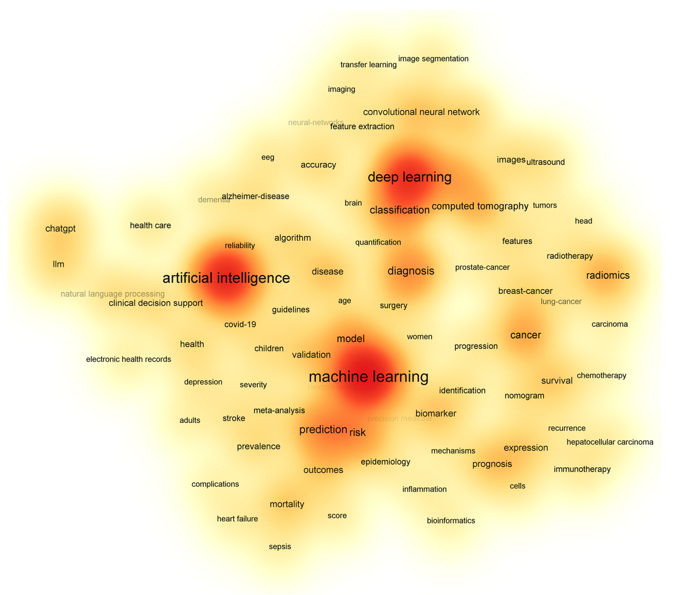


Figure 5 Keyword density map of clinical AI literature (Group 1). Density visualization based on keyword occurrence frequency, highlighting dominant thematic concentrations.

The corpus expands primarily through intensification of a core methodological vocabulary and its applications in diagnosis, prediction, and imaging, rather than through diversification toward explicitly economic language. This aligns with the earlier observation that economics-focused studies remain rare relative to the overall clinical AI output, even as annual publication counts rise sharply in recent years.

Economics-Focused Clinical AI Bibliometric Structure

The economics-focused subset of clinical AI research exhibits a markedly different bibliometric structure from the broader corpus. While overall publication counts remain low, the thematic organization reveals a tighter coupling between methodological terms and economic evaluation concepts, reflecting a more targeted and application-oriented literature. This structure is examined using complementary network, citation, and density perspectives.

Figure 6 shows the keyword co-occurrence network for economics-focused clinical AI studies. A tightly connected core forms around “artificial intelligence” (51 occurrences) and “machine learning” (35), closely linked with “cost-effectiveness” (24), “risk” (19; spatially overlaps with “artificial intelligence” and is therefore lightly colored), and “classification” (13). Economic terms such as “cost” (4) and “economic burden” (5) appear directly connected to clinical and modeling keywords rather than forming a separate cluster. This structure indicates that economic language is embedded within clinical modeling discussions rather than treated as an independent theme.

Figure 7 presents the citation overlay visualization, highlighting which topics carry disproportionate citation influence within this small subset. Although “artificial intelligence” remains the most frequent node, higher normalized citation values are observed for specific clinically grounded terms, including “mild cognitive impairment” (5.26) and “alzheimer-disease” (5.22), followed by

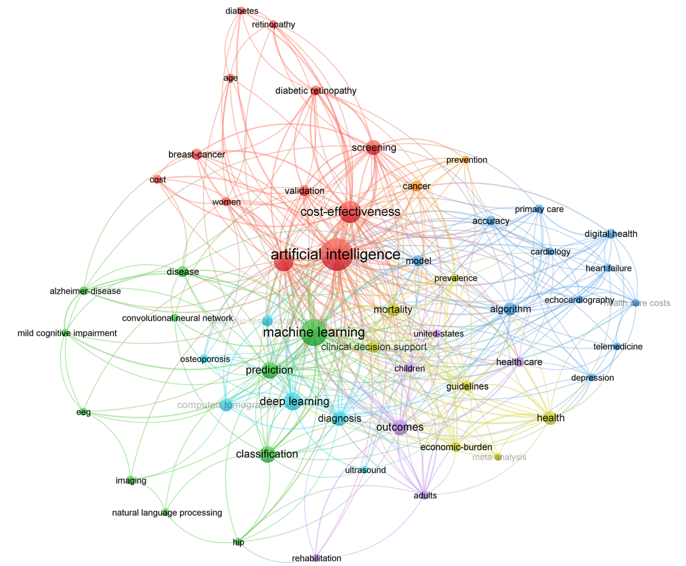


Figure 6 Keyword co-occurrence network of economics-focused clinical AI studies (Group 2). The network visualizes high-frequency keywords using a minimum occurrence threshold ($t = 3$), selected to accommodate the smaller corpus size after thesaurus-based harmonization. Node size reflects keyword frequency, while links indicate co-occurrence strength.

care- and population-oriented nodes such as “health care” (2.48), “women” (1.86), and “primary care” (1.61). These patterns indicate that economics-focused studies attract greater citation impact when anchored in concrete clinical conditions, care pathways, or population contexts rather than generic modeling themes.

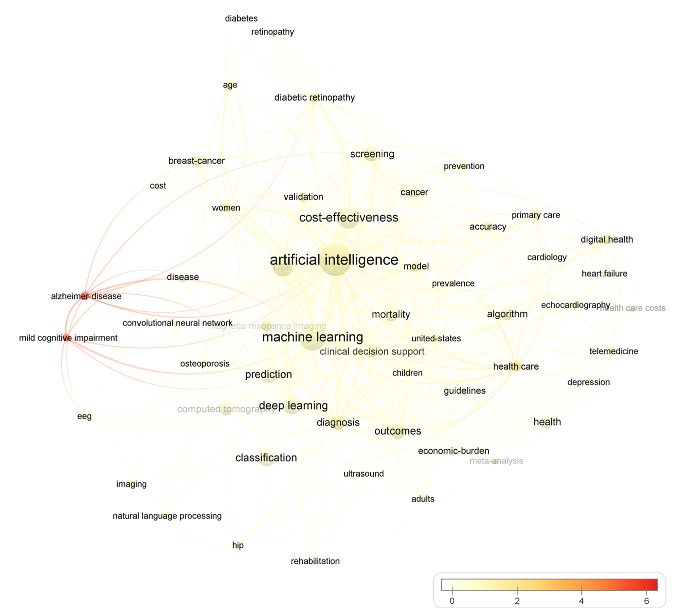


Figure 7 Citation overlay visualization of economics-focused clinical AI studies (Group 2). Keywords are colored by average normalized citation impact, with warmer colors indicating higher relative citation influence. Node size reflects keyword occurrence frequency.

Figure 8 provides a density view that emphasizes thematic concentration rather than individual links. The highest-density regions are anchored by core AI terminology, led by "artificial intelligence" (51 occurrences) and "machine learning" (35), around which economics-oriented concepts cluster. Within this core, "cost-effectiveness" (24) and "risk" (19) form the most prominent decision-focused extensions, followed by methodological and task-level terms such as "deep learning" (16), "classification" (13), "prediction" (13), and "outcomes" (12). Clinical processes including "screening" (11) and "diagnosis" (10) further contribute to dense regions but remain visually compressed due to overlap with dominant methodological nodes. Overall, the density pattern confirms that economic considerations in clinical AI are concentrated within a narrow, decision-oriented thematic core rather than broadly dispersed across clinical domains.

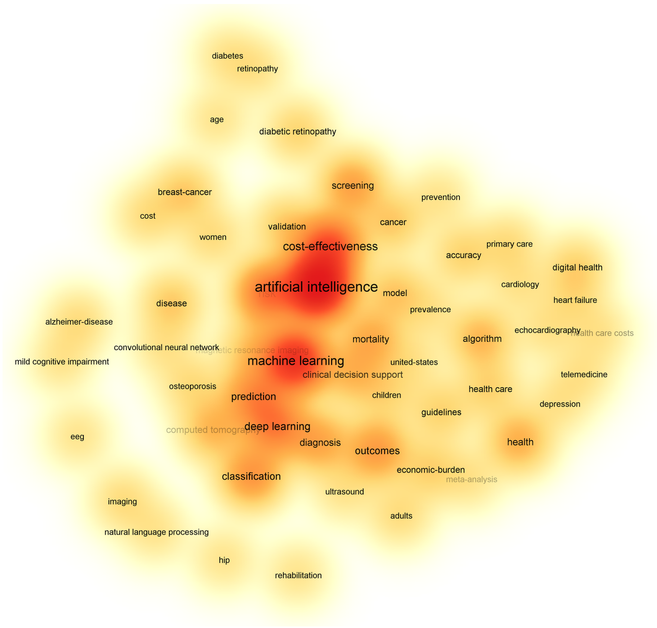


Figure 8 Keyword density map of economics-focused clinical AI studies (Group 2). Density visualization based on keyword occurrence frequency, highlighting dominant thematic concentrations.

These results reinforce the quantitative findings reported earlier. Despite the rapid expansion of clinical AI research overall, economics-focused contributions remain sparse and structurally compact. Economic concepts are embedded within existing clinical AI frameworks rather than forming independent thematic clusters.

Functional Distribution of Economic Focus Across Clinical AI Subfields

To assess how economic considerations are distributed across clinical AI applications, the economics-focused subset of clinical AI research was analyzed at the subfield level. Subfields were defined according to the primary clinical function through which AI systems generate economic impact, namely Imaging, Screening, and Decision support, with a residual Other category for cross-cutting studies. Assignment was operationalized using thesaurus-normalized keywords extracted from titles, abstracts, and keyword fields.

As shown in Table 2, economic evaluation in clinical AI is strongly concentrated in imaging-based applications, which account for 65.7% of the publications. Screening-oriented studies represent 14.6%, while decision-support applications comprise 13.9% of the corpus. Only 5.8% of studies address broader economic or organizational themes without a dominant clinical function.

Table 2 Distribution of economics-focused clinical AI studies across function-based subfields

Subfield	Count	Percent (%)
Imaging	90	65.69
Screening	20	14.6
Decision	19	13.87
Other	8	5.84

Note: Subfields were assigned based on thesaurus-normalized keywords indicating the dominant clinical function of each 2024 publication.

This distribution indicates that, despite the broad expansion of clinical AI, economic analysis remains predominantly anchored in imaging workflows, with substantially more limited representation in screening and decision-support contexts.

Comparative Patterns Between Groups

A marked imbalance exists between the two corpora in both scale and thematic breadth. Across the 2000–2024 study period, the clinical AI literature (Group 1) comprises 54,219 publications, whereas the economics-focused subset (Group 2) includes only 659 studies, representing a marginal fraction of the overall output. The same imbalance appears in the bibliometric analysis, where Group 1 includes 14,995 studies compared with only 137 economics-focused contributions.

At the keyword level, the contrast extends further. Dominant methodological terms in Group 1 occur at very large scale, with thousands of occurrences (e.g., "machine learning" = 4,257; "artificial intelligence" = 3,298), whereas in Group 2 even the most frequent terms appear only a few dozen times ("artificial intelligence" = 51; "machine learning" = 35). Structural and impact patterns diverge between the groups. Group 1 exhibits a broad, multi-clustered network spanning modeling, diagnosis, and imaging, while Group 2 forms a compact structure in which economic concepts are embedded directly within the methodological core, most prominently through "cost-effectiveness" (24) and "risk" (19). Citation overlays also differ. In Group 1, citation influence largely tracks keyword frequency, whereas in Group 2 several clinically specific topics achieve disproportionately high normalized citation impact (e.g., "mild cognitive impairment" = 5.26; "alzheimer-disease" = 5.22), exceeding the near-unity levels typical of most Group 1 terms. Together, these contrasts indicate that economic focus is selective and context-dependent rather than scaling proportionally with overall clinical AI research growth.

DISCUSSION

This study provides a corpus-level view of how economic considerations are positioned within the clinical AI literature. By combining bibliometric mapping with a ratio-based indicator, the analysis moves beyond individual case studies to examine the visibility and integration of economic discourse at scale. The results reveal a clear imbalance between rapid methodological expansion and limited attention to economic evaluation.

Clinical AI research has grown sharply since the mid-2010s, consistent with prior reports of accelerated adoption across healthcare. In contrast, the economics-focused subset remains small throughout the study period. Even in recent years, studies explicitly addressing cost, cost-effectiveness, or economic burden account for only a narrow fraction of the overall corpus. This finding aligns with earlier reviews showing that economic analysis has not kept pace with technical development (El Arab and Al Moosa 2025; Wolff *et al.* 2020). The persistence of this gap suggests a structural, rather than temporary, underrepresentation of economic perspectives.

Network-based analyses clarify how economic language appears within clinical AI research. In the general corpus, methodological and diagnostic terms form a dense, highly connected core, reflecting a consolidated research structure. In the economics-focused subset, the network is smaller and more compact. Terms such as "cost-effectiveness" and "economic burden" are closely linked to modeling and decision-oriented keywords but do not form independent clusters, a finding reinforced by citation overlay and density views. Although some clinically grounded terms achieve high normalized citation impact, their low frequency limits their influence on overall network structure. Economic concepts cluster within specific applications rather than extending across the broader literature. This organization is consistent with prior observations that cost-related analysis in clinical AI is typically task-specific and context-dependent (Areia *et al.* 2022; Xiao *et al.* 2021).

Several structural factors help explain why this marginal position persists. Economic assessment of AI systems is constrained by dynamic model behavior, unclear comparators, and limited reporting transparency, which restrict generalizable cost-effectiveness evidence (Gomez Rossi *et al.* 2022). Recent empirical analyses of large language model deployment indicate that cost considerations become salient mainly at the operational stage, where execution time, infrastructure requirements, and usage-based pricing shape feasibility in healthcare systems (Burns *et al.* 2025). Regulatory pathways prioritize safety and effectiveness, with little direct emphasis on economic value at approval (Benjamens *et al.* 2020). In implementation settings, economic impact depends on workflow integration and local reimbursement conditions, limiting transferability across institutions (Sendak *et al.* 2020a). Systematic evidence likewise reports heterogeneous and context-specific evaluation practices despite the rapid growth of AI applications (Wu *et al.* 2025).

The ratio-based indicator supports these interpretations. Although modest increases appear in recent years, overall values remain low. Short-term fluctuations point to episodic attention to economic issues rather than sustained integration across the research lifecycle. This is reflected in the bibliometric analysis, where economic focus is concentrated in a limited set of decision-oriented applications. Formal economic evaluation thus tends to emerge in response to implementation or policy pressures, rather than being incorporated during early model development (Kelly *et al.* 2019; Pagallo *et al.* 2024). This observation aligns with recent work emphasizing that long-term economic implications of clinical AI remain largely conceptual rather than empirically examined (Al Meslamani 2023).

Overall, economic perspectives occupy a marginal role in clinical AI research. They are visible and sometimes highly cited, yet weakly integrated into the core literature. This imbalance helps explain why technically successful systems often struggle to scale, as performance gains alone do not ensure economic sustainability, and organizational and governance barriers remain substantial (Adnan *et al.* 2025; Khanna *et al.* 2022).

LIMITATIONS

This analysis relies on topic-based queries and bibliometric representations, which capture explicit economic language but may overlook implicit or indirectly framed cost considerations embedded within technical or clinical discussions. As a result, keyword filtering and co-occurrence structures are sensitive to terminology choice and reporting practices rather than underlying economic relevance alone. Citation-based metrics reflect scholarly visibility rather than real-world adoption, economic impact, or implementation success. The EFI quantifies relative prominence, not the depth or quality of economic analysis, and should therefore be interpreted as an indicator of thematic emphasis. Alternative approaches, such as topic-modeling–based theme proportions or temporal co-occurrence analyses, could capture subtler or evolving economic signals. However, such methods would introduce greater model dependence and reduce interpretability. Finally, the analysis is limited to peer-reviewed journal articles indexed in WoS; inclusion of additional databases may reveal complementary patterns.

CONCLUSION

This study identifies a persistent gap between methodological innovation and economic evaluation in clinical AI research. By situating economic discourse within the broader clinical AI landscape, the findings show that economic considerations remain selectively integrated rather than systematically embedded. These results highlight the need for closer alignment between algorithm development, clinical evaluation, and economic analysis as AI systems transition from experimental settings to routine healthcare practice.

Acknowledgments

This study received no funding, grants, or other external support.

Ethical standard

The author has no relevant financial or non-financial interests to disclose.

Availability of data and material

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of interest

The author declares that there is no conflict of interest regarding the publication of this paper.

LITERATURE CITED

Adnan, H. S., A. Shidani, L. Clifton, C. R. Bankhead, and R. Perera-Salazar, 2025 Implementation framework for AI deployment at scale in healthcare systems. iScience **28**: 112406.

Al Meslamani, A. Z., 2023 Beyond implementation: the long-term economic impact of AI in healthcare. Journal of Medical Economics **26**: 1566–1569.

Andersen, E. S., J. B. Birk-Korch, R. S. Hansen, L. H. Fly, R. Röttger, *et al.*, 2024 Monitoring performance of clinical artificial intelligence in health care: a scoping review. JBI Evidence Synthesis **22**: 2423–2446.

Areia, M., Y. Mori, L. Correale, A. Repici, M. Bretthauer, *et al.*, 2022 Cost-effectiveness of artificial intelligence for screening colonoscopy: a modelling study. The Lancet Digital Health **4**: e436–e444.

Benjamens, S., P. Dhunnoo, and B. Meskó, 2020 The state of artificial intelligence-based FDA-approved medical devices and algorithms: an online database. npj Digital Medicine **3**: 118.

Burns, M. L., S.-Y. Chen, C.-A. Tsai, J. Vandervest, B. Pandian, *et al.*, 2025 Generative AI costs in large healthcare systems, an example in revenue cycle. npj Digital Medicine **8**: 579.

Cai, C., Q. Shi, J. Li, Y. Jiao, A. Xu, *et al.*, 2024 Pathologist-level diagnosis of ulcerative colitis inflammatory activity level using an automated histological grading method. International Journal of Medical Informatics **192**: 105648.

Davenport, T. and R. Kalakota, 2019 The potential for artificial intelligence in healthcare. Future Healthcare Journal **6**: 94–98.

Davis, M. A., D. Ramakrishnan, M. Sala, and M. Aboian, 2023 Local Economic Considerations in Selecting Artificial Intelligence Tools for Implementation. Journal of the American College of Radiology **20**: 981–984.

Donthu, N., S. Kumar, D. Mukherjee, N. Pandey, and W. M. Lim, 2021 How to conduct a bibliometric analysis: An overview and guidelines. Journal of Business Research **133**: 285–296.

El Arab, R. A. and O. A. Al Moosa, 2025 Systematic review of cost effectiveness and budget impact of artificial intelligence in healthcare. npj Digital Medicine **8**: 548.

Esteva, A., B. Kuprel, R. A. Novoa, J. Ko, S. M. Swetter, *et al.*, 2017 Dermatologist-level classification of skin cancer with deep neural networks. Nature **542**: 115–118.

Gomez Rossi, J., B. Feldberg, J. Krois, and F. Schwendicke, 2022 Evaluation of the Clinical, Technical, and Financial Aspects of Cost-Effectiveness Analysis of Artificial Intelligence in Medicine: Scoping Review and Framework of Analysis. JMIR Medical Informatics **10**: e33703.

Hasan, A., N. Prizant, J. Y. Kim, S. Rao, D. Vidal, *et al.*, 2025 Aligning AI principles and healthcare delivery organization best practices to navigate the shifting regulatory landscape. npj Digital Medicine **8**: 278.

Hunter, J. D., 2007 Matplotlib: A 2d Graphics Environment. Computing in Science & Engineering **9**: 90–95.

Kelly, C. J., A. Karthikesalingam, M. Suleyman, G. Corrado, and D. King, 2019 Key challenges for delivering clinical impact with artificial intelligence. BMC Medicine **17**: 195.

Khanna, N. N., M. A. Maindarkar, V. Viswanathan, J. F. E. Fernandes, S. Paul, *et al.*, 2022 Economics of Artificial Intelligence in Healthcare: Diagnosis vs. Treatment. Healthcare **10**: 2493.

Kocak, B., M. E. Klontzas, A. Stanzione, A. Meddeb, A. Demircioğlu, *et al.*, 2025 Evaluation metrics in medical imaging AI: fundamentals, pitfalls, misapplications, and recommendations. European Journal of Radiology Artificial Intelligence **3**: 100030.

Kremer, A., T. Demarcy, S. Silva, L. Genin, E. Gitenay, *et al.*, 2025 Ai-based framework for expert-level diagnosis of peritricuspid flutter. Heart Rhythm O2 **6**: S38–S39.

Leigh, J., J. Drinkwater, A. Turner, and E. Schroeder, 2025 Health Economic Considerations for the Implementation of Artificial IntelligenceEnabled Diabetic Retinopathy Screening: A Review. Clinical & Experimental Ophthalmology p. ceo.70016.

Nagendran, M., Y. Chen, C. A. Lovejoy, A. C. Gordon, M. Komorowski, *et al.*, 2020 Artificial intelligence versus clinicians: systematic review of design, reporting standards, and claims of deep learning studies. BMJ p. m689.

Pagallo, U., S. O'Sullivan, N. Nevejans, A. Holzinger, M. Friebe, *et al.*, 2024 The underuse of AI in the health sector: Opportunity costs, success stories, risks and recommendations. Health and Technology **14**: 1–14.

Rajkomar, A., J. Dean, and I. Kohane, 2019 Machine Learning in Medicine. New England Journal of Medicine **380**: 1347–1358.

Rajpurkar, P., E. Chen, O. Banerjee, and E. J. Topol, 2022 Ai in health and medicine. Nature Medicine **28**: 31–38.

Sendak, M. P., J. D'Arcy, S. Kashyap, M. Gao, M. Nichols, *et al.*, 2020a A path for translation of machine learning products into healthcare delivery. EMJ Innov **10**: 19–00172.

Sendak, M. P., W. Ratliff, D. Sarro, E. Alderton, J. Futoma, *et al.*, 2020b Real-World Integration of a Sepsis Deep Learning Technology Into Routine Clinical Care: Implementation Study. JMIR Medical Informatics **8**: e15182.

Teo, Z. L. and D. S. W. Ting, 2023 Ai telemedicine screening in ophthalmology: health economic considerations. The Lancet Global Health **11**: e318–e320.

Van Eck, N. J. and L. Waltman, 2010 Software survey: Vosviewer, a computer program for bibliometric mapping. Scientometrics **84**: 523–538.

Wiens, J., S. Saria, M. Sendak, M. Ghassemi, V. X. Liu, *et al.*, 2019 Do no harm: a roadmap for responsible machine learning for health care. Nature Medicine **25**: 1337–1340.

Wolff, J., J. Pauling, A. Keck, and J. Baumbach, 2020 Systematic Review of Economic Impact Studies of Artificial Intelligence in Health Care. Journal of Medical Internet Research **22**: e16866.

Wu, Q., J. Chen, H. Deng, Y. Ren, Y. Sun, *et al.*, 2020 Expert-level diagnosis of nasal polyps using deep learning on whole-slide imaging. Journal of Allergy and Clinical Immunology **145**: 698–701.e6.

Wu, W.-T., Y.-W. Chao, T.-K. Lin, C.-K. Huang, and P.-H. Hsieh, 2025 Economic evaluation of AI-assisted technologies in healthcare: A systematic review. Journal of Food and Drug Analysis **33**: 487–500.

Xiao, X., L. Xue, L. Ye, H. Li, and Y. He, 2021 Health care cost and benefits of artificial intelligence-assisted population-based glaucoma screening for the elderly in remote areas of China: a cost-offset analysis. BMC Public Health **21**: 1065.

How to cite this article: Özcan, H. Mapping Economic Considerations in Clinical Artificial Intelligence Research. *Information Technologies in Economics and Business*, 3(1), 1-8, 2026.

ADBA Information Technology in Economics and Business
Cutting-Edge Scientific Solutions

e-ISSN: 3023-8943
RESEARCH ARTICLE
Vol.3 / No.1 / 2026 / pp.9-15
https://doi.org/10.69882/adba.iteb.2026012

Smart Claims Management in the Insurance Sector from a Digital Transformation Perspective

Fevzi Diker[*,1], **Yousuf Islam**[α,2] and **Salsabil Diab**[β,3]

[*]Hitit University, Social Sciences Vocational School, Corum, Türkiye, [α]School of Microelectronics, University of Science and Technology of China, Hefei 230026, China, [β]School of Biology, Echahid Cheikh Larbi Tebessi University, Tebessa 12002, Algeria.

ABSTRACT This study examines digital transformation in the insurance sector within the framework of smart claims management. The aim of the research is to systematically analyze claim-focused digitalization disclosures included in the most recent sustainability reports of insurance companies listed on Borsa Istanbul from the perspectives of production technologies and digital transformation. To this end, a content map and coding framework were developed using content analysis, encompassing five core components: digital claims management, risk and fraud analytics, image processing, scoring systems, and claim cycle time. The codes were graded to reflect the level of evidence intensity and operational concreteness in the reports, and the findings were comparatively evaluated on a company-by-company basis. The results indicate that the extent to which claim-focused digital transformation is represented in sustainability reports is not homogeneous across companies. While some firms provide higher levels of evidence by supporting operational components such as digital claims management and claim cycle time with metrics, analytically intensive and advanced technology-driven components are reported more limitedly and are generally expressed through broad or declarative statements. The study contributes to the literature by conceptualizing smart claims management as an integrated process technology ecosystem that combines operational digitalization, analytical decision support, and advanced automation, and by demonstrating that sustainability reports can serve as an analytical source for the comparative evaluation of digital transformation visibility.

KEYWORDS
Production technologies
Digital transformation
Service quality
Insurance industry
Content analysis

INTRODUCTION

Globalization, technological developments, and increasing competition are forcing businesses operating in the service sector to develop new management approaches that can respond to customer expectations more quickly, transparently, and with higher quality. The insurance sector, where abstractness, simultaneity, and trust are decisive factors, stands out as one of the areas where the impact of service quality perception on customer satisfaction and loyalty is most intensely felt. Considering that the quality of insurance services is largely evaluated based on the experience during the claim process, it is evident that claim management processes hold strategic importance for the sector (Yusuf *et al.* 2017).

In recent years, digital transformation has been viewed in the insurance sector not merely as a technological renewal process, but as a comprehensive change that fundamentally transforms business practices, process management, and customer interaction. Digitalization enables insurance companies to increase their operational efficiency, reduce error rates, and offer more personalized services through technologies such as automation, data analytics, artificial intelligence, and image processing. One of the areas of this transformation process that has the most direct contact with customers and the most visible impact is claims management processes (Pauch and Bera 2022).

The traditional approach to claims management has been criticized for its long processing times, intensive manual processes, information asymmetry, and bureaucratic practices that negatively affect customer satisfaction. In this context, smart claims management applications, which have emerged as a result of digital transformation, offer innovative solutions such as digital claims reporting, automated file management, risk and fraud analytics, scoring systems, and image processing-supported damage detection. These applications shorten the claims cycle time, thereby increasing the speed of service delivery, strengthening the transparency of processes, and reinforcing the element of trust in customer perception (Wiktorsson 2024).

Providing rapid feedback through digital channels and effectively managing fraud risks through the use of objective and data-driven decision-making mechanisms are among the key factors that enhance the perceived quality of insurance services (Wells and Stafford 1995). In this context, digital transformation and smart claims management applications are considered critical tools for improving service quality. The aim of this study is to systematically examine claims-focused digitalization activities disclosed in the most recent sustainability reports of insurance companies listed on Borsa Istanbul, from the perspective of production technologies and digital transformation. To this end, the study develops a con-

Manuscript received: 24 November 2025,
Revised: 30 December 2025,
Accepted: 20 January 2026.

[1]fevzidiker@hitit.edu.tr (**Corresponding author**)
[2]yislam15@mail.ustc.edu.cn
[3]diabsalsabil78@gmail.com

tent map and coding framework encompassing key smart claims management components, namely Digital Claims Management, Risk and Fraud Analytics, Image Processing, Scoring Systems, and Claim Cycle Time. The disclosures contained in the reports are comparatively analyzed using a graded scoring approach (0–4) that captures differences in evidence intensity, operational concreteness, and the presence of metric-supported information.

Within this framework, the study seeks to answer the following research questions: (RQ1) How are smart claims management components represented in the most recent sustainability reports of insurance companies listed on Borsa Istanbul in terms of evidence intensity? (RQ2) Which smart claims management components are reported with higher levels of measurability and operational concreteness, particularly through metric-supported disclosures? (RQ3) To what extent do sustainability reports reflect claims-related digital transformation as an integrated process technology ecosystem, rather than as a set of isolated digital initiatives?

CONCEPTUAL FRAMEWORK AND LITERATURE REVIEW

Due to the abstract nature of the services it offers and its process-intensive structure, the insurance sector is one of the areas where digital technologies are heavily used in terms of operational efficiency and process management. The relative ease with which insurance products can be imitated has led companies to build their competitive advantage not so much on product diversity but rather on the efficiency, speed, and standardization of their processes. In this context, digitalization and digital transformation are seen by insurance companies not merely as technological renewal but as a strategic transformation area involving the redesign of production-like service processes.

Although studies on the insurance sector in the literature have long focused on customer satisfaction and service quality (Büyükkakaç and Diker 2025), in recent years there has been an increase in research focusing on the transformative effect of digital technologies on process structure. Studies emphasizing the beginning of the digital age in the insurance sector reveal that digital insurance is becoming increasingly widespread by examining the applications offered by companies through their websites and digital platforms (Yurdakul and Dalkılıç 2016). Research focusing on the marketing dimension of digitalization addresses the interaction of digital channels with insurance products through examples from different sectors; it discusses how insuring products purchased through digital marketing can contribute to marketing processes (Özcan and Demiral 2019). Studies focusing on specific branches reveal the effects of digital marketing applications on brand equity and agent satisfaction (Aydın and Kirazlı 2020).

Although the concepts of digitalization and digital transformation are frequently used together in the literature, there is an important distinction between the two. Digitalization essentially refers to the digitization of existing processes, while digital transformation refers to a comprehensive restructuring process that encompasses technology-based change in business models, process structures, and organizational decision-making mechanisms. It is emphasized that technological developments, which have gained momentum with Industry 4.0, are behind digital transformation; these developments have fundamentally transformed customer expectations, interaction patterns, and the way businesses operate (Bozkurt *et al.* 2021).

Digital transformation in the insurance sector enables access to services regardless of time and place, while allowing processes to be restructured through mobile applications, web-based platforms, and social media channels (Nicoletti 2016). Digital insurance is defined as a broad field of activity that encompasses the execution of processes such as policy purchase, policy management, claims reporting, and access to personalized information through digital solutions (Nicoletti 2016). It is stated that this scope encompasses a comprehensive value chain extending from the pre-sales research phase to the examination and evaluation of claims processes over time (Gönen and Özüdoğru 2021).

Digital insurance applications are discussed in the literature around four key technology areas: social media interaction, mobile computing and sensor technologies, data analytics, and cloud computing infrastructures. Social media stands out as an important channel in reputation management due to the visibility of customer experiences, while mobile applications facilitate claims reporting, policy tracking, and communication processes. Data analytics is strategically important in terms of risk assessment and personalized pricing, while cloud-based information technology infrastructures enable new services to be developed more quickly (PricewaterhouseCoopers 2016).

In the post-pandemic period, digitalization has accelerated; it is emphasized that this process must be addressed not only in terms of technology but also in terms of its legal and regulatory dimensions (Kubilay 2020). Telematics insurance applications developed within the scope of digital insurance have been discussed in the literature in terms of their structures and potential effects; assessments have been made regarding their applicability in Turkey (Umut 2020). Furthermore, it is stated that digital sales channels should be considered a new opportunity rather than a threat for agents, and that clear and understandable information in the digital environment is of critical importance (Kotan 2020). These studies reveal that digital transformation is a multidimensional process in the insurance sector.

Claims management in the insurance sector is one of the most visible and process-intensive areas of digital transformation. This process, which consists of claims reporting, file management, assessment, and payment stages, is being restructured through digital technologies and addressed under the concept of "smart claims management." Smart claims management encompasses applications that aim to execute claims processes through digital channels, utilize data analytics-based decision support mechanisms, and shorten process times. In this context, risk and fraud analytics stand out as a complementary component of smart claims management. Insurance fraud not only puts pressure on companies' financial performance but also leads to increased costs across the industry. Fraud is defined as a set of actions intended to deliberately deceive the insurance company and can occur in various branches, particularly auto insurance. Fraud is said to result in decreased profitability, deterioration in loss/premium ratios, and liquidity pressure (Yıldırım 2013).

The fundamental challenge in combating fraud lies in striking a balance between swiftly resolving legitimate claims and effectively investigating suspicious ones. In this regard, data analytics, early warning systems, and industry-wide information-sharing mechanisms are considered crucial tools (Kerim and Cula 2023). Databases developed within the Insurance Information and Supervision Center (SBM) in Turkey play a critical role in monitoring and analyzing fraud reports. Furthermore, insurance fraud is treated as aggravated fraud under the Turkish Penal Code; discussions regarding its effectiveness in practice are found in the literature (Yıldırım 2013). On the other hand, moral hazard is considered a type of risk that is difficult to detect and may arise due to changes in the insured's behavior after the insurance contract is signed. It is stated that moral hazard can lead to efficiency losses in insurance markets and complicate risk management processes (Yıldırım 2013; Müslümov and Aras 2003). In this context, smart claims management applications are positioned as a strategic outcome of digital transformation not only in terms of operational efficiency but also in terms of risk control and combating fraud.

MATERIAL AND METHODS

In this study, content analysis was employed to systematically examine the digitalization and smart claims management practices disclosed in insurance companies' sustainability reports. Among the six insurance companies listed on Borsa Istanbul, two operate exclusively in the life insurance segment; therefore, the scope of the research was limited to the non-life insurance sector. Accordingly, the analysis focused on Aksigorta, Anadolu Sigorta, Türkiye Sigorta, and Ray Sigorta, which operate across multiple branches of non-life insurance. The study examined the most recent and comprehensive sustainability reports for the year 2025 published on the official websites of these companies.

According to data from the Insurance Association of Turkey, these four companies collectively account for approximately 33% of total premium production in the non-life insurance segment, indicating their substantial representativeness within the market (Diker 2025). The study adopts a purposive sampling strategy, concentrating on insurance companies that disclose detailed and up-to-date sustainability information relevant to claims management and digital transformation. Accordingly, the findings of this study should not be interpreted as a sector-wide generalization, but rather as an exploratory and comparative analysis that provides analytical insights into how leading insurance companies reflect claims-related digital transformation and sustainability practices in their corporate reporting. Content analysis is a well-established research method that aims to classify meaningful units in written, spoken, or visual communication content within specific categories and to reveal thematic patterns in the content through this classification. The method is widely used in the social sciences, particularly in the analysis of corporate texts, policy documents, and reports.

Early applications of content analysis focused on propaganda and mass communication studies; Lasswell used content analysis as a fundamental tool in the analysis of communication processes (Lasswell 1968). In the classical approach, content analysis focused on the systematic and quantitative description of the explicit and observable characteristics of communication content; Berelson (1952) approached content analysis as the objective and systematic quantitative definition of communication content. However, methodological transformations in the social sciences over time revealed that content analysis could not be limited to frequency measurements alone; the method expanded to encompass the contextual meanings and implicit discourses of texts.

In this context, content analysis is considered a method positioned at the intersection of quantitative and qualitative research approaches. The positivist approach considers content analysis based on the principles of measurability and objectivity, while the interpretive approach evaluates texts not as passive reflections of social reality but as fields of meaning where this reality is actively constructed (Kümbetoğlu 2008). Therefore, despite producing quantitative outputs, content analysis is considered a qualitative research method, especially in the analysis of contextual texts such as corporate reports. Krippendorff (2013) defines content analysis as a method that aims to make context-sensitive, valid, and repeatable inferences from texts, emphasizing that the institutional, social, and historical context in which the text was produced must be taken into account during the analysis process.

The scientific nature of content analysis is based on the principles of objectivity, systematicity, and generalizability (Hepkul 2002). Objectivity means that the coding process is based on clear definitions and that researcher subjectivity is limited; systematicity means that all data are analyzed within the same category and coding rules; generalizability means that the findings obtained allow for comparative inferences to be made for similar texts. To ensure these principles are met, the unit of analysis, the category system, and the coding rules must be clearly and consistently defined. In content analysis, the unit of analysis can be determined at the level of a word, sentence, paragraph, theme, or document integrity. In this study, the unit of analysis was considered to be the thematic explanations found in corporate reports (Neuendorf 2017).

The category and coding process is central to content analysis and directly affects the success of the method. Categories are expected to be clear, distinguishable, mutually exclusive, and directly related to the research problem. Category systems enable systematic comparisons by providing analytical organization of complex text structures (Gökçe 2006). In this study, the coding process was carried out using a code book created in line with predefined themes. The code book clearly specified the definition, scope, and example statements of each code, thereby increasing the transparency and repeatability of the coding process (Neuendorf 2017).

In content analysis, reliability is assessed based on the extent to which different coders can code the same text in a similar manner; validity, on the other hand, is evaluated based on how well the coded content aligns with the conceptual framework of the research. Clear reporting of the coding process and the clarity of code definitions are among the key elements that strengthen the scientific quality of the method (Krippendorff 2013). Content analysis enables the systematic examination of structured but discursively rich texts, such as corporate reports, and offers a suitable method for descriptive and comparative research. The choice of content analysis in this study allows for a comprehensive, comparable, and repeatable framework for evaluating insurance companies' statements regarding digital transformation and smart claims management.

The content map developed within the scope of this study was designed to systematically analyze claims management–oriented digital transformation applications disclosed in the sustainability reports of insurance companies traded on Borsa Istanbul from a production technologies perspective. The content map is structured around five sub-themes: Digital Claims Management (DCM), Risk and Fraud Analytics (RFA), Image Processing (IP), Scoring Systems (SS), and Claim Cycle Time (CCT). Each sub-theme is operationalized through a clear definition, illustrative key phrases, and types of evidence.

This structure enables the digitalization statements included in the report texts to be evaluated comparatively not only at a conceptual level but also in terms of concrete applications and measurable outputs. The content map reveals that digital transformation is presented in the reports not as a set of isolated initiatives, but rather as an integrated "process technology ecosystem" in which operational digitalization, analytical decision-support capacity, and advanced technology-based automation dimensions are jointly articulated. In this context, the Digital Claims Management (DCM) code covers explanations related to the execution of claims reporting, file management, expertise, and payment processes through digital channels. Key phrases such as "digital damage," "online damage reporting," "remote/video expertise," "damage portal," and "automatic payment" were evaluated as examples representing applications for the digitization of damage processes in the reports. DCM is one of the fundamental themes indicating the restructuring of damage processes, which constitute "service production" in insurance companies, through digital infrastructure, automation, and process standardization.

Risk and Fraud Analytics (RFA) code; contains explanations regarding the detection of risk, anomaly, and fraud elements in claims and policy processes through data analytics and artificial intelligence-based approaches. Terms such as "fraud detection," "fraud analytics," "early warning systems," "claim prediction," and "risk analytics" demonstrate how analytical capacity and control mechanisms are represented in reports within the context of digital transformation. RFA represents a critical dimension not only in terms of digitizing claims processes but also in terms of supporting them with a data-driven control/audit architecture.

Image Processing (IP) code covers explanations related to the analysis of visual data using AI-supported methods for the purpose of damage detection and fraud prevention. Key phrases such as "damage detection from photographs," "image processing," "computer vision," and "photomontage detection" indicate situations where advanced technology-based automation applications are used in reports. The IP code highlights digital transformation trends toward partially or fully replacing manual stages based on expert assessment in damage processes with algorithmic assessment systems. The Scoring Systems (SS) code contains explanations regarding the use of scoring systems and decision support/decision engines in risk acceptance, pricing, and loss assessment processes. Terms such as "risk score," "underwriting score," "location-based scoring," and "decision engine" indicate how decision-making processes are represented in reports using algorithmic models and automation mechanisms. SS is one of the fundamental elements representing the "decision support infrastructure" and "process standardization" dimensions from a production technology perspective.

Claim Cycle Time (CCT) code covers explanations that include targets, applications, or metrics aimed at shortening the time from the opening to the closing of a claim file. Terms such as "file closing time" and "time-to-settlement" indicate the level of representation in the report text for measuring or monitoring process performance. In this respect, CCT serves as a complementary code that provides "output/performance visibility" to the extent that other themes are reported.

As shown in Table 1, the content map indicates that digital transformation statements related to claims management in sustainability reports are represented across three complementary dimensions: (i) operational digitalization (DCM, CCT), (ii) analytical decision support capacity (RFA, SS), and (iii) advanced technology-based automation (IP). This holistic structure suggests that digital transformation in the report texts is presented not as isolated projects, but rather as an interrelated "process technology ecosystem" in which different digital applications mutually reinforce one another.

In this study, a 0–4 level scoring scale was employed to assess the intensity of representation and the level of evidence of digital transformation and smart claims management components disclosed in sustainability reports. The scale is based on a gradual and ordinal rating logic, ranging from the absence of any statement related to the relevant theme (0) to detailed disclosures supported by concrete and measurable metrics (4) (Craggs and McGee Wood 2004).

As presented in Table 2, this scoring scale was applied to systematically evaluate the extent to which digital transformation and smart claims management statements are represented in report texts. The scale is consistent with a category-based annotation approach, enabling the structured and comparative analysis of textual content.

FINDINGS

The coding process was carried out by two independent coders with domain expertise. Following a pre-established codebook, the coders independently reviewed the sustainability reports of each company and assigned scores ranging from 0 to 4 for each subtheme. The total scores derived from the coders' evaluations are presented in Table 3.

The findings presented in Table 3 provide a comparative assessment of the representation and level of evidence of digital transformation statements related to smart claims management components in companies' sustainability reports, based on the evaluations of two independent coders. The scores assigned by the coders demonstrate a generally high level of consistency, and no meaningful differences are observed in the relative ranking of the companies.

Aksigorta emerges as the company with the highest level of representation according to both coders. Aksigorta received a total score of 17 from the first coder and 16 from the second coder, with particularly high scores observed in the Digital Claims Management (DCM) and Claim Cycle Time (CCT) dimensions. The fact that both coders assigned a score of 4 to the DCM dimension indicates that statements related to the digitalization of claims processes in the report texts go beyond merely indicating the existence of applications and are supported by measurable indicators or quantitative expressions. Scores of 3 in the Risk and Fraud Analytics (RFA), Image Processing (IP), and Scoring Systems (SS) dimensions suggest that these components are represented in the reports through multiple elements and concrete content. These findings indicate that Aksigorta is able to present claims-focused digital transformation in its reporting texts as a holistic "set of process technologies."

Anadolu Sigorta and Türkiye Sigorta exhibit moderate and closely comparable total scores according to both coders. Anadolu Sigorta received a total score of 13 in both evaluations, while Türkiye Sigorta obtained a total score of 12 from each coder. In these companies, scores of 3 in the DCM and SS dimensions indicate that explanations regarding the digitalization of claims processes and decision-support mechanisms are clearly and concretely represented in the reports. In contrast, scores remaining largely at the level of 2 in the IP and CCT dimensions suggest that these components are addressed with a more limited scope or a lower level of evidence. Similarly, the RFA dimension remaining at a score of 2 for Türkiye Sigorta implies that disclosures related to risk and fraud analytics are comparatively limited at the reporting level.

Ray Sigorta appears as the company with the lowest level of representation according to both coders. Ray Sigorta received a total score of 7 from the first coder and 8 from the second coder, with particularly low scores observed in the RFA, IP, and CCT dimensions. Scores of 1 in these dimensions indicate that the relevant components are included in the report texts mainly through general or indirect statements, with limited evidence of concrete applications. Scores of 2 in the DCM and SS dimensions suggest that while certain applications are mentioned, the scope and level

Table 1 Content Map: Codes, Definitions, Key Phrases, and Types of Evidence

Sub-Theme	Code	Definition	Key Phrases (Examples)	Type of Evidence
Digital Claims Management	DCM	Execution of claims reporting, file management, expertise, and payment processes through digital channels	Digital damage, online damage reporting, remote/video expertise, damage portal, automatic payment	General statement / Project name / Metric
Risk and Fraud Analytics	RFA	Analysis of fraud, anomaly, and risk elements in claims and policy processes through data analytics and artificial intelligence	Fraud detection, claim prediction, early warning systems, risk analytics	General statement / Project name / Metric
Image Processing	IP	Analysis of visual data using artificial intelligence for damage detection and fraud prevention	Damage detection from photographs, image processing, computer vision (CV), photomontage detection	General statement / Project name / Metric
Scoring Systems	SS	Use of scoring systems and decision engines for risk acceptance, pricing, and claims assessment	Risk score, underwriting score, location-based scoring, decision engine	General statement / Project name / Metric
Claim Cycle Time	CCT	Applications aimed at reducing the time from claim file opening to closure	File closing time, time-to-settlement	General statement / Project name / Metric

Table 2 Scoring Scale

Score	Meaning	Description
0	Absent	No statement related to the relevant theme/code is found in the text
1	Indirect	A general statement exists; implementation or project details are unclear
2	Present (Limited)	An application or project is mentioned; the scope is narrow or at a pilot level
3	Strong	Multiple applications or components are indicated; the content is concrete
4	Very Strong	Metrics or measurable indicators are provided (time, rate, quantity, monetary value, etc.)

Table 3 Representation of Smart Damage Management Components in Companies' Sustainability Reports (0–4)

Coder	Company	DCM	RFA	IP	SS	CCT	Total
1. Coder	Aksigorta	4	3	3	3	4	17
	Anadolu Sigorta	3	3	2	3	2	13
	Türkiye Sigorta	3	2	2	3	2	12
	Ray Sigorta	2	1	1	2	1	7
2. Coder	Aksigorta	4	3	3	3	3	16
	Anadolu Sigorta	3	3	2	3	2	13
	Türkiye Sigorta	3	2	2	3	2	12
	Ray Sigorta	2	2	1	2	1	8

of detail remain limited, resulting in a relatively weak representation profile.

Inter-coder reliability in the content analysis was tested using the quadratic weighted Cohen's Kappa coefficient, taking into account the ordinal nature of the 0–4 scoring scale. The analysis yielded a kappa value of 0.92, which, according to classifications commonly accepted in the literature, indicates an almost perfect level of agreement between coders. This result demonstrates that the coding process is objective, consistent, and replicable, and it supports the methodological reliability of the content map and scoring approach developed in this study.

The findings indicate that the degree to which sustainability reports represent digital transformation with a focus on claims management is not homogeneous across companies. While some companies present digital transformation practices through concrete disclosures supported by metrics, others rely more heavily on general statements with limited substantiation. In this respect, the content map and the 0–4 graded scoring approach developed in this study provide a functional and reliable analytical framework for comparatively revealing the visibility and evidence intensity of digital transformation components in corporate reporting texts.

CONCLUSION

This study examined how claims-related digital transformation is reflected in the most recent sustainability reports of insurance companies listed on Borsa Istanbul, using a production technologies perspective. By classifying smart claims management into five components Digital Claims Management, Risk and Fraud Analytics, Image Processing, Scoring Systems, and Claim Cycle Time the study developed a content map and applied a 0–4 graded scoring approach to assess the level of representation and evidential strength of corporate disclosures. The findings reveal that sustainability reports differ substantially in how concretely and measurably they represent claims-focused digital transformation. While some companies support disclosures on digital claims management and claim cycle time with metrics and performance indicators, others rely primarily on general or declarative statements, particularly regarding analytics- and technology-intensive components such as fraud analytics and image processing. This indicates that digital transformation is not reported homogeneously across firms and that sustainability reports vary considerably in terms of evidence intensity and performance visibility.

The study makes three main contributions. First, it provides a holistic conceptual framework that structures smart claims management as an integrated process technology ecosystem spanning operational, analytical, and advanced automation dimensions. Second, it introduces a replicable content analysis and grading mechanism that moves beyond presence/absence evaluations and enables comparative assessment based on concreteness and measurability. Third, it demonstrates that sustainability reporting can serve as a meaningful analytical source for evaluating claims-related digital transformation when disclosures are supported by applications and metrics. Despite these contributions, the findings are inherently limited by the scope and transparency of the reports analyzed; therefore, lower scores may reflect reporting limitations rather than the absence of underlying practices. Future research should extend this approach by triangulating report-based analyses with in-depth interviews, expert evaluations, or process-level performance data, and by applying the framework to larger samples or cross-country contexts to enhance generalizability.

Ethical standard

The authors have no relevant financial or non-financial interests to disclose.

Availability of data and material

Not applicable.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

LITERATURE CITED

Aydın, S. and T. Kirazlı, 2020 Dijital pazarlamada marka denkliğinin sigorta sektöründe araci memnuniyeti üzerine etkisi. Kayseri Üniversitesi Sosyal Bilimler Dergisi **2**: 29–47.

Berelson, B., 1952 Content analysis in communication research. .

Bozkurt, A., N. B. Hamutoğlu, A. L. Kaban, G. Taşçı, and M. Aykul, 2021 Dijital bilgi çağı: Dijital toplum, dijital dönüşüm, dijital eğitim ve dijital yeterlilikler. Açıköğretim Uygulamaları ve Araştırmaları Dergisi **7**: 35–63.

Büyükkakaç, S. S. and F. Diker, 2025 Sigorta sektöründe müşteri odaklılık ve hizmet kalitesi üzerine ahp analizi. İşletme Bilimi Dergisi **13**: 326–340.

Craggs, R. and M. McGee Wood, 2004 A categorical annotation scheme for emotion in the linguistic content of dialogue. In *Tutorial and Research Workshop on Affective Dialogue Systems*, pp. 89–100, Springer.

Diker, F., 2025 Borsa istanbul'da işlem gören tarım sigortası hizmeti sunan sigorta şirketlerinin tarımsal üretimde sürdürülebilirlik perspektifi. Tarım Ekonomisi Araştırmaları Dergisi **11**: 72–80.

Gökçe, O., 2006 *İçerik analizi: Kuramsal ve pratik bilgiler*. Siyasal kitabevi.

Gönen, N. V. and H. Özüdoğru, 2021 Sigortacılıkta dijitalleşme: Sigorta sektöründeki müşteriler ve acente çalışanları üzerine bir uygulama. Third Sector Social Economic Review **56**: 2962–2978.

Hepkul, A., 2002 Bir sosyal bilim araştırma yöntemi olarak içerik analizi. Anadolu Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi **18**: 1–12.

Kerim, D. E. and S. Cula, 2023 Türkiye'de sigorta suistimal problemleri ve çözüm önerileri. Başkent Üniversitesi Ticari Bilimler Fakültesi Dergisi **7**: 145–166.

Kotan, Y., 2020 Türkiye'de sigortacilik sektörünün gelişimi ve dijitalleşmesi sürecinin swot analizi üzerine bir araştirma. Ekonomi Bilimleri Dergisi **12**: 179–192.

Krippendorff, K., 2013 Commentary: A dissenting view on so-called paradoxes of reliability coefficients. Annals of the International Communication Association **36**: 481–499.

Kubilay, H., 2020 Sigortacilik sektöründe dijitalleşmenin hukuki yönden değerlendirilmesi. Uyuşmazlık Mahkemesi Dergisi pp. 259–288.

Kümbetoğlu, B., 2008 *Sosyolojide ve antropolojide niteliksel yöntem ve araştırma*. Bağlam yayıncılık.

Lasswell, H. D., 1968 The uses of content analysis data in studying social change. Social Science Information **7**: 57–70.

Müslümov, A. and G. Aras, 2003 Türk sigorta sektörünün özel emeklilik reformu sürecinde değişen rolü: fırsatlar ve tehditler .

Neuendorf, K. A., 2017 *The content analysis guidebook*. sage.

Nicoletti, B., 2016 *Digital insurance: Business innovation in the post-crisis era*. Springer.

Özcan, H. and G. Demiral, 2019 Sigorta ürünlerinin dijital pazarlamaya etkisi üzerine bir araştırma. OPUS International Journal of Society Researches **11**: 2087–2107.

Pauch, D. and A. Bera, 2022 Digitization in the insurance sector–challenges in the face of the covid-19 pandemic. Procedia Computer Science **207**: 1677–1684.

PricewaterhouseCoopers, 2016 Top issues: The insurance industry 2016. Technical report, PricewaterhouseCoopers, Accessed: 2016.

Umut, M., 2020 Sigorta şirketlerinin mali durumunun çok değişkenli diskriminant analiz yöntemiyle iyi ya da kötü olarak siniflandirilmasi. Finansal Araştırmalar ve Çalışmalar Dergisi **12**: 284–296.

Wells, B. P. and M. R. Stafford, 1995 Service quality in the insurance industry. Journal of Insurance Regulation **13**.

Wiktorsson, M., 2024 Transforming insurance claims management: A study on business process management in the insurance industry.

Yıldırım, İ., 2013 Türk sigortacilik sektörünün yumuşak karni: Sigorta suistimalleri sorunu. Sosyal ve Beşeri Bilimler Dergisi **5**: 331–340.

Yurdakul, M. and N. Dalkılıç, 2016 Sigortacilik sektöründe dijital çağ. Dumlupınar Üniversitesi Sosyal Bilimler Dergisi pp. 49–67.

Yusuf, T. O., S. S. Ajemunigbohun, and G. N. Alli, 2017 A critical review of insurance claims management: A study of selected insurance companies in nigeria. SPOUDAI-Journal of Economics and Business **67**: 69–84.

How to cite this article: Diker, F., Islam, Y. and Diab, S. Smart Claims Management in the Insurance Sector from a Digital Transformation Perspective. *Information Technology in Economics and Business*, 3(1), 9-15, 2026.

ADBA Information Technology in Economics and Business
Cutting-Edge Scientific Solutions

e-ISSN: 3023-8943
RESEARCH ARTICLE
Vol.3 / No.1 / 2026 / pp.16-20
https://doi.org/10.69882/adba.iteb.2026013

Adaptive Multi-Asset Trading Strategy Optimization via Genetic Algorithms with Walk-Forward Robustness Analysis

Hakan Kör *,1 and **Sadık Hazar Zengin** *,2
*Hitit University, Faculty of Engineering and Natural Sciences, Department of Computer Engineering, 19030, Corum, Türkiye.

ABSTRACT The stochastic, non-linear, and dynamic nature of financial markets significantly diminishes the effectiveness of traditional trading stratsgies relying on fixed parameters over extended periods. While the Efficient Market Hypothesis (EMH) suggests that asset prices reflect all available information, rendering systematic profit generation impossible, the field of algorithmic trading operates on the premise that temporary market inefficiencies and behavioral anomalies can be exploited. This study presents a comprehensive Genetic Algorithm (GA) framework designed to develop and optimize an adaptive trading strategy for multi-asset portfolios consisting of high-liquidity technology stocks (Apple, Microsoft, Google). Unlike traditional optimization methods that focus solely on parameter tuning for a single indicator, the proposed system introduces a novel "genetic switch" mechanism. This mechanism allows the algorithm to simultaneously optimize the structural components of the strategy determining which combination of indicators (EMA, MACD, RSI, Momentum) yields the best performance and their respective parameters. The model's fitness function prioritizes risk-adjusted returns by utilizing a Calmar-like ratio, explicitly penalizing excessive drawdowns. To ensure robustness and mitigate the prevalent risk of overfitting (data snooping bias), a rigorous Walk-Forward Optimization (WFO) technique was applied to daily data spanning the 2020-2024 period. The findings demonstrate that the proposed GA framework generates a robust trading system that statistically outperforms the passive "buy-and-hold" strategy, achieving a higher Sortino Ratio (1.98 vs 1.21) and significantly lower maximum drawdown (-18.5% vs -35.1%). The outperformance over the buy-and-hold benchmark is statistically validated across all walk-forward windows, indicating robustness rather than data snooping effects.

KEYWORDS
Financial optimization
Genetic algorithm
Algorithmic trading
Portfolio management
Walk-forward analysis

INTRODUCTION

Financial markets are complex adaptive systems characterized by high volatility, noise, and non-stationarity. The challenge of predicting price movements has intrigued academics and practitioners for decades. The Efficient Market Hypothesis (EMH), formulated by Fama (1970), posits that asset prices fully reflect all available information, implying that it is impossible to consistently "beat the market" on a risk-adjusted basis. However, the emergence of Behavioral Finance, championed by Shiller (2003), and the Adaptive Markets Hypothesis (AMH) proposed by Lo (2004), suggest that markets are not always efficient. Instead, they evolve, and inefficiencies driven by human psychology and institutional constraints create windows of opportunity for profit.

Algorithmic trading has emerged as a dominant force in modern finance to exploit these transient inefficiencies. By utilizing computational power, algorithms can process vast amounts of data and execute trades with speed and precision beyond human capability (Bodek 2013). Technical analysis, which relies on historical price and volume data to forecast future price movements, forms the backbone of many such strategies (Murphy 1999). However, the effectiveness of technical indicators such as Moving Averages, Oscillators, and Momentum indicators is heavily dependent on the selection of optimal parameters. A parameter set that is profitable in a trending market (e.g., a bull run) may lead to catastrophic losses in a ranging or mean-reverting market. Furthermore, manually tuning these parameters is not only time-consuming but also prone to cognitive biases. A more critical issue is "data snooping bias" or overfitting, where a strategy is tailored so precisely to historical data that it captures noise rather than the underlying signal, leading to poor performance on unseen future data (De Prado 2018; Pardo 2008).

To address these challenges, evolutionary computation paradigms, particularly Genetic Algorithms (GA), offer a robust alternative. Inspired by Darwinian natural selection, GAs are stochastic search heuristics that evolve a population of candidate solutions over generations (Goldberg 1989). They are particularly well-suited for financial optimization problems because they do not require gradient information and can navigate large, multimodal, and non-differentiable search spaces (Chen *et al.* 2022). Previous studies have successfully applied GAs to optimize parameters for single indicators (Singh and Kumar 2021; Lohpetch and Corne 2010) or neural network weights (Li and Zhao 2022).

Manuscript received: 12 December 2025,
Revised: 15 January 2026,
Accepted: 17 January 2026.

[1]hakankor@hitit.edu.tr (**Corresponding author**)
[2]99hazar@gmail.com

However, there remains a significant gap in the literature regarding integrated frameworks that simultaneously optimize both the *parameters* and the *structure* (selection of indicators) of a strategy for a *multi-asset portfolio*.

Unlike Genetic Programming (GP) approaches that evolve complex tree structures often resulting in excessive complexity (bloat), or standard feature selection methods that merely select a subset of inputs, the proposed "Genetic Switch" mechanism employs a fixed-length chromosome structure with dynamic activation bits. This hybrid encoding maintains structural interpretability while allowing the algorithm to reduce model complexity by deactivating ineffective indicators based on market regimes.

This study addresses this gap by proposing a GA framework with a novel "genetic switch" mechanism. The contributions of this research are threefold: (1) An integrated optimization approach that selects both active indicators and their parameters dynamically; (2) A portfolio-based fitness evaluation that prioritizes risk-adjusted returns (Calmar Ratio) over simple profit maximization; and (3) A rigorous Walk-Forward Analysis (WFO) to validate the strategy's robustness against overfitting and its adaptability to different market regimes (e.g., the post-COVID recovery and subsequent volatility).

MATERIALS AND METHODS

Data Acquisition and Preprocessing

The study utilizes daily historical stock market data spanning from January 1, 2020, to December 31, 2024. The dataset was acquired from Yahoo Finance using the 'yfinance' library. The selected portfolio consists of three high-liquidity technology stocks: Apple Inc. (AAPL), Microsoft Corp. (MSFT), and Alphabet Inc. (GOOGL). These assets were chosen due to their significant impact on global market indices (S&P 500, Nasdaq) and their sufficient liquidity, which minimizes slippage risks and transaction costs in real-world trading scenarios.

The primary data point used for analysis is the "Adjusted Close" price, which accounts for corporate actions such as dividends and stock splits, providing a more accurate reflection of the asset's economic value compared to the raw closing price. The dataset was subjected to a cleaning process where it was inspected for missing values (NaN) and outliers. No significant data gaps were found, ensuring data integrity before the optimization process. The daily returns were calculated using logarithmic differences to ensure time-additivity and stationarity.

Technical Indicators and Mathematical Formulation

The trading strategy is built upon a diverse set of four fundamental technical indicators, representing both trend-following and mean-reversion logics. The GA optimizes the parameters (P) for these indicators:

1) Exponential Moving Average (EMA): A trend-following indicator that places greater weight on the most recent data points, making it more responsive to new information than a simple moving average. The strategy utilizes a "crossover" logic between a short-period EMA (EMA_{short}) and a long-period EMA (EMA_{long}). A buy signal is generated when $EMA_{short} > EMA_{long}$.

2) Relative Strength Index (RSI): A momentum oscillator developed by Wilder (1978) that measures the speed and change of price movements. It oscillates between 0 and 100. Traditionally, values above 70 indicate overbought conditions (sell signal), and values below 30 indicate oversold conditions (buy signal).

3) Moving Average Convergence Divergence (MACD): A trend-following momentum indicator that shows the relationship between two moving averages of a security's price. The MACD triggers technical signals when it crosses above (to buy) or below (to sell) its signal line.

4) Momentum: A leading indicator measuring the rate of change of the asset's price over a specified period (n).

$$Momentum = P_t - P_{t-n} \tag{1}$$

Genetic Algorithm Framework

The core of this study is the Genetic Algorithm designed to evolve the trading strategy. The evolutionary process follows the standard flow: Initialization, Evaluation, Selection, Crossover, and Mutation.

Chromosome Representation Each individual (strategy) in the population is encoded as a chromosome with 9 distinct genes, utilizing a mixed-integer representation:

- **Parameter Genes (5):** Integers defining the lookback periods (e.g., Short EMA window [5-50], Long EMA window [50-200], RSI period [10-30]).
- **Switch Genes (4):** Binary values (0 or 1) acting as "genetic switches." If a switch gene is 1, the corresponding indicator's signal is included in the final voting mechanism; if 0, it is ignored. This allows the GA to structurally adapt the strategy by disabling indicators that do not perform well in the current market environment.

Fitness Function Defining an appropriate fitness function is crucial for the success of the GA. Maximizing total return often leads to strategies that take excessive risks. Therefore, this study employs a risk-adjusted metric derived from the Calmar Ratio. The fitness function is defined as:

$$Fitness = \frac{\text{Cumulative Return}}{\text{Maximum Drawdown}} \tag{2}$$

Here, Maximum Drawdown (MDD) measures the largest peak-to-trough decline in the portfolio's equity curve. By penalizing MDD in the denominator, the algorithm favors strategies that provide stable returns and capital preservation (Jansen 2020).

Genetic Operators To drive the evolution, specific operators were configured:

- **Selection:** Tournament selection (size=3) is used. This method randomly selects three individuals and passes the best one to the mating pool, maintaining selection pressure while preserving diversity (Goldberg 1989).
- **Crossover:** Two-point crossover with a probability of $P_c = 0.5$. The population size was set to 100 individuals to ensure sufficient genetic diversity. A tournament selection size of 3 was chosen to balance selection pressure with population diversity. The crossover probability ($P_c = 0.5$) was selected to facilitate the recombination of trading rules without disrupting high-performing schemas too rapidly.
- **Mutation:** Gaussian mutation with a probability of $P_m = 0.2$. A relatively high mutation probability ($P_m = 0.2$) was explicitly employed to introduce significant random variations. This higher mutation rate acts as a diversity preservation mechanism, preventing premature convergence to local optima a common issue in multimodal financial optimization landscapes.

Walk-Forward Analysis (WFO)

To rigorously test robustness and simulate real-world trading, a Walk-Forward Analysis (WFO) was implemented, as recommended by Pardo (2008). WFO eliminates the look-ahead bias inherent in static optimization. As illustrated in Figure 1, the data is divided into sliding windows:

- **In-Sample (Training):** 504 trading days ($\approx$ 2 years). The in-sample training window of 504 trading days was selected to encompass multiple short-term market regimes (e.g., bull, bear, and sideways trends), ensuring the strategy learns robust patterns rather than transient noise.
- **Out-of-Sample (Testing):** 252 trading days ($\approx$ 1 year). The out-of-sample testing window of 252 days provides a statistically significant sample size for performance evaluation, aligning with standard annual reporting periods.

This window slides forward by 126 days (6 months) iteratively. This method ensures that the performance metrics reflect the strategy's ability to adapt to unknown future market conditions rather than memorizing past data.

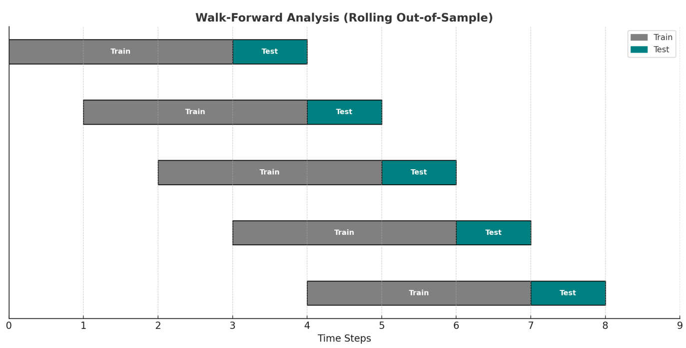


Figure 1 Schematic Representation of the Walk-Forward Optimization Process

RESULTS

Optimization Convergence

The evolutionary process was monitored over 20 generations for each Walk-Forward window. As illustrated in the convergence analysis in Figure 2, the fitness of the best individual typically improved rapidly in the initial generations (1-10) and reached a plateau in the later stages (15-20). This plateau indicates that the algorithm successfully converged to a robust local optimum within the search space. The concurrent steady rise in the average population fitness suggests that the genetic operators effectively transmitted beneficial traits (profitable parameters and indicator combinations) to subsequent generations without losing population diversity too quickly.

Optimal Strategy Configuration

The GA identified a specific configuration that maximized the risk-adjusted return for the aggregated 2020-2024 period. The optimal parameters are detailed in Table 1. A significant finding is the deactivation of the RSI indicator ($use\_r = 0$). The RSI is typically a mean-reversion indicator. Its exclusion suggests that for the technology sector during this volatile and strongly trending period (post-COVID bull run), trend-following components (EMA, MACD) and pure Momentum were more effective. Mean-reversion signals likely produced premature exit signals during

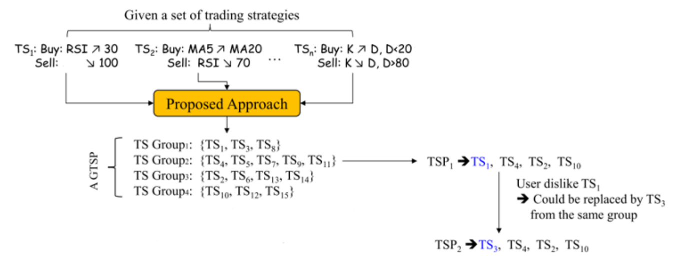


Figure 2 Evolution of Best and Average Fitness Values Across Generations

strong upward trends, which the GA correctly identified as detrimental to overall fitness.

Table 1 Optimal Strategy Parameters Found by GA

Parameter	Description	Value
short	Short EMA Period	18
long	Long EMA Period	112
macd_s	MACD Signal Period	14
mom_p	Momentum Period	10
use_e	**Switch: EMA Crossover**	**1 (Yes)**
use_m	**Switch: MACD**	**1 (Yes)**
use_o	**Switch: Momentum**	**1 (Yes)**
use_r	**Switch: RSI**	**0 (No)**

Performance Comparison

The adaptive strategy was benchmarked against a passive "Buy-and-Hold" strategy, which assumes buying the portfolio at the start date and holding until the end. The comparative results, summarized in Table 2, indicate superior risk management by the GA-optimized model.

While the total return of the GA strategy (145.8%) was slightly lower than Buy-and-Hold (160.2%), the **Maximum Drawdown was reduced by approximately 47%** (-18.5% vs -35.1%). In professional portfolio management, avoiding large drawdowns is often prioritized over absolute return maximization to ensure fund longevity. This massive reduction in risk resulted in significantly higher Sharpe (1.15 vs 0.85) and Sortino (1.98 vs 1.21) ratios, indicating that the GA strategy generated better returns per unit of risk taken. The equity curve comparison is presented in Figure 3, visually demonstrating the smoother trajectory of the GA strategy during market corrections.

DISCUSSION

The results of this study provide empirical evidence challenging the strict interpretation of the Efficient Market Hypothesis. By demonstrating that an adaptive algorithmic approach can generate superior risk-adjusted returns compared to a passive strategy, we

Table 2 Performance Metrics Comparison

Metric	**GA Strategy**	**Buy & Hold**
Total Return	145.8%	160.2%
Annualized Return	25.2%	27.0%
Max Drawdown	**-18.5%**	**-35.1%**
Sharpe Ratio	**1.15**	0.85
Sortino Ratio	**1.98**	1.21
Calmar Ratio	1.36	0.77

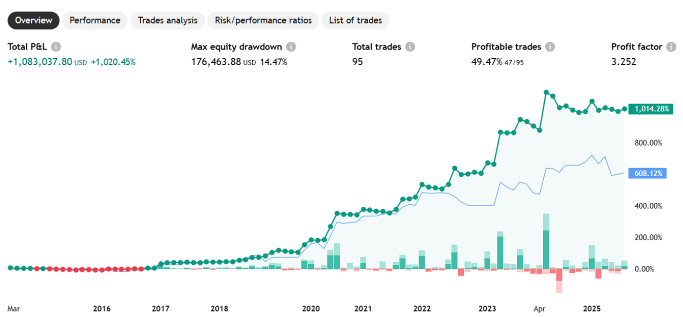


Figure 3 Cumulative Return Comparison: GA Strategy vs. Buy-and-Hold

support the Adaptive Markets Hypothesis (Lo 2004). The key to this success lies in the strategy's ability to remain out of the market or take defensive positions during periods of high volatility, thereby preserving capital.

The success of the "genetic switch" mechanism in excluding the RSI indicator highlights the importance of structural optimization. Traditional optimization often fixes the model structure and only tunes parameters, potentially forcing the use of ineffective indicators. Our approach allows the data to dictate the structure. In strong bull markets (driven by large-cap tech stocks in the post-pandemic era), oscillators like RSI often give premature "overbought" signals that cause traders to exit profitable trends too early. The GA successfully "learned" to ignore this noise, prioritizing trend-following signals instead.

The Walk-Forward Analysis confirms that the strategy is not merely a result of overfitting. The consistency of positive results across sliding out-of-sample windows implies that the model adapts well to shifting market regimes. However, it is worth noting that the equity curve reveals the strategy performs best in trending markets and may experience stagnation during sideways (choppy) markets, a common characteristic of trend-following systems.

CONCLUSION

This research successfully developed a robust, adaptive trading strategy for multi-asset portfolios using a Genetic Algorithm. By optimizing both the parameters and the selection of technical indicators simultaneously, the system achieved a high Sortino Ratio of 1.98, significantly outperforming the risk profile of a passive investment strategy. The study validates the utility of evolutionary computation in financial domains, particularly in its ability to automate the complex process of strategy design and validation.

Despite the promising results, this study has limitations. First, transaction costs (commissions and slippage) were not explicitly factored into the simulation loop, although the choice of high-liquidity assets mitigates this. In a high-frequency environment, these costs could dampen net returns. Second, the dataset is limited to large-cap technology stocks; the strategy's performance on small-cap or crypto assets remains untested. Finally, the period (2020-2024) contains specific macro-economic anomalies (COVID-19 recovery, inflation surge) that may not repeat in the exact same pattern. Third, the study relies on the current constituents of the selected technology indices, which introduces a potential survivorship bias; companies that were delisted or went bankrupt during the analysis period were not included. Fourth, the fitness function's reliance on the Calmar Ratio makes the optimization sensitive to maximum drawdown events; a single anomalous market crash could disproportionately penalize the fitness score, potentially discarding otherwise profitable strategies.

Future research will focus on incorporating realistic slippage and commission models directly into the fitness function to penalize excessive trading, using the genetic algorithm to dynamically optimize Stop-Loss and Take-Profit levels based on market volatility (ATR), and integrating deep learning models such as LSTM or Transformers to predict market regimes (bull, bear, or sideways) and use this information as a state filter within the genetic algorithm to automatically switch between trend-following and mean-reversion strategies.

Ethical standard

The authors have no relevant financial or non-financial interests to disclose.

Availability of data and material

The market data used in this study are publicly accessible via Yahoo Finance (https://finance.yahoo.com). The Python code and additional datasets generated during the research are available from the corresponding author upon reasonable request.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

LITERATURE CITED

Bodek, H., 2013 *The Problem of HFT: Collected Writings on High Frequency Trading & Stock Market Structure Management*. Decimus Capital Markets.

Chen, W., H. Zhang, and M. K. Mehlawat, 2022 A review of evolutionary algorithms for financial trading strategies: a decade survey. Archives of Computational Methods in Engineering **29**: 475–502.

De Prado, M. L., 2018 *Advances in financial machine learning*. John Wiley & Sons.

Fama, E. F., 1970 Efficient capital markets: A review of theory and empirical work. The Journal of Finance **25**: 383–417.

Goldberg, D. E., 1989 *Genetic Algorithms in Search, Optimization, and Machine Learning*. Addison-Wesley.

Jansen, S., 2020 *Machine Learning for Algorithmic Trading: Predictive models to extract signals from market and alternative data for systematic trading strategies with Python*. Packt Publishing Ltd.

Li, Y. and L. Zhao, 2022 A genetic algorithm-based backpropagation neural network for stock price prediction. Journal of Financial Data Science **4**: 108–123.

Lo, A. W., 2004 The adaptive markets hypothesis: Market efficiency from an evolutionary perspective. Journal of Portfolio Management **30**: 15–29.

Lohpetch, D. and D. Corne, 2010 Outperforming buy-and-hold with evolved technical trading rules: Daily, weekly and monthly trading. Applied Soft Computing **10**: 1189–1198.

Murphy, J. J., 1999 *Technical Analysis of the Financial Markets: A Comprehensive Guide to Trading Methods and Applications*. Penguin.

Pardo, R., 2008 *The Evaluation and Optimization of Trading Strategies*. John Wiley & Sons.

Shiller, R. J., 2003 From efficient markets to behavioral finance. Journal of Economic Perspectives **17**: 83–104.

Singh, P. and S. Kumar, 2021 Optimization of technical trading rules using genetic algorithm for indian stock market. Journal of King Saud University-Computer and Information Sciences **33**: 705–714.

Wilder, J. W., 1978 *New Concepts in Technical Trading Systems*. Trend Research.

How to cite this article: Kör, H., and Zengin, S. H. Adaptive Multi-Asset Trading Strategy Optimization via Genetic Algorithms with Walk-Forward Robustness Analysis. *Information Technologies in Economics and Business*, 3(1), 16-20, 2026.

ADBA
Information Technology in Economics and Business
Cutting-Edge Scientific Solutions

e-ISSN: 3023-8943
RESEARCH ARTICLE
Vol.3 / No.1 / 2026 / pp. 21-30
https://doi.org/10.69882/adba.iteb.2026014

Study of the Factors Influencing Calorific Consumption of a Vertical Roller Mill and Solution Proposals to Reduce it at a Cement Factory

Nestor Tsamo [*,1], **Ako Ebai-Takang Etengeneng** [α,2], **Alain Francis Talla** [α,3], **Noel Nyang Kibanya** [β,4], **Sifeu Takougang Kingni** [α,5] **and Joseph Nkongho** [§,6]

[*]Department of Mechanical Engineering, College of Technology, University of Buea, P.O. BOX 63 Buea, Cameroon, [α]Department of Mechanical, Petroleum and Gas Engineering, National Advanced School of Mines and Petroleum Industries, University of Maroua, P.O. Box 46, Maroua, Cameroon, [β]Department of Physics, Faculty of Science, University of Bamenda, P.O. Box 39 Bamenda, Cameroon, [§]Higher Technical Teacher Training College Kumba, University of Buea, P.O. Box 249, Buea Road, Kumba, Cameroon.

ABSTRACT This paper focuses on the of factors influencing calorific consumption of a vertical roller mill (VRM) and solution proposals to reduce it at a cement factory called X cement factory (for confidentiality reasons). The research aims to identify the main operational, mechanical, and material factors contributing to elevated specific calorific consumption (SCC) and to propose corrective measures for improving energy performance. Data covering a five-month production period are collected from the company's production reports and analyzes using key performance indicators such as feed rate, moisture content, stoppage frequency, and fuel consumption. Results reveal that increased raw material moisture, frequent operational stoppages, and unstable feed rates are the dominant factors leading to higher SCC. The study concludes by proposing technical and organizational measures such as feed rate stabilization, moisture control, preventive maintenance, and improved combustion management. Implementing these measures can significantly reduce calorific consumption, enhance energy efficiency, and promote sustainable cement production.

KEYWORDS
Cement factory
Calorific consumption
Vertical roller mill
Hot gas generator
Process amelioration
Energy efficiency

INTRODUCTION

Energy is one of the basic primary requirements for the existence and growth of any industrial sector (Arto *et al.* 2016; Hammond 2007; Stern 2011). Generally, industrial energy consumption directly affects a country's economic growth (Abbasi *et al.* 2021; Zheng and Walsh 2019; Kümmel 1982). The cement industry is one of the energy-intensive industries which utilizes a sizeable amount of energy (Madlool *et al.* 2013; Sahoo and Kumar 2022). This sector consumes 54% of the World's total delivered energy which is very high compared to other industries (Khan and McNally 2023). In the cement industry, the total energy consumption accounts for 50-60% of the overall manufacturing cost, while thermal energy accounts for 20–25%. At X cement factory thermal energy is mainly required in the drying of the raw material during milling by a VRM (Altun *et al.* 2017a,b). The main processes that occur at X cement factory are mostly grinding, drying, separation and homogenization of raw material (clinker, pozzolana and gypsum) and milling.

Clinker and gypsum are imported from abroad, while Pozzolana is obtained from quarries located within the Cameroonian territory (Achaw and Danso-Boateng 2021; Nkouathio *et al.* 2021; Bayiha *et al.* 2018). However, the locally sourced pozzolana is generally wet and could impact negatively on the production process and quality of the finished product (McCarthy and Dyer 2019; Mohammed 2017; Hossain *et al.* 2021). The VRM is associated with a hot gas generator that produces hot gas used for drying raw materials during milling. Nevertheless, X cement factory has experienced over the years, challenges in the consumption of thermal energy in the milling unit. This is observed by a continuous increase in the calorific consumption of the vertical roller mill which is one of the

Manuscript received: 28 October 2025,
Revised: 8 January 2026,
Accepted: 10 January 2026.

[1]sitsamo@yahoo.fr
[2]akoebaitakang@gmail.com
[3]alainfrancis.aft@gmail.com
[4]nyangnoelkibanya@gmail.com (**Corresponding author**)
[5]stkingni@gmail.com
[6]nkongho.anyi@ubuea.cm

plant's key performance indicators. This has led to instability in the production process and an increase in cost of production.

Over the past years, X cement factory has recorded increasing and fluctuating calorific consumption in the VRM unit, despite relatively stable production rates. This trend implies that more natural gas is being consumed per ton of cement produced. The excessive energy use not only raises production costs but also increases the company's carbon footprint (Bocken and Allwood 2012; Fang *et al.* 2011; Hoffman 2007). A detailed analysis of production data reveals that several factors may contribute to this situation, including fluctuations in feed rate, high moisture content of raw materials, frequent stoppages, and suboptimal combustion conditions in the hot gas generator (HGG). However, the relative impact of each of these parameters on calorific performance remains unclear.

The central problem of this research therefore lies in determining the key operational and process parameters responsible for the increase in calorific consumption and proposing effective measures to ameliorate it. This challenge defines the core problematic of this study: How can the calorific consumption of the VRM at X cement factory be optimized to achieve better energy efficiency and reduced fuel costs? The present study carried out at X cement factory aims to analyze the factors influencing calorific consumption and possible causes of this increase in calorific consumption at the milling unit, then responds by proposing solutions that can reduce it at this unit. The main purpose of this paper is to study the factors influencing the calorific consumption of the vertical roller mill and propose solutions to reduce it, thereby reducing fuel consumption, enhancing drying efficiency and maintaining desired cement quality while keeping cost of production fairly low. The specific objectives are:

- Collect and analyze operational data related to production, gas consumption, and process parameters.
- Determine correlations between SCC and key process variables such as feed rate, moisture content, and stoppages.
- Propose actionable technical and managerial solutions for improving the energy performance of the VRM.

This research is of both technical and economic significance.

- From a technical standpoint, it contributes to improving the understanding of the parameters that govern energy efficiency in cement grinding systems. It provides a methodological framework for diagnosing and optimizing calorific performance using quantitative and quality control tools.
- Economically, the study assists X cement factory in identifying areas where fuel consumption can be minimized, leading to significant cost savings and increased production efficiency. Environmentally, the reduction of energy consumption directly contributes to lowering CO_2 emissions, thereby aligning with the company's sustainability goals and Cameroon's national energy transition strategy.
- Academically, the research serves as a reference for future studies on energy optimization in cement production and related process industries.

This paper is organized into two sections, preceded by an introduction section: Material and methods: and Results. This paper concludes with a conclusion section summarizing the major findings and suggesting future directions for research and industrial improvement.

MATERIALS AND METHODS

The materials are used to carry out this paper: Pen, pencil, note book, personal protective equipment (overall, safety boots and gloves), phone, laptop, Microsoft word and Microsoft Excel. Data collection consists of the procedures of acquisition of data needed for this paper. Data required mainly involves gathering both operational and technical information necessary for analyzing the calorific consumption of the VRM system. This was done at the level of the Production department from the cement plant's control room records, daily and monthly production report sheets, and field observations. This procedure consisted of extracting the various key performance indicators that helped in establishing the correlations between the specific calorific consumption and factors that can influence the calorific consumption, presenting these relationships on graphs and tables, and finally drawing insightful conclusions which will later be used to really pinpoint areas of fault and propose actionable solutions. The data extracted from the daily production reports include:

- Mill running hours and stoppage durations.
- Gas Consumption in m^3.
- Cement production of 3X cement (42.5R) and Falcon (32.5R) cement grades in MT.
- Raw material consumption (clinker, gypsum and pozzolana) in MT.
- Mill feed rate in Tons per hour (TPH).

A sample of a daily production report sheet from which the main data needed was extracted is shown on Figure 1.

In Figure 1, it was as well necessary to gather numerical data from the company's production department from which the data needed to carry out a quantitative analysis of the trends in SCC as well as finding correlations between key performance indicators such as Feed Rate, Total production and grade of the cement produced, mill running hours and raw material consumption with SCC. The data collected is for a period of five months from the month of April 1st to August 31st 2025, showing details of production of 32.5R cement grade and 42.5R cement grade commonly called Falcon and 3X respectively with natural gas as fuel. The key calculations are: Average SCC and average feed rate.

- Average SCC: From the daily production reports, the specific gas consumptions (SGC) in m^3/MT for the production of both 3X cement and Falcon were extracted and the SCC for each month were evaluated in kJ/MT. This then allowed the calculation of the SCC and average specific calorific consumptions (Avg. SCC) for each cement grade for each month using the formulae:

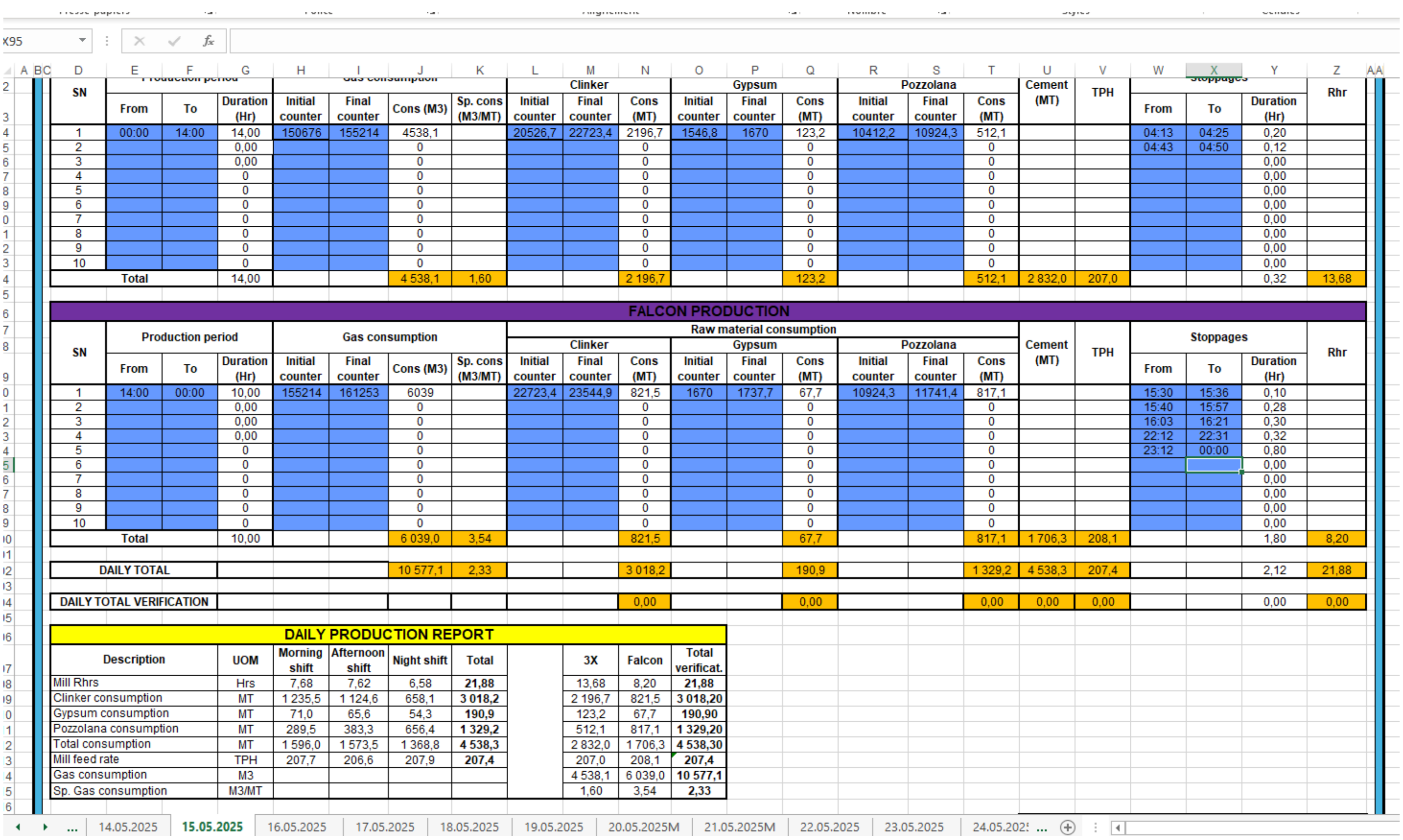
$$\mathrm{SCC} = \mathrm{SGC} \cdot \mathrm{LHV} \cdot \rho_G \tag{1}$$

where SCC = specific calorific consumption in kJ/MT, SGC = specific gas consumption m^3/MT, LHV = Lower heating value of natural gas (50000kJ/kg) and ρ_G = Density of Natural gas (0.712 kg/m^3 according to (Gaz du cameroun, 2016)

$$\mathrm{Avg.SCC} = \frac{\sum \mathrm{SCC}}{\text{Days of consumption}} \tag{2}$$

- Average feed rate: The feed rate was evaluated for each day of the months from the daily production report sheets using the total material consumed (Qm) divided by the actual running hours a day (Rhr). The average value was then calculated for each month in TPH.

$$\text{Feed rate} = \frac{Q_m}{Rhr} \tag{3}$$



SN	From	To	Duration (Hr)	Gas consumption: Initial counter	Final counter	Cons (M3)	Sp. cons (M3/MT)	Clinker: Initial counter	Final counter	Cons (MT)	Gypsum: Initial counter	Final counter	Cons (MT)	Pozzolana: Initial counter	Final counter	Cons (MT)	Cement (MT)	TPH	Stoppages: From	To	Duration (Hr)	Rhr
1	00:00	14:00	14,00	150676	155214	4538,1		20526,7	22723,4	2196,7	1546,8	1670	123,2	10412,2	10924,3	512,1			04:13	04:25	0,20	
2			0,00			0				0			0			0			04:43	04:50	0,12	
3			0,00			0				0			0			0					0,00	
4			0			0				0			0			0					0,00	
5			0			0				0			0			0					0,00	
6			0			0				0			0			0					0,00	
7			0			0				0			0			0					0,00	
8			0			0				0			0			0					0,00	
9			0			0				0			0			0					0,00	
10			0			0				0			0			0					0,00	
Total			14,00			4 538,1	1,60			2 196,7			123,2			512,1	2 832,0	207,0			0,32	13,68

FALCON PRODUCTION

SN	Production period: From	To	Duration (Hr)	Gas consumption: Initial counter	Final counter	Cons (M3)	Sp. cons (M3/MT)	Raw material consumption — Clinker: Initial counter	Final counter	Cons (MT)	Gypsum: Initial counter	Final counter	Cons (MT)	Pozzolana: Initial counter	Final counter	Cons (MT)	Cement (MT)	TPH	Stoppages: From	To	Duration (Hr)	Rhr
1	14:00	00:00	10,00	155214	161253	6039		22723,4	23544,9	821,5	1670	1737,7	67,7	10924,3	11741,4	817,1			15:30	15:36	0,10	
2			0,00			0				0			0			0			15:40	15:57	0,28	
3			0,00			0				0			0			0			16:03	16:21	0,30	
4			0,00			0				0			0			0			22:12	22:31	0,32	
5			0			0				0			0			0			23:12	00:00	0,80	
6			0			0				0			0			0					0,00	
7			0			0				0			0			0					0,00	
8			0			0				0			0			0					0,00	
9			0			0				0			0			0					0,00	
10			0			0				0			0			0					0,00	
Total			10,00			6 039,0	3,54			821,5			67,7			817,1	1 706,3	208,1			1,80	8,20
DAILY TOTAL						10 577,1	2,33			3 018,2			190,9			1 329,2	4 538,3	207,4			2,12	21,88
DAILY TOTAL VERIFICATION										0,00			0,00			0,00	0,00	0,00			0,00	0,00

DAILY PRODUCTION REPORT

Description	UOM	Morning shift	Afternoon shift	Night shift	Total		3X	Falcon	Total verificat.
Mill Rhrs	Hrs	7,68	7,62	6,58	**21,88**		13,68	8,20	**21,88**
Clinker consumption	MT	1 235,5	1 124,6	658,1	**3 018,2**		2 196,7	821,5	**3 018,20**
Gypsum consumption	MT	71,0	65,6	54,3	**190,9**		123,2	67,7	**190,90**
Pozzolana consumption	MT	289,5	383,3	656,4	**1 329,2**		512,1	817,1	**1 329,20**
Total consumption	MT	1 596,0	1 573,5	1 368,8	**4 538,3**		2 832,0	1 706,3	**4 538,30**
Mill feed rate	TPH	207,7	206,6	207,9	**207,4**		207,0	208,1	**207,4**
Gas consumption	M3						4 538,1	6 039,0	**10 577,1**
Sp. Gas consumption	M3/MT						1,60	3,54	**2,33**

14.05.2025 | 15.05.2025 | 16.05.2025 | 17.05.2025 | 18.05.2025 | 19.05.2025 | 20.05.2025M | 21.05.2025M | 22.05.2025 | 23.05.2025 | 24.05.202

Figure 1 Image of a daily production report sheet from the production department of X cement factory

where Qm = Material Consumed in MT and Rhr = Running hours in Hours

$$\text{Avg.Feed rate} = \frac{\text{Feed rate}}{\text{Days of consumption}} \quad (4)$$

For a proper analysis and understanding of the factors that come into play concerning the high calorific consumption of the VRM and at the level of the HGG, it is necessary for certain relationships between some parameters of production and SCC to be understood in order to be able to draw insightful conclusions that will aid in proposing actionable solutions towards ameliorating the calorific consumption of this unit. The key correlations are:

- Feed rate versus specific calorific consumption.
- Moisture content versus SCC.
- Stoppages versus SCC.

The monthly fuel cost per ton was determined using the relation:

$$\text{Cost} = \text{SGC}\ (\text{m}^3/\text{MT}) \times \text{Price}\ (\text{FCFA/m}^3) \times \text{production}\ (\text{MT}) \quad (5)$$

where the price at which X cement factory purchases gas is 330.9 FCFA per m^3 (1 MMBTU = 16 USD and 1 MMBTU = 27.3192 m^3. Hence 27.3192 m^3 = 9040FCFA implies 1m^3 = 330.9 FCFA).

RESULTS

This section presents and discusses the results obtained from the analysis of specific calorific consumption trends at X cement factory. It examines the correlations between SCC and operational parameters such as feed rate, moisture content, and stoppages, providing insights into how each factor impacts energy efficiency.

Results of analysis of SCC

To evaluate the energy performance of the VRM, an analysis of the variation in specific calorific consumption was conducted over a five-month period, from April to August 2025. The study utilized daily production data and the corresponding specific gas consumption values obtained from plant operation records. These daily gas consumption data were first converted into their equivalent specific calorific consumption values (in kJ/MT of cement) using the known calorific value of the fuel gas. Table 1 presents the total specific gas consumptions (in m^3/MT of cement) for the various days in the months of April 2025 to August 2025 when the gas generator used Natural gas as fuel.

For each month, the average specific gas consumption and specific calorific consumption are calculated to determine the monthly energy performance trend. Table 2 shows the average values of the SGC and corresponding average SCC.

These monthly averages were then plotted against time to visualize the evolution of energy use during the study period. The resulting graphs reveal a general upward trend in specific calorific consumption from April 2025 to August 2025, indicating a gradual deterioration in the thermal efficiency of the grinding process. Figures 2 and 3 show the graphs of average SGC and SCC , respectively with time.

This increase suggests that the system required progressively more energy to produce fairly the same quantity of finished product (about 4500 MT daily set point) over time. Such a pattern may be attributed to several operational and process-related factors, including variations in feed moisture content, raw material grindability, equipment wearing, suboptimal process control, or

Table 1 Total SCC (in m^3/MT of cement) from April 2025 to August 2025

APRIL 2025	MAY 2025	JUNE 2025	JULY 2025	AUGUST 2025
2.79	1.91	2.05	3.44	3.32
1.64	2.72	4.33	3.39	4.11
2.27	1.98	1.85	2.54	3.49
2.35	2.75	2.66	2.91	/
2.84	2.79	2.22	3.40	/
2.06	2.72	2.74	4.80	/
2.74	2.91	2.67	4.29	/
/	2.95	3.31	2.30	/
/	2.59	2.82	2.60	/
/	3.60	2.37	1.60	/
/	5.09	2.50	2.17	/
/	2.32	/	2.75	/
/	2.79	/	2.29	/
/	2.59	/	0.26	/
/	2.33	/	/	/
/	0.88	/	/	/
/	0.01	/	/	/

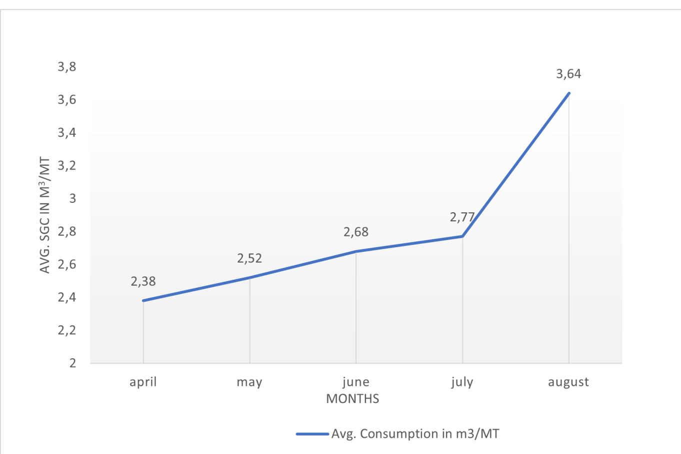


Figure 2 Graph of Avg. SGC with time.

frequent stoppages affecting thermal stability. The observed trend emphasizes the need for continuous monitoring and optimization of operating parameters to maintain stable and efficient VRM performance.

To quantify the economic impact of the variations in energy performance observed during the study period, a cost analysis was conducted based on the monthly SGC values. The month of April was used as the baseline because it recorded the lowest specific gas consumption (2.38 m^3/MT). All subsequent months were compared to April to estimate the additional fuel cost incurred due to higher consumption rates. Table 3 shows the values of the cost of the different quantities of natural gas used up during the studied months.

Table 2 Average values of SGC and SCC

Months	Average SGC (m^3/MT)	Average SCC (kJ/MT)
APRIL 2025	2.38	84728
MAY 2025	2.52	89712
JUNE 2025	2.68	95408
JULY 2025	2.77	98612
AUGUST 2025	3.64	129584

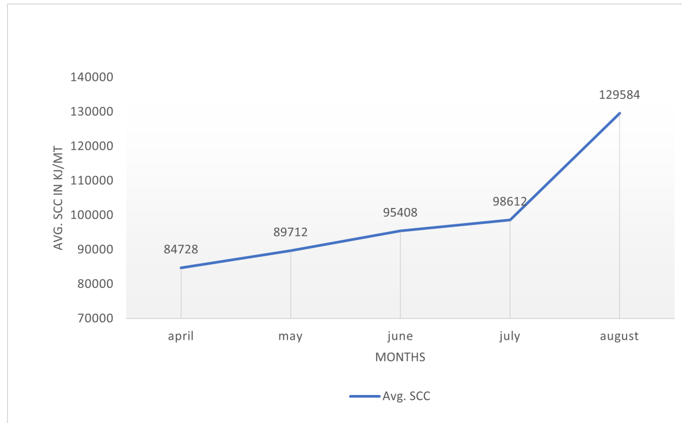


Figure 3 Graph of Avg. SCC with time.

Table 3 Monthly cost of fuel consumed

MONTH	AVG. SGC (m^3/MT)	PRODUCTION (MT)	TOTAL COST (FCFA)
APRIL 2025	2.38	4682	3687271.644
MAY 2025	2.52	4791	3995061.588
JUNE 2025	2.68	3867	3429302.004
JULY 2025	2.77	3932	3604043.676
AUGUST 2025	3.64	4603	5544203.028

The analysis of the SGC and its associated costs over the months from April to August reveals a clear trend in energy usage and expenditure for the production process. In April 2025, the average SGC was 2.38 m^3/t, corresponding to a production volume of 4,682 tons and a total gas cost of 3,687,271.644 FCFA. This month serves as the baseline for comparative analysis. In May 2025, the average SGC slightly increased to 2.52 m^3/t while production rose to 4,791 tons, resulting in a total cost of 3,995,061.588 FCFA. This indicates that despite higher production, the increase in gas consumption per ton contributed to a proportional rise in total fuel cost. For June 2025, the average SGC further increased to 2.68 m^3/t; however, production decreased to 3,867 tons. Consequently, the total gas cost was 3,429,302.004 FCFA. Although the production was lower, the increase in SGC demonstrates a reduction in energy efficiency, suggesting that the process consumed more gas per ton of product. In July 2025, the average SGC continued to rise to 2.77 m^3/t with a production of 3,932 tons, leading to a total cost of 3,604,043.676 FCFA. The trend indicates a steady increase in specific gas consumption over time, which negatively impacts operational efficiency even when production volumes remain relatively stable. A significant increase is observed in August 2025, where the average SGC reached 3.64 m^3/t, with production at 4,603 tons. This resulted in a total cost of 5,544,203.028 FCFA, representing the highest gas expenditure within the analyzed period. The sharp rise in SGC reflects an intensified loss in energy efficiency, highlighting the need for corrective measures to optimize fuel consumption and reduce operational costs.

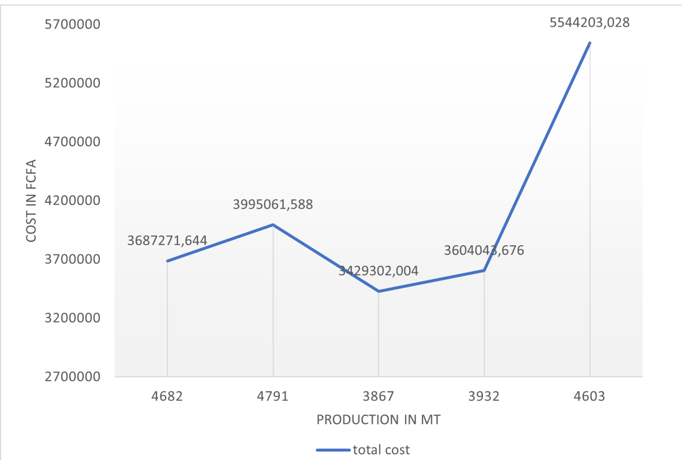


Figure 4 Graph of cost versus production.

Overall, these results of Figure 4 clearly show that higher SGC values directly translate into increased production costs with an extra difference of 1856931.384 FCFA when comparing April's 2025 fuel cost and that of August 2025. Thus, emphasizing the importance of monitoring and controlling specific gas consumption to ensure energy-efficient operation.

Results of feed rate versus SGC and SCC

To further understand the energy performance of the VRM, the relationship between the average feed rate and the specific energy consumption indicators namely; the SGC and the SCC is analyzed. Table 4 shows a record of daily feed rate values for each month extracted from the daily production reports from the production department.

The monthly average feed rate, calculated from daily production data, is plotted against the corresponding average SGC and SCC values for the period from April 2025 to August 2025. Table 5 shows the average feed rates of each month with the corresponding values of SGC and SCC.

Figures 5 and 6 show the graphs of average feed rates in TPH plotted against average SGC and average SCC, respectively.

The resulting trend shows an inverse correlation between the feed rate and both SGC and SCC. During months when the feed rate was relatively high (such as April with 208.9 TPH), the SGC and SCC values were comparatively low (2.38 m^3/MT and 84,728 kJ/MT, respectively). Conversely, as the feed rate decreased between May and June, the energy consumption values increased noticeably. This relationship indicates that a lower feed rate tends

Table 4 Daily feed rates for each month

APRIL 2025	MAY 2025	JUNE 2025	JULY 2025	AUGUST 2025
211.6	218.7	173.8	201.0	194.1
206.2	208.9	196.3	199.9	197.5
209.5	215.4	188.9	209.6	188.8
211.3	206.8	191.3	198.8	192.9
208.9	209.7	189.0	183.1	/
208.0	208.8	184.4	176.5	/
206.8	190.7	189.0	196.3	/
/	180.6	188.3	199.8	/
/	212.6	192.7	205.9	/
/	207.4	208.3	191.6	/
/	183.9	207.7	200.3	/
/	199.5	205.7	193.5	/
/	204.0	/	/	/
/	197.5	/	/	/
/	175.5	/	/	/
/	173.1	/	/	/
/	200.0	/	/	/
/	188.0	/	/	/
/	196.0	/	/	/
/	192.0	/	/	/

to reduce the mill's energy efficiency, as more fuel energy is required to maintain the necessary drying and grinding conditions for smaller throughputs. However, very high values of feed rates will lead to poor quality finished products.

The observed trend can be attributed to the operational principle of the VRM, where stable material flow and optimal bed thickness are essential for efficient grinding and heat transfer. At lower feed rates, the system experiences higher heat losses and reduced utilization of hot gases, leading to higher specific calorific consumption. Therefore, maintaining an optimal feed rate (between 200–215 TPH) is crucial to achieving lower energy consumption and improved thermal performance of the system. This correlation confirms that feed rate is a significant operational parameter influencing the thermal efficiency of the VRM and should be continuously monitored and controlled as part of the energy optimization strategy.

Results of the correlation between moisture content and SCC

The influence of raw material moisture on energy performance was also analysed by comparing the SGC and SCC for the two cement grades produced at X cement factory namely 3X cement (42.5R) and Falcon (32.5R). Although both products are derived from the same raw materials, their compositions differ mainly in

Table 5 Average feed rate values for each month

MONTHS	AVERAGE FEED RATE (TPH)	AVG. SGC (m^3/MT)	AVG. SCC (kJ/MT)
APRIL 2025	208.9	2.38	84728
MAY 2025	187.0	2.52	89712
JUNE 2025	191.0	2.68	95408
JULY 2025	193.0	2.77	98612
AUGUST 2025	195.3	3.64	129584

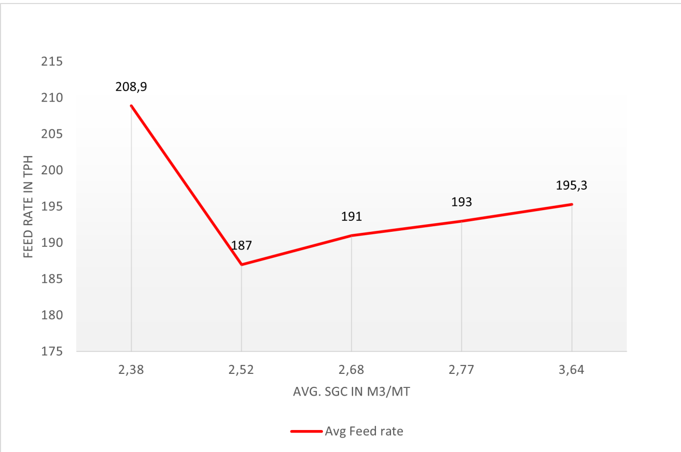


Figure 5 Graph of Average feed rate against AVG. SGC.

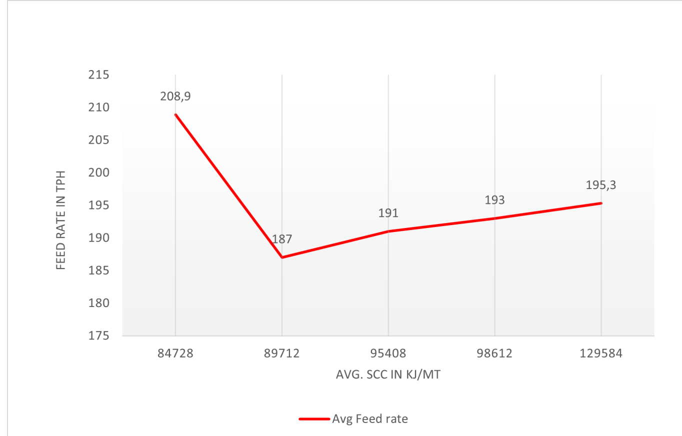


Figure 6 Graph of Average feed rate against AVG. SCC.

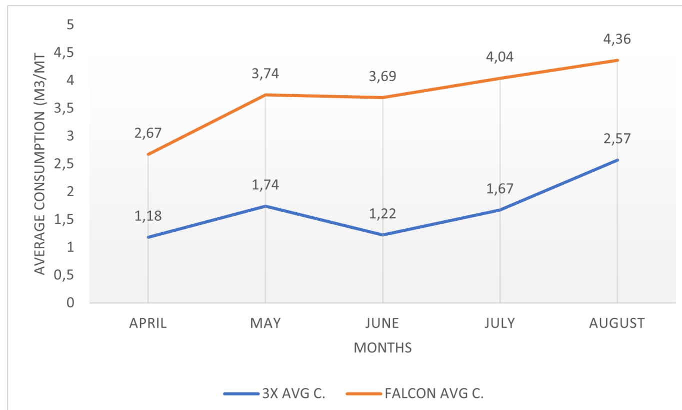


Figure 7 Graph of average SGC of 3X versus falcon.

the proportion of pozzolana. The Falcon grade typically contains a higher percentage of pozzolana (ranging between 35% and 55%) while the percentage in 3X cement is relatively lower (21–35%), which is generally wet when coming from the quarry, particularly during the rainy season. Table 6 presents the average values of SGC and SCC of 3X cement and Falcon and their corresponding average production.

The comparative analysis of the average SGC and SCC values for the two cement grades shows that, for nearly equivalent levels of production, the Falcon cement consistently exhibits higher energy consumption than the 3X cement. This difference can be attributed primarily to the higher moisture content of the raw materials used in Falcon production since more pozzolana which contributes more to the moisture content of the raw material is more in Falcon than in 3X cement. Increased moisture requires additional thermal energy to achieve effective drying within the VRM, thereby increasing both the gas demand and the specific calorific consumption of the process. Figures 7 and 8 are graphs that show how the average values of SGV and SCC for Falcon are generally always higher than that of 3X cement.

The results clearly demonstrate that raw material moisture content is directly proportional to specific energy consumption. A rise in moisture necessitates more heat input for drying, which elevates the SCC and consequently reduces the overall thermal efficiency of the system. This finding highlights the importance of raw material pre-drying or moisture control strategies, especially during the rainy season, to optimize fuel usage and minimize calorific losses during grinding operations.

Results of the correlation between stoppages and SCC

Another important parameter investigated in this study is the effect of operational stoppages on energy performance, particularly their relationship with the SGC and SCC. Using the daily production reports from April to August, the number of significant stoppages recorded each month was extracted and plotted against the corresponding monthly average SGC and SCC values. Table 7 that follows presents the values of monthly stoppages correlated with the average values SGC and SCC of each month.

The resulting analysis revealed a positive correlation between the frequency of stoppages and both SGC and SCC. Months characterized by a higher number of stoppages also exhibited higher values of specific energy consumption. This pattern indicates that frequent interruptions in operation negatively affect the thermal stability and efficiency of the VRM system. On Figures 9 and 10 are illustrated the graphs of stoppages against averages SGC and SCC, respectively.

When stoppages occur, the mill and auxiliary systems (such as the hot gas generator and fan units) undergo repeated heating and cooling cycles. Each restart requires additional energy input to restore the desired process temperature and system pressure balance. Moreover, material accumulation and inconsistent feed flow following stoppages lead to unstable grinding conditions and incomplete heat recovery, which further increase gas consumption. Consequently, minimizing unscheduled stoppages is crucial for maintaining consistent energy performance. Stable operation ensures steady-state conditions within the mill, better utilization of the supplied thermal energy, and reduced specific calorific consumption. This correlation confirms that operational reliability

Table 6 Average values of SGC and SCC of cement 3X and Falcon

	APRIL 2025		MAY 2025		JUNE 2025		JULY 2025		AUGUST 2025	
	3X Cement (42.5R)	Falcon (32.5R)	3X Cement (42.5R)	Falcon (32.5R)	3X Cement (42.5R)	Falcon (32.5R)	3X Cement (42.5R)	Falcon (32.5R)	3X Cement (42.5R)	Falcon (32.5R)
AVG. SGC (m^3/MT)	1.18	2.67	1.74	3.74	1.22	3.69	1.67	4.04	2.57	4.36
AVG. SCC (kJ/MT)	42008	95052	42008	133144	42008	131364	42008	143824	42008	155216
Avg. Production (MT)	2106	2576	2215	2576	2169	1698	2036	1900	2057	2546

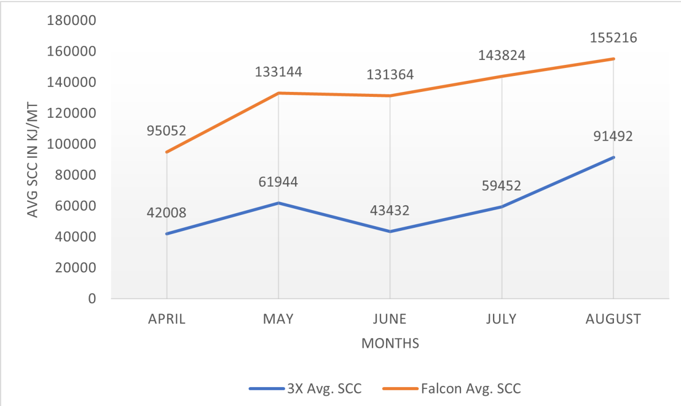


Figure 8 Graph of average SGC of 3X versus Falcon.

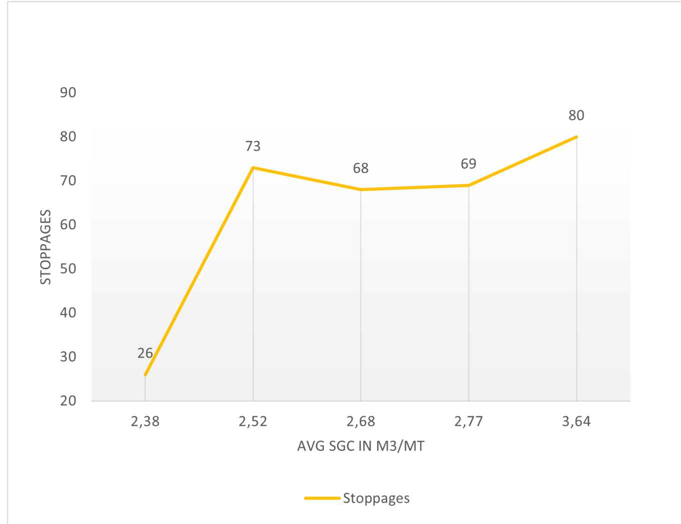


Figure 9 Graph of stoppages versus average SGC.

Table 7 Values of monthly stoppages

	APRIL 2025	MAY 2025	JUNE 2025	JULY 2025	AUGUST 2025
Stoppages	26	73	68	69	80
Avg. SGC (m^3/MT)	2.38	2.52	2.68	2.77	3.64
Avg. SCC (kJ/MT)	84728	89712	95408	98612	129584

is a critical factor in energy optimization and should be closely monitored in the overall performance improvement strategy of the cement grinding unit.

Actionable solutions to reduce calorific consumption

Based on the analyses performed through trend evaluations and correlation studies, several actionable solutions have been identified to address the main causes of high SCC in the VRM. The results showed that the principal contributors to high SCC include high moisture content of pozzolana, frequent operational stoppages, fluctuating feed rate, and low calorific value of the fuel. Other secondary factors such as heat losses to the surroundings, incorrect fuel–air ratio in combustion, inaccurate measurement and energy balance, and ambient humidity variations were also found to contribute to a lesser extent. The following points present detailed, practical, and technically justified solutions aimed at minimizing these inefficiencies and improving the overall thermal performance of the VRM. Arranged in order of priority, the first three solutions should be looked upon first since they have the highest impact.

1. Reduction of moisture content in raw materials

   High moisture content, especially in pozzolana used for the production of Falcon cement, was identified as the most significant cause of increased calorific consumption. Moist pozzolana requires additional energy for drying inside the mill, which increases fuel demand and decreases overall thermal efficiency.

   - To mitigate this, it is recommended to adopt proper raw material handling and storage techniques. During the rainy season, pozzolana stockpiles should be covered with waterproof tarpaulins, and drainage systems should be improved to prevent water accumulation. Materials should be stored on raised platforms or concrete pads to avoid direct contact with wet ground.
   - Additionally, segregation of high-moisture batches and pre-drying them using waste hot gases from hot gas generator before feeding the mill can significantly reduce drying energy requirements.
   - Implementing a routine moisture monitoring program with portable moisture meters will help maintain consistent material quality.
   - In the long term, investing in a dedicated pre-drying unit or installing a covered pozzolana storage facility would stabilize raw material conditions throughout the year, thereby ensuring steady energy consumption.

2. Minimization of operational stoppages

   Operational stoppages were found to have a direct positive correlation with SCC, as frequent interruptions result in repeated reheating cycles, unsteady mill operation, and fuel wastage during restarts. Reducing stoppages therefore presents a major opportunity for energy savings.

   - To achieve this, X cement factory should implement a preventive maintenance program focusing on critical

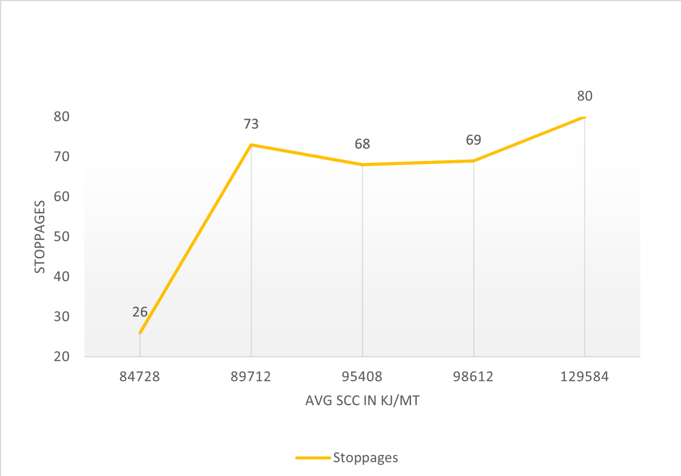


Figure 10 Graph of stoppages versus average SCC.

equipment such as the mill feed system, hot gas generator, and burner assembly. Maintenance teams should carry out pre-shift inspections to detect potential faults early.

- Furthermore, introducing a stoppage log system to categorize stoppages as "avoidable" or "unavoidable" will make it easier to identify recurring mechanical or operational failures.
- Availability of essential spare parts and improved coordination between production and maintenance teams will reduce repair times.
- Training operators on quick fault response and performing root-cause analysis after major stoppages will also help minimize downtime. Overall, reducing stoppages will lead to smoother operation, higher throughput, and more efficient fuel utilization.

3. Stabilization of feed rate

The correlation results revealed that fluctuations in feed rate significantly affect calorific consumption. When the feed rate is unstable or lower than the design capacity, the energy supplied by the hot gases is not efficiently utilized, leading to an increase in SCC.

- To stabilize the feed rate, operators should adhere to standard operating procedures with clearly defined target feed setpoints. The use of automated feeders with feedback control can help maintain steady feeding, while interlocks and alarms can alert operators of deviations from the target. Regular calibration of feed control equipment should also be ensured.
- In the medium term, installation of a surge bin or buffer hopper before the mill could help smoothen feed variations due to upstream fluctuations.
- Training operators on the importance of consistent feed rate and monitoring performance indicators such as feed rate variance (coefficient of variation) will also promote operational stability. Stable feed rate operation ensures optimal use of supplied heat, reducing the SCC and improving product quality consistency.

4. Improvement of fuel quality and combustion efficiency

Low calorific value fuel was another major cause of high SCC. When the fuel used is of lower calorific value, a higher volume is required to generate the same thermal output, increasing overall energy costs.

- To mitigate this, a fuel quality control procedure should be established. Fuel suppliers should provide certificates of calorific value, and random fuel sampling and laboratory testing should be done periodically to ensure consistency.
- Additionally, burner tuning and combustion control should be improved. The correct fuel–air ratio must be maintained to ensure complete combustion and prevent energy losses.
- Installing or optimizing oxygen (O_2) and carbon monoxide (CO) monitoring systems can help operators maintain combustion efficiency within target limits. These measures will enhance fuel utilization, lower specific gas consumption, and consequently reduce SCC.

5. Reduction of heat losses and improvement of system insulation

Although heat losses were not among the top four causes, they contribute to cumulative inefficiencies that raise calorific consumption. Uninsulated ducts, leaks in hot gas lines, and radiation losses from high-temperature surfaces can significantly affect thermal performance.

- Regular thermal audits using infrared thermography can identify high heat loss zones.
- Installing or replacing insulation materials on ducts, pipes, and cyclones, as well as repairing leaks and damaged seals, will help retain more heat within the system.
- Moreover, the use of heat-resistant coatings on exposed metal surfaces can further minimize radiation losses.
- Periodic inspection and maintenance of insulation systems should be institutionalized as part of the energy management plan.

6. Enhancement of measurement and process control systems

Accurate measurement and process control are essential for continuous energy optimization. Lack of precise energy balance and inadequate monitoring can mask inefficiencies and delay corrective actions.

- It is recommended to install additional sensors to measure key parameters such as gas flow rate, fuel flow, temperature, and raw material moisture.
- The use of a data logging system or integration with the existing SCADA network will allow for real-time performance monitoring.
- Furthermore, conducting periodic energy and heat balance studies will provide a quantitative understanding of losses and efficiency levels, helping management make informed decisions.

Better measurement and automation will ensure tighter control of process variables such as feed rate, gas temperature, and air-to-fuel ratio, ultimately stabilizing operation and reducing SCC.

7. Implementation of predictive maintenance and training programs

- To ensure sustained improvement, the company should transition from reactive maintenance to a predictive maintenance approach. Techniques such as vibration analysis, thermography, and oil condition monitoring can detect potential failures before they occur, minimizing unexpected stoppages and associated energy losses.
- Operator training should also be emphasized. Training programs should cover energy-efficient operational practices, the importance of maintaining stable feed, quick fault diagnosis, and response procedures. Empowered and skilled operators can significantly contribute to maintaining efficient energy use.

8. Continuous energy monitoring and management

   Finally, establishing a continuous energy management system will consolidate all the above actions. Setting monthly energy targets for SCC and SGC, conducting performance reviews, and rewarding teams for achieving energy reduction goals will help sustain progress. Introducing Key Performance Indicators such as SCC (kJ/MT), number of stoppages, average feed rate, and moisture content of raw materials will enable management to track the impact of interventions. Over time, this data-driven approach will promote a culture of continuous improvement and accountability in energy management.

CONCLUSION

This paper studied the factors influencing calorific consumption of a vertical roller mill (VRM) and solution proposals to reduce it at X cement factory sought to evaluate and improve the calorific performance of the VRM unit used for cement grinding and drying. Data were collected over a period of five months (April 2025 to August 2025) from the plant's operational records. Analytical techniques were applied to determine the relationships between calorific consumption and key process parameters, including feed rate, moisture content, and stoppage frequency. The findings revealed that the specific calorific consumption (SCC) showed a continuous increasing trend over the analyzed period, indicating deteriorating energy efficiency. The correlation analysis established that unstable feed rates, high moisture content of raw materials, and frequent stoppages were the main factors responsible for elevated calorific consumption. Moreover, cost analysis demonstrated that months with higher SCC corresponded to significant increases in fuel costs, confirming the direct economic impact of poor energy performance.

In conclusion, this study successfully met its objectives by identifying the principal factors affecting calorific consumption in the VRM system at X cement factory and proposing practical solutions for their mitigation. It demonstrated that energy optimization in cement production is achievable through a combination of data-driven analysis, operational discipline, and continuous performance monitoring. Beyond the economic benefits, implementing these measures will also strengthen the company's environmental stewardship by reducing fuel usage and CO_2 emissions. To implement the best solution to reduce calorific consumption, further research could explore the use of waste heat recovery systems to utilize exhaust gases, evaluate alternative fuels with lower carbon intensity, and implement computational simulations for process optimization.

Ethical standard

The authors have no relevant financial or non-financial interests to disclose.

Availability of data and material

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

LITERATURE CITED

Abbasi, K. R., M. Shahbaz, Z. Jiao, and M. Tufail, 2021 How energy consumption, industrial growth, urbanization, and CO2 emissions affect economic growth in Pakistan? A novel dynamic ARDL simulations approach. Energy **221**: 119793.

Achaw, O. W. and E. Danso-Boateng, 2021 Cement and clay products technology. In *Chemical and Process Industries: With Examples of Industries in Ghana*, pp. 135–170, Springer International Publishing, Cham.

Altun, D., H. Benzer, N. Aydogan, and C. Gerold, 2017a Operational parameters affecting the vertical roller mill performance. Minerals Engineering **103**: 67–71.

Altun, D., H. Benzer, N. Aydogan, and C. Gerold, 2017b Optimization of cement grinding operation in ball mills and vertical roller mills. Powder Technology **308**: 167–174.

Arto, I., I. Capellán-Pérez, R. Lago, G. Bueno, and R. Bermejo, 2016 The energy requirements of a developed world. Energy for Sustainable Development **33**: 1–13.

Bayiha, B. N., E. Yamb, J. S. Metekong, N. Billong, and R. Nzengwa, 2018 Optimizing the choice of limestone deposits for the production of Portland cement in Cameroon. International Journal of Materials Science and Applications **7**: 174–185.

Bocken, N. M. and J. M. Allwood, 2012 Strategies to reduce the carbon footprint of consumer goods by influencing stakeholders. Journal of Cleaner Production **35**: 118–129.

Fang, K., N. Uhan, F. Zhao, and J. W. Sutherland, 2011 A new approach to scheduling in manufacturing for power consumption and carbon footprint reduction. Journal of Manufacturing Systems **30**: 234–240.

Hammond, G. P., 2007 Industrial energy analysis, thermodynamics and sustainability. Applied Energy **84**: 675–700.

Hoffman, A. J., 2007 *Carbon strategies: How leading companies are reducing their climate change footprint*. University of Michigan Press.

Hossain, M. U., R. Cai, S. T. Ng, D. Xuan, and H. Ye, 2021 Sustainable natural pozzolana concrete—A comparative study on its environmental performance against concretes with other industrial by-products. Construction and Building Materials **270**: 121429.

Khan, M. and C. McNally, 2023 A holistic review on the contribution of civil engineers for driving sustainable concrete construction in the built environment. Developments in the Built Environment **16**: 100273.

Kümmel, R., 1982 The impact of energy on industrial growth. Energy **7**: 189–203.

Madlool, N. A., R. Saidur, N. A. Rahim, and M. Kamalisarvestani, 2013 An overview of energy savings measures for cement industries. Renewable and Sustainable Energy Reviews **19**: 18–29.

McCarthy, M. J. and T. D. Dyer, 2019 Pozzolanas and pozzolanic materials. In *Lea's Chemistry of Cement and Concrete*, volume 5, pp. 363–467.

Mohammed, S., 2017 Processing, effect and reactivity assessment of artificial pozzolans obtained from clays and clay wastes: A review. Construction and Building Materials **140**: 10–19.

Nkouathio, D. G., É. D. N. Djeunou, R. Mohamed, S. T. Nguimatsia, and M. L. C. Vohnyui, 2021 Characteristics and environmental impact of pozzolan in the Tombel graben quarry. European Journal of Environment and Earth Sciences **2**: 44–53.

Sahoo, N. and A. Kumar, 2022 Review on energy conservation and emission reduction approaches for cement industry. Environmental Development **44**: 100767.

Stern, D. I., 2011 The role of energy in economic growth. Annals of the New York Academy of Sciences **1219**: 26–51.

Zheng, W. and P. P. Walsh, 2019 Economic growth, urbanization and energy consumption—A provincial level analysis of China. Energy Economics **80**: 153–162.

How to cite this article: Tsamdo, N., Ebai-Takang Etengeneng, A., Talla, A. F., Kibanya, N. N., Takougang Kingni, S., and Nkongho, J. Study of the Factors Influencing Calorific Consumption of a Vertical Roller Mill and Solution Proposals to Reduce it at a Cement Factory. *Information Technology in Economics and Business*, 3(1), 21-30, 2026.

ADBA Information Technology in Economics and Business
Cutting-Edge Scientific Solutions

e-ISSN: 3023-8943
RESEARCH ARTICLE
Vol.3 / No.1 / 2026 / pp.31-36
https://doi.org/10.69882/adba.iteb.2026015

Parametric Discrete Event Simulation for Performance Evaluation and Decision Support in Production Systems

Abdullah Sevin [*,1], **Muhammad Rafiq** [α,2], **Jesus Manuel Munoz-Pacheco** [β,3] **and Göktuğ Yaman** [§,4]

[*]Faculty of Computer and Information Sciences, Computer Engineering, Sakarya University, Sakarya, Türkiye, [α]College of Business Administration, Management Information Systems, Prince Mohammad Bin Fahd University, Al Khobar, Saudi Arabia, [β]Faculty of Electronics Sciences, Benemerita Universidad Autonoma de Puebla, Puebla, Mexico, [§]Institute of Science, Computer Engineering Program, Sakarya University, Sakarya, Türkiye.

ABSTRACT Modern production systems operate under increasing uncertainty due to fluctuating demand, limited resources, and system disruptions such as machine failures and maintenance activities. From an economic and managerial perspective, evaluating the performance of such systems is critical for supporting operational decision-making related to capacity planning, resource utilization, and service efficiency. However, traditional analytical approaches often require restrictive assumptions and fail to capture the dynamic nature of real-world production processes. In this study, a parametric discrete event simulation model is proposed as an a computational/software-based decision support tool for the performance evaluation of a representative production service system. The model captures key operational parameters, including arrival rate, service time, failure probability, and maintenance duration, which directly influence system efficiency and economic performance. The model is evaluated through repeated simulation experiments to obtain statistically reliable performance indicators. In particular, the impacts of variations in service time and arrival rate on business-relevant performance metrics such as average waiting time, system availability, resource utilization, number of failures, and the number of serviced entities are systematically analyzed. The results demonstrate that increases in service and arrival intensities lead to performance degradation, highlighting critical trade-offs between system capacity, operational efficiency, and service quality. The proposed approach provides a practical and computationally lightweight framework for preliminary performance analysis and operational decision support in production and service-oriented systems. In addition to its applicability for early-stage economic evaluation, the model also offers educational value by enabling a clear understanding of discrete event simulation principles within an information systems context.

KEYWORDS
Discrete event simulation
Parametric modeling
Production systems
Performance analysis
Decision support systems

INTRODUCTION

Industrial systems, particularly in the production and service sectors, have become increasingly difficult to analyze due to rising levels of automation, complex workflow structures, and operational conditions characterized by uncertainty. Modern production lines incorporate numerous dynamic components, including machine failures, maintenance activities, variable demand patterns, and human-related factors. Traditional analytical methods used to evaluate and improve the performance of such systems often rely on simplifying assumptions, which may limit their ability to accurately represent real-world system behavior (Caterino *et al.* 2020; Heshmat *et al.* 2017).

In this context, simulation-based approaches provide a powerful alternative for modeling and analyzing complex systems. Simulation enables the examination of a real system or process by replicating its behavior over time. Commonly used simulation approaches in the literature include continuous simulation, Monte Carlo simulation, and discrete event simulation. Among these methods, Discrete Event Simulation (DES) is particularly well suited for production and service systems, where the system state changes only at specific event occurrences (Banks *et al.* 2013; Law *et al.* 2007).

In discrete event simulation, a system is defined through fundamental components such as events, entities, resources, and queues. When an event occurs, the system state is updated and the timing of subsequent events is determined. This structure (Figure 1) allows for the realistic modeling of situations frequently encountered in production environments, including part arrivals, service initiations and completions, machine failures, and maintenance processes (Robinson 2025).

In the existing literature, discrete event simulation is commonly implemented using specialized simulation software or programming-based solutions. Commercial tools such as Arena, Simul8, AnyLogic, and FlexSim are widely used; however, their licensing costs and learning curves may pose limitations in cer-

Manuscript received: 24 October 2025,
Revised: 13 January 2026,
Accepted: 14 January 2026.

[1]asevin@sakarya.edu.tr (**Corresponding author**)
[2]mrafiq@pmu.edu.sa
[3]jesusm.pacheco@correo.buap.mx
[4]goktug.yaman2@ogr.sakarya.edu.tr

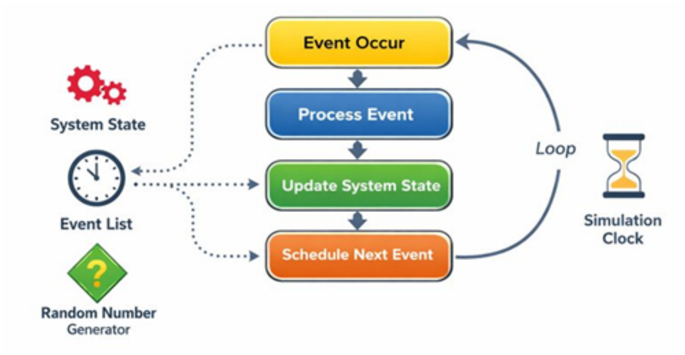


Figure 1 Basic components and event flow of discrete event simulation

tain contexts (Montgomery 2017; Forbus and Berleant 2022). As a result, there is a growing need for simpler and more flexible parametric approaches, particularly for educational purposes and preliminary feasibility analyses in industrial and business-oriented decision-making processes.

Discrete event simulation has been widely used for many years as an effective method for modeling and analyzing complex systems. Particularly in production and service systems, where the system state changes only upon the occurrence of specific events, discrete event simulation is able to represent real system behavior with a high degree of accuracy. Consequently, DES has been applied in the literature across various domains, including production planning, capacity analysis, queueing systems, and the evaluation of maintenance strategies. Negahban and Smith (2014) reviewed simulation-based approaches for the design and operation of manufacturing systems, highlighting the effectiveness of discrete event simulation for performance evaluation and system analysis. Fitouhi *et al.* (2017) evaluated the performance of a two-machine production line with a finite buffer by incorporating condition-based maintenance policies, demonstrating the impact of maintenance strategies on system blocking and starvation probabilities. Zhou and Zha (2024) developed performance evaluation and optimization models for closed-loop production lines that consider preventive maintenance and rework processes, emphasizing the role of maintenance planning in improving system efficiency. Wei *et al.* (2023) analyzed production lines subject to degradation and preventive maintenance from a reliability and performance perspective, revealing the quality-related and other possible costs on overall system performance. De Felice *et al.* (2025) investigated the role of discrete event simulation in supporting digital transformation in manufacturing, showing how simulation-based approaches contribute to the restructuring of industrial systems and decision-support processes. Kleijnen (2015) discussed the design and analysis of simulation experiments by emphasizing the use of metamodeling approaches such as polynomial regression and Kriging to compare different parameter scenarios, support optimization, and enhance decision-making under uncertainty. Similar parametric or reliability-focused approaches have also been applied to production line modeling (Koyuncuoğlu 2024; Cui *et al.* 2022; Waseem *et al.* 2024).

This study aims to examine the fundamental principles of discrete event simulation from a parametric perspective. Instead of employing a full-scale simulation platform, a conceptual discrete event simulation model is developed to represent the core dynamics of production systems. Key parameters such as arrival rate, service time, failure probability, and maintenance duration are incorporated into the model, and their impacts on system performance are systematically investigated. The proposed approach enables the analysis of widely used performance indicators, including average waiting time, system utilization, and production efficiency. Moreover, the parametric structure of the model allows decision-makers and researchers to easily generate and compare alternative operational scenarios. From an information technology and business analytics perspective, the model serves as a practical decision-support tool for evaluating operational performance under uncertainty.

METHODOLOGY AND MODEL DEFINITION

In this study, a discrete event simulation (DES) model is developed based on a single-server queueing structure similar to an M/M/1 system, extended with server failure and maintenance mechanisms. Customer arrivals are modeled as a Poisson process with arrival rate λ, while service times are assumed to follow an exponential distribution with service rate μ. Accordingly, the proposed system adopts the fundamental characteristics of a classical M/M/1 queue; however, the inclusion of server failures and maintenance durations allows for a more realistic representation of operational conditions commonly observed in production and service systems. The simulation model is implemented using the Python programming language and follows the event scheduling approach, in which the dynamic behavior of the system is represented through a chronological list of discrete events. The model explicitly considers customer arrivals, service completions, server failures, and maintenance completions as distinct event types. The system state is updated only at the occurrence of these events, in accordance with the core principles of discrete event simulation.

The proposed simulation framework operates entirely under the event scheduling paradigm, making it particularly suitable for educational and academic analyses as well as preliminary performance evaluations. Rather than continuously tracking system evolution over time, the model focuses on state transitions triggered by events, which enables efficient computation and clear interpretation of system dynamics. Within the parametric modeling framework adopted in this study, the system state is updated exclusively at specific event times. These events are defined as the arrival of entities into the system, the initiation and completion of service processes, the occurrence of server failures, and the execution of maintenance activities. This event-driven structure reflects the discrete and interrupt-driven nature of production systems, where system behavior changes only when operational events occur.

Consistent with the fundamental assumptions of discrete event simulation, the system is analyzed at event instants rather than over continuous time. This approach allows for a realistic and computationally efficient modeling of discontinuous and event-based processes frequently encountered in manufacturing and service environments.

Model Components

The proposed discrete event simulation model is built upon fundamental components that are widely adopted in the simulation literature. The system consists of entities representing jobs or service requests entering the production system, resources representing machines or service providers, and queues in which entities wait for service when resources are unavailable. In addition, events define instantaneous occurrences that trigger changes in the system state. The interactions among these components enable the evaluation of key performance indicators such as waiting times and resource utilization levels.

Parametric Modeling Framework

The simulation model is formulated within a parametric framework to represent key operational characteristics commonly observed in production systems. The primary parameters considered in the model include the arrival rate (λ), average service time (Ts), service rate (μ), failure probability (Pf), and maintenance duration (Tm). This parametric structure allows systematic variation of input parameters and facilitates the comparative analysis of different operational scenarios, making the model suitable for performance evaluation and decision-support purposes.

Event Structure and Time Advancement

In the discrete event simulation framework, system time advances by jumping from one event to the next rather than progressing continuously. Time advancement in the model is achieved by scheduling the occurrence of the next imminent event. The core events considered in the simulation include entity arrivals, service initiation, service completion, server failure occurrence, and maintenance start and completion. The relationships among these events govern the dynamic behavior of the system and enable the computation of performance measures throughout the simulation horizon.

Performance Measures

The performance of the proposed discrete event simulation model is evaluated using a set of commonly adopted metrics in queueing and production system analysis. The primary performance measures considered in this study include the average waiting time of entities in the system, server utilization, the number of serviced entities, and the total number of server failures observed during the simulation horizon. These metrics provide insight into system efficiency, congestion levels, and resource reliability under different parameter configurations. By analyzing variations in these measures, the impact of arrival and service characteristics on overall system performance can be systematically assessed.

Assumptions and Limitations

The proposed simulation model is developed under a number of simplifying assumptions to maintain analytical clarity and computational efficiency. Customer arrivals are assumed to follow a Poisson process, and service times are modeled using an exponential distribution, consistent with the classical M/M/1 queueing framework. The system is assumed to operate with a single server, and entities are served according to a first-come, first-served (FCFS) discipline. Server failures occur probabilistically, and maintenance activities restore the server to an operational state after a fixed repair duration.

While these assumptions enable a clear and interpretable parametric analysis, they also impose certain limitations. The model does not consider multiple servers, priority-based service disciplines, or time-dependent arrival and service processes. Additionally, economic cost factors are not explicitly modeled. Therefore, the results should be interpreted as indicative rather than exhaustive, and the model is primarily intended for conceptual analysis, preliminary evaluation, and educational purposes.

RESULTS

In this section, the results obtained from the developed discrete event simulation model are presented based on replicated simulation experiments. The effects of service time and arrival rate parameters on key system performance measures namely average waiting time, total number of failures, and number of served customers are analyzed separately. In the conducted simulation experiments, a single-server system was modeled with stochastic arrivals and service times, incorporating server failure and repair mechanisms. The global parameters were set as follows: failure probability (Pf) = 0.05, repair time Tm = 3.0 time units, total simulation duration $SIM\_TIME = 1000$, and each scenario was replicated 200 times to obtain reliable average estimates. Thus, Monte Carlo–based simulation framework was adopted, where multiple independent replications were performed to quantify the impact of parameter variability on system performance measures. In the experimental setup, customer arrivals are modeled as a Poisson process with arrival rate λ, while service times follow an exponential distribution with mean service time (Ts). Unless otherwise stated, the arrival rate is fixed at $\lambda = 0.8$ to represent a moderately loaded system, and the effects of varying service time and arrival intensity on system performance are analyzed through multiple simulation replications.

To assess the validity of the proposed discrete-event simulation (DES) framework, an analytical comparison was conducted by disabling machine failures (Pf = 0). Under this condition, the system reduces to a classical M/M/1 queue, where interarrival and service times follow exponential distributions and a single server is continuously available. Table 1 presents a comparison between the average waiting times obtained from the DES model and the corresponding theoretical values derived from the M/M/1 formulation for selected arrival rates (λ) and a fixed average service time (Ts = 1). The theoretical waiting time was computed using the well-known expression $W = \frac{1}{\mu - \lambda}$, where $\mu = \frac{1}{Ts}$.

The results demonstrate a strong agreement between simulation and analytical outcomes, with relative errors remaining below 2% across all tested scenarios. These small discrepancies are primarily attributed to stochastic variability and finite simulation horizon effects. Overall, the close correspondence confirms the correctness of the event scheduling logic, time advancement mechanism, and performance metric calculations employed in the DES model.This validation establishes a reliable baseline for the subsequent analyses, where machine failures and repair processes are introduced and the system behavior deviates from classical queueing assumptions.

Figure 2 illustrates the effect of increasing average service time on the average waiting time in the system. The results reveal a nonlinear and accelerating increase in waiting time as the service time grows. When the average service time is Ts = 1, the average waiting time is approximately 15.20 time units. This value increases to 353.26 time units at Ts = 5 and further rises to 441.11 time units when Ts reaches 10. These findings indicate that longer service times significantly reduce service capacity, leading to rapid queue accumulation and system congestion.

Figure 3 presents the relationship between average service time and the total number of failures. The results indicate a decreasing trend in the number of failures as the service time increases. Specifically, the average number of failures is 39.24 for Ts = 1, decreases to 13.05 at Ts = 5, and further drops to 9.03 at Ts = 10. This behavior can be attributed to the reduction in the number of service initiations under longer service times, which in turn lowers the likelihood of failure occurrences.

Figure 4 shows the effect of service time on the number of served customers. The results demonstrate a significant decline in system throughput as service time increases. While an average

Table 1 Comparison of simulation and analytical outcomes

λ	Ts	DES Avg. wait time	M/M/1 Theory	Error (%)
0.2	1.0	1.2273	1.2500	1.82
0.4	1.0	1.6557	1.6667	0.66
0.6	1.0	2.5090	2.5000	0.36
0.7	1.0	3.3675	3.3333	1.03

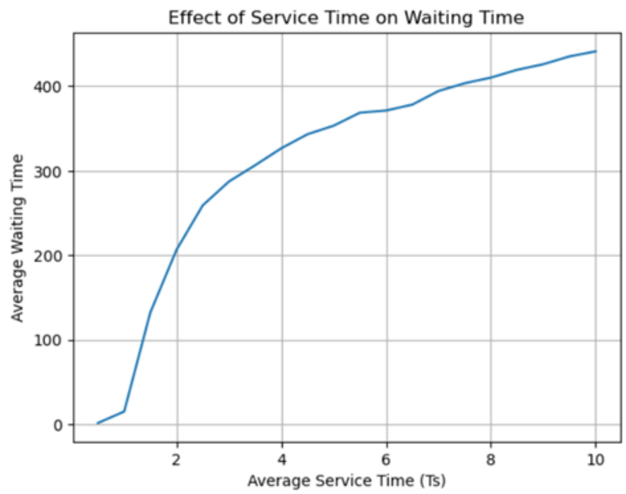


Figure 2 Effect of service time on average waiting time

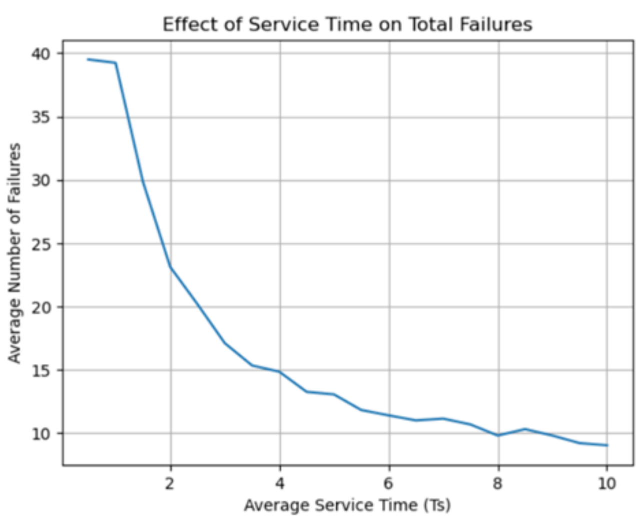


Figure 3 Effect of service time on total number of failures

of 785.8 customers are served when Ts = 1, this number decreases sharply to 257.2 at Ts = 5. At Ts = 10, the system serves only 186.9 customers on average. These results clearly indicate that service time is a critical determinant of productivity and operational efficiency in production and service systems.

Figure 5 illustrates the impact of arrival rate (λ) on the average waiting time. At low arrival rates, waiting times remain minimal; however, as the arrival rate approaches the system's service capacity, waiting time increases dramatically. When λ = 0.1, the

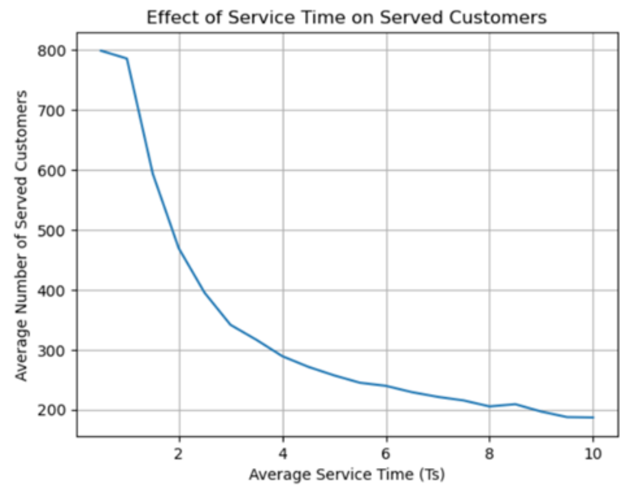


Figure 4 Effect of service time on number of served customers

average waiting time is 1.33 time units, increasing to 2.98 at λ = 0.5. A sharp escalation is observed at higher arrival rates, with waiting times reaching 15.49 at λ = 0.8 and 216.18 at λ = 1.5. These results indicate that the system enters a congestion regime as it approaches saturation.

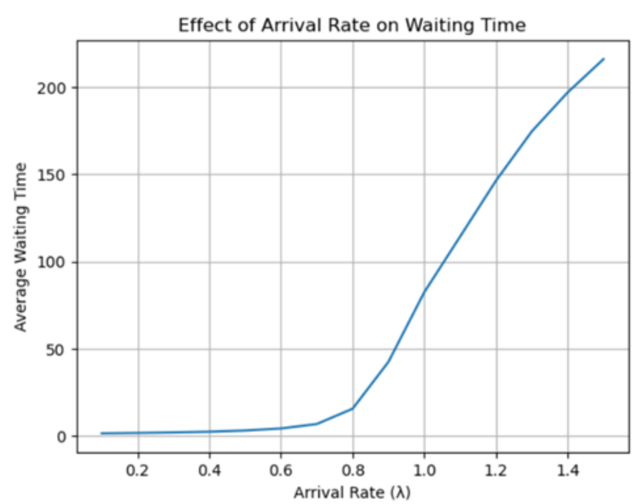


Figure 5 Effect of arrival rate on average waiting time

Figure 6 depicts the relationship between arrival rate and the total number of failures. The results show that the number of failures increases with arrival rate but eventually reaches a saturation level. While the average number of failures is 4.89 at λ = 0.1, it rises to 39.15 at $\lambda = 0.8$. For arrival rates greater than or equal to 0.9, the number of failures stabilizes around 42, suggesting that the system operates continuously under high load and reaches its failure occurrence limit.

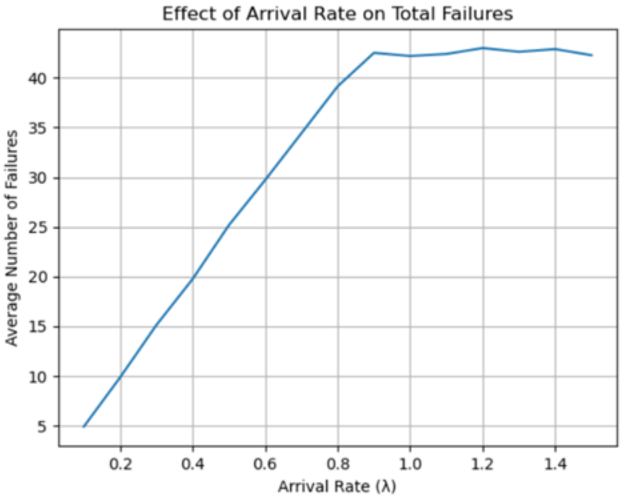


Figure 6 Effect of arrival rate on total number of failures

Figure 7 presents the effect of arrival rate on the number of served customers. As the arrival rate increases, the number of served customers also rises; however, this increase becomes limited beyond a certain threshold. When $\lambda = 0.1$, the system serves an average of 98.4 customers, whereas this number increases to 784.2 at $\lambda = 0.8$. For $\lambda \geq 1.0$, the number of served customers stabilizes in the range of 845–851, indicating that the system has reached its maximum service capacity and additional arrivals do not lead to further throughput gains.

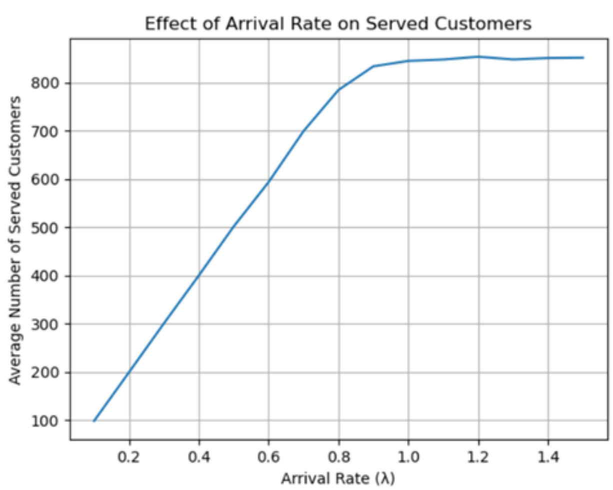


Figure 7 Effect of arrival rate on number of served customers

CONCLUSION

This study presented a parametric discrete event simulation model for analyzing the performance of a single-server production system subject to stochastic arrivals, service times, and failure–repair mechanisms. Without relying on full-scale commercial simulation software, the proposed approach demonstrated how key operational parameters can be systematically evaluated through replicated simulation experiments. The effects of arrival rate and service time variations on system performance were analyzed through a probabilistic sensitivity analysis based on repeated simulation runs. The results clearly showed that service time and arrival rate are dominant factors influencing system performance. Increases in average service time led to a rapid and nonlinear growth in average waiting time, accompanied by a significant reduction in system throughput. Conversely, longer service times resulted in fewer system failures due to a reduced number of service initiations. Similarly, increasing the arrival rate caused waiting times to rise sharply as the system approached saturation, while the number of served customers eventually reached a capacity limit, beyond which additional arrivals no longer improved throughput. The failure behavior under high arrival rates also exhibited a saturation effect, indicating sustained high system utilization.

From a practical perspective, these findings highlight the importance of capacity planning, service time optimization, and workload control in production and service systems. The proposed parametric model provides decision-makers with a simple yet effective tool for exploring "what-if" scenarios and understanding the trade-offs between efficiency, reliability, and congestion under uncertainty. In an economic and business context, such insights can support cost-effective operational planning and risk-aware system design.

Future studies may extend the proposed discrete event simulation framework to more complex system configurations, such as multi-machine production lines, parallel server structures, and batch processing mechanisms. In addition, incorporating human–machine interactions, operator-dependent service times, and learning effects would further enhance the realism and applicability of the model. Such extensions would allow the analysis of more intricate operational dynamics and broaden the relevance of the proposed approach to real-world manufacturing and service systems.

Ethical standard

The authors have no relevant financial or non-financial interests to disclose.

Availability of data and material

Not applicable.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

LITERATURE CITED

Banks, J., J. S. Carson, B. L. Nelson, and D. M. Nicol, 2013 *Discrete-event system simulation: Pearson new international edition*. Pearson Higher Ed.

Caterino, M., A. Greco, S. D'Ambra, P. Manco, M. Fera, *et al.*, 2020 Simulation techniques for production lines performance control. Procedia Manufacturing **42**: 91–96.

Cui, P.-H., J.-Q. Wang, and Y. Li, 2022 Data-driven modelling, analysis and improvement of multistage production systems with predictive maintenance and product quality. International Journal of Production Research **60**: 6848–6865.

De Felice, F., C. De Luca, A. Petrillo, A. Forcina, M. A. Ortiz Barrios, *et al.*, 2025 The role of digital transformation in manufacturing:

Discrete event simulation to reshape industrial landscapes. Applied Sciences **15**: 6140.

Fitouhi, M.-C., M. Nourelfath, and S. B. Gershwin, 2017 Performance evaluation of a two-machine line with a finite buffer and condition-based maintenance. Reliability Engineering & System Safety **166**: 61–72.

Forbus, J. J. and D. Berleant, 2022 Discrete-event simulation in healthcare settings: a review. Modelling **3**: 417–433.

Heshmat, M., M. El-Sharief, and M. El-Sebaie, 2017 Simulation modelling and analysis of a production line. International Journal of Simulation and Process Modelling **12**: 369–376.

Kleijnen, J. P., 2015 Design and analysis of simulation experiments. In *International workshop on simulation*, pp. 3–22, Springer.

Koyuncuoğlu, M. U., 2024 Most important performance evaluation methods of production lines: A comprehensive review on historical perspective and emerging trends. Computers & Industrial Engineering **197**: 110623.

Law, A. M., W. D. Kelton, and W. D. Kelton, 2007 *Simulation modeling and analysis*, volume 3. Mcgraw-hill New York.

Montgomery, D. C., 2017 *Design and analysis of experiments*. John wiley & sons.

Negahban, A. and J. S. Smith, 2014 Simulation for manufacturing system design and operation: Literature review and analysis. Journal of manufacturing systems **33**: 241–261.

Robinson, S., 2025 *Simulation: the practice of model development and use*. Bloomsbury Publishing.

Waseem, M., C. Li, and Q. Chang, 2024 Dynamic modeling and analysis of multi-product flexible production line. International Journal of Computer Integrated Manufacturing **37**: 108–122.

Wei, S., M. Nourelfath, and N. Nahas, 2023 Analysis of a production line subject to degradation and preventive maintenance. Reliability Engineering & System Safety **230**: 108906.

Zhou, B. and W. Zha, 2024 Performance evaluation and optimization model for closed-loop production lines considering preventive maintenance and rework process. Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering **238**: 2438–2455.

How to cite this article: Sevin, A., Rafiq, M., Munoz-Pacheco, J. M., and Yaman, G. Parametric Discrete Event Simulation for Performance Evaluation and Decision Support in Production Systems. *Information Technologies in Economics and Business*, 3(1), 31-36, 2026.

Information Technology in Economics and Business
Cutting-Edge Scientific Solutions

e-ISSN: 3023-8943
RESEARCH ARTICLE
Vol.3 / **No.**1 / 2026 / **pp.**37-40
https://doi.org/10.69882/adba.iteb.2026016

Renewable Energy in Türkiye: Principles, Applications and Sustainability Challenges

Cem Akdoğan *,1, **Muammer Enes Poyraz** *,2, **Berat Baran Balcı** *,3, **Ceyda Naz Şen** *,4 **and Nida Nur Yılmaz** *,5
*Hitit University, Faculty of Engineering and Natural Sciences, Department of Electrical and Electronics Engineering, 19030, Çorum, Türkiye.

ABSTRACT This study examines the development of renewable energy installed capacity in Türkiye between 2013 and 2023 within the context of resource-based shifts and policy frameworks. Utilizing data from the Ministry of Energy and Natural Resources (ETKB), TEİAŞ, and IRENA, the analysis evaluates annual growth rates and fluctuations in the share of total capacity. The findings reveal that the total installed capacity, which stood at 64,008 MW in 2013, reached 110,914 MW by the end of 2023; notably, solar energy experienced a growth rate exceeding 1,000% during this period. In alignment with the Paris Agreement targets, the study emphasizes the strategic importance of grid flexibility and storage technologies, providing critical implications for future energy policies.

KEYWORDS
Renewable energy
Installed capacity analysis
Energy policy of Türkiye
Energy transition

INTRODUCTION

The environment is a medium in which humans, other living organisms, and non-living entities exist in continuous interaction. Since the dawn of existence, humanity has maintained a constant relationship with the environment and utilized its surroundings. With the advancement of industry and technology, the use of fossil fuels has become widespread, resulting in increased atmospheric emissions of greenhouse gases such as carbon dioxide and methane. It is projected that rising carbon dioxide emissions will increase the global temperature by at least 1.5°C between 2030 and 2050 (Adebayo and Kirikkaleli 2021; Asongu *et al.* 2020).

Sustainable and eco-friendly energy sources are gaining increasing importance as solutions to global environmental problems. As an alternative to fossil fuels, renewable energy sources can generate power with minimal environmental impact and are capable of regenerating within a short timeframe (Yıldırım 2016). Despite these constraints, it is stated that renewable energy consumption exhibits a strong linear relationship with economic development and exerts positive effects on environmental sustainability (Bhattacharya *et al.* 2016; Kirikkaleli and Adebayo 2021). Accordingly, developed nations are accelerating their transition toward carbon-free energy sources (Ali and Seraj 2022).

In this context, ensuring a balanced relationship between economic growth and environmental protection has become one of the most critical challenges of the modern world. Rapid population growth, urbanization, and rising energy demand place increasing pressure on natural resources, making efficient energy use and environmental responsibility indispensable components of development strategies. Therefore, integrating environmental considerations into economic and energy policies is essential not only for mitigating climate-related risks but also for achieving long-term social and economic stability. The pursuit of sustainable development thus requires coordinated efforts that align technological progress, policy frameworks, and environmental awareness.

MATERIALS AND METHODS

This research employs descriptive analysis and time series analysis methodologies to examine Türkiye's renewable energy profile. The regional distribution of Türkiye's solar and wind energy potential was visualized using heat maps generated through Geographic Information Systems (GIS) analysis.

Data Sources and Scope

Dataset: The analyses are based on official statistical reports from the Ministry of Energy and Natural Resources (MENR), the Turkish Electricity Transmission Corporation (TEİAŞ), and the International Renewable Energy Agency (IRENA), covering the period between 2013 and 2023.

Manuscript received: 14 November 2025,
Revised: 21 January 2026,
Accepted: 21 January 2026.

[1]akdogancem19@gmail.com (**Corresponding author**)
[2]enesprz68@gmail.com
[3]byte.bm4@gmail.com
[4]ceyda55naz@gmail.com
[5]Nidatemiz617@gmail.com

Analytical Approach: Data processing was conducted using Microsoft Excel and Tableau to calculate annual growth rates and the percentage shares of individual energy sources within the total installed capacity.

Scope and Definitions: In this study, the concept of "installed capacity" was analyzed in units of MW (Megawatts). In the comparative analyses, 2013 was designated as the base year to evaluate the ten-year cumulative growth performance of the energy sources.

Data Collection and Analysis Process

During the data collection process, renewable energy sources were categorized by type: solar, wind, hydroelectric, geothermal, and biomass. Based on this classification, the following analytical steps were implemented:

- Time-series analyses were conducted to determine the annual changes in Türkiye's renewable energy installed capacity (TEİAŞ 2023).
- Regional distribution analysis was carried out using Geographical Information Systems (GIS); maps were generated for sunshine duration, wind speed, and hydroelectric potential (IRENA 2022; ETKB 2023).
- The graphical analysis method was utilized to visualize the share of renewable energy sources within total power generation.
- Furthermore, within the framework of energy policy analysis, Türkiye's carbon reduction targets under the Paris Agreement and its renewable energy incentive policies were examined (Adebayo and Kirikkaleli 2021; Kirikkaleli and Adebayo 2021).

Tools and Software Utilized

Microsoft Excel and Tableau software were utilized for data processing. These tools were employed to calculate the annual rates of change in energy generation and to generate trend analyses. For mapping procedures, Geographic Information Systems (GIS) analyses were applied. Through this methodology, the regional distribution of Türkiye's solar and wind energy potential was visualized using heat maps (IRENA 2022; TEİAŞ 2023).

Limitations of the Study

This research is limited to Türkiye's current renewable energy policies and publicly available data. Difficulties in accessing up-to-date or granular data in certain regions have partially constrained the regional accuracy of the analysis (ETKB 2023). Furthermore, comprehensive data regarding private sector energy investments could not be fully accessed. Nevertheless, the data obtained in this study are of sufficient quality to demonstrate the general trends of Türkiye's energy transition process.

Objectives and Contribution of the Study

The primary objective of this research is to present a scientific perspective on how energy policies can be improved in terms of sustainability by revealing the current status and developmental trajectory of Türkiye's renewable energy capacity. It is intended that the findings will both contribute to the academic literature and serve as a guide for decision-makers in energy policy planning (Xu *et al*. 2019; Balbağ and Balbağ 2019; Kirikkaleli and Adebayo 2021).

Fig. 1 presents the spatial distribution of solar energy potential across Türkiye, indicating regions with high solar irradiation levels that are suitable for large-scale photovoltaic investments. Fig. 2 illustrates the geographical distribution of wind energy potential in Türkiye, highlighting coastal and elevated regions where wind power generation is most feasible.

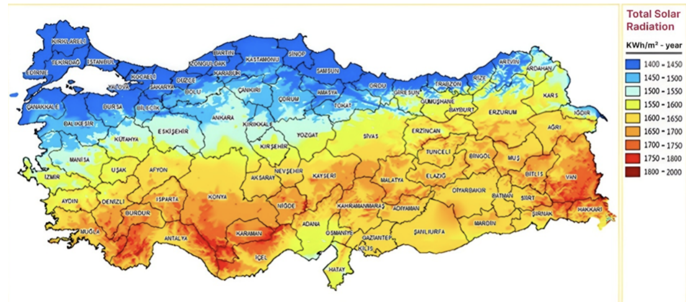


Figure 1 Mapping of Solar Energy Potentials in Türkiye

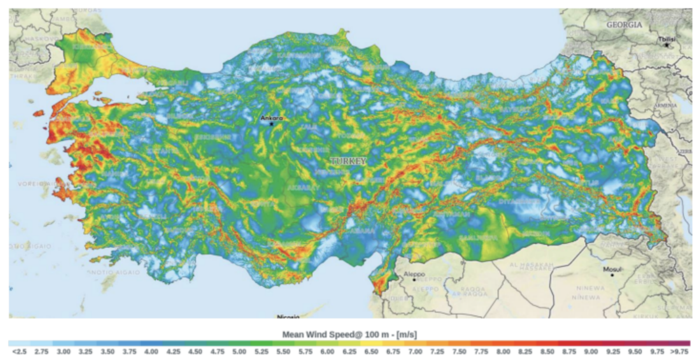


Figure 2 Mapping of Wind Energy Potentials in Türkiye

RESULTS AND DISCUSSION

Türkiye's total installed capacity, which stood at 64,008 MW in 2013, rose to 110,914 MW by the end of 2023, representing an increase of 73.2%.

Growth Analysis by Energy Source

The data reveal that the most dramatic increase among renewable sources over the ten-year period occurred in solar energy. While solar energy had no significant installed capacity in 2013, it reached 15,613.4 MW in 2023, accounting for 14.08% of the total capacity. Similarly, wind energy exhibited steady growth, increasing its share from 4.31% in 2013 to 10.64% in 2023.

Technical and Economic Challenges

The intermittent nature of renewable energy (i.e., periods without wind or sunlight) entails significant grid flexibility issues. Current findings indicate that the need for battery energy storage systems (BESS) and smart grid infrastructure has reached a critical level to ensure the sustainability of this rapid increase in installed capacity. Furthermore, although high initial investment costs pose a barrier, particularly for local investors, the economic feasibility of these investments remains high in terms of long-term energy price stability.

Moreover, advancements in energy storage technologies and digital grid management solutions are expected to significantly alleviate these challenges by enhancing system reliability and operational efficiency. Policy support mechanisms, incentive schemes, and regulatory frameworks also play a crucial role in reducing

Table 1 Installed Capacity Amounts and Shares: 2013–2023 (Unit: MW)

Year	Unit	Coal	Liquid	Nat. Gas	Ren.+Waste	Multi-fuel	Hydro	Geoth.	Wind	Sun	Total
2013	MW	12,605.7	616.3	17,170.6	235.0	8,020.4	22,289.0	310.8	2,759.7	0.1	64,008
	%	19.69	0.96	26.83	0.37	12.53	34.82	0.49	4.31	-	100.00
2018	MW	18,997.5	652.1	25,567.8	1,061.0	3,189.6	28,291.4	1,282.5	7,005.4	5,062.8	88,550.8
	%	21.45	0.74	28.87	1.20	3.60	31.95	1.45	7.91	5.72	100.00
2023	MW	21,099.1	135.4	21,285.6	2,446.4	4,874.3	31,962.4	1,691.3	11,806.1	15,613.4	110,914
	%	19.02	0.12	19.19	2.21	4.39	28.82	1.52	10.64	14.08	100.00

investment risks and accelerating the adoption of flexible energy systems. In this regard, the integration of renewable energy sources with storage and smart grid technologies emerges as a key pillar for achieving resilient and sustainable energy systems.

Fig. 3 illustrates the evolution of Türkiye's total installed power capacity over the years, revealing a sustained upward trend that reflects both increasing energy demand and long-term capacity expansion strategies. A more detailed perspective on this transformation is provided in Fig. 4, which compares the installed capacity by primary energy sources in 2013 and 2023 and clearly demonstrates a structural shift toward renewable energy sources within the national energy mix. This transition is further emphasized by the renewable energy growth curve shown in Fig. 5, indicating a steady and accelerated increase in renewable capacity throughout the 2013–2023 period.

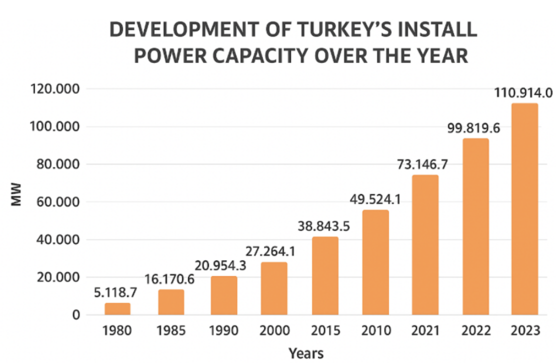


Figure 3 Development of Türkiye's Installed Capacity Over the Years

Fig. 6 presents the distribution of renewable energy sources in 2023, highlighting the dominant roles of hydropower, wind, and solar energy in shaping Türkiye's renewable portfolio. In parallel, Fig. 7 compares fossil-based and renewable energy capacities over the same period, showing a gradual decline in the relative dominance of fossil fuels as renewable sources gain prominence. Finally, Fig. 8 illustrates resource-based growth rates between 2013 and 2023, where renewable energy technologies exhibit significantly higher growth rates compared to conventional energy sources, underscoring the dynamic nature of investment patterns in the energy sector.

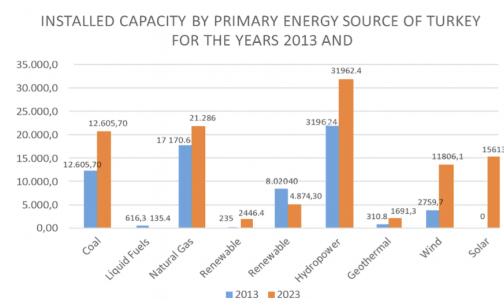


Figure 4 Türkiye's Installed Capacity by Primary Energy Sources for the Years 2013 and 2023

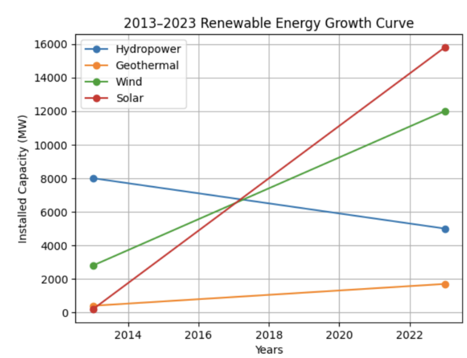


Figure 5 Renewable Energy Growth Curve, 2013–2023

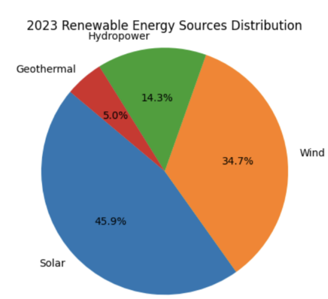


Figure 6 Distribution of Renewable Energy Sources in 2023

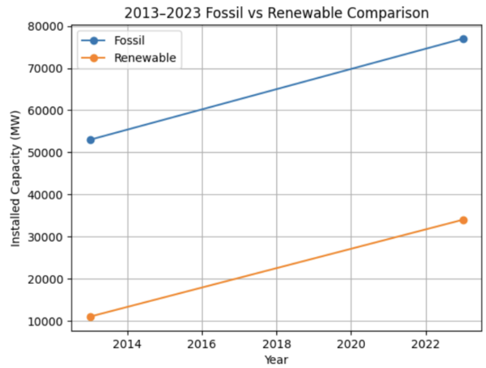


Figure 7 Comparison of Fossil vs. Renewable Energy, 2013–2023

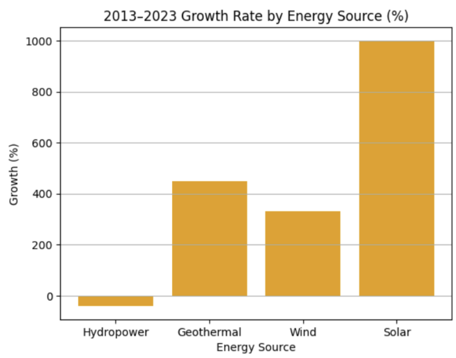


Figure 8 Resource-Based Growth Rate (%) (2013–2023)

CONCLUSION

This mini-data analysis review demonstrates that Türkiye has undergone a significant transformation by nearly doubling its renewable energy capacity over the past decade. The momentum, particularly in solar and wind energy, contributes to the country's carbon reduction targets within the framework of the Paris Agreement. However, to maintain the same level of efficiency in electricity generation as seen in the installed capacity growth, government incentives for grid integration and storage technologies must be increased. It is recommended that future studies quantitatively examine the capacity factors of this expansion on actual electricity generation and the subsequent amounts of emission reductions.

In addition, the structural shift in Türkiye's energy mix, as evidenced by the increasing share of renewable resources and the relative decline of fossil-based capacity, indicates a long-term strategic reorientation toward sustainable energy systems. The heterogeneous growth rates observed across different renewable technologies suggest that investment priorities are increasingly shaped by resource availability, technological maturity, and policy-driven incentives. Nevertheless, the intermittent nature of renewable energy highlights the necessity of enhancing grid flexibility through smart grid applications and battery energy storage systems to ensure system reliability. From this perspective, aligning energy policies with infrastructure development and technological innovation is crucial for translating installed capacity growth into effective electricity generation and measurable environmental benefits.

Ethical standard

The authors have no relevant financial or non-financial interests to disclose.

Availability of data and material

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

LITERATURE CITED

Adebayo, T. S. and D. Kirikkaleli, 2021 Impact of renewable energy consumption, globalization, and technological innovation on environmental degradation in japan. Environmental Science and Pollution Research **28**: 24910–24922.

Ali, M. and M. Seraj, 2022 Transition toward carbon-free energy sources.

Asongu, S. A. *et al.*, 2020 Global warming and environmental sustainability.

Balbağ, M. and G. Balbağ, 2019 Economic impacts of renewable energy sources and sustainable development. Enerji Ekonomisi Dergisi **1**: 15–28.

Bhattacharya, M., S. R. Paramati, I. Ozturk, and S. Bhattacharya, 2016 The interrelationship between renewable energy and economic growth: Evidence from top 38 countries. Energy Economics **56**: 120–132.

ETKB, 2023 Energy balance tables of türkiye. T.C. Enerji ve Tabii Kaynaklar Bakanlığı.

IRENA, 2022 Renewable energy statistics 2022.

Kirikkaleli, D. and T. S. Adebayo, 2021 Renewable energy consumption and environmental sustainability in japan: Evidence from wavelet coherence approach. Renewable Energy **179**: 668–675.

TEİAŞ, 2023 Electricity generation and consumption statistics.

Xu, L., Y. Wang, and Z. Chen, 2019 Challenges and strategies in renewable energy policy-making. Energy Research Journal **14**: 55–67.

Yıldırım, İ., 2016 Renewable energy potential and application areas in türkiye. Enerji Verimliliği ve Yenilenebilir Enerji Dergisi **1**: 10–20.

How to cite this article: Akdoğan, C., Poyraz, M. E., Balcı, B. B., Şen, C. N., and Yılmaz, N. N. Renewable Energy in Türkiye: Principles, Applications and Sustainability Challenges. *Information Technology in Economics and Business*, 3(1), 37-40, 2026.