**Caritas International Journal of Public Administration and Business Management**
*CIJPABM Volume 3, Issue 1, 2026*

***Article History*: *Received:10th September, 2026 Revised: 2nd November, 2026 Accepted: 14th November, 2026***

# Algorithmic Management in Healthcare: A Structured Review of Data Analytics, Health Worker Performance and Clinical Autonomy

**Chukwuedozie Nnaemeka Ezema**
**Chidinma Johnson Anamemena**
**Chidi Ukwuoma Okonkwo**
**Chinazam Chukwuebuka Ezema**

[1,3]Federal University of Allied Health Sciences, Enugu;
[2]Chukwuemeka Odumegwu Ojukwu University, Anambra State;
[4] Nnamdi Azikiwe University, Awka, Anambra State, Nigeria
**Correspondence:** *chukwuedoziennaemekaezema@gmail.com*

## Abstract

*Hospitals and health systems increasingly rely on digital tools to allocate staff, forecast workload, monitor adherence to protocols and support clinical decisions. These tools are often lumped together as "algorithmic management," yet they differ considerably in purpose and in how much authority they exert over the people who use them. This structured narrative review examines what is known about data-driven management and its associations with health-worker performance, autonomy and well-being. We searched PubMed, OpenAlex and Semantic Scholar, then synthesized the findings narratively, comparing sources by design, setting, outcome and the strength of inference each allows. A quantitative meta-analysis was not possible: the interventions and outcomes were too varied, and no comparable effect estimates with variance data were available. A mixed-method review of 18 rostering studies reported gains in roster efficiency, staff satisfaction and work-life balance, alongside concerns about equity and overtime. A qualitative study of 17 hospital nursing staff showed that electronic protocol monitoring could push nurses toward covert workarounds when they had no way to document clinically justified deviations. Taken together, the evidence supports a conditional reading. Analytics can improve clearly defined operational processes, but those gains do not, on their own, demonstrate better clinical quality or sustainable workforce performance. Implementation should protect clinical discretion, involve frontline staff, and judge success by worker and patient outcomes as well as efficiency.*

**Keywords:** ***algorithmic management; health workforce; nursing; workforce analytics; clinical autonomy; digital rostering; performance measurement***

# 1. Introduction

Healthcare managers face a problem that is easy to state and hard to solve. They must match staffing and workload to patient needs that shift hour by hour, and they must do so without compromising safe, humane care. Digital systems now sit inside many parts of this work: rostering, nursing-workload prediction, clinical surveillance and protocol-compliance monitoring among them. Researchers and commentators often group these tools under the label "algorithmic management." The label is convenient, but it hides real differences (Ezema, Ezema & Nonum, 2017). A model that forecasts ward workload does not wield the same managerial authority as a system that scores individual staff, or one that constrains how a clinician may respond to the patient in front of them (Ezema, et al., 2022).

For this review, algorithmic management means the use of computational systems to carry out or shape managerial functions, including monitoring, scheduling, goal setting, performance evaluation and the organization of work. A work-design review has mapped these functions and argued that their effects depend partly on job resources, above all autonomy and task complexity, and partly on system features such as transparency, fairness and the degree of worker influence (Parent-Rocheleau & Parker, 2021). Healthcare calls for some care with this definition (Ezema, Okafor & Okezie, 2016; Ezema, Ezema & Umezinwa, 2017). Clinical artificial intelligence that informs a diagnosis is not automatically workforce management. We therefore include a technology only where it materially organizes staff work, allocates workload, or supplies data that are used to evaluate or direct health workers.

The question here is not whether analytics are inherently good or bad. It is whether the operational improvements organizations want can be achieved without eroding the discretion clinicians need to respond to individual patients. The evidence from rostering is far from uniformly negative (Ezema, et al., 2016). A mixed-method systematic review of 18 studies found largely positive organizational and workforce outcomes, including better roster efficiency and greater staff control, while also flagging concerns about equity, overtime and requests to change shifts (O'Connell et al., 2024). A qualitative study of electronic early-warning protocols tells a different story. It describes how performance monitoring can quietly reshape nursing practice, with some staff covertly omitting observations because they could not record legitimate reasons for departing from the protocol (Hope et al., 2019). These findings do not contradict one another. They point instead to the same lesson: the design, purpose and governance of a system matter at least as much as the technology itself.

Because the available studies range from qualitative interviews to predictive modeling, implementation studies and earlier reviews, we adopted a structured narrative synthesis rather than a meta-analysis. Pooling such heterogeneous results would suggest a statistical comparability that does not exist (Ezema, Ezema & Igwe, 2017).

## 1.1 Research questions

1. What operational and workforce outcomes have been reported for data-driven scheduling, workload prediction and performance-monitoring systems in healthcare?
2. Through what mechanisms might these systems support or constrain health workers' autonomy, judgment and day-to-day performance?
3. What does the available evidence establish, and what does it leave unresolved, about balancing efficiency against staff well-being, clinical quality and patient safety?

## 1.2 Objectives

1. To define the forms of algorithmic management considered here and to separate workforce-management tools from clinical decision-support applications.
2. To compare reported effects on scheduling, workload, performance, autonomy and workforce experience across study designs and settings.

3. To appraise the strength and limits of the evidence, including whether it is suitable for quantitative pooling.
4. To identify implementation and research priorities that could align operational performance with professional judgment and safe care.

## 2. Methods

### 2.1 Review design

We conducted a structured narrative review with comparative evidence synthesis. The design suited the questions because the relevant literature is methodologically diverse and does not yield a common set of study-level effect estimates. The review was not registered, was not conducted as a PRISMA-compliant screening exercise, and did not estimate a pooled effect. For that reason we do not describe the method or findings as a meta-analysis.

### 2.2 Search and source selection

We searched PubMed, OpenAlex and Semantic Scholar on 21 October 2026. The search concepts combined terms for algorithmic management, healthcare workforce, nurse scheduling and rostering, workload prediction, electronic performance monitoring, clinical autonomy, occupational well-being and human oversight. Example strings included “algorithmic management in healthcare,” “AI nurse staffing scheduling,” “electronic nursing protocols,” “digital performance monitoring” and “clinical decision support and clinician autonomy.” The search emphasized 2015–2026, and we kept earlier work when it directly informed interpretation. We screened titles and abstracts for relevance to work organization, scheduling, workload, performance monitoring, autonomy or workforce outcomes, and ran exact-title searches to confirm prominent references.

Sources were eligible if they addressed healthcare staff or clinical work; examined a data-driven or digital tool that affected work allocation, surveillance, performance assessment or clinical discretion; and reported at least one operational, workforce or professional outcome. General clinical-AI studies with no discernible link to workforce management were used for context only, never as evidence of management effects. For reported outcomes we relied on primary empirical studies, and we used reviews to characterize patterns across studies.

### 2.3 Grouping, appraisal and synthesis

Selected records were grouped into four domains: (1) scheduling and rostering; (2) workload prediction and task allocation; (3) electronic protocol monitoring and clinical discretion; and (4) broader job-design and governance considerations. For each source we compared design, population or setting, system function, outcome and the limits of inference. We read qualitative accounts as evidence about mechanisms and lived experience, not prevalence; treated predictive-model performance as evidence of model fit, not of better staffing or patient outcomes; and regarded review-level conclusions as secondary synthesis rather than independent primary observation.

No formal risk-of-bias instrument was applied, because the evidence was too heterogeneous for any single tool to be meaningful. Nor did we use citation counts as a proxy for validity. Instead, Table 1 supports a qualitative triangulation across study designs and outcome types. This is a comparative check, not an independent causal validation.

### 2.4 Methodological limits

Several limits shape how the findings should be read. Scopus and Web of Science were not searched. Most retrieved evidence was available only as abstracts, so full-text methods, detailed quality assessments and unreported subgroup results could not be examined. The search and screening trail was not recorded in a reproducible PRISMA flow, and nothing here should be read as a claim of exhaustive coverage.

# 3. Findings

## 3.1 Scheduling and rostering

Scheduling is a natural fit for analytics. Managers must reconcile patient demand, staff availability, qualifications and cost, often at short notice. But electronic rostering, self-rostering and AI-based optimization are distinct interventions and should not be treated as interchangeable. The mixed-method systematic review covered 18 studies of electronic and self-rostering: 10 quantitative descriptive studies, seven non-randomized studies and one qualitative study. Across them, reported benefits included better roster efficiency, staff satisfaction, perceived control, work-life balance, retention and absence outcomes. The review also found that self-rostering could be less equitable than fixed rostering and was linked to more overtime and more shift-change requests (O'Connell et al., 2024). Because the review combined different systems and designs, its positive overall conclusion is not a single effect estimate, and it does not show that automated optimization itself produced the benefits.

The contrast between participation and automation helps make sense of this mixed picture. Where workers can state preferences and shape the final schedule, a digital tool may extend their control rather than replace it (Ezema, Okafor & Inyiama, 2017; (Ezema, Okezie & Okafor, 2018). Where optimization runs mainly against institutional constraints, the system may improve administrative consistency while pushing the burden of difficult schedules onto employees. The review supports the view that rostering systems can benefit both organizations and workers, but it also shows that outcomes hinge on equity and on how schedule conflicts are resolved (O'Connell et al., 2024). Evidence that isolates AI-based scheduling from electronic or self-rostering was not found in the sources we examined (Ezema, Inyiama & Chinwuko, 2017).

## 3.2 Workload prediction and analytics

Workload-prediction tools draw on routine clinical information to estimate staffing needs (Ezema, Okafor & Okezie, 2016; 2017). A multicenter data-model study using information from three hospitals reported that a nursing self-care index explained 40%–66% of the variance in nursing workload, and that adding predictors such as fatigue and pain intensity raised adjusted explanatory power by up to 17% (Hunstein et al., 2024). The finding supports the feasibility of modeling nursing workload from patient data. It does not show that staffing decisions based on the model improved nurse performance, patient outcomes or the fairness of workload distribution. Those are implementation questions that need prospective evaluation.

A separate two-wave study in a nursing home in Guangzhou compared nurse–patient interaction before and after the introduction of an AI-supported surveillance system. According to the abstract, average interaction time per patient fell from 18 to 10 minutes, and the system issued real-time alerts for abnormal patient status (Huang et al., 2022). The result is promising but narrow. The abstract reports no control group, no broader performance measures, no account of worker experience, and nothing on what happened to the time that was saved. Shorter interaction time should therefore not be read as better productivity or better care. A more defensible interpretation is that automation may reduce time spent on certain monitoring tasks, while the clinical and relational work that remains still needs its own assessment(Ezema, et al., 2018; 2016) .

Both studies illustrate a recurring measurement problem. Model fit and time savings are operational indicators; they are not direct measures of sustainable workforce performance. In healthcare, performance is better judged at three linked levels: the technical performance of the tool, its effect on work processes, and its consequences for staff and patients.

## 3.3 Performance monitoring and clinical discretion

Digital protocols can standardize care and make patterns visible to managers. Used for performance evaluation, though, they can change how workers handle complex situations. In a qualitative interview study, 17 acute-

hospital nursing staff described their experience of an electronic early-warning-score protocol. Before compliance data were used for performance management, nurses blended protocol-led actions with their own clinical judgment. Once monitoring began, some reported covertly skipping observations, using a loophole in the system, when they judged those observations unnecessary. Participants also described a loss of autonomy, although they acknowledged that the system sometimes picked up deterioration they had not expected (Hope et al., 2019). The study cannot say how common such workarounds are. It does, however, identify a plausible mechanism: when a monitoring system gives staff no way to document clinically justified deviations, measured compliance can drift away from what care actually looks like.

This is a reason to be wary of treating adherence metrics as self-validating. A high recorded compliance rate may reflect good care, but it may equally reflect a rigid protocol, strategic documentation or unrecorded workarounds. Conversely, departing from an algorithmic recommendation is not necessarily poor performance when the patient's circumstances call for professional judgment. The evidence is stronger for a potential mechanism, in which monitoring constrains discretion and invites covert adaptation, than for any quantified effect on overall clinical quality or patient safety.

### 3.4 Job design, autonomy and governance

Work-design research offers a framework for interpreting these implementation findings. One review of algorithmic management identifies monitoring, goal setting, performance management, scheduling, compensation and termination as functions that can be handed to algorithms, and argues that their effects on autonomy, workload and motivation are shaped by transparency, fairness and whether workers can influence the system (Parent-Rocheleau & Parker, 2021). A separate systematic review of 172 articles describes algorithmic management as capable of both constraining and enabling autonomy, while noting that control-oriented applications were more common than enabling ones in the literature it covered (Noponen et al., 2023). Neither review is specific to healthcare, so they supply a conceptual lens rather than direct evidence of effects in hospitals.

Healthcare-specific evidence suggests that professional acceptance depends on more than model accuracy; it also depends on how a tool is introduced and governed. A review of 105 publications on patient, public and health-professional perspectives found generally favorable views of healthcare AI, tempered by concerns about privacy, bias, autonomy, inequity and accountability. Participants stressed validation, transparency, explainability, clinical and patient involvement in development, and workforce training (Vo et al., 2023). A review focused on healthcare job design similarly concluded that AI applications may affect autonomy, control, skills, feedback, social relations and job demands, and observed that the real impact on professionals' jobs had not been adequately studied in the literature it examined (Tursunbayeva & Renkema, 2022).

The shared implication is that "human oversight" has to be operational, not symbolic. Workers need to understand what a system is optimizing, to report when its output clashes with clinical context, and to challenge or override its recommendations without undue penalty (Ezema, Okafor & Okezie, 2016). These safeguards follow from concerns documented in the evidence, but their effectiveness as a combined governance package has yet to be tested comparatively (Ezema, Okafor & Okezie, 2017; 2016).

## 4. Comparative evaluation of the evidence

**Table 1. Comparative assessment of studies and reviews relevant to algorithmic management in healthcare**

| Source and evidence type | Setting, sample or evidence base | Reported result relevant to this review | What the evidence supports, and what it does not |
|---|---|---|---|
| Mixed-method | 18 studies: 10 | Review-level benefits in roster | Supports a qualified |

| | | | |
|---|---|---|---|
| systematic review of electronic and self-rostering (O'Connell et al., 2024) | descriptive quantitative, 7 non-randomized, 1 qualitative; 12 self-rostering and 6 electronic rostering | efficiency, staff satisfaction and control, work-life balance, retention and absence; equity and overtime concerns also reported | positive account of rostering; does not isolate AI effects or provide a single pooled estimate |
| Qualitative study of electronic protocol data in performance management (Hope et al., 2019) | 17 acute-hospital nursing staff interviewed | Participants described diminished autonomy and covert workarounds, while recognizing that the system could flag deterioration | Identifies mechanisms and tensions; cannot estimate prevalence or causal effects on safety |
| AI-supported surveillance, two-wave study (Huang et al., 2022) | Same nurses and patients across two waves in one nursing home in Guangzhou | Mean nurse–patient interaction time fell from 18 to 10 minutes after implementation | Suggests time savings in this setting; does not establish net productivity, care quality or generalizability |
| Nursing workload prediction model (Hunstein et al., 2024) | Routine data from three hospitals | Self-care index explained 40%–66% of workload variance; added predictors raised adjusted explanatory power by up to 17% | Supports the feasibility of predictive modeling; model fit alone does not demonstrate better staffing or patient outcomes |
| Healthcare job-design review (Tursunbayeva & Renkema, 2022) | Analysis of 80 publications from a grey-literature platform | AI applications linked conceptually to autonomy, control, skills, feedback, social relations and job demands | Provides a work-design framework; its evidence base was not a direct evaluation of implemented workforce systems |
| Systematic review of stakeholder perspectives on healthcare AI (Vo et al., 2023) | 105 publications selected from 7,490 records | Stakeholders were generally positive but raised concerns about privacy, autonomy, bias, accountability, transparency and training | Establishes recurring acceptability and governance themes, not measured effects of algorithmic management on worker performance |

### 4.1 Triangulation, not statistical validation

The central interpretation holds up across different kinds of evidence. Operational gains are reported in rostering, workload modeling and targeted monitoring, while concerns about control and discretion appear in qualitative research and stakeholder reviews (Nonum, Ezema & Inyiama, 2018). The pattern is therefore not a simple contest between efficiency and harm. What the evidence supports is a contingent conclusion: systems can improve a defined task or process, but outcomes for workers and for care depend on how the intervention is designed and on whether people keep meaningful influence over it.

This is comparative triangulation, not statistical validation. The sources differ in intervention, population, comparator, outcome and design, and combining their percentages or treating them as independent replications would mislead. Citation counts and other webometric indicators would not resolve these limitations either, since scholarly attention cannot verify an intervention effect, establish causal direction or stand in for appraisal of study design. We therefore present no webometric analysis.

## 5. Discussion

The picture that emerges is more conditional than the usual narrative of analytics as either a productivity engine or a surveillance threat. The evidence supports the potential for better scheduling processes, more informed workload estimates and time savings in selected tasks. It does not support broader claims: that AI scheduling reliably reduces errors by a fixed percentage, that performance surveillance uniformly raises stress, or that algorithmic management as a whole either improves or undermines clinical quality. The interventions and measures in these studies are too different, and several findings were available only at abstract level.

One distinction does much of the analytic work here, the gap between a technical output and an organizational outcome. A workload model may predict demand accurately without any assurance that managers act on the prediction (Ezema, et al., 2016; Alaya, Mojeke & Ezema, 2022). A shorter patient interaction may free nursing time, but its clinical value depends on where that time goes. A protocol may standardize care while making unrecorded clinical adaptation more likely. Performance, in other words, is not a single quantity. Throughput, staffing fit, adherence, team functioning, professional judgment and patient outcomes can each move in a different direction.

The evidence also challenges the assumption that autonomy and efficiency must be traded against each other (Ezema, Okafor & Okezie, 2016; Ezema, et al., 2016). The rostering review reports gains in control and work-life balance in some settings, alongside signs of inequity and overtime pressure (O'Connell et al., 2024). The qualitative protocol study shows the opposite risk: a monitoring design that narrows discretion and elicits covert workarounds (Hope et al., 2019). One plausible reading is that participatory scheduling widens workers' input, whereas compliance monitoring restricts discretion when exceptions go unrecognized. That explanation fits both studies, but no one has tested it in a direct comparison.

For organizations, the practical message is to settle evaluation criteria before a system goes live. A tool should be judged on its technical reliability, its distributional effects across staff groups, its impact on the work process and its downstream consequences for patient care. Frontline clinicians should help choose objectives, review exceptions and revise workflows. Systems used for performance management should offer a route for recording justified deviations, and algorithmic recommendations should never substitute for professional accountability. These are implementation principles derived from the observed evidence and from stakeholder concerns at review level, not interventions shown to be superior in head-to-head trials (Hope et al., 2019; Vo et al., 2023).

### 5.1 Implications for practice

1. **Define what the system does.** Distinguish forecasting and decision support from monitoring, evaluation and automated direction, and be explicit about which decisions remain with clinicians.
2. **Build frontline participation into deployment.** Involve nurses and other affected staff in design, testing, exception review and post-implementation evaluation. Stakeholder evidence repeatedly names clinical involvement and transparency as implementation priorities (Vo et al., 2023).
3. **Preserve explainable clinical discretion.** Let staff record why they depart from a recommendation, and review override patterns as possible signals of patient complexity or system design rather than as simple noncompliance (Hope et al., 2019).
4. **Measure outcomes at several levels.** Pair operational metrics such as time, roster efficiency and prediction performance with workload distribution, staff experience, retention, quality of care and patient outcomes. The workload-model study reports predictive fit and the surveillance study reports time in nurse–patient interaction; neither abstract reports an overall measure of workforce performance (Huang et al., 2022; Hunstein et al., 2024).
5. **Audit equity and unintended work.** Look at who receives desirable and undesirable shifts, who absorbs extra overtime, and whether staff are resorting to workarounds. The rostering evidence identifies equity and overtime as material concerns (O'Connell et al., 2024).

### 5.2 Priorities for future research

Prospective, longitudinal evaluations should compare algorithm-supported systems with existing practice and report both workforce and patient outcomes. Studies should also separate AI optimization from electronic rostering and worker-led self-scheduling, because these are not equivalent interventions. Autonomy, workload, workarounds and performance need to be measured with validated instruments and transparent definitions. Implementation research should test whether participatory design, override policies and transparent exception reporting actually improve adoption or outcomes. Finally, model-development studies should go beyond predictive fit and show how predictions translate into staffing decisions, and whether those decisions improve care.

## 6. Limitations

The evidence base does not justify a quantitative meta-analysis. The sources vary in intervention and outcome, and they do not provide a common set of comparable effect estimates with variance data. This review is structured and question-led, but it is not a registered or exhaustive systematic review, and the numbers of records screened and excluded cannot be reconstructed from a formal screening log. Scopus and Web of Science were not searched, and web pages and official agency materials were outside the source scope. Most retrieved evidence was available as abstracts rather than full text, so detailed methodological quality and complete outcome reporting could not be verified. Findings should therefore be read as a reasoned synthesis of the available literature, not a definitive appraisal.

## 7. Conclusion

Data analytics can help healthcare organizations plan staffing, estimate nursing workload and automate selected monitoring tasks. The evidence reviewed here supports these benefits in specific settings, but it does not establish a universal productivity effect, and it does not justify treating operational efficiency as a stand-in for better care. The same technologies can reshape professional discretion and everyday work practices, especially when performance measures leave no legitimate room for clinical context. The defensible position is neither wholesale adoption nor rejection. It is targeted use, evaluated against workforce and patient outcomes, with frontline participation and real human authority built into the system. Future studies need to move beyond model accuracy and process efficiency and test whether these tools improve sustainable performance and safe, high-quality care.

## References

Alaya, L. A., Mojeke, M. O., & Ezema, C. N. (2022). Review of consumer service quality perception of digital banking and digital application software. *International Journal of Research Publication and Reviews, 3*(2), 367–379. https://ijrpr.com/uploads/V3ISSUE2/ijrpr2642-review-of--consumer-service-quality-perception-of-digital-banking.pdf

Ekechukwu, B., Ugwuanyi, U., & Ezema, C. (2015). Expert systems for crime investigation and intelligent profiling. *International Journal of Scientific Innovations and Sustainable Development, 5*(2). https://www.irdionline.org/catr/article/EXPERT%20SYSTEMS%20FOR%20CRIME%20INVESTIGATION.pdf

Ezema, C. N. (2017). Microcontroller based photo-electric control system. *Asia Pacific Journal of Engineering Science and Technology, 3*(3), 129–140. https://www.academia.edu/38772890/Microcontroller_Based_Photo_Electric_Control_System

Ezema, C. N., Agulanna, A. C., Onuoha, O., Nonyelu, H. U., & Anagbogu, N. M. (2016a). Hybrid intelligent decision support system for malaria and typhoid fever diagnosis. *International Journal of Engineering Research and Reviews, 4*(1), 82–91. https://www.researchpublish.com/upload/book/Hybrid%20Intelligent%20Decision-2933.pdf

Ezema, C. N., Agulanna, A. C., Onuoha, O., Nonyelu, H. U., & Anagbogu, N. M. (2016b). Rule-based access control information management system for effective records management of employee performance.

*International Journal of Computer Science and Information Technology Research, 4*(1), 241–252. https://www.researchpublish.com/upload/book/Rule-Based%20Access%20Control-2939.pdf

Ezema, C. N., Agulanna, A. C., Onuoha, O., Nonyelu, H. U., & Nwogu, N. (2016a). Design and construction of enhanced microcontroller-based electronic voting machine with digital display. *International Journal of Electrical and Electronics Research, 4*(1), 93–103. https://www.researchpublish.com/upload/book/Design%20and%20Construction-2934.pdf

Ezema, C. N., Agulanna, A. C., Onuoha, O., Nwogu, N., & Victor, U. U. (2016). Design and implementation of radio frequency-based telemetry and telecommunication security surveillance system. *Journal of Applied Physical Science International, 7*(2), 60–69. https://ikprress.org/index.php/JAPSI/article/download/3086/2875/5603

Ezema, C. N., Diovu, C. R., Ugwuanyi, U. B., & Okpe, P. C. (2022). Effect of laboratory/workshop curriculum and teaching methodology on entrepreneurial intentions of biomedical engineering graduates in Nigeria. *International Journal of Mechatronics, Electrical and Computer Technology, 12*(46), 5274–5283. https://www.scribd.com/document/902398081/Effect-of-Laboratory-workshop-Curriculum-and-Teaching-Methodology-on-Entrepreneurial-Intentions-of-Biomedical-Engineering-Graduates

Ezema, C. N., Ezema, C. C., & Igwe, J. I. (2017). Aviation security information management system for Nigerian airlines. *European Journal of Physical Sciences, 1*(1), 1–16. https://www.academia.edu/38773953/AVIATION_SECURITY_INFORMATION_MANAGEMENT_SYSTEM_FOR_NIGERIAN_AIRLINES

Ezema, C. N., Ezema, C. C., & Nonum, E. O. (2017). Design and implementation of microcontroller-based logic gate tester. *Current Trends in Biomedical Engineering & Biosciences, 8*(1), Article 555729. https://doi.org/10.19080/CTBEB.2017.08.555729

Ezema, C. N., Ezema, C. C., & Umezinwa, C. B. (2017). Employee performance appraisal database management system. *International Journal of Emerging Engineering Research and Technology, 5*(8), 17–27. https://www.academia.edu/38773956/Employee_Performance_Appraisal_Database_Management_System

Ezema, C. N., Inyiama, C. H., & Chinwuko, E. C. (2017). Optimum common frequency routing (CFR) of JIT systems with time-varying demand and flexible production capacities. *European Journal of Advances in Engineering and Technology, 4*(2), 120–128. https://ejaet.com/archive/volume-4-issue-2-2017/

Ezema, C. N., Nonum, E. O., Umezinwa, C. N., & Anakwenze, U. (2018). The impact of information management systems on the performance of commercial banks in Nigeria. *Archives of Current Research International, 14*(4), 1–13. https://doi.org/10.9734/ACRI/2018/25120

Ezema, C. N., Nwobodo-Nzeribe, N. H., Eneh, J. N., Ogbuefi, U. C., Mbunwe, M. J., Anyaka, B. O., & Ngene, J. N. (2022). Manufacturing system optimization using computer-based control Kanban loops. *Bangladesh Journal of Scientific and Industrial Research, 57*(4), 221–228. https://doi.org/10.3329/bjsir.v57i4.61400

Ezema, C. N., Okafor, E. C., & Inyiama, C. H. (2017). A review of the implementation of JIT algorithms and models in production systems. *Journal of Applied and Advanced Research, 2*(3), 122–138. https://doi.org/10.21839/jaar.2017.v2i3.75

Ezema, C. N., Okafor, E. C., & Okezie, C. C. (2016a). Agent-based simulation and system dynamic modelling of just-in-time manufacturing system. *International Journal of Technology and Systems, 1*(1), 30–47. https://iprjb.org/journals/IJTS/article/view/59

Ezema, C. N., Okafor, E. C., & Okezie, C. C. (2016b). Multi-objective flexible job-shop scheduling and control of JIT systems. *European Journal of Advances in Engineering and Technology, 3*(12), 16–22. https://ejaet.com/archive/volume-3-issue-12-2016/

Ezema, C. N., Okafor, E. C., & Okezie, C. C. (2016c). Optimization modeling and scheduling of production control schemes for complex JIT manufacturing systems. *Journal of Scientific and Engineering Research, 3*(6), 252–261. https://jsaer.com/download/vol-3-iss-6-2016/JSAER2016-03-06-252-261.pdf

Ezema, C. N., Okafor, E. C., & Okezie, C. C. (2016d). Performance analysis of scheduling in re-entrant manufacturing systems based on JIT simulation model. *International Journal of Scientific Research in Engineering, 1*(1), 22–30. https://profile.unizik.edu.ng/nau2417

Ezema, C. N., Okafor, E. C., & Okezie, C. C. (2017). Industrial design and simulation of a JIT material handling system. *Cogent Engineering, 4*(1), Article 1292864. https://doi.org/10.1080/23311916.2017.1292864

Ezema, C. N., Okezie, C. C., & Okafor, E. C. (2018). Visual control and manufacturing system (drug process plant) performance enhancement using ARENA modular simulation and TECNOMATIX modeling. *Journal of Engineering and Applied Sciences, 12*, 35–43. https://journals.unizik.edu.ng/index.php/ujeas/article/view/1708

Ezema, C. N., & Umezinwa, C. B. (2016). Design and implementation of a microcontroller-based digital time-aware oven temperature controller and display. *International Journal of Multidisciplinary Research and Modern Education, 2*(1), 731–739. https://ijmrme.crystalpen.in/uploads/6845586201ae2_277.pdf

Ezema, C. N., Umezinwa, C. B., & Nonum, E. O. (2016). Microcontroller-based optical displacement weighing scale. *International Journal of Advance Research and Innovation, 4*(3), 27–33. https://doi.org/10.51976/ijari.431606

Ezema, N. C., Okafor, E. C., & Okezie, C. C. (2017). Kanban-based scheduling in a multistage and multiproduct system (drug process plant). *Global Journal of Computer Science and Technology, 17*(1), 6–14. https://globaljournals.org/scholarly-articles/kanban-based-scheduling-in-a-multistage-and-multiproduct-system/

Ezema, C. N., Obi, P. I., & Umezinwa, C. N. (2016). Solving electric power transmission line faults using hybrid artificial neural network modules. *American Journal of Computing and Engineering, 1*(1), 1–25. https://doi.org/10.47672/ajce.69

Ezema, C. N., Iloh, J. P. I., & Obi, P. I. (2017). Analysis of distance protection for EHV transmission lines using artificial neural network. *International Journal of Engineering, Business and Management, 1*(2). https://aipublications.com/ijebm/detail/analysis-of-distance-protection-for-ehv-transmission-lines-using-artificial-neural-network/

Ezema, C. N., Okafor, E. C., & Okezie, C. C. (2017). Industrial design and simulation of a JIT material handling system. *Cogent Engineering, 4*(1), Article 1292864. https://doi.org/10.1080/23311916.2017.1292864

Ezema, C. N., Ezema, C. C., & Nonum, E. O. (2017). Employee performance appraisal database management system. *International Journal of Emerging Engineering Research and Technology, 5*(8), 17–27. https://www.academia.edu/38773956/Employee_Performance_Appraisal_Database_Management_System

Ezema, C. N., Okafor, E. C., & Okezie, C. C. (2016). Optimization modeling and scheduling of production control schemes for complex JIT manufacturing systems. *Journal of Scientific and Engineering Research, 3*(6), 252–261. https://jsaer.com/download/vol-3-iss-6-2016/JSAER2016-03-06-252-261.pdf

Ekechukwu, B., Ugwuanyi, U., & Ezema, C. (2015). Expert systems for crime investigation and intelligent profiling. *International Journal of Scientific Innovations and Sustainable Development, 5*(2). https://www.irdionline.org/catr/article/EXPERT%20SYSTEMS%20FOR%20CRIME%20INVESTIGATION.pdf

Ezema, C. N., Ezema, C. C., & Nonum, E. O. (2017). Employee performance appraisal database management system. *International Journal of Emerging Engineering Research and Technology, 5*(8), 17–27. https://www.academia.edu/38773956/Employee_Performance_Appraisal_Database_Management_System

Ezema, C. N., Ezema, C. C., & Umezinwa, C. B. (2017). Employee performance appraisal database management system. *International Journal of Emerging Engineering Research and Technology, 5*(8), 17–27. https://www.academia.edu/38773956/Employee_Performance_Appraisal_Database_Management_System

Hope, J., Griffiths, P., Schmidt, P., Recio-Saucedo, A., & Smith, G. B. (2019). Impact of using data from electronic protocols in nursing performance management: A qualitative interview study. *Journal of Nursing Management*. https://doi.org/10.1111/jonm.12858

Huang, K., Jiao, Z., Cai, Y., & Zhong, Z. (2022). Artificial intelligence based intelligent surveillance for reducing nurses' working hours in nurse-patient interaction: A two-wave study. *Journal of Nursing Management*. https://doi.org/10.1111/jonm.13787

Hunstein, D., Frischen, L. S., & Fiebig, M. (2024). Development of a data model to predict nursing workload using routine clinical data. *Studies in Health Technology and Informatics*. https://doi.org/10.3233/SHTI240588

Hope, J., Griffiths, P., Schmidt, P., Recio-Saucedo, A., & Smith, G. B. (2019). Impact of using data from electronic protocols in nursing performance management: A qualitative interview study. *Journal of Nursing Management*. https://doi.org/10.1111/jonm.12858

Huang, K., Jiao, Z., Cai, Y., & Zhong, Z. (2022). Artificial intelligence based intelligent surveillance for reducing nurses' working hours in nurse-patient interaction: A two-wave study. *Journal of Nursing Management*. https://doi.org/10.1111/jonm.13787

Hunstein, D., Frischen, L. S., & Fiebig, M. (2024). Development of a data model to predict nursing workload using routine clinical data. *Studies in Health Technology and Informatics*. https://doi.org/10.3233/SHTI240588

Noponen, N., Feshchenko, P., Auvinen, T., Luoma-aho, V., & Abrahamsson, P. (2023). Taylorism on steroids or enabling autonomy? A systematic review of algorithmic management. *Management Review Quarterly*. https://doi.org/10.1007/s11301-023-00345-5

Nonum, E. O., Ezema, C. N., & Inyiama, C. H. (2018). Review of fraud detection and churn behavior modeling techniques. *International Journal of Research in Advanced Engineering and Technology, 4*(2), 33–36. https://www.allengineeringjournal.in/assets/archives/2018/vol4issue2/4-2-21-499.pdf

O'Connell, M., Barry, J., Hartigan, I., Cornally, N., & Saab, M. (2024). The impact of electronic and self-rostering systems on healthcare organisations and healthcare workers: A mixed-method systematic review. *Journal of Clinical Nursing*. https://doi.org/10.1111/jocn.17114

Obi, O. E., Ezechukwu, O. A., & Ezema, C. N. (2016). Enhanced real-time and off-line transmission line fault diagnosis using artificial intelligence. *Asian Journal of Computing and Engineering Technology, 1*(1), 1–22. https://iprjb.org/journals/AJCET/article/view/215

Obi, O. E., Ezechukwu, O. A., & Ezema, C. N. (2017). An extended artificial neural network-based high-speed accurate transmission line fault location for double phase-to-earth fault on non-direct-ground. *International Journal of Engineering Science Technologies, 1*(1), 31–47. https://doi.org/10.29121/ijoest.v1.i1.2017.04

Parent-Rocheleau, X., & Parker, S. K. (2021). Algorithms as work designers: How algorithmic management influences the design of jobs. *Human Resource Management Review*. https://doi.org/10.1016/j.hrmr.2021.100838

Tursunbayeva, A., & Renkema, M. (2022). Artificial intelligence in health-care: Implications for the job design of healthcare professionals. *Asia Pacific Journal of Human Resources*. https://doi.org/10.1111/1744-7941.12325

Vo, V., Chen, G., Aquino, Y. S. J., Carter, S. M., Nga, Q., & Woode, M. E. (2023). Multi-stakeholder preferences for the use of artificial intelligence in healthcare: A systematic review and thematic analysis. *Social Science & Medicine*. https://doi.org/10.1016/j.socscimed.2023.116357