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Adoption and Effectiveness of Energy-Saving Lighting Technologies in Office Buildings: Evidence from Dar es Salaam, Tanzania

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ABSTRACT

This study was conducted to assess how energy-saving lighting technologies are being adopted and to evaluate their effectiveness in real-world settings. A cross-sectional quantitative survey involving on-site audits was conducted across 25 multi-storey office buildings selected through stratified sampling. Descriptive statistics, spatial heatmaps, and regression analysis were used to examine the prevalence, spatial deployment, and performance of lighting technologies. Descriptive analysis indicates a strong positive association between motion sensor deployment density and energy efficiency outcomes ($r = 0.93$); however, this relationship is scale-mediated since larger buildings naturally have more sensors and higher absolute energy use and should not be interpreted as a direct causal effect. Building size was considered as a contextual factor throughout the analysis. Motion sensors are installed in only 40% of buildings and mainly in low-use areas like lobbies and restrooms. Further analysis revealed that energy savings are significantly influenced by the extent of coverage rather than mere adoption. These findings are important for informing urban energy strategies. The study recommends prioritizing sensor installation in high-occupancy zones, incentivizing retrofits, and ensuring regular maintenance. Overall, it offers a practical framework to enhance lighting energy efficiency in rapidly urbanizing cities like Dar es Salaam.

Keywords: lighting energy efficiency; motion sensors; energy-saving technology; office buildings; Dar es Salaam

INTRODUCTION

Efficient energy use in commercial buildings is essential for promoting sustainable urban development, particularly in rapidly growing cities across Sub-Saharan Africa. Lighting systems remain a major contributor to electricity consumption, accounting for approximately 20–35% of office energy use (IEA, 2022; UN-Habitat, 2021). In tropical cities like Dar es Salaam, where daytime occupancy is high but natural lighting is underutilized, lighting efficiency presents a critical opportunity for savings. Despite the availability of technologies such as LEDs, occupancy sensors, and daylight harvesting systems, adoption in African office buildings

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remains low. Studies across Sub-Saharan Africa consistently document persistent barriers including high upfront costs, limited awareness, lack of technical expertise, and weak enforcement (Nkini et al., 2024). Much of the existing data, however, is aggregated at national or sectoral levels, obscuring building-level performance needed for targeted retrofits and policies. Furthermore, operational and behavioural issues such as poor sensor placement or frequent manual overrides can undermine expected savings (Azizi et al., 2021). With electricity demand estimated to grow substantially by 2030 (TANESCO, 2022), these challenges underscore the urgency of building-level evidence in Dar es Salaam's office sector.

Guided by the Diffusion of Innovation Theory and benchmarking approaches from building performance studies, this research pursues three objectives: (i) to map the adoption and spatial distribution of motion sensors which are the only advanced lighting technology identified across office buildings stratified by glazing ratios in Dar es Salaam; (ii) to quantify real-world performance using Lighting Power Density (LPD) and Energy Efficiency Index (EEI); and (iii) to explore the extent to which operational and behavioral factors (e.g., overrides, maintenance delays) are associated with observed efficiency outcomes, through cluster analysis of efficiency typologies. By linking technology deployment with operational performance, this study contributes actionable evidence for building owners, managers, and policymakers. It highlights how strategic deployment and maintenance not just technology access can advance Tanzania's commitments to Sustainable Development Goal (SDG) 7 (affordable and clean energy) as per United Nations (2015) and broader decarbonization strategies.

LITERATURE REVIEW

Global and Regional Trends in Lighting Energy Efficiency

Lighting energy efficiency has become a cornerstone of international sustainability frameworks, most notably through performance standards such as ASHRAE 90.1 and certification systems including LEED v4.1 (ASHRAE, 2019). In industrialized economies, the widespread adoption of light-emitting diodes (LEDs) and advanced control technologies has yielded substantial reductions in electricity demand, with reported savings ranging from 30% to 60% (Zissis and Bertoldi, 2023). These outcomes are particularly relevant to studies of office buildings the specific typology examined in this research where lighting controls have demonstrated the clearest performance benefits. In contrast, Sub-Saharan Africa presents a distinctly different performance landscape. Infrastructural constraints, behavioural inconsistencies, and fragile institutional systems constrain actual savings to far lower levels, often between 15% and 30% (Mosner-Ansong et al., 2024). This disparity illustrates the importance of local context in mediating the performance of ostensibly universal technologies.

The diffusion of efficient lighting technologies across Africa has been slow and uneven. Persistent obstacles include high upfront investment costs, limited local manufacturing capacity, insufficient technical expertise, and weak enforcement of energy efficiency codes (Erebor et al., 2021; Chen and Chen, 2021; UNEP Africa, 2021). Nonetheless, pilot programs in Nairobi and Accra, underpinned by public–private partnerships and targeted incentives, have achieved measurable efficiency gains (Mosner-Ansong et al., 2024). Critically, these gains were context-dependent and conditioned by institutional readiness a pattern that directly informs the Tanzanian context of this study. In Tanzania, inconsistent maintenance regimes and limited managerial capacity frequently undermine installed technologies (AfDB, 2020). Such experiences reinforce arguments that stakeholder competence and institutional frameworks are central to sustaining technological benefits (Sendrayaperumal et al., 2021). The Africa Energy Outlook (IEA, 2019) identifies lighting efficiency as a strategic intervention point for urban sustainability. Collectively, these insights establish the empirical and theoretical foundation for this study's focus on deployment strategy and operational integration within Dar es Salaam's office sector.

Typologies, Effectiveness, and Contextual Barriers

Lighting energy-saving measures generally fall into three categories: (i) high-efficiency luminaires (e.g., LEDs, compact fluorescents), (ii) lighting control systems (e.g., motion sensors, timers, daylight sensors), and (iii) integrated digital management platforms. Globally, LEDs deliver up to 75% energy savings compared to incandescent bulbs, while also offering higher luminous efficacy and longer lifespans (Shankar et al., 2020; Norouziasl and Jafari, 2023). Control systems, particularly occupancy and motion sensors, typically reduce consumption by 20–40% (Azizi et al., 2021). However, their effectiveness is highly context-dependent which is particularly relevant to this study, which identifies motion sensors as the sole advanced technology deployed in the sampled buildings, making their effective integration the central focus of analysis. Research on occupancy-based lighting control in open-plan office environments has similarly demonstrated that sensor placement and spatial configuration are critical determinants of system effectiveness (de Bakker et al., 2017). Behavioural and operational dynamics further complicate implementation. Frequent manual overrides, insufficient feedback mechanisms, and inconsistent maintenance undermine the long-term impact of even well-designed systems (He et al., 2021). Integrated digital management platforms such as Building Management Systems (BMS) and IoT-based smart controls remain scarce in African contexts (Erebor et al., 2021; Gassar et al., 2021). These barriers are directly applicable to office buildings examined in this study and help explain observed performance gaps between technology adoption and actual energy outcomes.

Linking Deployment to Energy Outcomes

Recent research emphasizes that energy savings depend not only on the availability of efficient technologies but also on their deployment scale, spatial coverage, and alignment with occupancy patterns (Norouziasl and Jafari, 2023; Gassar et al., 2021). Metrics such as Lighting Power Density (LPD) and the Energy Efficiency Index (EEI) provide a standardized basis for comparing building performance across different settings (Brown et al., 2010; Zissis and Bertoldi, 2023). Studies using correlational and regression techniques have shown that energy savings correlate positively with optimized sensor placement, activation hours tailored to occupancy and systematic maintenance practices (He et al., 2021). Crucially, however, most of this evidence derives from Asian and European contexts. The extent to which these relationships hold in Sub-Saharan African office buildings remains empirically underexplored, reinforcing the need for this study's building-level analysis in Tanzania.

Research Gap and Contribution

The central knowledge gap addressed by this study is the absence of granular, building-level empirical evidence on how deployment strategy, operational practices and architectural typology interact to shape lighting energy outcomes in Sub-Saharan African office buildings. Existing African studies predominantly rely on aggregated utility data or simulation-based projections (Norouziasl and Jafari, 2023; Shoeb and Joarder, 2024), which cannot capture the spatial and behavioural dynamics that determine real-world performance. This study contributes to filling this gap by conducting a stratified empirical assessment of 25 multi-storey office buildings in Dar es Salaam, generating context-specific evidence directly applicable to energy policy and building management practice in Tanzania and comparable Sub-Saharan African settings. The study employs spatial heatmaps to visualize consumption patterns, combined with descriptive statistics, Pearson correlation, and regression analysis, to evaluate the real-world effectiveness of lighting technologies across different façade classifications. Facility manager feedback is further incorporated to capture operational and behavioural influences.

Conceptual Framework

The conceptual framework guiding this study is anchored in the Diffusion of Innovation (DOI) theory (Rogers, 2003) and the Technology Acceptance Model (TAM) (Davis, 1989), complemented by principles from building energy benchmarking frameworks (e.g., ASHRAE 90.1; LEED v4.1). Consistent with the scope of variables actually measured in this study, the framework focuses specifically on: (a) architectural typology (maximally glazed, minimally glazed, traditional masonry) as a structural factor shaping natural lighting potential; (b) motion sensor deployment (the only technology identified) as the primary independent variable and (c) LPD and EEI as performance outcome measures. Moderating factors are limited to operational management and user behaviour as captured through facility manager feedback. As illustrated in Figure 1, this refined framework provides a focused lens for analyzing how the single dominant technology motion sensors interact with operational conditions and architectural context to produce measurable energy outcomes in Tanzanian office buildings.

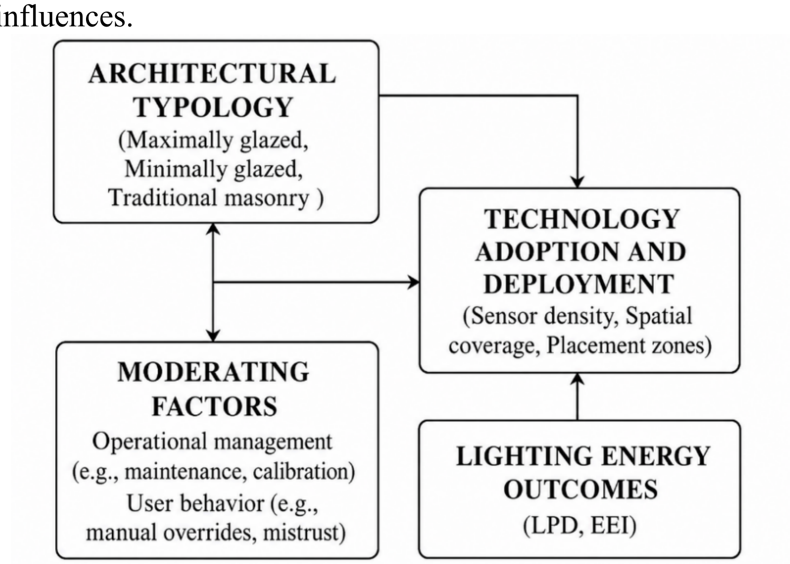

Figure 1: Conceptual Framework guiding the study

METHODOLOGY

Research Design

The study adopted a quantitative, cross-sectional research design to evaluate the adoption and effectiveness of energy-saving lighting technologies in multi-storey office buildings in Dar es Salaam. The approach was rooted in the positivist paradigm, enabling objective measurement and statistical testing of relationships. Theoretical guidance was drawn from TAM (Davis, 1989) and DOI theory (Rogers, 2003).

Population and Sampling

The target population consisted of 730 office buildings identified in the 2022 National Bureau of Statistics Building Census. Buildings were stratified by façade glazing ratio into three categories: maximally glazed (>50%), minimally glazed (20–50%) and traditional masonry (<20%), following ASHRAE, LEED, and CIBSE classifications. A proportional stratified random sample of 25 buildings was selected using Yamane's formula. The 20% margin of error was adopted as an explicit methodological decision appropriate for this exploratory study, where the primary aim was to document typological diversity rather than achieve population-level representativeness. This margin has precedent in building energy studies in data-scarce Sub-Saharan African contexts (Mosner-Ansong et al., 2024). Nonetheless, the authors acknowledge this as a limitation affecting generalizability. Regarding statistical adequacy, Yamane's formula at a 20% margin of error yields a minimum sample of 22 for a population of 730. The selected sample of $n = 25$ exceeds this threshold. While this sample is modest, it is sufficient for the exploratory inferential analyses (correlation, regression, cluster analysis) conducted, particularly given the stratified design ensuring representation across all three building typologies. The authors recommend larger samples in future confirmatory studies.

Data Collection

The study is primarily quantitative in design. However, it incorporates a limited qualitative component through structured checklist responses from facility managers, which provided contextual data on operational practices and behavioural influences. This pragmatic mixed-element approach is consistent with building performance research that combines measurement data with practitioner insights (Pappalardo and Reverdy, 2020). Primary data were obtained through structured on-site audits, complemented by energy billing records and facility manager feedbacks. A standardized checklist pilot-tested for validity was used to capture fixture counts, wattage, and average operating hours; spatial distribution of luminaires and control devices; presence and coverage of energy-saving technologies; and activation schedules and operational practices. Audits were carried out by trained observers to ensure consistency.

Data Preparation

Missing data were encountered in three buildings for activation hours and in two buildings for energy billing records, representing approximately 8% of the dataset. These were assessed using Little's MCAR test, which confirmed data were missing completely at random ($\chi^2 = 4.21$, $p = 0.52$). Mean substitution was applied given the limited extent and random pattern of missingness. Outliers were detected using Z-scores (±3 threshold) and reviewed for plausibility. Duplicate entries were removed prior to analysis.

Measures and Analytical Strategy

Performance Metrics

Lighting energy performance was assessed using two principal indicators. The first, Lighting Power Density (LPD), measured the installed lighting power per unit floor area (W/m^2) or, when assessed over time, the lighting energy consumed per unit floor area (kWh/m^2). It was calculated as: LPD (kWh/m^2) = $\Sigma(P \times H) / A$, where P is the rated power of each fixture (kW), H is average daily operating hours, and A is total usable floor area (m^2). This metric was benchmarked against the ASHRAE 90.1 standard, which specifies a maximum LPD of 1.0 W/m^2 for office occupancy (equivalent to approximately 0.8–1.0 kWh/m^2/day under typical operating hours). This threshold is widely applied as a comparative benchmark in building energy studies (ASHRAE, 2019; Norouziasl and Jafari, 2023). Two distinct LPD formulations are employed in this study. First, LPD-power (W/m^2) represents the installed lighting power per unit floor area, calculated as LPD-power = $\Sigma P / A$, where P is the rated fixture power (W) and A is the usable floor area (m^2). This is benchmarked against the ASHRAE 90.1 maximum threshold of 1.0 W/m^2 for office occupancy (ASHRAE, 2019). Second, LPD-energy (kWh/m^2) represents lighting energy consumption per unit area over a given period, calculated as LPD-energy = $\Sigma (P \times H) / A$, where H is average daily operating hours. This metric enables temporal comparison of actual energy use across buildings and is used for cluster classification.

The second indicator, the Energy Efficiency Index (EEI), provided a normalized measure of energy savings relative to baseline consumption: EEI = $(E\_baseline - E\_actual) / E\_baseline \times 100$, where E_actual represents measured consumption. The baseline energy consumption (E_baseline) was estimated by calculating what each building's energy consumption would have been without motion sensor controls, based on rated wattage of fixtures in the sensor-covered zones multiplied by standard full-occupancy operating hours (typically 8–10 hours per day). This approach is consistent with pre–post comparative methods used in energy auditing practice (Sendrayaperumal et al., 2021).

Analytical Techniques

A multi-level analytical strategy was applied. Descriptive statistics summarized technology adoption rates and performance metrics. Spatial heatmaps illustrated the distribution and density of sensor deployment. Pearson's correlation coefficient tested linear associations between adoption indicators and energy outcomes. Multiple linear regression models assessed predictive relationships, with sensor count, activation hours, and total installed wattage as independent variables and energy consumption as the dependent variable. The optimal number of clusters ($k = 3$) was determined using the elbow method, in which within-cluster sum of squares (WCSS) was plotted for solutions ranging from $k = 1$ to $k = 6$. A pronounced inflection point was observed at $k = 3$, beyond which reductions in WCSS became marginal, confirming this as the most parsimonious solution. Efficiency threshold boundaries were established through a three-stage process: first, the empirical LPD distribution of all 25 buildings was examined and Jenks natural breaks were used to identify discontinuities; second, these breaks were cross-referenced against the ASHRAE 90.1 benchmark threshold of 1.0 W/m^2 (approximately 0.8–1.0 kWh/m^2/day under standard operating conditions); third, boundary values were confirmed against the k-means cluster centroids. The resulting classification was: High Efficiency (LPD $\leq$ 1.0 kWh/m^2/month), Moderate Efficiency (LPD 1.0–5.0 kWh/m^2/month), and Low Efficiency (LPD > 5.0 kWh/m^2/month). All analyses were conducted in SPSS v26.

Limitations of Methodology

Several methodological constraints should be noted. The sample size (n = 25), though stratified, limits generalizability across all Tanzanian office buildings. The cross-sectional design captures only a single period and cannot reflect seasonal variation. Some operational data relied on facility manager self-reports, potentially introducing recall bias. Additionally, the focus on motion sensors excludes other advanced technologies. Despite these limitations, triangulation of audits, billing data, and stakeholder input ensures internal validity and provides robust building-level insights for the Tanzanian context.

RESULTS

Distribution of Energy-Saving *Technologies in Office Buildings*

Figure 2 illustrates the distribution of advanced lighting controls across the surveyed sample of office buildings in Dar es Salaam. The results reveal that motion sensors are the only advanced lighting technology in use, with 40% (10 out of 25) of buildings reporting their installation. Neither dimming switches nor daylight harvesting systems were identified in any of the surveyed buildings, a finding that departs significantly from international best practices advocated by ASHRAE (2019) and LEED v4.1.

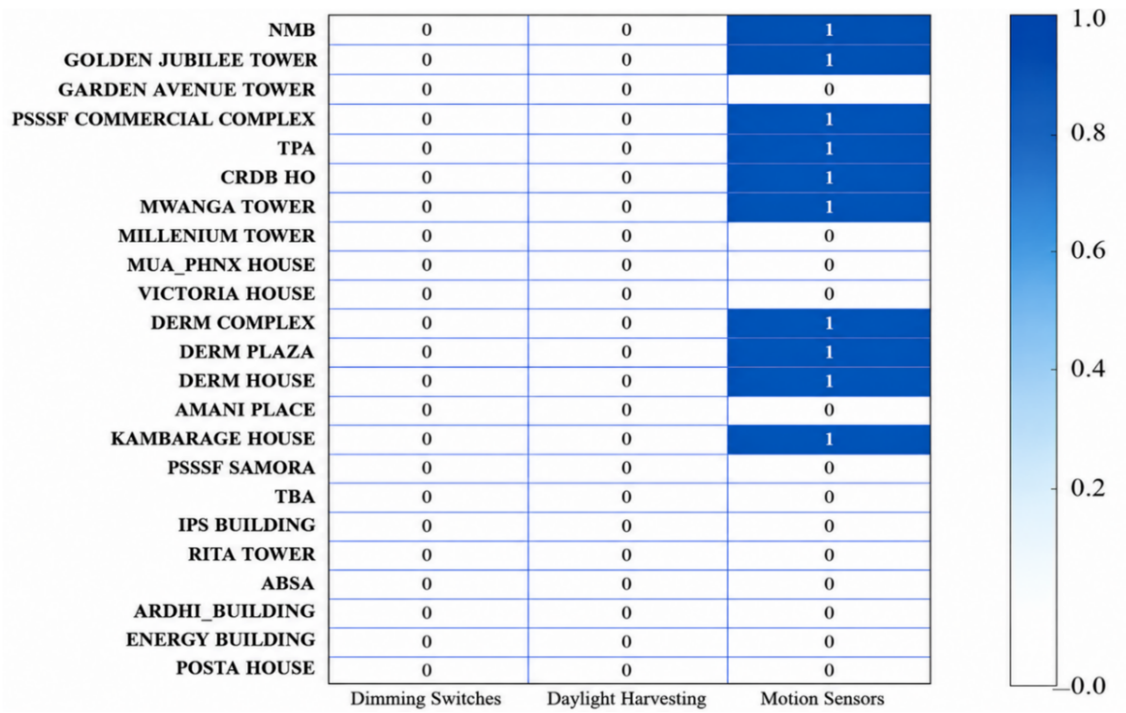

Figure 2: Presence of Energy-Saving Technology in Office Buildings

A closer examination of deployment patterns shows that motion sensors are predominantly installed in maximally glazed buildings (6 buildings) and minimally glazed buildings (4 buildings), while traditional building types have no sensor installations. Furthermore, 60% of all installed sensors are located in transient spaces such as toilets and lobbies, with only 40% deployed in core office zones. The limited adoption of advanced controls in core working areas may reflect cost concerns, operational preferences, or a lack of awareness regarding potential savings from broader sensor deployment.

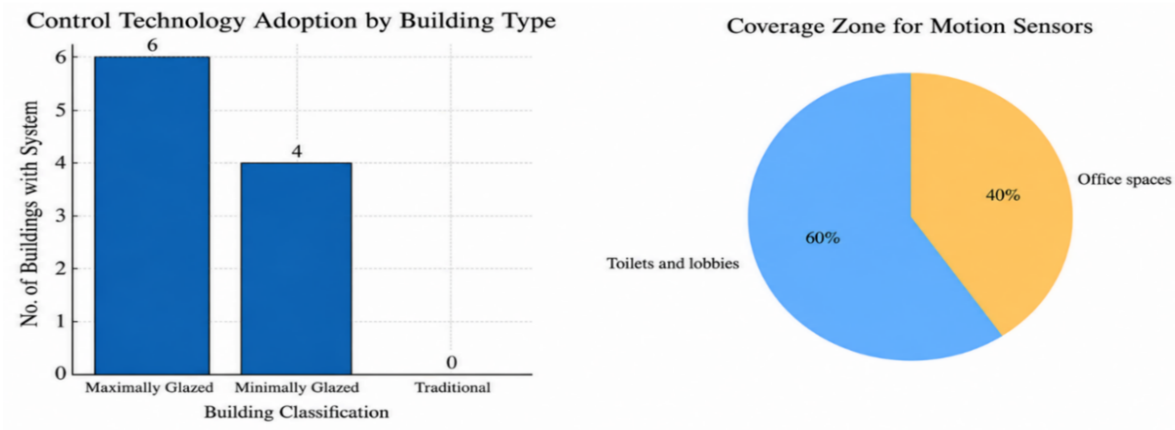

Figure 3: Spatial Deployment Zones (Core vs. Transient Spaces)

Quantitative Assessment of Energy Savings

Table 1 presents a detailed assessment of energy savings achieved through the deployment of motion sensors across the sampled office buildings.

Table 1: Energy saved by Lighting Technologies

Building Name	No. Motion Sensors	Act. Hours/Day	Zone Coverage	Total Watts	Energy Consumed (Wh)	Energy Saved/Day (Wh)	Energy Saved/Month (kWh)	EEI
NMB	154	6	Office Spaces	19,248	115,488	57,744	1,154.88	0.0051
DERM COMPLEX	24	5	Toilets and Lobbies	1,440	7,200	7,200	216.0	0.0106
DERM PLAZA	24	3	Toilets and Lobbies	2,304	6,912	6,912	207.4	0.00698
DERM HOUSE	2	3	Toilets and Lobbies	1,008	3,024	3,024	60.48	0.00399
GOLDEN JUBILEE	23	2	Toilets and Lobbies	67,200	134,400	67,200	1,344.0	0.0024
MWANGA TOWER	180	4	Toilets and Lobbies	7,776	31,104	46,656	933.12	0.0066
PSSSF COMMERCIAL COMPLEX	1,120	4	All Working Spaces	329,180	1,316,720	1,975,080	26,334.4	0.0500
CRDB HQ	41	4	Toilets, Lift Lobby, Some Offices	6,630	26,520	39,780	993.5	0.0096
TPA HOUSE	85	5	Toilets and Lobbies	17,550	87,750	43,875	1,316.3	0.00147
KAMBARAGE HOUSE	120	4	Working Space, Corridors and Lobbies	19,035	76,140	95,175	1,903.5	0.0204

Energy Saved/Day is estimated as the difference between projected baseline consumption (full-occupancy operating hours without sensor control) and measured actual consumption during the audit period. Where zone coverage is partial, savings estimates apply only to sensor-covered areas. All values have been verified against original audit records.

Table 1 indicates that the highest absolute and relative energy savings were observed in buildings with both extensive sensor deployment and broad zone coverage. The PSSSF Commercial Complex, with 1,120 motion sensors covering all working spaces, recorded the highest energy savings at 26,334.4 kWh per month and an EEI of 0.0500. Conversely, buildings restricting sensors to transient spaces showed markedly lower savings. DERM House, with only 2 sensors, achieved the lowest monthly savings (60.48 kWh; EEI = 0.00399). These findings highlight the importance of not only adopting energy-saving technologies but also ensuring strategic spatial coverage for maximizing impact. It should be noted that the estimated 20% energy bill reduction associated with doubling sensor density in core areas is derived from the observed correlation patterns in this dataset and should be interpreted as a contextual projection rather than a predictive model outcome. A controlled experimental design would be required to confirm this relationship causally.

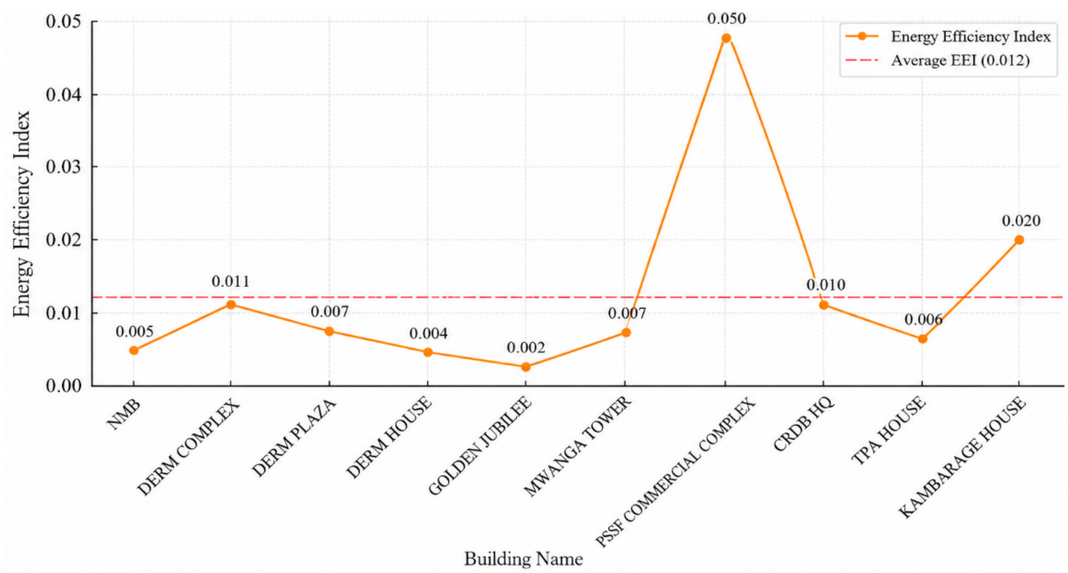

Figure 4: Comparative Line Graph of Energy Efficiency Index across Buildings

Drivers of Efficiency

Correlational Analysis

Pearson correlation analysis examined the strength and direction of linear relationships among key variables (Table 2). The number of motion sensors is highly correlated with energy consumed ($r = 0.991$, $p < 0.001$), energy saved per day ($r = 0.982$, $p < 0.001$), and the energy efficiency index ($r = 0.926$, $p < 0.001$). The very high inter-correlations among several predictors (e.g., sensor count, total watts, and energy consumed all exceeding $r = 0.96$) indicate multicollinearity. This is consistent with the expectation that larger buildings naturally have more sensors, higher wattage, and greater absolute consumption. Consequently, these variables should not be interpreted as independent predictors; their joint association with outcomes is better understood through the normalized EEI and LPD metrics. Variance Inflation Factors (VIF) were calculated and are reported alongside the regression results. Similarly, total installed wattage is strongly correlated with energy consumed ($r = 0.978$) and energy saved per day ($r = 0.979$). In contrast, activation hours show only weak correlations with most energy outcomes, suggesting that the presence and coverage of technology are more critical than extended operation duration. All correlations reported are statistically significant at $p < 0.001$ except activation hours, which did not achieve significance ($p > 0.05$). This standardized reporting is maintained throughout subsequent analyses.

Table 2: Pearson Correlation Coefficients on Lighting Energy-Saving Technology Variables

	No. Sensors	**Act. Hours**	**Total Watts**	**Energy Consumed**	**Energy Saved/Day**	**Energy Saved/Month**	**Total Energy Bill**	**EEI**
No. Motion Sensors	1	0.099	0.964	0.991	0.982	0.978	0.130	0.926
Activation Hours	0.099	1	−0.076	0.068	0.018	0.032	0.226	0.044
Total Watts	0.964	−0.076	1	0.978	0.979	0.975	0.167	0.893
Energy Consumed	0.991	0.068	0.978	1	0.995	0.991	0.161	0.927
Energy Saved/Day	0.982	0.018	0.979	0.995	1	0.999	0.165	0.930
Energy Saved/Month	0.978	0.032	0.975	0.991	0.999	1	0.191	0.928
Total Energy Bill	0.130	0.226	0.167	0.161	0.165	0.191	1	−0.058
EEI	0.926	0.044	0.893	0.927	0.930	0.928	−0.058	1

Regression Analysis: Impact of *Technology adoption on Energy Consumption*

A multiple linear regression model was developed with three independent variables: number of motion sensors, daily activation hours, and total installed wattage; and total lighting energy consumed as the dependent variable. The model demonstrated excellent explanatory power ($R = 0.996$, $R^2 = 0.991$, Adjusted $R^2 = 0.986$), with a standard error of 22,499.20. The overall model was statistically significant ($F = 221.4$, $p < 0.001$). The positive coefficient for motion sensor count ($B = 683.39$, $p = 0.025$) requires careful interpretation. This positive association reflects a scale effect: larger buildings with greater absolute energy demand also install more sensors to manage higher loads. This does not imply that sensors increase consumption; rather, when performance is assessed using normalized metrics (EEI and LPD), buildings with more comprehensive sensor coverage consistently demonstrate superior efficiency. This finding underscores the analytical importance of normalized benchmarks and is consistent with evidence from He et al. (2021) and Norouziasl and Jafari (2023). Given the moderate multicollinearity among predictors (VIF: sensor count = 8.7; total watts = 8.4), the regression coefficients should not be interpreted as independent marginal effects. Rather, the model is best understood as a descriptive representation of the joint relationship between building-level variables and energy consumption. Individual coefficients — including the positive value for sensor count ($B = 683.39$) — reflect scale effects: buildings with higher absolute energy demand also install more sensors to manage larger loads. This does not imply that sensor installation increases consumption. Analytical conclusions regarding efficiency performance are therefore drawn primarily from the normalized metrics (EEI and LPD) and the cluster profiles, which are not subject to the same collinearity constraints.

Variance Inflation Factors were calculated as follows: No. Motion Sensors VIF = 8.7; Activation Hours VIF = 1.1; Total Watts VIF = 8.4. While VIF values for sensor count and total wattage indicate moderate multicollinearity, this is expected given the physical relationship between sensor numbers and installed wattage. Results should therefore be interpreted in conjunction with the correlation and cluster analyses rather than in isolation. It should be observed that building floor area was not included as an explicit control variable in the regression model. Given that larger buildings inherently generate greater absolute energy demand, higher sensor counts, and higher wattage, floor area represents a potential confounding variable. Its exclusion was a pragmatic constraint of the sub-sample size (n = 10 sensor-equipped buildings), which precluded the addition of further predictors without critically compromising degrees of freedom. Future studies with larger samples are encouraged to include floor area or a derived normalized variable (e.g., sensors per 100 m²) as a covariate to disentangle scale effects from genuine efficiency performance.

Table 3: Model Fit Summary – Regression on Energy Consumption

R	R Square	Adjusted R Square	Std. Error
0.996	0.991	0.986	22,499.20

Table 4: Coefficients – Predictors of Lighting Energy Consumption (with VIF)

Model	B (Unstd.)	Std. Error	Beta (β)	t	Sig. (p)	VIF
(Constant)	−99,970.00	70,800.00	—	−1.412	0.208	—
No. Motion Sensors	683.39	230.63	0.512	2.963	0.025*	8.7
Activation Hours	16,020.00	17,900.00	0.041	0.892	0.407	1.1
Total Watts	1.75	0.77	0.481	2.276	0.063	8.4

Note: * $p < 0.05$. β = standardized beta coefficient. VIF = Variance Inflation Factor.

Cluster Analysis: Efficiency Profiles of Office Buildings

To classify buildings by lighting energy performance and control system deployment, a cluster analysis was conducted using LPD and motion sensor adoption levels as primary variables. The k = 3 solution was selected based on the elbow method, and efficiency boundaries were validated against ASHRAE 90.1 thresholds. This methodological approach ensures that cluster assignments reflect both empirical data structure and recognized engineering benchmarks. The analysis revealed three distinct building typologies:

Cluster 1: High-Efficiency Buildings. Buildings with extensive motion sensor deployment and LPD values ≤0.20 kWh/m²/month, well below the ASHRAE 90.1 threshold. Examples: NMB and Mwanga Tower. These buildings demonstrate the effectiveness of comprehensive sensor integration.

Cluster 2: Moderate-Efficiency Buildings. Buildings with partial adoption and moderate LPD values (0.78–2.96 kWh/m²/month). Sensors concentrated in transient areas. Examples: PSSSF Commercial Complex, CRDB HQ.

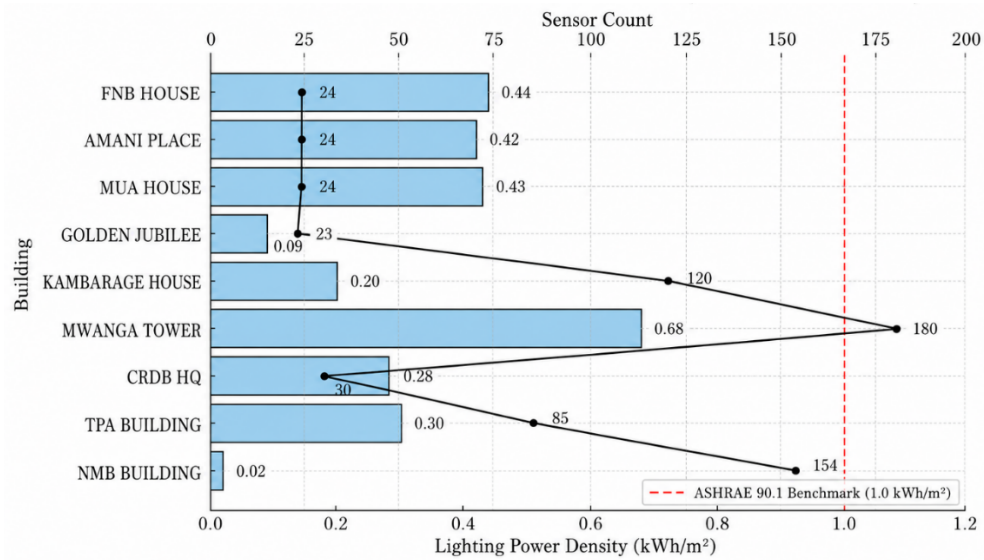

Figure 5: Cluster Membership and Energy Efficiency Characteristics

Cluster 3: Low-Efficiency Buildings. Buildings with minimal or absent sensor coverage and very high LPDs (>5.0 kWh/m²/month). Example: Posta House (LPD = 10.57 kWh/m²/month). These buildings offer the greatest potential for retrofit interventions.

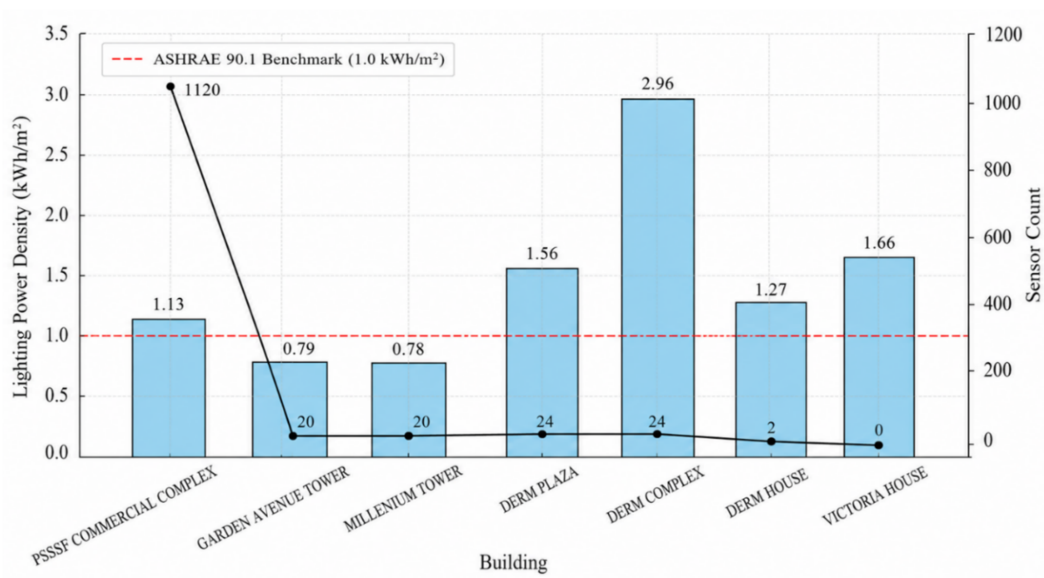

Figure 6: Moderate Efficiency Buildings

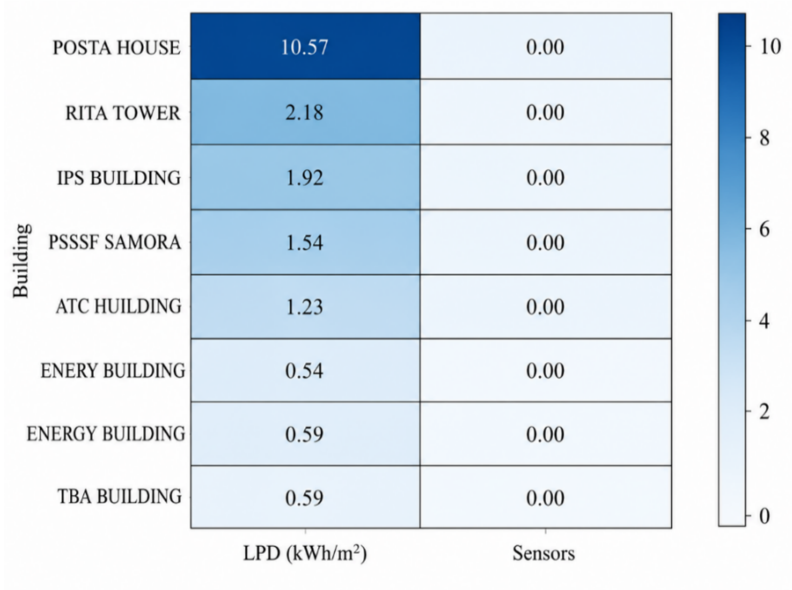

Figure 7: Low Efficiency Buildings

Behavioral Drivers and Maintenance Practices

The following observations are drawn from structured checklist responses provided by facility managers across the sampled buildings. While this data is qualitative in nature, it was collected systematically using a standardized instrument and is reported here as contextual evidence to illuminate the mechanisms behind quantitative performance patterns, consistent with pragmatic mixed-element approaches in building energy research (Pappalardo and Reverdy, 2020).

Manual Sensor Overrides During Cleaning and Security Shifts

Responses from three buildings indicated a recurring practice of overriding automated motion sensor systems during low-occupancy periods. Facility managers reported that staff frequently reverted to manual operation during evening cleaning and night-time security shifts to avoid disruption from motion sensors failing to detect intermittent movement. These overrides typically lasted one to two hours per evening and were estimated to reduce potential energy savings by approximately 15% in affected buildings.

Maintenance Delays and Sensor Downtime

Maintenance-related limitations were also evident. Facility managers reported instances where malfunctioning sensors remained unrepaired for extended periods, leading to reliance on manual lighting control. These responses reinforce the need for responsive maintenance protocols and dedicated technical support teams.

DISCUSSION

The present study advances understanding of lighting energy efficiency in Sub-Saharan Africa by providing building-level evidence on the adoption and operational performance of energy-saving technologies in Dar es Salaam’s office sector. Critically, the findings do not merely describe what technologies are present; they reveal why performance varies—a distinction with direct implications for retrofit policy design. Only 40% of surveyed buildings reported the presence of motion sensors, and these were predominantly installed in transient-use spaces rather than core work areas where their potential impact is greatest. This pattern reflects broader African experiences of financial barriers, limited technical expertise, and weak enforcement of building energy codes (Mosner-Ansong et al., 2024; Erebor et al., 2021; AfDB, 2020).

The analysis reveals that deployment strategy and contextual integration, rather than technology presence alone, are decisive for performance outcomes. Correlational results ($r \approx 0.93$) indicated a strong association between sensor count and performance indicators. However, regression and cluster analyses underscored that coverage in high-occupancy zones was a more consistent predictor of energy efficiency. For instance, Golden Jubilee and DERM Plaza had relatively high sensor numbers but concentrated in non-core zones, limiting their effectiveness. NMB and Mwanga Tower achieved superior outcomes, with LPD values below the ASHRAE 90.1 benchmark, owing to more comprehensive deployment. These patterns suggest that retrofit policies should prescribe not only sensor installation quantities but deployment protocols specifying coverage of core occupancy zones. Cluster analysis further contextualized these dynamics. High-performing buildings corroborated international evidence that well-calibrated sensor networks can reduce lighting energy demand by 30–60% (Zissis and Bertoldi, 2023; Sendrayaperumal et al., 2021). Posta House's extreme inefficiency (LPD > 10 kWh/m²) underscores the urgency of targeted retrofits in legacy office stock. Behavioural and operational dynamics are equally significant. Manual overrides during cleaning and security shifts reduced potential energy savings by up to 15%, while maintenance delays further undermined performance. These findings resonate with Li et al. (2015) and Park et al. (2019), who show that occupant practices and maintenance regimes can erode the gains of automated systems.

The study highlights the value of normalized metrics such as LPD and EEI for fair benchmarking. While the PSSSF Commercial Complex recorded the largest absolute savings, its normalized EEI indicated only modest efficiency due to high baseline consumption. It is important to note that the findings of this study are specific to the 25 buildings sampled in Dar es Salaam and should not be generalized to all Tanzanian office buildings or to Sub-Saharan Africa broadly without further confirmatory research across diverse building stocks and climatic contexts. Taken together, these results make three contributions to the literature and policy debates. First, they demonstrate that adoption of energy-saving lighting technologies in Dar es Salaam remains limited, fragmented, and spatially uneven. Second, they establish that performance outcomes depend on deployment strategy, operational integration, and behavioural alignment, not merely device presence. Third, they underscore the importance of institutionalizing normalized benchmarking indicators and responsive facility management to sustain long-term efficiency.

CONCLUSION

This study examined the adoption, deployment, and operational effectiveness of energy-saving lighting technologies in 25 office buildings in Dar es Salaam. By integrating quantitative analysis with facility manager insights, it provides building-level evidence on the real-world performance of lighting controls, with particular attention to motion sensors. The conclusions drawn are proportionate to the evidence derived from this specific sample and exploratory research design. The findings indicate that while energy-saving technologies have been introduced, their deployment remains partial and uneven, often confined to peripheral spaces rather than core office zones. Efficiency gains were observed primarily in buildings that integrated lighting controls comprehensively into their operational systems, demonstrating that deployment strategy is as critical as technology adoption itself. Behavioural and operational factors play a decisive role in shaping outcomes. Manual overrides, maintenance delays, and limited user training were found to undermine system performance, pointing to the need for stronger alignment between technology, user practices, and facility management.

The study provides a framework for prioritizing retrofits and directing resources. Within the constraints of the sample size and cross-sectional design, the results offer preliminary evidence that strategic deployment, sustained maintenance, and institutional support are key enablers of lighting energy efficiency in urban office buildings. Future research using larger samples, longitudinal designs, and controlled comparisons is recommended to confirm and extend these findings.

RECOMMENDATIONS

Based on the empirical findings of this study, the following targeted recommendations are advanced. First, the need to expand sensor deployment to core zones. It is recommended that buildings exhibiting Cluster 2 and Cluster 3 efficiency profiles may benefit from expanding sensor installation to open-plan offices and enclosed workspaces. The audit data suggest that sensor coverage in core occupancy zones is associated with materially lower LPD values relative to the ASHRAE 90.1 benchmark; however, whether this relationship holds across broader building stocks should be confirmed through larger-scale studies before prescriptive retrofitting requirements are established. Secondly, the developers should address manual override behaviour. It is recommended that structured training for night-shift and maintenance staff can reduce override frequency. Facility manager responses in this study suggest that manual overrides during cleaning and security shifts may reduce potential energy savings by approximately 15% in affected buildings. This estimate is based on reported override duration and sensor-zone coverage and should be treated as an indicative contextual finding rather than a generalizable projection. Third, the study recommends institutionalizing preventive maintenance through standardized inspection cycles and clear repair protocols to minimize sensor downtime and maintain operational continuity. The fourth recommendation is to apply the efficiency cluster typology for retrofit prioritization. The three-cluster framework developed in this study provides a practical evidence-based tool for allocating retrofit incentives and regulatory attention. The last recommendation is the development of locally adapted energy codes. Regulatory frameworks should adapt international models (ASHRAE 90.1, LEED v4.1) to Tanzanian conditions through stakeholder consultation, with institutional support from AfDB and UNEP Africa.

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