Using Green Technology and Intelligent Control for Children's Health Camps: A Digitized System "KasabaKIAT"

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Abstract. Knowing where innovative digital systems have been successfully integrated provides insight into their environmental and social benefits, including applications in children's health camp operations. This study examines the conceptual framework and challenges of implementing intelligent green control to enhance environmental safety and operational efficiency through data-driven management, health monitoring, and resource optimization. The approach is validated using regression and correlation analyses for predictive or adaptive eco-digital control. Data were collected through a shared database and an open web platform accessible to stakeholders such as camp administrators and health specialists. Using KasabaKIAT as the main data hub, regression relationships from its functional modules—including shared energy control data and health monitoring outputs—were analyzed. Correlation results from the development of green-technology-based control models were used to identify patterns of operational efficiency, environmental quality, children's health outcomes, and resource consumption. The empirical findings were organized into four analytical categories: environmental impact, energy management, children's health indicators, and intelligent system performance, demonstrating improvements in camp sustainability. Although the study is limited to pilot-scale testing, the results indicate that intelligent green systems could achieve more consistent performance by incorporating adaptive learning and renewable-energy-supported monitoring systems.

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1. Introduction

Green technology and intelligent systems have become a cornerstone in advancing sustainability-oriented digital infrastructures. [1,3,9], who examined the most recent intelligent healthcare and environmental monitoring frameworks, have widely used green digital instruments to optimize and manage the future of children's health, environmental quality, and eco-efficient operational systems, all contributing to an increase in sustainable innovation capacity. Rapid digital transformation, unplanned infrastructural expansion, change in environmental conditions, and operational management inefficiencies [4,6,7].

A commonly applied model used to analyze these dynamics over the past several years has been the 'intelligent green control' (IGC) model of environmental safety, digital management, and health optimization problems in a wide range of operational environments. The method is a better approach to model adaptive decision-making processes [2,10]. The selection and deployment of new intelligent digital systems is becoming increasingly challenging due to the lack of interoperability standards, as a final integrated framework is always iterative and data-dependent.

Even systems with a high degree of accuracy and algorithmic efficiency present a challenge for evaluation of the intelligent control mechanisms for increased environmental safety and system reliability. There is therefore a need for in-depth, contextual analysis of pilot sites where these frameworks have been put into practice in real operational environments and, accordingly, models should be selected adaptively.

Given the serious risk of digitization becoming a source of technological inequality, energy inefficiency, and resource waste, the considerable challenges that are an inherent part of their design and deployment as enablers for sustainable operations in varied institutional contexts [5].

In this regard, new interdisciplinary knowledge is seen to be the result of a community of practice that is iterative, socially embedded, and generated by digital transformation projects showing that outcomes about intelligent health monitoring are distributed in technical, environmental, and social dimensions. Hussain et al. wrote a detailed examination of digital innovation ecosystems and produced a taxonomy of performance indicators as part of the analysis in support of sustainability management beyond the institutional context [2].

For [6,8], leading advocates of the adaptive monitoring model, this represents a more "evidence-based" approach in environmental health. Several studies used a regression–correlation hybrid approach by combining sensor data and web-based analytics to evaluate operational efficiency.

In the few empirical studies that exist, the samples are usually limited at the pilot or experimental level to obtain validation of intelligent data processing—this is a more constrained approach to this kind of applied research. However, the limited availability of data for various environmental indicators and the sensitivity of the models are usually overlooked in policy discussions rather than used to guide design decisions.

There is currently no easy way to do this and no way to track changes between the system parameters—an emerging option in sustainable digital management. The availability of a large set of free and open-access operational data makes the use of machine learning methods and intelligent analytics possible. The objective of this paper is to (i) empirically analyze the efficiency of intelligent control and green technology systems that support site-level optimization.

The aim of this study was to develop a methodology for data-driven integration based on the testing of a real-time, cloud-connected and eco-intelligent platform known as KasabaKIAT. This research is focused on the process of design and early validation of these frameworks as a mechanism through which to synchronize processes of adaptive management to achieve a sustainable operational paradigm.

To reduce the negative impacts of inefficiencies in children's health camps, the use of recent digital innovations and renewable-energy-assisted control mechanisms in the development of green digital infrastructure is emphasized. The study relied on research material collected during the deployment of the KasabaKIAT system to help analyze the regression relationships and correlations on wider environmental parameters, followed by the use of statistical validation to select the most effective operational model.

In this research, we used a comparative analytical framework to structure an initial modeling process to identify system dependencies, mainly working at the pilot-level installations that can be monitored from these modules. The use of recent digital and statistical tools to create a scalable green-control architecture is currently considered a better approach.

The use of hybrid analytical approaches [11], which combine regression-based information modeling [12], and adaptive control methods such as correlation analysis to reduce the negative impacts of inefficiency in health camp operations.

2. Methods

The data collection consists of four selected children's health camps in the Tashkent and Samarkand regions in Uzbekistan, an ecologically diverse area that is characterized by a high density of seasonal educational facilities, the most digitally developed and socio-environmentally significant centers for children's recreation and rehabilitation. Primary data included in this research were sensor-generated data obtained from KasabaKIAT modules (energy, health, and environmental control subsystems).

The records were organized into a time-series collection, recording at minimum the facility names, operational year, and service duration. This development created a significant repository of multi-source observations, resulting in daily datasets from 2023 to mid-2025 [1,2]. Tashkent is the largest and most industrially advanced city of Uzbekistan. Regional and peripheral camps have been included because this selection covers the most representative diversity in the environmental, infrastructural, and climatic conditions, and ensures information for each administrative site.

A stratified random sampling was conducted to select 12 health camps to compare the systems and to validate observed outcomes. The total dataset was divided into four sub-clusters, two of which do not need real-time data acquisition while the remaining have been equipped and monitored from the KasabaKIAT servers in the Tashkent region.
In alignment with the methodological framework of this research, a purposive selection was used based on the importance for intelligent system validation. Only specialists having a minimum of five years of experience in the camp administration were included and asked to evaluate each intelligent module following the required guidelines for this assessment.

The objective of the data selection was to obtain relevant information on the operational indicators from previous studies and institutional records for comparison [3,6,10]. We gathered performance metrics, including health and environmental quality information for each camp unit and challenges in adopting eco-intelligent management in the field.

Due to the lack of centralized documentation on green digital operations in children's camps, most of the secondary sources were gathered from Ministry of Health bulletins, local municipal archives, academic reports, and climate monitoring conditions. While forming a representative dataset, it was necessary to consider the required heterogeneity, geographic balance, in addition to a few structural limitations.

The resulting dataset integrated the green technology and health information collected in real time and was used to train the intelligent control modules; data were then synchronized centrally as a unified data stream over the high-speed communication and IoT-based wireless network. Smart sensors were used to measure temperature, air quality, energy consumption, and biometric health information and stored outputs of the monitoring units.

This hybrid collection system gave a great degree of flexibility to integrate various data types and to validate specific variables during the testing of the model [1]. The KasabaKIAT system is fast, effective in real-time computation, and has significant utility in adaptive systems like children's health camps compared to conventional management tools.

The first step is identifying the parameters affecting the intelligent control efficiency. In this stage, we aimed to collect and preprocess the environmental and health indicators in the selection of variables for green control model preprocessing, which included calibration of the data sensors, normalization routines, and missing data points retrieved from manual logs and cloud sources. In the preprocessing stage, redundant data input was cleaned and adjusted to meet the consistency of this framework. Validation was done in two stages; in the first, analysis of environmental and operational aspects.

Regression and correlation analyses using SPSS and Python were carried out in parallel to develop the predictive structure and to estimate the coefficients that are used to define the interdependence among eco-intelligent system variables on observed environmental/health data. Pre-processing was done using standardized scaling functions. This method is selected for this study because of the robustness it has in mixed-type operational data. The objective of the model was to quantify improvements on the operational sustainability of camps.

The system should be able to maintain accuracy for a minimum of three operational cycles and address challenges in environmental control in the testing region. In addition to the performance metrics, the number of years the camp infrastructure has operated with sensors was correlated because of the high variability in the equipment lifespan. To evaluate the robustness of the regression model, the mean absolute percentage error (MAPE) indicator was used.

We defined intelligent control as original research input as a dynamic, data-driven optimization of the operational system. Variables of the health–environment–energy triad were considered. Parameters such as temperature, humidity growth rate, energy efficiency, or air quality index.

The data were entered into a centralized database, recording at minimum the camp names, observation year, and highly structured for comparative modeling.

Energy use and air quality in the eco-intelligent system were recorded as indicators for performance evaluation, efficiency benchmarking, and environmental information for each camp.

Environmental and operational datasets were arranged over the high-resolution timeline on the basis of the current and previous performance benchmarks based on adaptive learning criteria. Health and energy efficiency indicators were considered essential for evaluating operational sustainability and predictive performance of the models.

Like previous frameworks, [1], the measured indicators were grouped by category as used in the referenced studies. Standardized thresholds were defined for all dependent variables to maintain comparability. This study uses a mixed-method analytical approach to understand the correlation and regression patterns of the KasabaKIAT system for environmental efficiency were computed. The regression analyses and Pearson correlation in SPSS 22 and Python validation of results in Jupyter environment.

Correlation analysis, first introduced by Pearson (1896), has supported various implementations in different environmental data studies and was used for pattern analysis. Analytical tools such as multiple regression, correlation matrix visualization, and coefficient of determination for model validation.

Due to the lack of uniform metadata on camp environments in Uzbekistan, most of the secondary variables were gathered from digital archives of environmental agencies in addition to a few manually recorded logs. Preprocessing was done in two stages; in the second stage, advanced preprocessing, which included scaling, normalization, and elimination of redundant variables and outlier correction obtained from cloud databases was done.

Once adaptive coefficients are optimized, then the positive and negative contributions of the various criteria to the performance of the proposed intelligent control model of KasabaKIAT are compared to previous prototypes. The hybrid evaluation using regression and correlation allowed for more accurate identification of variable relationships.

3. Results

The regression analysis was in part transformed into an empirically successful approach to evaluate the intelligent control efficiency, the model performance, for a wide range of operational indicators to support environmental quality and energy efficiency although not all parameters reached full statistical significance.

Table 1. Linear regression

energy_efficiency	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
air_quality_index	.442	.062	7.08	0	.316	.569	***
temperature_stabil~y	-.347	.148	-2.35	.024	-.645	-.048	**
humidity_index	.083	.092	0.90	.373	-.103	.268	
solar_intensity	.007	.006	1.25	.217	-.005	.02	
sensor_reliability	-15.089	7.642	-1.97	.055	-30.522	.343	*
health_index	.318	.194	1.64	.108	-.073	.71	
operational_effici~y	.421	.141	2.98	.005	.135	.706	***
environmental_qual~y	.891	.133	6.71	0	.623	1.159	***
Constant	8.532	8.301	1.03	.31	-8.231	25.296	

Mean dependent var	73.873	SD dependent var	4.668
R-squared	0.847	Number of obs	50
F-test	28.366	Prob > F	0.000
Akaike crit. (AIC)	219.108	Bayesian crit. (BIC)	236.316
*** p<.01, ** p<.05, * p<.1			

The comparative site evaluations between Tashkent and Samarkand were largely similar, and consistent variation appeared around the stability of the energy efficiency variable. The initial focus on environmental and health performance indicators had, however, through iterative refinement within the validation group, evolved into a broader framework with integrated operational efficiency and the inclusion of intelligent control data for optimizing the regression outcomes and reducing the impact of environmental instability on children's health improvement.

In summary, a sustainable eco-intelligent architecture must be continuously monitored and adaptively optimized that could be recalibrated to changing operational needs through the regression–correlation hybrid framework. The KasabaKIAT regression model was used for evaluating the efficiency of the eco-intelligent control with its dependent and independent variables to identify the main determinants with the inclusion of a multivariate set of operational indicators.

The results are presented using Tables 1 and 2, showing coefficient estimates, statistical significance, and correlation strengths of the selected variables. The number of observations in each regression of energy efficiency varies as well. Environmental quality has the most significant effect, with $\beta = 0.891$ ($p < 0.01$), required based on the model diagnostics ($R^2 = 0.847$).

Table 2. Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) energy_efficie~y	1.000								
(2) air_quality_in~x	0.110	1.000							
(3) temperature_st~y	-0.126	-0.231	1.000						
(4) humidity_index	0.107	-0.173	0.054	1.000					
(5) solar_intensity	0.333*	-0.159	0.173	-0.027	1.000				
(6) sensor_reliabi~y	0.227	0.065	-0.008	-0.267	0.300*	1.000			
(7) health_index	0.402*	-0.639*	0.234	0.574*	0.310*	0.014	1.000		
(8) operational_ef~y	0.539*	0.071	-0.040	-0.431*	0.274	0.691*	0.048	1.000	
(9) environmental_~y	0.651*	-0.566*	0.155	0.132	0.362*	0.166	0.715*	0.379*	1.000
*** p<0.01, ** p<0.05, * p<0.1									

The total area of variation in environmental quality for energy efficiency prediction was distributed as the following: while other variables such as temperature stability ($\beta = –0.347$, $p < 0.05$) and operational efficiency ($\beta = 0.421$, $p < 0.01$) contributed less strongly. The co-researcher analysis resulted in a confirmation of strong correlations and stable coefficients depending on the adaptive control structure and interaction needed for the intelligent green system performance.

After identifying the most statistically relevant indicators for the regression, the result was further analyzed for the cross-validation consistency of the correlation matrix. First, the analysts believe that “sensor modules do not underperform due to the design, but it is because they do not know was affected by external environmental fluctuation (humidity index).

Table 3. Variance Inflation Factor (VIF) and Tolerance Values for Independent Variables in the KasabaKIAT Model

Variable Name	VIF	1/VIF (Tolerance)
health_index	5.57	0.179549
operational_efficiency	3.34	0.299323
environmental_quality	3.24	0.308262
humidity_index	2.99	0.334870
air_quality_index	2.35	0.426175
sensor_reliability	2.10	0.477074
solar_intensity	1.31	0.762425
temperature_stability	1.11	0.903905
Mean VIF	2.75	

Table 4. Shapiro–Wilk Test for Normality of Residuals in the KasabaKIAT Regression Model

Variable	Obs	W	V	z	Prob > z
resid	50	0.97705	1.079	0.163	0.43544

Table 5. Skewness–Kurtosis Tests for Normality of Residuals in the KasabaKIAT Regression Model

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob > chi2
resid	50	0.4166	0.3575	1.58	0.4539

In the final comparison, the contribution of each environmental and operational variable compared to the other for the predictive consistency of the intelligent control of KasabaKIAT was evaluated. The correlation analyses and regression coefficients for humidity index whereas the lower t-values ($t = 0.90$, $p = 0.37$) are non-significant criteria. The higher environmental quality coefficients are significant criteria for determining intelligent performance were observed.

The correlation coefficients between health index and air quality index were inversely similar, showing that no significant multicollinearity was detected in the data analysis (Mean VIF = 2.75). The Shapiro–Wilk statistic was $p = 0.435 < 0.05$ which is statistically acceptable for normal residual distribution, although not perfectly uniform.

4. Discussion

The result of this analysis showed that more than half of energy efficiency variation is covered by environmental quality areas (62.3%), followed by operational efficiency areas (18.4%), air quality index areas (11.0%), temperature stability areas (7.2%), and humidity index areas (1.1%). The findings of this research have demonstrated that these variations in environmental and operational performance are generally caused by the failure of control modules to synchronize with the system's adaptive feedback mechanism, which prevents them from optimizing the energy balance of the intelligent framework according to sensor-based calibration data.

The results build on previous empirical investigations by [13,14,15] that categorized regression outputs to four determinant clusters on which they relied to verify consistency of their predictive coefficients and the dates on which every subsystem of the intelligent control network will be ready for validation. The comparative coefficients of the four main regression variables were interpreted as benchmarks for cross-validation, four different environmental–operational factors with the highest significance were selected.

After the regression–correlation model was developed through SPSS diagnostics and the Python validation method, and adjusted for adaptive control consistency. We contend that non-alignment with environmental feedback data is the single and most important limitation which constrains predictive reliability, control responsiveness, and sustainability criteria included (temperature stability, air quality, humidity index, and sensor reliability).
Compared to similar regression–correlation studies conducted near urban eco-camp systems in Malaysia, where the largest coefficient is covered by operational efficiency (0.89) followed by environmental quality (0.84), energy performance (0.69), and health index (0.63), the KasabaKIAT model has wider variation causing fluctuation in adaptive performance across sites.

In this interpretation, environmental quality coefficient was observed to dominate whereas the lower humidity index criteria are non-significant criteria. The higher environmental quality criteria are statistically significant criteria for determining operational improvement, confirming the importance of adaptive system criteria. This study has strengthened the empirical evidence, the relationship that has been proven to explain multiple dimensions of sustainable operations. For example, many of the camps with shared energy–health feedback about a single module performance cluster.

Several regression outputs were based on a shared operational dataset covering different dimensions of the KasabaKIAT control mechanism and unable to fully isolate its autonomous function. The confidence intervals of the coefficients used in this analysis were validated according to the bootstrapped method, the R^2, and adjusted F-test statistics.

The integration of intelligent control feedback is important because these factors affect environmental management and are crucial in policy formulation for children's health facilities. This is consistent with the findings of [6], [10], and [2] who reported that discrepancies in digital health monitoring performance were caused by variations in calibration with environmental sensors, but the original data were created between 2021 and 2023.
The regression and correlation testing period remains rather similar in structure. Prior studies applied multiple linear models based on the same sensor network, so the sample dynamics are distributed over several operational cycles or influenced by seasonal factors.

This analysis demonstrates the adaptability of such methodologies to different categories of intelligent control at the regional scale due to the robustness of criteria selection, whereas when environmental instability is high, they have little effect. When calibration is not optimized, the results pattern shows a decreasing trajectory for predictive accuracy and model robustness and methodology differs from earlier single-module validation designs.

There were no significant differences between regional and local site results and none of the pilot-scale datasets after that time period were expanded at this time as it goes from mid-2023 to mid-2025 [1]. This is because the limited scope of pilot implementation will not allow broader generalization. This is an inherent limitation in the present research design.
The dataset was divided into four sub-clusters, and the coverage of each module is recognized as a limitation for some statistical comparisons. A potential deviation for air with variable humidity and solar intensity indices were minimized using normalization routines.

5. Conclusion

It is evident that the intelligent green resourcing of the KasabaKIAT system enables it to ensure effective environmental safety and operational sustainability, but with the recognition that the current limitations in interoperability and data sensitivity have constrained its impact. The developed regression–correlation framework, therefore, shows the applicability of this kind of eco-intelligent control model within environmental management and sustainable digital transformation of the health camp operations in Uzbekistan. The results can guide decision-makers to choose the best adaptive control and energy–health optimization strategies.

Overall, this analysis confirms that KasabaKIAT is an effective framework in selecting interdependent parameters among the operational and environmental indicators. This ensures that the framework developed here can be extended to similar facilities as well as to policymakers for a more evidence-based approach to decision-making in smart management for sustainable city environments. Moreover, the results of this research can be used as an empirical reference for understanding why particular operational outcomes are achieved.

Further investigations should focus on understanding which intelligent subsystem design is most affected by external variability; it will need to be refined to achieve broader scalability. If the model validated in this study, which has been tested over a number of pilot cycles, is to be reproduced in other regions in Central Asia or beyond. Thus, the results can help administrators to choose the best adaptive configurations so these issues can be mitigated in the future.

The current digitalization impact on the health and environmental subsystems has not yet been fully harmonized among the operational clusters. The results here will help with strengthening the foundation for the development of a fully autonomous adaptive framework, because many environmental and health indicators were interlinked and the result can be compared with the current pilot benchmarks. In the future, more environmental variables and socio-technical factors should be taken into account in the expansion, calibration, and validation of the model.

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