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Data-driven cleaning optimisation strategy for multi-technology PV systems in the higher education sector in arid climate: A case study perspective in MENA region

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ABSTRACT

The accumulation of dust and other contaminants on photovoltaic (PV) panels is a multifactorial process that significantly affects system performance. While cleaning is vital to maintaining energy output and efficiency, its methods, frequency, and procedures also influence environmental impact, resource use, and operational costs.

This study investigates the effects of cleaning protocols on PV energy generation at the Applied Science University (ASU) campus in Amman, Jordan, addressing challenges faced by higher education institutions (HEIs) in the Middle East and North Africa (MENA) region. A controlled intervention was implemented on eight PV arrays with different technologies and installation configurations over a 19-week period. Machine learning techniques were applied for data imputation, and Analysis of Covariance (ANCOVA) was used to assess the significance of cleaning interventions on energy performance.

The findings demonstrate that uniform cleaning schedules are suboptimal, as different PV technologies and orientations exhibit varying responses to maintenance interventions. The study underscores the importance of customised cleaning strategies that account for technological type and system configuration to maximise power generation and efficiency. These results provide valuable insights for developing sustainable PV maintenance frameworks for HEIs and other institutions operating in arid climates across the MENA region.

1. Introduction

1.1. Variables affecting PV solar power generation

Photovoltaic (PV) solar power generation is influenced by a wide range of environmental and operational variables. The anticipated energy yield loss in PV systems can be estimated based on factors such as geographical location, atmospheric dust concentration, wind velocity and direction, Relative Humidity (RH) variations, temperature, precipitation rates and dust episodes. Additionally, the tilt angle of PV panels plays a crucial role in mitigating dust deposition, as steeper angles improve the natural cleaning effects of wind and rain [1].

Experimental findings highlight the significance of soiling on PV performance degradation [2]. For instance, an indoor study assessing the effects of dust accumulation on mono and polycrystalline PV modules found that even a nominal deposition of 5 g/m^2 led to a 4 %–12 % power reduction in mono crystalline modules and a 1 %–5 % reduction in polycrystalline modules, depending on particle type [3] *. Similarly, an accumulation of 6.10 g/m^2 dust over 70 days (without rain or cleaning) in Iran resulted in a 21.47 % decline in PV power output [4].

Beyond direct dust accumulation, other environmental factors also play a significant role. A numerical study found that 8 g/m^2 of dust

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* The types, categories and chemical compositions of the particles studied for monocrystalline and polycrystalline PV modules share some of the tested materials but are not exactly the same.

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reduced PV electrical efficiency by 26.36 %, and in PVT systems caused comparable electrical losses (26.42 %) and a 16.11 % drop in thermal efficiency [5]. Lab tests in Sharjah, UAE, reported a linear decrease in PV power of 1.7 % per g/m^2 of dust, while outdoor tests showed that 5.44 g/m^2 caused a 12.7 % loss, suggesting the relationship may be generalisable for UAE conditions [6]. A linear correlation between pollution layer thickness and PV productivity loss has also been observed in three installations in Gdańsk, Poland [7].

Tilt angle is a key factor in reducing dust-related PV power losses. While predictable loss patterns occur under normal conditions, extreme events such as dust storms significantly worsen performance. Storm-induced losses of 58.2 %, 27.8 %, 21.7 %, and 20.7 % at tilt angles of 0°, 15°, 30°, and 45°, were reported, compared to only 8.6 % at 0° and 0.8 % at the other three angles under normal conditions [8].

Adverse weather conditions beyond dust storms, e.g. high humidity, mist, fog, rain, and overcast skies, also reduce PV efficiency. In Indonesia, two weeks of dust accumulation at 52.24 % RH caused a 10.8 % drop in PV output, whereas rainy conditions (76.32 % RH) led to losses exceeding 40 %, and partially cloudy conditions (60.45 % RH) resulted in more than a 45 % decline [9]. These results underscore the need to account for location-specific seasonal variations when designing and operating PV systems to optimise performance [10].

1.2. Impact of dust deposition on PV panels' performance

The efficiency of solar PV systems is strongly impacted by a range of surface-related variables. Even minor surface imperfections – whether temporary, such as accumulation of dust, particles, or debris, or permanent, such as ageing, wear and tear, physical, chemical or mechanical (surface) damages – can significantly reduce power generation and overall system performance. Among these, the accumulation of dust pollutants has been shown to have a greater impact on PV transmittance beyond efficiency [11].

Dust accumulation on PV panels is a multifactorial phenomenon influenced by dust particle physicochemical properties, ambient wind speed, PV module type and specifications, and panel tilt angle. While numerous studies have examined dust characteristics across geographical regions, many provide limited insights into effects on energy yields or cleaning regime implications [12]. 15 distinct dust pollutants affecting PV performance were identified, with the six most impactful being limestone, ash, red soil, calcium carbonate, silica, and sand [13]. The influence of dust on degradation of electrical output on several technologies including (pc-Si, a-Si, mc-Si) has been examined with varying morphologies in different geographical locations concluding that different dust types result in comparable degrees of performance degradation across these technologies [14].

Multi-criteria analysis of 20-year historical data on radiation effects, dust emission and deposition rates, alongside 15 cleaning scenarios were conducted by Ref. [15] to propose optimised cleaning schedules. A Chinese study found minimum dust accumulation (1.45 g/m^2) at 3 m/s wind speed, with accumulation increasing linearly with humidity and showing negative correlation with particle size under 30 % RH. When particle size increased from 10 μm to 30 μm at 1 m/s wind speed, dust accumulation decreased from 9.76 g/m^2 to 2.59 g/m^2, reducing PV efficiency loss from 14.64 % to 3.89 % and transmittance reduction from 25.32 % to 8.38 % [11]. A Hong Kong study using particle resuspension theory estimated that wind speeds required for resuspending particles (0.1–100 μm diameter) on flat PV panels ranged from 0.82 to 2219.8 m/s [16]; failing to notice that windspeed over 32 m/s (118 km/h or 73 mph) represents a Beaufort wind scale 12 or a Hurricane that will cause violent destruction.

Dust accumulation significantly degrades the optical performance of PV modules, with transmittance affected far more than reflectance (35.0 % vs. 1.1 % across 0–10 g/m^2 dust density) [17]. The Soiling Loss Index (SLI) has been applied to model dust impacts and evaluate cleaning strategies in Jordan [18]. Experimental data from East China show that 0.644 g/m^2 of dust can accumulate in one dry-season week, reducing PV output by 7.4 %, with attenuation reaching 13.9 % after two weeks [19]. A 20 % drop in relative transmittance caused by natural deposition within only eight days was recorded in northwest China [20]. Similarly, in Kathmandu, 9.67 g/m^2 of dust accumulated over five months reduced efficiency by 29.76 % compared to daily-cleaned panels, with dust concentrating near the module bottom, increasing risk pf hot-spot, leading to potential permanent module damage [21].

Computational analysis of airflow effects shows that maximum particle mass flux occurs at a 90° tilt for particles <1 μm and at 30° for particles >10 μm on south-facing modules, with larger particles depositing more. The effects of wind direction angle (against the panel surface) have been tested with the flux peaks at 90° for <1 μm particles and at 10° for >10 μm particles (at 30° panel tilt) [22].

It is important to note that although the contribution of dust is still significant at 16–29 %, long-term performance degradation of PV modules might be more due to other factors such as corrosion, delamination, and discoloration, which account about 71–84 % [23]. Another study reported a monthly average decrease or 4.5 % and 8 % for a 1.5 kWp system in Perth, Australia and a 50 Wp system in Nusa Tenggara Timur, Indonesia respectively [24].

1.3. Cleaning regimes

Cleaning is essential to maintain the energy output, efficiency, and performance of PV panels within the intended or target margines. However, the methods, procedures, and frequency of cleaning can significantly influence lifecycle performance of PV systems. Such factors, hence, are particularly critical in less robust or competitive economies, where such costs may pose additional challenges to achieving renewable energy transitions.

Cleaning methods for PV systems have been extensively studied and classified. Cleaning techniques were categorised into: (1) forced airflow from air conditioning systems, (2) natural cleaning via rain and wind, (3) water cleaning, (4) manual cleaning, (5) mechanical cleaning, (6) electrical screens, (7) superhydrophobic coatings, (8) high-pressure water jets, and (9) self-cleaning ultrasonic systems [3]. Similarly, others proposed: (1) natural cleaning, (2) mechanical methods, (3) self-cleaning nanofilms, and (4) electrostatic methods [25]. The classification has been expanded to: (1) rainfall, (2) manual cleaning, (3) self-cleaning systems, (4) robotic cleaning, (5) airflow-based cleaning, (6) surface coatings, (7) electrodynamic screens, and (8) surface vibration [26]. Automated or unmanned cleaning methods were classified into: (1) electrical, (2) mechanical, (3) chemical, and (4) electrostatic approaches [27]. Smart system based techniques were clustered as: (1) robotic cleaning, (2) electrostatic cleaning, and (3) vibration-based cleaning methods [28].

These classifications underscore the diversity of cleaning technologies, reflecting the continuous efforts to optimise PV system maintenance and enhance efficiency across varied environmental conditions.

Studies on PV panel cleaning regimes across different regions highlight the need to balance efficiency with environmental considerations. In East China, limited rainfall necessitates manual cleaning every three weeks [19]. In Hong Kong, a simplified particle deposition model suggested a 20-day cleaning cycle for desert regions [29]. Analyses in Perth, Australia, and Timur, Indonesia, proposed schedules based on energy loss costs [24]. Northern Oman exhibited regional differences: sodium solutions showed more effective for chemical deposits in some cities, while water sufficed in others [30], with cleaning intervals of 10–15 days for mono- and polycrystalline modules depending on location [3]. Despite low daily efficiency losses of 0.05 % in Northern Oman – compared to up to 0.8 % for 37°-tilted silicon modules in northern Poland [7] – studies reported cumulative drops of 35–40 % over three months, suggesting longer cleaning intervals may risk efficiency given the water stress concerns [31]. In contrast, PV systems in heavily polluted Thar Desert have been recommended for daily cleaning, though water resource implications were not addressed [32].

While cost and profit are important in deciding cleaning cycles, other factors may outweigh financial metrics. Economic modelling showed dust-related losses of A$0.26/kWh in Australia and A$0.15/kWh in Indonesia. Although these savings are not economically significant, a cleaning schedule is recommended, especially for small systems in Indonesia, where increased output can meaningfully improve life in remote villages [24].

1.4. The study overview and scope

Notable gaps persist in the literature that warrant deeper and more systematic investigation. While previous research has explored the effects of dust accumulation and various cleaning methods on PV systems, there remains a significant gap in understanding how cleaning protocols influence different PV technologies and orientations, particularly within higher education settings in the MENA Region. This study address this gap through: (1) conducting a comprehensive, real-world, mid-term intervention to evaluate the impact of cleaning regimes on diverse PV technologies and orientations on a university campus, providing valuable empirical insights into their performance; (2) developing a robust methodological framework for PV cleaning projects, integrating machine learning for data imputation and ANCOVA for controlling environmental variables, thus offering a replicable approach for future PV maintenance studies; (3) establishing a normalised yet customisable methodology for PV optimising maintenance strategies in higher education institutions in the MENA Region; and (4) delivering actionable recommendations for optimising PV maintenance strategies tailored to higher education institutions in arid climates. The novelty and significance of this study lie in its comprehensive approach to directly linking the performance of PV systems with the factors that have the greatest impact on their efficiency. Furthermore, it offers a tailored intervention strategy for cleaning schedules, specifically designed to optimise system performance. This dual focus contributes to the development of practical, data-driven solutions for improving the efficiency, efficacy and sustainability of PV systems in real-world applications. It will, furthermore, lay the foundation for future research to help establish a knowledgebase for a more data-driven decision support systems for maintenance of PV systems in higher education institution with a special concentration on such institutions in the MENA Region.

2. Methods

2.1. Case study research

Founded in 1991, Applied Sciences University (ASU) is situated 21 km north of Amman, Jordan (Fig. 1).

The campus accommodates nine faculties, serving approximately 6000 students and supported by 216 academic and administrative staff. Encompassing an area of 11,600 m^2, the campus integrates a diverse array of facilities, including a conference palace, serviced parking, a student activity centre, banking services, a post office, bookshops, a central library, a health clinic, a student affairs hall, a multi-purpose sports hall, a football stadium, playgrounds, dedicated student parking zones, the Deanship building, and fourteen auxiliary support centres (Fig. 2). The architectural design of the campus is inspired by the region's rich cultural and historical heritage, with a distinctive layout shaped by a pronounced topographical gradient exceeding 10 %. This steep incline contributes to a visually dynamic spatial arrangement, marked by a series of interconnected platforms and varied elevations.

Demonstrating its commitment to renewable energy, ASU installed a 500-kW PV solar system in 2013 on the rooftops of the Engineering Faculty, Deanship Building, and the library. In 2015, a local weather station was added to collect accurate climatic data on temperature, humidity, wind speed, wind direction, and solar irradiance, supporting ongoing sustainability initiatives.

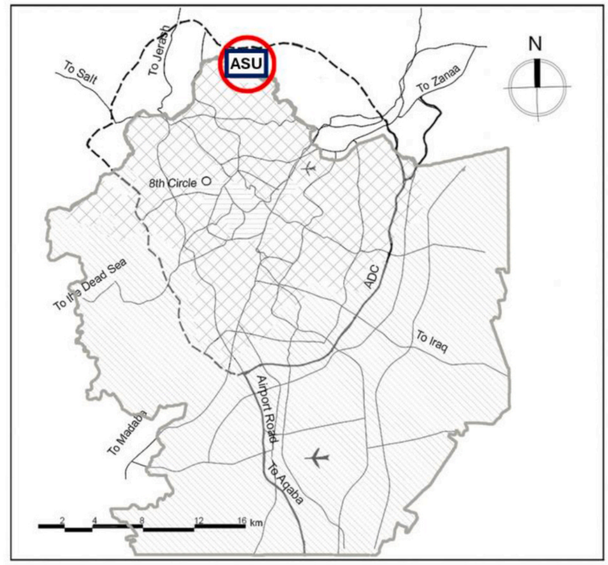

Fig. 1. ASU location in the north of city of Amman, Jordan.

The PV system installed in ASU has a peak power of 500kWp. The specification of the system installed on three different buildings at SU are indicated in Table 1.

2.2. Data collection: design and implementation

The normal cleaning cycle at ASU is a fortnightly (10 working-day) cycle. We designed an intervention schedule for the summer season based on historical data of extreme environmental conditions. In coordination with university facilities management, we altered the standard regime as detailed in Table 3. The intervention, which ran from 5th May to 14th September 2022, included periods of no cleaning, bi-weekly cleaning, and the establishment of a control case (the Dean building) from 17th July to 31st July to assess local micro-climate effects.

2.3. Data pre-processing: methodology and procedures

The data preprocessing methodology employed in this study is illustrated in Fig. 3, presenting a step-by-step approach used to prepare the data for analysis. This methodology begins with data extraction from CSV files generated by the ASU Energy Management System (EMS) and progresses through various stages, including data imputation using machine learning models, filtering non-generation hours, and normalisation processes.

Missing values in the dataset were addressed through data imputation using four machine learning algorithms: Categorical Boosting (CatB), Histogram-based Gradient Boosting (HGB), Extreme Gradient Boosting Regressor (XGBoost), and K-Nearest Neighbours Regressor (KNN-R). These models were selected for their ability to handle NAN entries; in addition to their more advanced and superior performance in estimation as evidenced in Refs. [33,34] to name but a few. For KNN-R, which does not natively handle missing values, the KNNImputer from scikit-learn was used as a preprocessing step.

The dataset was partitioned for model validation, with non-missing data split 90 %/10 % into training and test sets. All available environmental variables were included as features because each of the environmental parameter included affects PV performance in practice. or each system, the four algorithms were evaluated, and the model with the lowest Mean Absolute Error (MAE) and Mean Squared Error (MSE) was selected to perform the final imputation (see Fig. 4).

The dataset was filtered to include only the specified date range (5th May – 14th Sep 2022). To factor in the generation hours of the PV

Fig. 2. ASU Campus; main buildings, facilities and open spaces.

Table 1
Photovoltaic System of 500 kWp Grid connected.

	ASU08 The Library	ASU09 Faculty of Engineering	ASU10 Deanship of Student Affairs
System Power	130 kWp	264 kWp	117 kWp
DC/AC ratio	1.14	1.14	1.15
Array Orientation	12° (from S to W)	36° (from S to E)	36° (from S to E)
Array tilt angle	11°	11°	11°
Inverters type	SMA SUNNY TRIPOWER	SMA SUNNY TRIPOWER	SMA SUNNY TRIPOWER
Power of inverters	6 × 17000 W + 1 × 12000 W	13 × 17000 W + 1 × 10000 W	6 × 17000 W
Solar panels type	YL 245P-29b-PC (Polycrystalline)	YL 245P-29b-PC (Polycrystalline)	YL 245P-29b-PC (Polycrystalline)
Number of panels	531	1078	478
Commissioning date	18/2/2013	27/2/2013	18/2/2013

In addition, ASU also has a test field system with the peak power of 58kWp with following specifications (see Table 2).

systems only, rows where the PV Systems had 0 generation values were removed. The data was resampled to daily mean values. MinMax scaler was used to normalise the environmental parameters onto a comparable scale. MinMax scaler was fitted only on the training set and then applied to transform both testing set to prevent information leakage. The energy generation data for each PV system was normalised by dividing it by the respective system's kWp shown in Table 4.

2.4. Data analysis

The overall data analysis methodology employed in this study is illustrated in Fig. 5. This flowchart outlines the process used to evaluate the impact of cleaning interventions on the energy generation of PV systems, starting from the resampled daily dataset and progressing through regression model fitting, outlier removal, and statistical testing.

To ensure the normality of data for each PV system, a systematic outlier removal process was implemented. This involved fitting a linear regression model using the normalised energy generation data as the dependent variable and the intervention periods along with normalised environmental factors as independent variables. After fitting the model, the SW test was performed on the residuals to check for normality. If normality was not met (p-value <0.01), standardised residuals were

Table 2
Test Field system of 58 kWp Grid connected.

	Poly-crystalline Tracking System	CPV Tracking System	Poly-crystalline Fixed System	Mono-crystalline Fixed System	Poly-crystalline Fixed System	Mono-crystalline Fixed System	Thin-film Fixed System
System Power	9 kWp	17.5 kWp	5 kWp	5.2 kWp	5 kWp	5.2 kWp	10 kWp
Array Orientation	Tracking	Tracking	0°	0°	East-West	East-West	0°
Array tilt angle	Tracking	Tracking	11°	11°	11°	11°	11°
Inverters type	SMA SUNNY TRIPOWER	REFUsol	SMA SUNNY BOY	SMA SUNNY BOY	SMA SUNNY BOY	SMA SUNNY BOY	SMA SUNNY MINI CENTRAL
Power of inverters	1 × 9000 W	1 × 17000 W	1 × 5000 W	1 × 5000 W	1 × 5000 W	1 × 5000 W	2 × 5000 W
Solar panels type	YL 250P-29b (Polycrystalline)	Semprius SM-U01 (Triple Junction Si)	YL 250P-29b (Polycrystalline)	YL 260C-30b (Monocrystalline)	YL 250P-29b (Polycrystalline)	YL 260C-30b (Monocrystalline)	NA-E125G5 (a-Si, microcrystalline)
Number of panels	36	200	20	20	20	20	80

Table 3
The intervention schedule.

Date	Cleaning intervention (Action introduced)	Notes, explanations and justifications
Before 5th May	Normal (fortnightly) cleaning regime	**N/A**
5th May	All PV arrays	Beginning the interventions: Establishing a baseline in each unit and comparing the pattern of production and isolating any other performance issue unrelated to the maintenance regime
5th June	All PV arrays	Measuring the impact of environmental factors on the production during the period of intervention (2 weeks). **NB:** The solar radiation and intensity need to be factored in for the normalisation purposes
19th June	All PV arrays	Measuring the impact of environmental factors on the production during the period of intervention (2 weeks) **NB:** The solar radiation and intensity need to be factored in for the normalisation purposes
3rd July	All PV arrays	Measuring the impact of environmental factors on the production during the period of intervention (2 weeks) **NB:** The solar radiation and intensity need to be factored in for the normalisation purposes
17th July	Arrays on all buildings except the "control case"	Measuring the impact of environmental factors on the production during the period of intervention (2 weeks) to investigate the impact of micro-climate conditions specific to university campus **NB:** The solar radiation and intensity need to be factored in for the normalisation purposes
31st July	Arrays on all buildings except the "control case"	Measuring the impact of environmental factors on the production during the period of intervention (2 weeks) to investigate the impact of micro-climate conditions specific to university campus **NB1:** The solar radiation and intensity need to be factored in for the normalisation purposes **NB2:** At this point, we will have our "control case" with no cleaning for a full period of 4 weeks
14th August	All PV arrays	Measuring the impact of environmental factors on the production during the period of intervention (4 weeks). **NB:** The solar radiation and intensity need to be factored in for the normalisation purposes
14th September	All PV arrays	Preparing the systems for switching back to normal maintenance regimes (end of intervention)
After 14th September	Back to normal/ fortnightly cleaning regime	**N/A**

calculated, and outliers exceeding a threshold were removed. This threshold began at 10 and was reduced by 0.1 per iteration until the SW test confirmed normality (p-value >0.01). This iterative method ensured valid statistical analysis by eliminating significant outliers. This iterative approach ensured the removal of significant outliers for valid statistical analysis. After normality was achieved, Levene's Test was conducted to verify homogeneity of variances across intervention periods, with the null hypothesis stating that variances were equal.

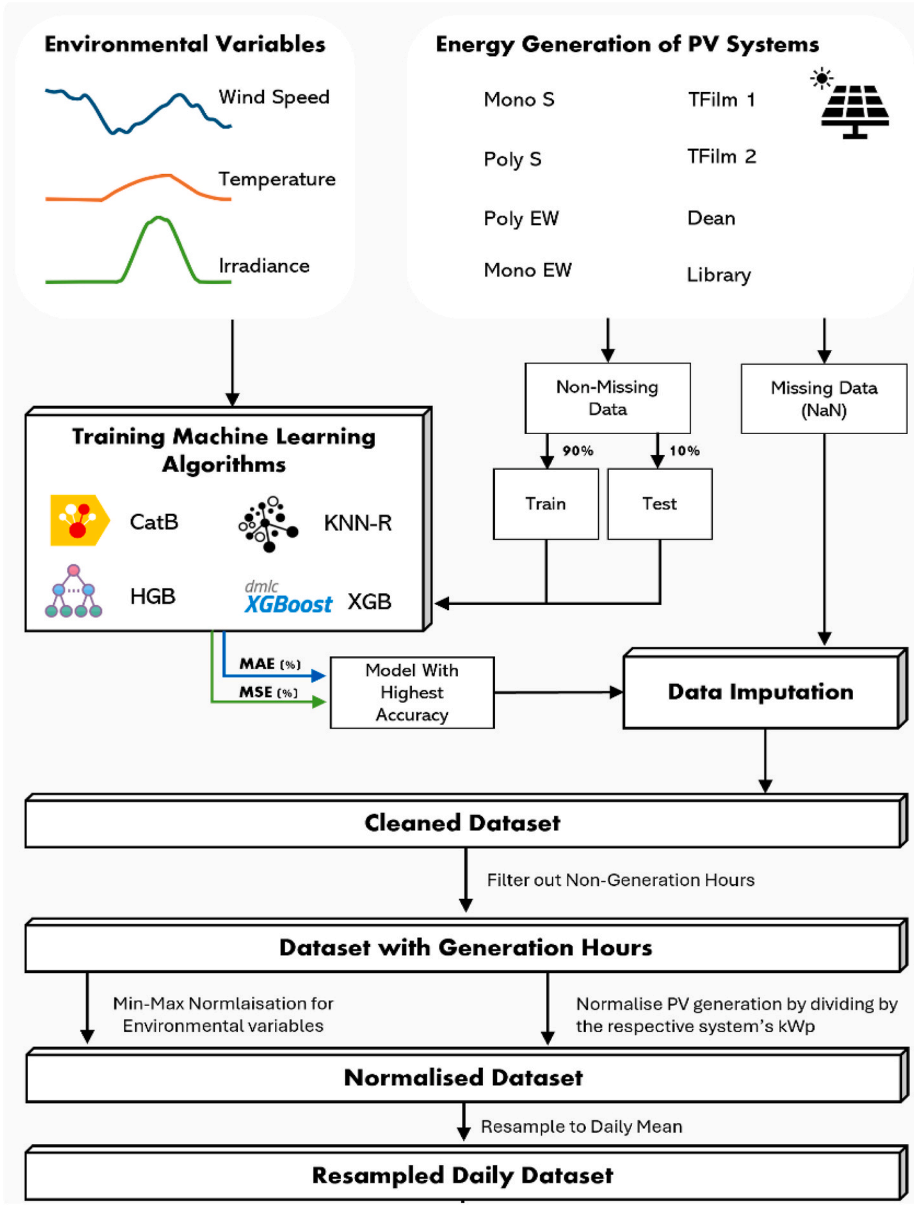

Fig. 3. Data pre-processing methodology.

Following the verification of normality and homogeneity of variances, an Analysis of Covariance (ANCOVA) test was conducted to assess the effect of cleaning interventions on the normalised energy generation of each PV system. The ANCOVA test was applied at multiple levels of analysis to compare energy generation distinct phases (baseline, intervention, and post-intervention), while adjusting for environmental factors as covariates. The Null Hypothesis (H_0) stated that there is no significant difference in energy generation between the baseline and intervention periods.

To conduct a comprehensive assessment of the impact of cleaning interventions, significance tests were performed using three analytical approaches:

1. Overall Period Analysis, comparing of energy generation in the baseline, intervention, and post-intervention periods.
2. Detailed Intervention Analysis, dividing the intervention period into early and late stages, compared with baseline and post-intervention periods.
3. Stepwise Intervention Analysis, examining individual intervention stages (I1 to I5) compared with baseline and post-intervention periods.

The breakdown of these analytical approaches and their corresponding date ranges is presented in Table 5, which outlines how each approach segments the intervention timeline for a detailed assessment.

3. Results

This section presents the findings of the statistical tests conducted to evaluate the impact of cleaning interventions on the energy generation of PV systems at ASU. The results include preliminary checks and significance tests conducted across various analytical levels.

3.1. Preliminary checks

The SW test was used to assess the normality of the normalised energy generation data for each PV system during the cleaning periods.

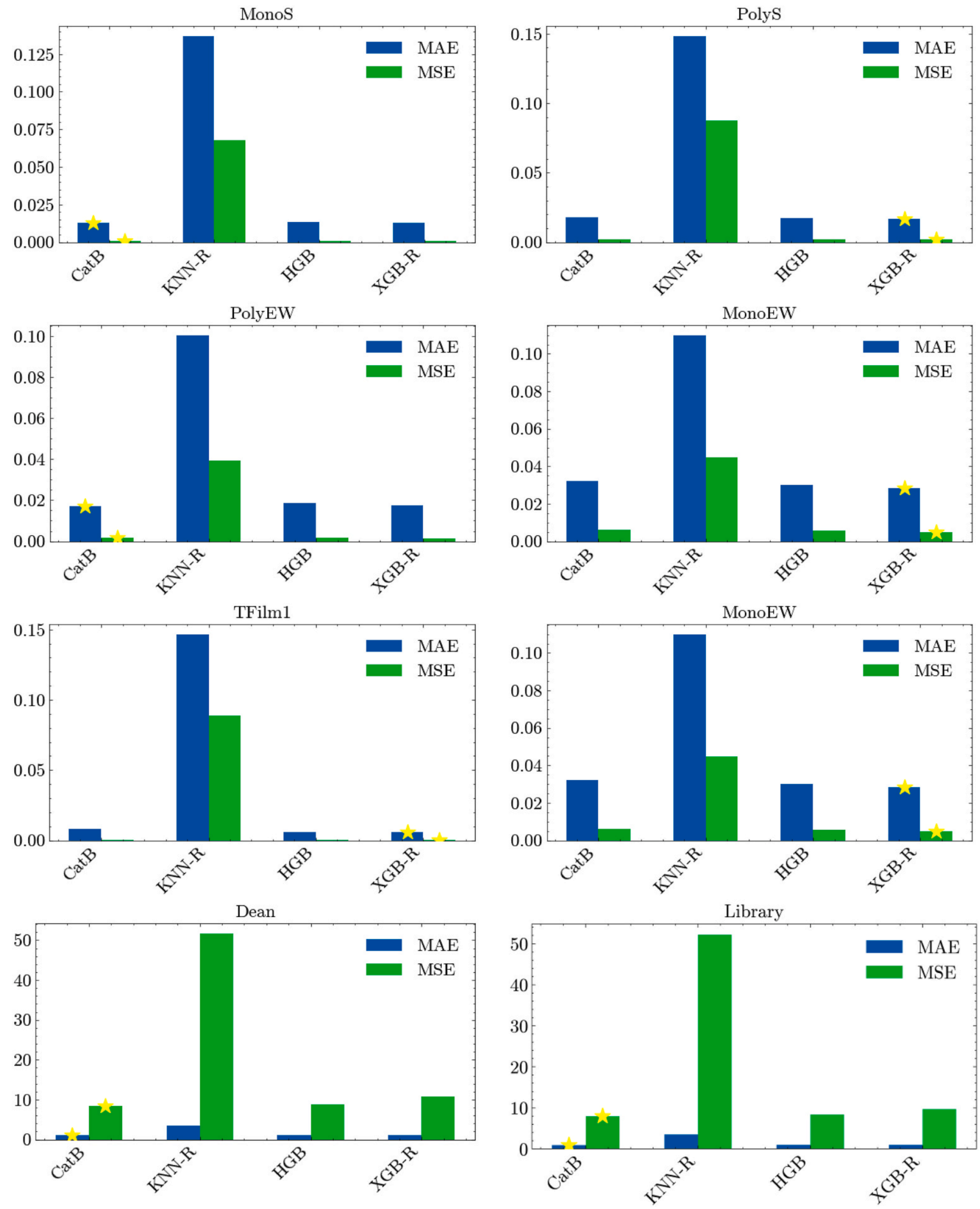

Fig. 4. Models Performance Evaluation Results; star (★) highlights the chosen model based on lowest errors.

Table 4
Specifications of PV Systems under investigation.

PV System	Shorter Name	Orientation	Nominal Capacity (kWp)
Monocrystalline South	MonoS	S	5.2
Polycrystalline South	PolyS	S	5
Polycrystalline East-West	PolyEW	EW	5
Monocrystalline East-West	MonoEW	EW	5.2
Thin-Film 1	TFilm1	S	5
Thin-Film 2	TFilm2	S	5
Deanship Building (Polycrystalline)	Dean	SE	117
Library Building (Polycrystalline)	Library	SW	130

The results shown in Table 6 confirmed that all systems had p-values greater than 0.01, indicating that the data followed a normal distribution, and the Null Hypothesis (H_0) was not rejected for any system.

To visually confirm the distribution of data, Q-Q plots shown in Fig. 6 compare the data before and after outlier removal for each PV system. These plots further illustrate the results of the outlier removal process implemented on the normality of data distribution and reinforce the results indicated by the SW Test.

For further evaluation, Levene's Test was conducted to check the homogeneity of variances across intervention periods. The results, as shown in Table 7, indicated that all systems had p-values greater than 0.01, confirming homogeneous variances and supporting the assumptions needed for subsequent ANCOVA analysis.

Additionally, to validate the appropriateness of ANCOVA, the homogeneity of slopes assumption was tested by examining interactions between intervention periods and environmental covariates. This test determines whether the relationship between environmental variables and PV generation remains consistent across intervention periods.

The homogeneity of slopes assessment shown in Table 8 demonstrated that the fundamental ANCOVA assumption was satisfied across the majority of covariate-system interactions, with 21 of 24 combinations (87.5 %) exhibiting non-significant interaction effects ($p > 0.05$). Notably, two systems exhibited statistically significant period-by-

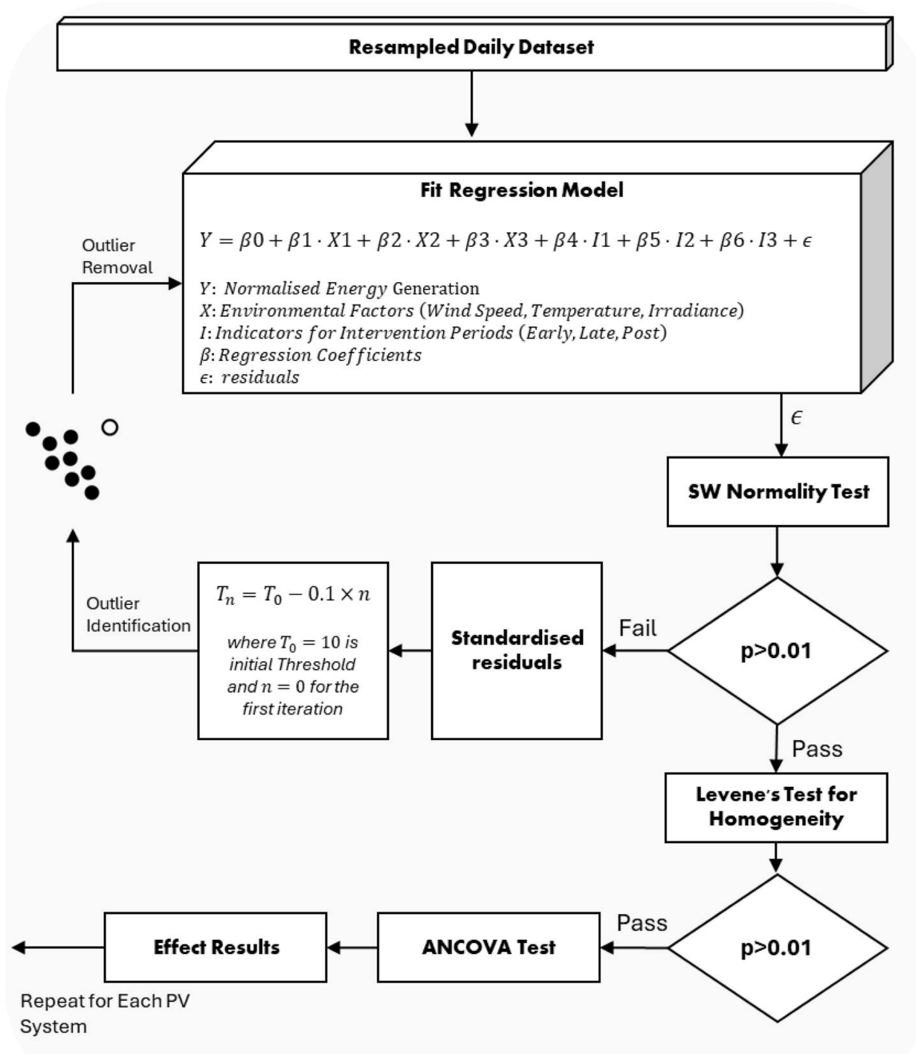

Fig. 5. Data analysis methodology.

Table 5
Date ranges for analytical approaches.

Date Range	Overall Period Analysis	Detailed Intervention Analysis	Stepwise Intervention Analysis
5th **May** – 5th **Jun**	Baseline	Baseline	Baseline
5th **Jun** – 19th **Jun**	Intervention	Early-Intervention	I1
19th **Jun** – 3rd **Jul**			I2
3rd **Jul** – 17th **Jul**		Late-Intervention	I3
17th **Jul** – 31st **Jul**			I4
31st **Jul** – 14th **Aug**			I5
14th **Aug** – 14th **Sep**	Post-Intervention	Post-Intervention	Post-Intervention

Table 6
Results of Shapiro-Wilk (SW) Test to check the normality of data distribution in 8 PV systems in ASU.

System	Threshold for Outlier Removal	p-value (After)	H_0	Follow Normal Distribution?
MonoS	10.0	0.072613	Fail to Reject	Yes
PolyS	2.9	0.101885	Fail to Reject	Yes
PolyEW	3.1	0.063089	Fail to Reject	Yes
MonoEW	5.5	0.326642	Fail to Reject	Yes
TFilm1	3.0	0.134342	Fail to Reject	Yes
TFilm2	10	0.366676	Fail to Reject	Yes
Dean	2.1	0.050536	Fail to Reject	Yes
Lib	2.1	0.080963	Fail to Reject	Yes

irradiance interactions: PolyEW ($F = 3.16$, $p = 0.028$) and MonoEW ($F = 5.26$, $p = 0.002$). These findings indicate that while the irradiance-generation relationship remains stable across intervention periods for most systems, it varies temporally for the east-west oriented systems. Consequently, ANCOVA results are statistically robust for the majority of systems analyzed, with appropriate interpretative caution applied to the period-specific irradiance effects observed in PolyEW and MonoEW systems.

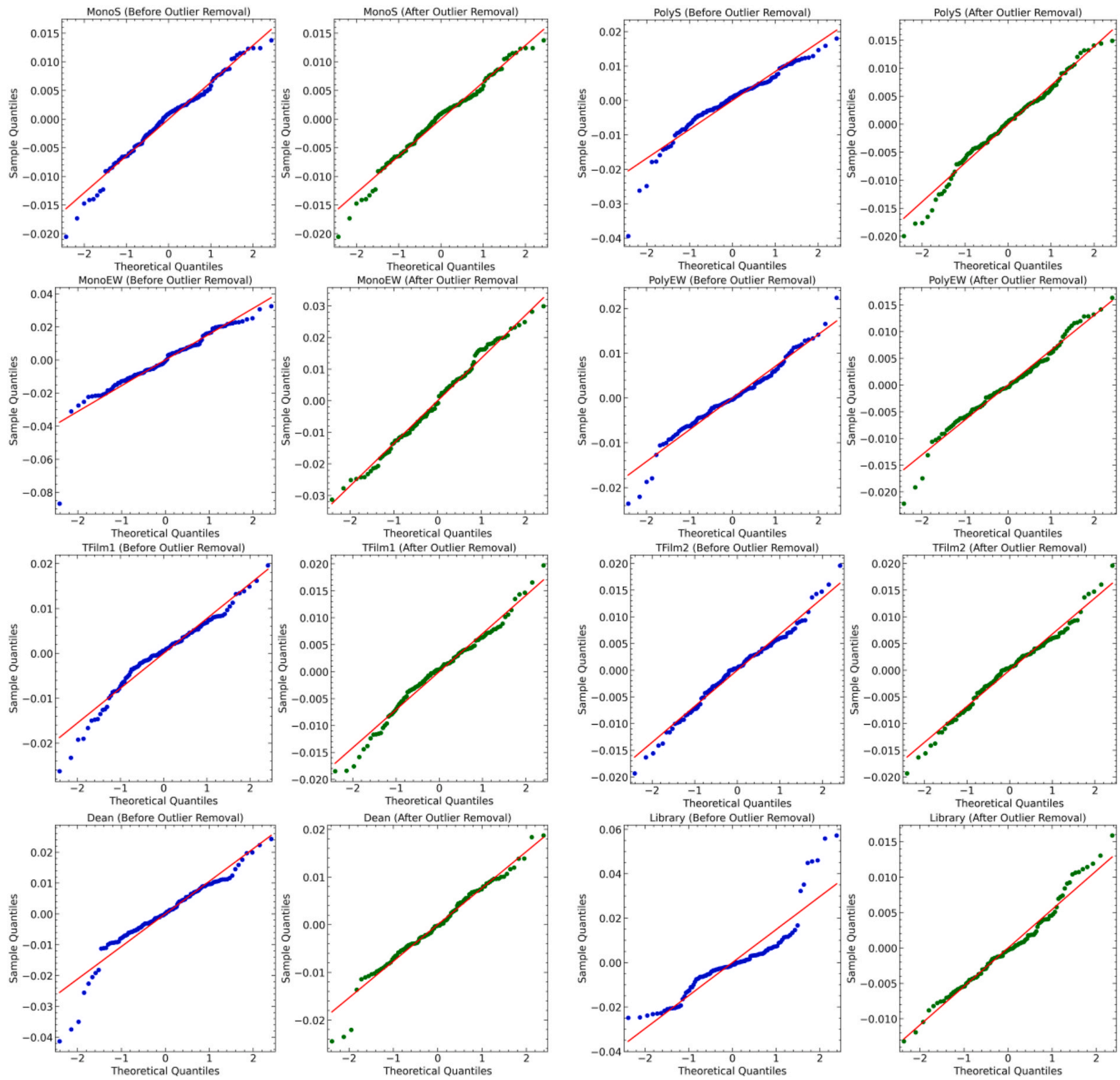

Fig. 6. Q-Q plots showing the data distribution before and after outlier removal for each PV system.

Table 7
Results of Levene's Test to assess the homogeneity of variances in 8 PV systems in ASU.

System	p-value	H_0	Follow Homogeneous Variances?
MonoS	0.047	Fail to Reject	Yes
PolyS	0.085	Fail to Reject	Yes
PolyEW	0.155	Fail to Reject	Yes
MonoEW	0.331	Fail to Reject	Yes
TFilm1	0.054	Fail to Reject	Yes
TFilm2	0.026	Fail to Reject	Yes
Dean	0.142	Fail to Reject	Yes
Library	0.025	Fail to Reject	Yes

Table 8
Homogeneity of slopes assessment for period-covariate interactions.

System	Irradiance	Temperature	Wind Speed
	F (p-value)	F (p-value)	F (p-value)
MonoS	1.39 (0.251)	0.92 (0.436)	1.54 (0.208)
PolyS	1.32 (0.271)	1.07 (0.365)	1.28 (0.286)
PolyEW	**3.16 (0.028)***	2.06 (0.110)	2.67 (0.051)
MonoEW	**5.26 (0.002)***	1.90 (0.134)	0.95 (0.417)
TFilm1	2.59 (0.057)	2.62 (0.055)	1.47 (0.226)
TFilm2	2.52 (0.062)	1.48 (0.224)	1.95 (0.126)
Dean	2.15 (0.099)	2.30 (0.082)	0.57 (0.638)
Library	0.33 (0.805)	0.49 (0.693)	1.26 (0.291)

*Values in bold indicate significant interactions ($p < 0.05$).

3.2. *Significance tests*

This section presents the results of significance tests to assess the impact of cleaning interventions on PV energy generation using ANCOVA, adjusting for environmental factors as covariates. The analysis was conducted at three levels as discussed in Section 2.4.

3.2.1. *Overall Period Analysis*

Fig. 7 shows that the intervention had varying effects across the PV systems. The Dean system (control case) showed a significant negative coefficient relative to the baseline during the intervention period. This decline suggests that in the absence of regular cleaning regime, environmental factors such as dust accumulation could have a pronounced

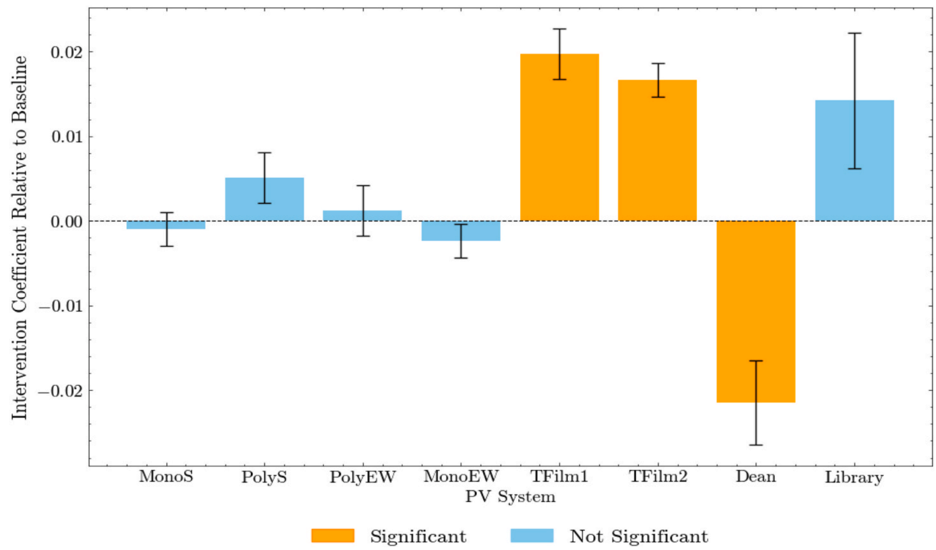

Fig. 7. Effect of Intervention compared to baseline across PV systems.

negative impact on energy generation. On the contrary, the TFilm1 and TFilm2 systems demonstrated significant positive intervention coefficients, suggesting that the cleaning protocols during the intervention period resulted in an improvement in energy generation compared to the baseline.

This finding implies that the thin-film PV modules have higher sensitivity to surface cleaning compared to other types of PV modules. It also highlights the potential for targeted interventions to optimise performance, particularly for module types prone to rapid efficiency loss due to soiling. The performance of MonoS, PolyS, PolyEW, MonoEW, and Library showed non-statistically significant changes relative to the baseline. This overall analysis underscores the importance of adopting a potential customised cleaning regime tailored to each type of PV technology to maximise the performance of the PV systems throughout the university.

The comparison of these results with the post-intervention period shown in Fig. 8 further validates the observations made during the intervention period. Performance of systems such as TFilm1 and TFilm2 continued to show positive outcomes during post-intervention relative to the baseline.

This continuity suggests that the positive effects of the intervention continued beyond the immediate intervention period showcasing the long-term benefits of adopting more frequent cleaning regime for certain PV types. Additionally, the Dean system remained in a negative coefficient range, confirming that the absence of intervention (as a "control case") led to continued performance decline. Interestingly, the analysis showed statistically significant differences in the performance of PolyEW and MonoEW during post-intervention relative to baseline. This significant decline in performance could be directly linked to their EW orientation which may have influenced their exposure to dust or cleaning, as PolyS and MonoS showed positive response. This highlights the importance of considering orientation in addition to the PV type when deciding the cleaning regime for PV systems, requiring tailored cleaning protocols to ensure optimal performance.

3.2.2. *Detailed Intervention Analysis*

The detailed analysis of the intervention period, illustrated in Figs. 9 and 10, provides critical insights into the impact of cleaning protocols on

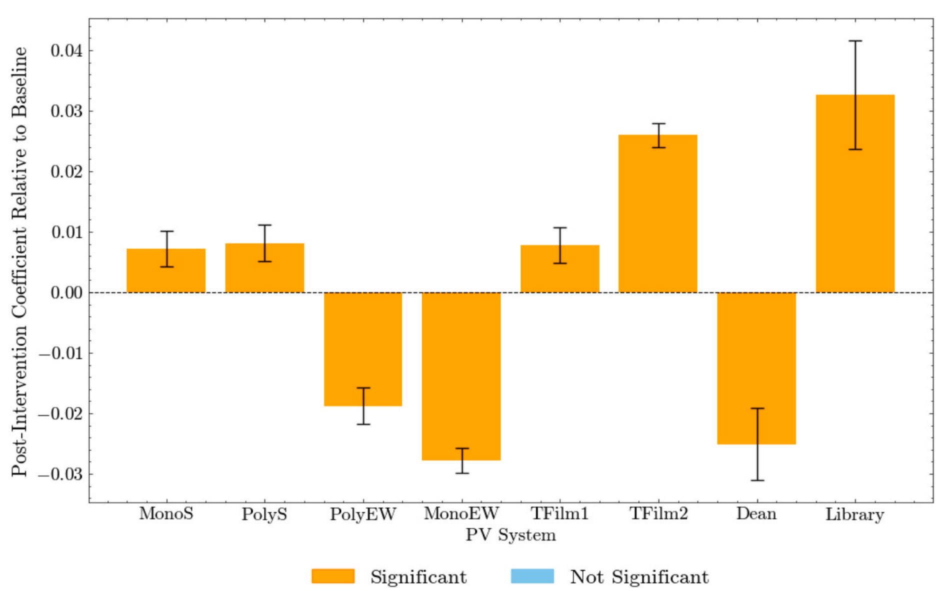

Fig. 8. Effect of post-intervention compared to baseline across PV systems.

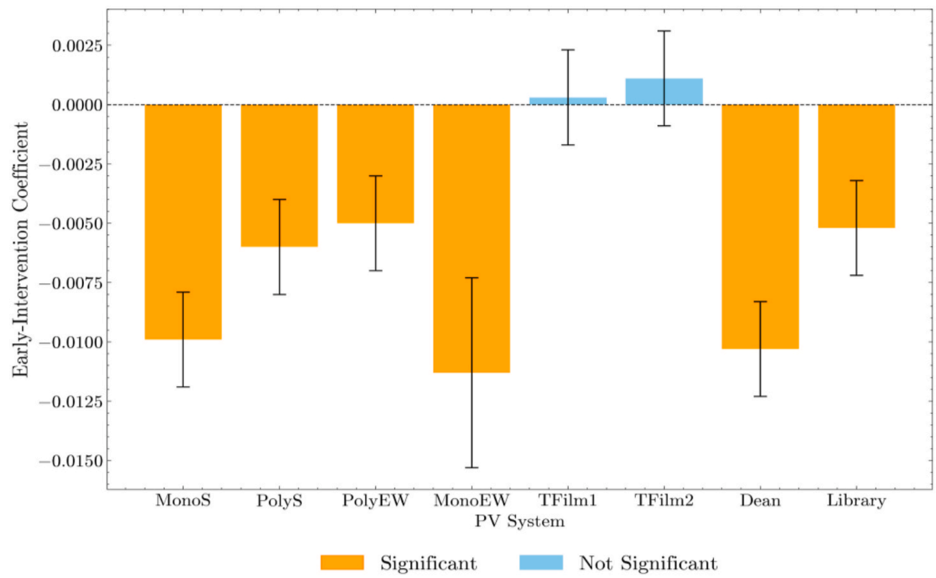

Fig. 9. Effect of early-intervention compared to baseline across PV systems.

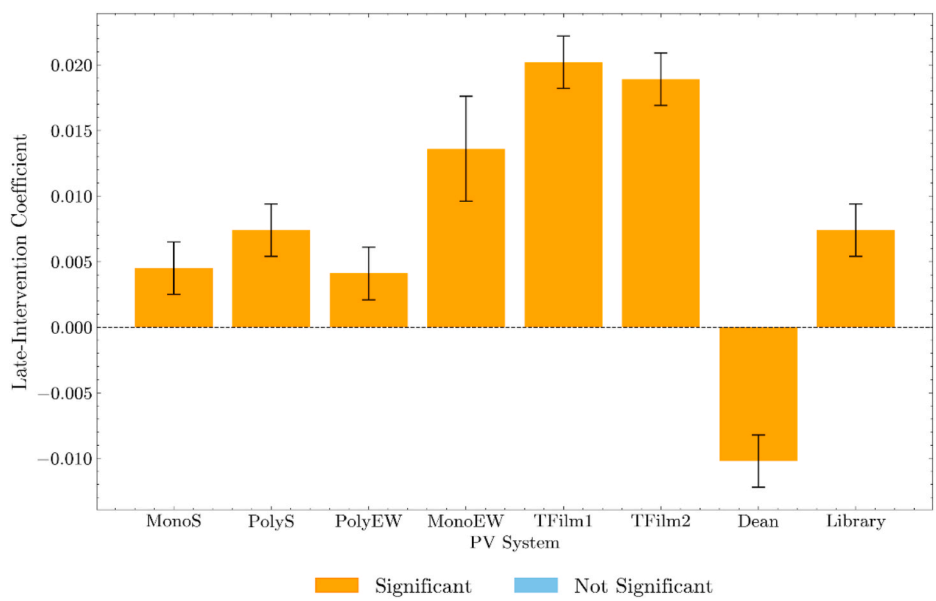

Fig. 10. Effect of late-intervention compared to baseline across PV systems.

PV system performance relative to the baseline. During the early-intervention phase (Fig. 9), the proposed cleaning regime generally resulted in a statistically significant decrease in energy generation for PV systems such as MonoS, PolyS, PolyEW, MonoEW, Dean, and Library.

In contrast, thin-film PVs (TFilm1 and TFilm2) showed a positive but non-significant response, However, it is important to note that the early-intervention results are compared to the baseline period, which took place after a month without cleaning but before the baseline month, the PV systems had been cleaned regularly. Therefore, the PV systems at baseline may not have experienced severe performance declines due to accumulated dust, making the early-intervention phase appear more disruptive as it followed a period of no cleaning. During the late-intervention phase as demonstrated in Fig. 10, most PV systems, including TFilm1, TFilm2, MonoEW, PolyS, and MonoS, showed significant improvements in energy generation compared to the baseline.

This indicates that consistent cleaning effectively mitigated the accumulated soiling and enhanced performance where Thin-film PVs benefited the most. However, the Dean system, as the “control case” without any cleaning, continued to show a significant negative response, as demonstrated in Fig. 11.

This consistent decline reinforces the impact of not having a consistent cleaning regime, emphasising that without intervention, PV performance steadily degrades. Fig. 12 compares trends across all phases. PolyEW and MonoEW shifted from negative (early) to positive (late) and back to negative (post), suggesting inconsistent performance likely tied to orientation. This underscores the need to consider both PV type and orientation when designing cleaning regimes.

3.2.3. *Stepwise intervention analysis*

The stepwise intervention analysis shown in Fig. 13 highlights the impact of each intervention stage (I1 to I5) and the post-intervention period compared to the baseline.

Fig. 13 illustrates the impact of each intervention stage (I1–I5) and post-intervention. MonoS and PolyS initially declined (I1–I2) but

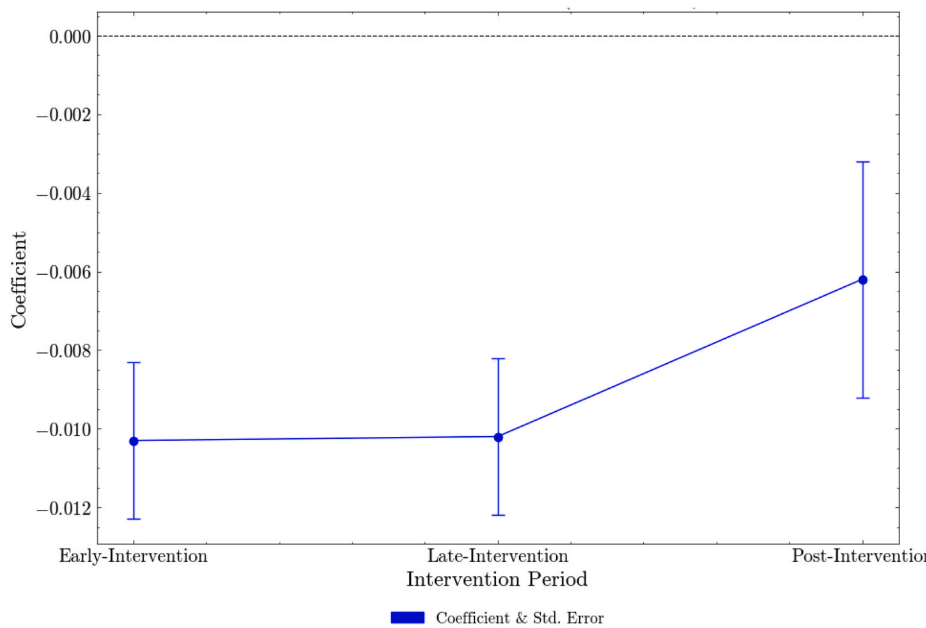

Fig. 11. Effect of Intervention on Dean PV system.

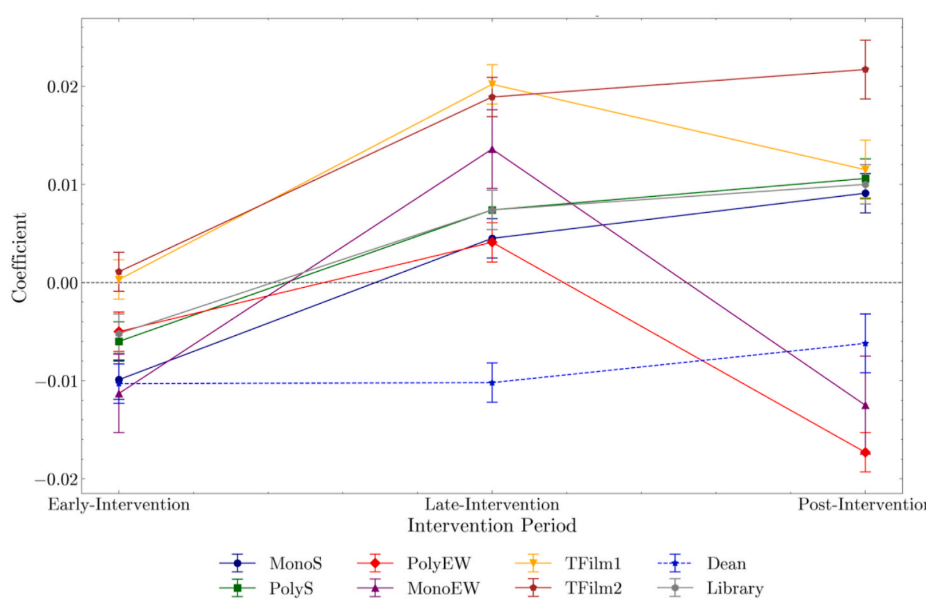

Fig. 12. Comparative trend for all PV systems across early, late and post-intervention phases.

improved significantly from I4 onward, showing the benefits of sustained cleaning. This positive shift suggests that continued cleaning efforts effectively enhanced energy generation over time, emphasising the importance of sustained cleaning practices.

MonoEW and PolyEW also declined early and showed some recovery mid-intervention, but performance dropped again post-intervention. This inconsistency suggests east-west systems may require more frequent or targeted cleaning.

Thin-film PV systems (TFilm1 and TFilm2) generally showed a consistent positive response throughout most of the intervention stages, highlighting their resilience and enhanced performance when subjected to a structured cleaning regime. This trend aligns with findings from earlier analyses that demonstrated their higher sensitivity to cleaning interventions.

4. Discussion of findings

The findings of this study afford critical insights into the management of PV systems within higher education sector in the MENA Region. Although cleaning methods have been widely investigated and categorised – into nine types [3], four types [25,27], or eight types [26], depending on the criteria and factors considered – this lies beyond the scope of our study. Instead, we focus specifically on the status quo of cleaning practices in the case study context, where all cleaning activities are undertaken manually. In particular, the results highlight adopting tailored and context specific maintenance and cleaning strategies that consider both technological characteristics of the PV systems and their spatial orientation. The different response patterns observed across different PV technologies indicate that standard maintenance practices are insufficient for installations comprising multiple types of PV technologies.

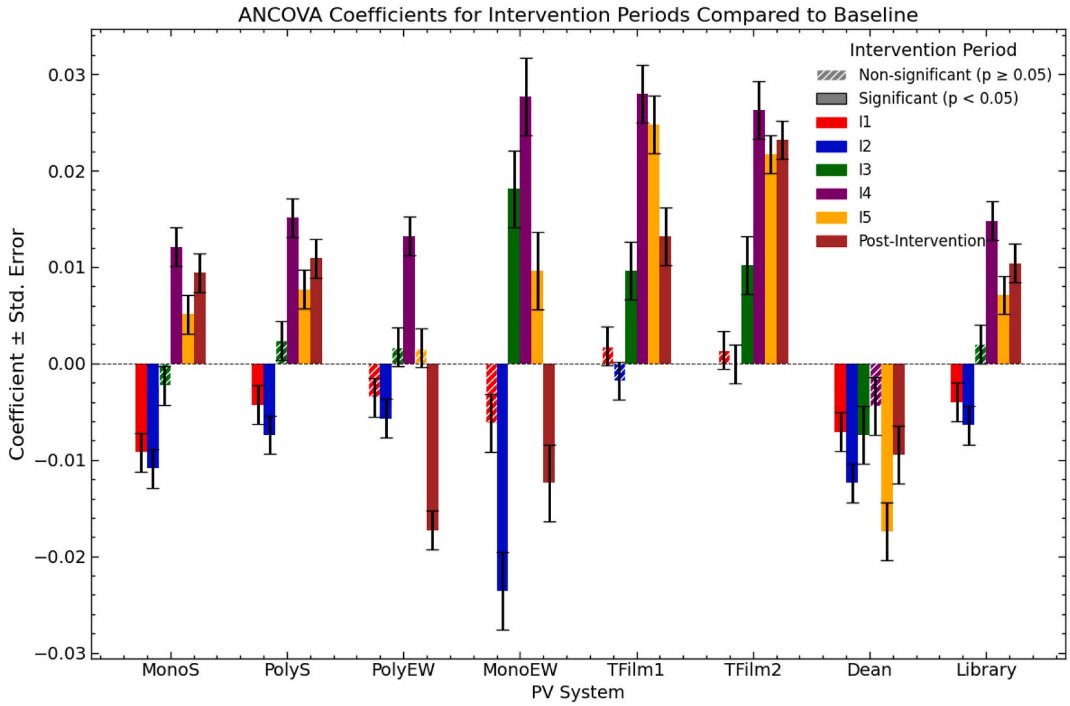

Fig. 13. ANCOVA coefficients for intervention periods (Stepwise Intervention) compared to baseline.

Previous research has highlighted differences in the impact of dust deposition on monocrystalline and polycrystalline PV modules. It has been reported, for example by Ref. [3], that polycrystalline modules showed lower sensitivity to dust deposition, with a 1–5 % power reduction, compared to a 4–12 % reduction in monocrystalline modules, under nominal (5 g/m^2) dust deposition in controlled indoor environments. Other studies have produced different, and sometimes debatable, results. Elsewhere the correlation between dust deposition and reductions in electrical or thermal efficiency has been examined through numerical simulations [5]. A linear correlation between PV productivity loss and pollution layer thickness has been documented by Ref. [7]. Similarly, linear relationship between dust accumulation and power reduction has been identified under lab conditions – reporting a 1.7 % drop per g/m^2 of dust – but was later contradicted by field tests showing that 5.44 g/m^2 of dust accumulation resulted in a 12.7 % power loss [6].

Our findings diverge from these studies, contributing novel insights in:

i) Field tests of operational systems are the most reliable method for assessing the real performance of PV systems under dust and pollution deposition; and
ii) Scheduled (time-based) interventions, in which cleaning cycles are planned and adjusted over time, are more effective foundations for empirical, pragmatic guidelines than weight- or size-based methodologies, which rely on correlating dust mass or particle size with power loss.

The limited number of studies adopting scheduled (time-based) interventions face their own shortcomings. For example, some restricted their intervention period to just eight days [20], limiting the generalisability of their findings. Conversely, data was collected over a longer, 70-day period by others [4] but without a designed schedule with clear aim to measure the effect of interventions on the energy output of different PV systems.

S-facing systems using MonoS and PolyS technologies showed consistent performance gains, especially in later intervention stages. In contrast, EW-oriented systems (PolyEW, MonoEW) exhibited irregular patterns and persistent declines, highlighting the complex interplay between orientation, technology, and cleaning efficacy. Moreover, the existing literature on PV cleaning best practices has extensively discussed and emphasises the role of tilt angle in influencing soiling losses and the effectiveness of cleaning regimes. Another study highlighted that tilt angles of 23°, 33°, and 43° produced differential effects on both soiling accumulation losses and cleaning effectiveness, thereby confirming the direct relationship between tilt angle and energy recovery [35]. Similarly, a non-linear correlation between tilt angle and efficiency loss due to dust deposition was reported [8].

Nevertheless, while increasing the tilt angle can improve self-cleaning effects through gravity- or wind-induced mechanisms that help mitigate dust accumulation, some previous studies – for example, in Ref. [16] – appear to have gone to considerable lengths to validate this point, while overlooking important practical and operational considerations in real-world scenarios. Moreover, a comparison of our findings with prior research – e.g. Ref. [8] – indicates that tilt adjustment on their own may not represent the most effective strategy. Assessing power loss in PV systems in isolation risks producing outcomes that diverge substantially from real operational contexts, where performance is shaped by a complex interplay of multiple factors. Specifically, an increased tilt angle intended to minimise dust deposition, may compromise the system's ability to optimise solar energy capture, particularly in regions where solar irradiance profiles favour lower tilt angles. Therefore, tilt angle optimisation cannot be viewed in isolation from other critical design parameters, such as orientation and PV technology type. Although this issue – both in the narrow sense discussed above and in the wider context – was acknowledged by Ref. [12], who observed that many investigations offered only limited insights into the consequential effects of dust on energy yields and the implications for cleaning regimes, little progress has been made in addressing this gap ever since.

The results of the present study extend this body of knowledge by demonstrating that beyond tilt angle, the orientation and type of PV system significantly influence the effectiveness of cleaning interventions. The variability in energy generation observed in EW-oriented systems suggests that such configurations may necessitate more frequent or specialised cleaning protocols to sustain optimal performance levels. This evidence challenges the applicability of generic cleaning strategies commonly employed in PV maintenance practices, advocating instead for a more localised, case-specific approach.

While our findings conform, in principles, with general findings of the literature, they challenge the "one-size-fits-all" approach to cleaning thereby calling for a much necessary tailored and localised (case-by-case) analysis to determine the best cleaning regime(s) for each PV array system even in one single institution.

Studies on thin-film PV systems remain relatively few and far between. A key contribution of this study is the comparative performance analysis of thin-film modules alongside other PV technologies. The stepwise intervention analysis highlighted key temporal patterns in how PV systems responded to cleaning interventions. S-facing TFilm1 and TFilm2, displayed consistent positive responses throughout the intervention stages, confirming the findings that thin-film PVs are particularly sensitive to soiling and respond well to cleaning compared to other PV technology types. On the other hand, the inconsistent and less effective outcomes for EW-oriented systems highlight potential challenges in maintaining their performance over time. This indicates that orientation and type of PV technology can be very important factors to consider when designing cleaning regimes in the MENA Region.

These findings collectively underscore the importance of a more sophisticated and integrated approach to PV system management within higher education sector in the MENA region. Such an approach should combine strategic technology selection, orientation optimisation, and the development of customised maintenance and cleaning protocols. This would not only enhance system efficiency and energy generation but also contribute meaningfully to sustainability objectives by reducing resource consumption and mitigating environmental impacts.

This study has been carried out in the context of a higher education institution in city of Amman, Jordan using multiple PV technologies. While modest in scale, it provided an ideal setting for designing and testing a carefully tailored intervention plan within the existing cleaning regime. Although coordinating and securing approval for the intervention plan from university senior management team bore its own challenges, the study environment offered an open, agile, and responsive framework that enabled effective implementation aligned with the research aims and objectives. All the processes, actions and procedures have been documented with immaculate level of detail and high level of precision to ensure the study's generalisability and scalability for other similar or comparable contexts. The findings, together with their comparative analysis against the findings of the review of the state-of-the-art, underscore the need for specific, case-by-case investigations of PV systems to develop cleaning and maintenance strategies that are environmentally responsible, efficient, and optimised for the unique characteristics of each system in their respected settings. The rigorously designed, and clearly documented modular methodological framework established in this study provides a transferable model that can be applied and scaled to other PV settings and case studies of a similar nature.

5. Conclusions

This study underscores the critical importance of customised cleaning protocols for photovoltaic (PV) systems in the MENA Region, particularly within higher education sector. A uniform cleaning approach proved ineffective for installations with varied PV technologies and orientations. Instead, the analysis revealed significant differences in how PV types respond to cleaning, underscoring the need for tailored maintenance strategies.

Notably, thin-film PV modules exhibited the greatest performance improvement with regular cleaning, reflecting their higher sensitivity to soiling and maintenance interventions. In contrast, East-West (EW) oriented systems showed inconsistent performance trends, with statistically significant declines during post-intervention period, suggesting that panel orientation plays a critical role in dust accumulation and cleaning regime efficacy. Additionally, the control systems (Dean system), which received no cleaning interventions, exhibited a continuous decline in performance, reinforcing the negative impact of neglecting regular maintenance.

The stepwise intervention analysis further revealed that South-facing (S-facing) monocrystalline and polycrystalline (MonoS and PolyS) systems initially exhibited negative responses in early cleaning stages but demonstrated significant improvements over time, emphasising the importance of sustained and adaptive cleaning strategies rather than short-term interventions.

The contribution of this paper lies in providing empirical, methodological, regional, and practical advances to the current body of knowledge. It offers real-world evidence through a mid-term intervention assessing the impact of cleaning regimes across multiple PV technologies and orientations on a university campus, generating insights into actual system performance. Methodologically, it introduces a robust framework that combines machine learning for data imputation and ANCOVA to control environmental variables, creating a replicable model for future PV maintenance research. Regionally, it establishes a normalised yet adaptable approach tailored to optimising PV maintenance strategies for higher education institutions in the MENA region. Practically, it delivers actionable recommendations that support more efficient PV management in arid climates, thereby strengthening the link and bridging the gap between research and practice.

Future research should validate these findings across diverse microclimates and a broader range of PV technologies and institutional settings to enhance the generalisability of cleaning strategies. Subsequent work should also integrate economic modelling to develop cost-benefit analyses and employ lifecycle assessments (LCA) to evaluate the long-term trade-offs between cleaning frequency, water/chemical use, potential surface wear, and overall system performance and sustainability. Extended longitudinal monitoring studies building upon our methodology are needed to characterise the temporal decay patterns of cleaning effectiveness across different PV technologies and orientations. For HEIs particularly in developing economies, achieving a balance between energy independence and sustainability targets is crucial, as it directly impacts institutional green credentials, corporate social responsibility (CSR), and national/international reputation.

CRediT authorship contribution statement

Shatha Malhis: Writing – review & editing, Writing – original draft, Visualization, Resources, Data curation, Conceptualization. **Reem Shadid:** Writing – original draft, Visualization, Resources, Data curation. **Mohammed Al-Alawi:** Writing – original draft, Visualization, Formal analysis. **Abdullahi Ahmed:** Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Investigation, Conceptualization. **Eric Farr:** Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Conceptualization. **Poorang Piroozfar:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The data collected, collated and analyzed for/in this study is available upon request. Please contact the corresponding author.

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