Adult weight estimation in a tertiary hospital in Ghana

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Abstract

Accurate weight estimation is essential for estimating nutritional requirements for patients, especially among bedridden patients, where direct measurement is often not feasible due to the absence of bed scales. In such scenarios, clinicians rely on existing predictive equations, visual assessments, or patient-reported estimates. However, many existing predictive equations were developed in distinct demographic groups and may lack applicability without localised validation. This study employed a cross-sectional design involving 389 adult patients at the Cape Coast Teaching Hospital to develop and evaluate weight estimation models. Standardised protocols were followed to collect anthropometric measurements, including weight, height, mid-upper arm circumference (MUAC), and calf circumference (CC). Each variable was measured twice, and the mean of the two measurements was used for subsequent analysis. The dataset was partitioned into a training set (80%) and a testing set (20%). Automated machine learning algorithms were trained utilising the H2O.ai framework. Model performance was assessed using the mean absolute error (MAE), root mean squared error (RMSE), coefficient of determination (R^2), and the proportion of predictions falling within 10% (P10) and 20% (P20) of the actual weight. Pre-existing, relevant equations were applied to predict weight on the complete dataset, and the resulting predictions were evaluated against the actual weight using MAE, RMSE, R^2, P10, and P20. The average age of participants

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in the study was 57 years (interquartile range [IQR]: 42-66). The majority of the participants were females (66%). The average weight was 65 kg (IQR: 58-72), with the majority (46%) of participants having a normal body mass index (BMI) status. Our AutoML-derived stacked ensemble model outperformed all evaluated methods, achieving lower error rates (MAE of 3 kg and RMSE of 4 kg), a high R^2 of 0.9 and P10 and P20 values of 90% and 100%, respectively. While this current study highlights the importance of locally trained models, generalisability remains a limitation and warrants further validation across broader populations. Regardless, this study contributes important evidence for the development of population-specific adult weight estimation models to support clinical decision making.

1 Introduction

Weight estimation in the adult population is a critical aspect of healthcare, especially in emergency medicine, critical care, and nutrition assessment, as accurate weight is often required for drug dosing, calculating nutritional requirements, and diagnosing nutrition-related problems[Cattermole and Wells, 2021, Priya et al., 2012, Wells et al., 2022]. However, obtaining an accurate weight can be challenging in various situations, such as when patients are unresponsive, critically ill, have disabilities, or when appropriate weighing equipment is not available [Katherina and Sudiarti, 2020, Kokong et al., 2018, Mukasa et al., 2024, Priya et al., 2012, Wells et al., 2022]

Several methods for estimating weight in adults have been studied, each with its advantages and limitations. These include patient self estimates [Wells et al., 2022], visual estimation by healthcare workers [Cattermole and Wells, 2021, Mukasa et al., 2024, Priya et al., 2012], anthropometric methods which employ height or alternative height based estimates [Cattermole and Wells, 2021, Henry et al., 2020, Kokong et al., 2018], mid upper arm circumference [Cattermole and Wells, 2021, Cattermole et al., 2017, Wells et al., 2022], a combination of anthropometric measurements [Henry et al., 2020, Katherina and Sudiarti, 2020, Abdel-Rahman et al., 2013, Mukasa et al., 2024, Wells et al., 2022, Wells and Goldstein, 2022], pediatric methods such as the Mercy method [Akinola et al., 2021, Cattermole and Wells, 2021, Wells et al., 2017a, 2022], Lorenz method [Lorenz et al., 2007, Cattermole and Wells, 2021] , Rabito [Rabito et al., 2006], Chumlea [Chumlea et al., 1988], Broca Index and Buckley Method [Akinola et al., 2021].

All the above methods have shown varying accuracy in the literature. For example, the Lorenz method was the most accurate compared to other adult weight estimation methods [Cattermole and Wells, 2021]. However, it requires waist circumference (WC) and hip circumference (HC), which are difficult to measure at the bedside. In a study conducted on a Ugandan population, the Rabito equation demonstrated superior accuracy in estimating weight compared to the Lorenz, Chumlea, and Crandall equations [Mukasa et al., 2024]. In non-obese patients, the Pediatric Advanced Weight Prediction in Emergency Room (PAWPER) XL-MAC and the Mercy methods performed acceptably, even though they were originally validated for the pediatric population [Cattermole and Wells, 2021]. Patient self-estimates have also shown high accuracy in some studies, but are generally unreliable [Wells et al., 2022]. There are also limitations in the use of patient-reported weight estimates in subgroups such as obese patients [Wells et al., 2022]. Crandall and colleagues developed a model based on MUAC and height for obese patients [Crandall et al., 2009]. However, the coefficient of determination for their model was low, especially a little above 50% of the variation in weight. The development and validation of population-specific and easy-to-use methods in the adult population are still warranted [Wells et al., 2022], and more especially for the Ghanaian population, where there is limited data. Empirical evidence and observation from practice experience suggest that the use of visual estimates by health workers is a predominant approach in the Ghanaian population, which is less accurate compared to other existing methods [Wells et al., 2022]. There is limited published research on the use of weight estimation methods in the Ghanaian population. Thus, the current study aimed to evaluate existing weight estimation equations for adults in the Ghanaian population as well as develop population-specific models using machine learning algorithms.

2 Methods

2.1 Study design

A quantitative cross-sectional study design was used for this study.

2.2 Study population and sampling method

This cross-sectional study recruited adult outpatients ($\geq$ 18 years) from the outpatient department of the Cape Coast Teaching Hospital (CCTH) who were able to stand unassisted and provided informed consent for anthropometric measurements, including weight, height, mid-upper arm circumference (MUAC), and calf circumference (CC). Individuals excluded from participation were pregnant or breastfeeding women, those with eating disorders, and patients with conditions known to affect mobility or body composition, such as obesity-related complications, musculoskeletal or endocrine disorders, cancers, renal failure, amputations, or severe physical disabilities. While necessary for measurement feasibility, this exclusion limits generalisability of these population group. A convenience sampling method was employed to enroll 389 eligible participants.

2.3 Data collection proceduce

Data were collected using a structured questionnaire to obtain socio-demographic information, followed by anthropometric assessments conducted with standard procedures and equipment [Madden and Smith, 2016]. Each variable was measured twice and the average of the two values was used for analysis. Weight was measured using a standard weighing scale. Participants stood still, facing forward, barefoot, and in light clothing. Weight was recorded to the nearest 0.1 kg. Height was measured with a stadiometer. Participants stood upright, barefoot, with heels together, back straight, arms at sides, and head in the Frankfort plane. Height was recorded to the nearest centimetre. MUAC was measured using a tape measure at the midpoint between the acromion and olecranon on the left arm and recorded to the nearest centimetre. CC was measured at the widest part of the calf with a tape measure. Participants were seated with their knees at 90° and feet flat on the floor.

2.4 Ethical consideration

Ethical approval was obtained from the CCTH Ethics Committee (CCTHERC/EC/2024/097), ensuring adherence to ethical principles in human subject research. Written informed consent was secured from all participants, with assurances of confidentiality and voluntary participation. No personal identifiers were collected.

2.5 Existing weight estimation methods

We evaluated the performance of three weight estimation models, Kokong (Height (cm) - 100) [Kokong et al., 2018], the Simplified MUAC formula ((MUAC * 4) - 50) [Cattermole et al., 2017], and the Crandall equations (Women: - 64.6 + (MUAC * 2.15) + (height * 0.54); Men: - 93.2 + (MUAC * 3.29) + (height * 0.43)) [Crandall et al., 2009] on our dataset. Predictions were evaluated using mean absolute error (MAE), root mean squared error (RMSE), coefficient of determination (R^2), and the proportion of predictions within 10% (P10) and 20% (P20) of the actual weight. For this study, model performance was evaluated against P10 and P20 benchmarks of $\geq$70% and $\geq$95%, respectively, as recommended in the literature [Wells et al., 2017b].

2.6 Modelling

The automated machine learning (AutoML) framework, H2O, was employed to train and evaluate a suite of supervised machine learning models for adult weight estimation. H2O's AutoML framework automates the machine learning workflow, including automatic training and tuning of many models. It generates a ranked leadership of the trained models. The dataset was partitioned into 80% for training and 20% for testing. The dataset had no missing values for included varaibles, so no imputation was necessary. Model performance was assessed on the test set using MAE, RMSE, R^2, and the P10 and P20 of the actual weight. The developed weight estimation models incorporated mid-upper arm circumference (MUAC), calf circumference (CC), age, sex, height, and body mass index (BMI) status (categorised as underweight, normal weight, overweight, and obese) as predictor variables. Model hyperparameters were optimised using five-fold cross-validation. Furthermore, an analysis of feature importance was conducted to ascertain the relative contribution of each predictor to model performance.

3 Results

3.1 Descriptive statistics

The median participant age was 57 years, with an interquartile range (IQR) of 42 to 66. Females constituted the majority at 66%. The median height and weight were 162 cm (IQR: 158-166) and 65 kg (IQR: 58-72), respectively. MUAC had a median of 32.0 cm (IQR: 29.5-34.9), and CC had a median of 35.5 cm (IQR: 32.5-37.6). A normal BMI was observed in the majority of participants (46%).

Table 1: Descriptive statistics of study population

Characteristic	**N = 389**
Sex	
Female	257 (66%)
Male	132 (34%)
Age (years)	57 (42, 66)
Height (cm)	162 (158, 166)
Weight (kg)	65 (58, 72)
Mid-upper arm circumference (cm)	32.0 (29.5, 34.9)
Calf circumference (cm)	35.4 (32.5, 37.6)
Body mass index (kg/m²)	24.6 (21.9, 27.6)
Body mass index category	
Underweight	28 (7.2%)
Normal	180 (46%)
Overweight	125 (32%)
Obese	56 (14%)

[1] n (%); Median (Q1, Q3)

3.2 Correlation matrix of numeric variables

A correlation matrix of key numeric variables (Figure 1) revealed strong positive correlations between weight and MUAC ($r = 0.78$) and CC ($r = 0.78$). A weak positive correlation was observed between weight and height ($r = 0.23$). Age exhibited negligible correlation with weight ($r = 0.08$) within the study sample.

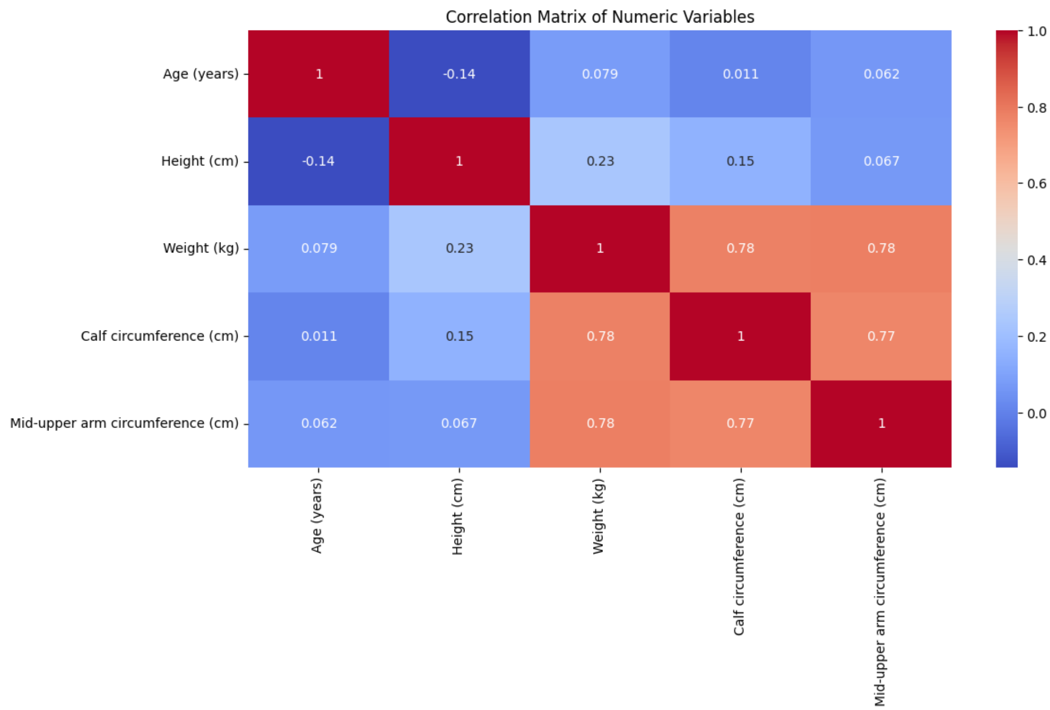

Figure 1: Correlation of numeric variables

3.3 Metrics evaluation of existing equations

Figure 2 presents a comparative analysis of the predictive performance of the model developed in this study against established weight estimation equations. The findings indicate that the locally derived model exhibited superior performance, characterised by the lowest MAE of 3 kg and RMSE of 4 kg. Furthermore, the local model achieved the highest coefficient of determination (R^2 = 0.9). Notably, 90% and 100% of the weight predictions fell within 10% (P10) and 20% (P20) of the actual measured weights, respectively.

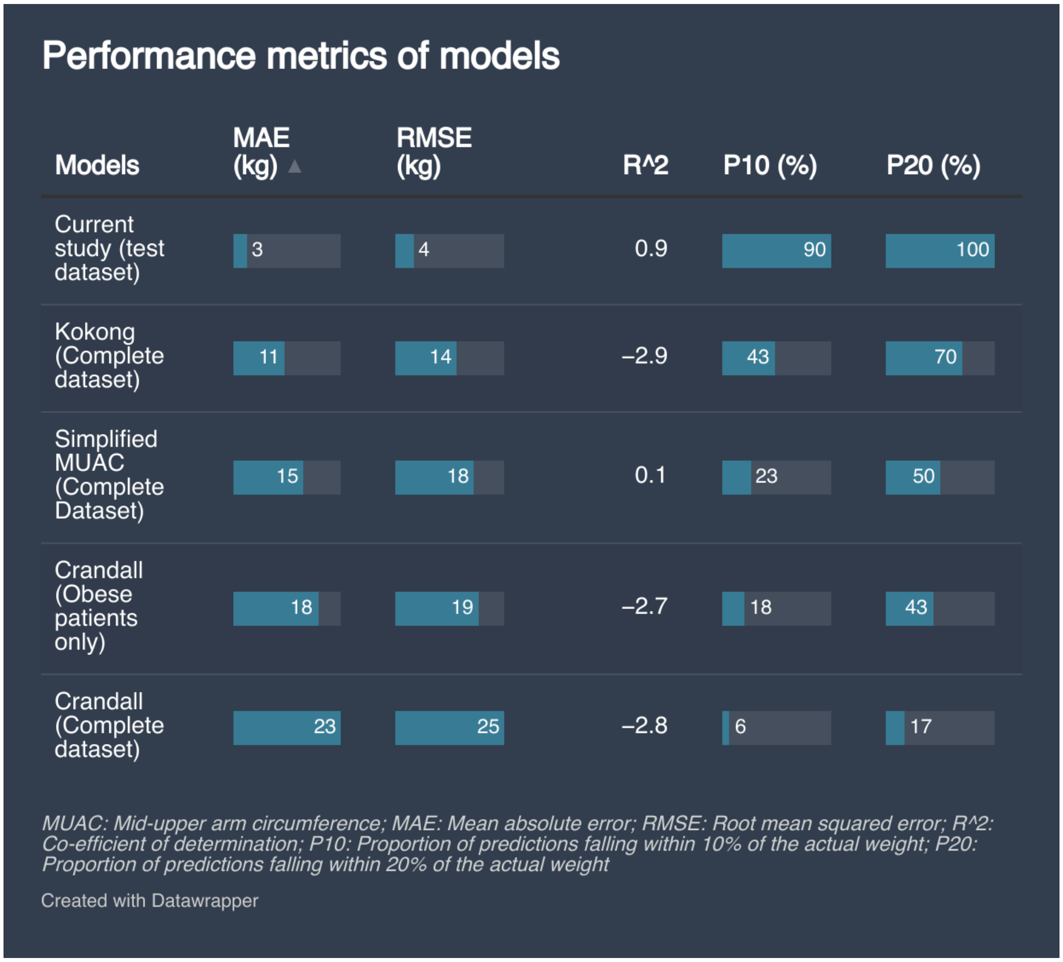

Figure 2: Performance metrics of existing equations

3.4 AutoML leaderboard for test data

Table 2 presents the top 10 models generated by the H2O AutoML framework, ranked by RMSE on the test dataset. The best-performing model was a stacked ensemble achieving an RMSE of 4.44, mean absolute error (MAE) of 3.19, and the lowest residual deviance. The final stacked ensemble model consisted of two base learning algorithms, namely Gradient Boosting Machine (GBM), and Deep Learning models selected by H2Oś AutoML. The ensemble used a 5-fold cross-validation strategy, with a Generalised Linear Model (GLM) serving as the meta-learner to aggregate predictions. Other high-ranking models included deep learning and gradient boosting machines.

Table 2: Top 10 AutoML Models Ranked by RMSE

Model ID	RMSE	MSE	MAE	RMSLE	Mean Residual Deviance
StackedEnsemble_BestOfFamily_4	4.4385	19.7003	3.19276	0.0671234	19.7003
DeepLearning_grid_1_model_1	4.51273	20.3647	3.27259	0.0681726	20.3647
StackedEnsemble_BestOfFamily_6	4.5484	20.688	3.25998	0.0674318	20.688
StackedEnsemble_AllModels_3	4.6908	22.0036	3.33751	0.0716831	22.0036
GBM_lr_annealing_selection	4.71553	22.2363	3.3566	0.0712469	22.2363
StackedEnsemble_AllModels_4	4.73218	22.3935	3.38713	0.0722531	22.3935
GBM_grid_1_model_170	4.73577	22.4275	3.32386	0.0709102	22.4275
GBM_grid_1_model_42	4.7386	22.4543	3.40016	0.0713492	22.4543
GBM_grid_1_model_172	4.74017	22.4692	3.35129	0.0706266	22.4692
StackedEnsemble_AllModels_2	4.75974	22.6551	3.46993	0.0708652	22.6551

3.5 Feature importance plot

Figure 3 presents the variable importance for the Deep Learning model trained using the H2O AutoML framework. The most influential predictors of weight in the model were BMI categories. Among continuous variables, calf circumference (CC) and mid-upper arm circumference (MUAC) ranked highest. Sex and height had moderate importance, with male sex contributing more than female sex, while age showed the least influence on the model's predictions.

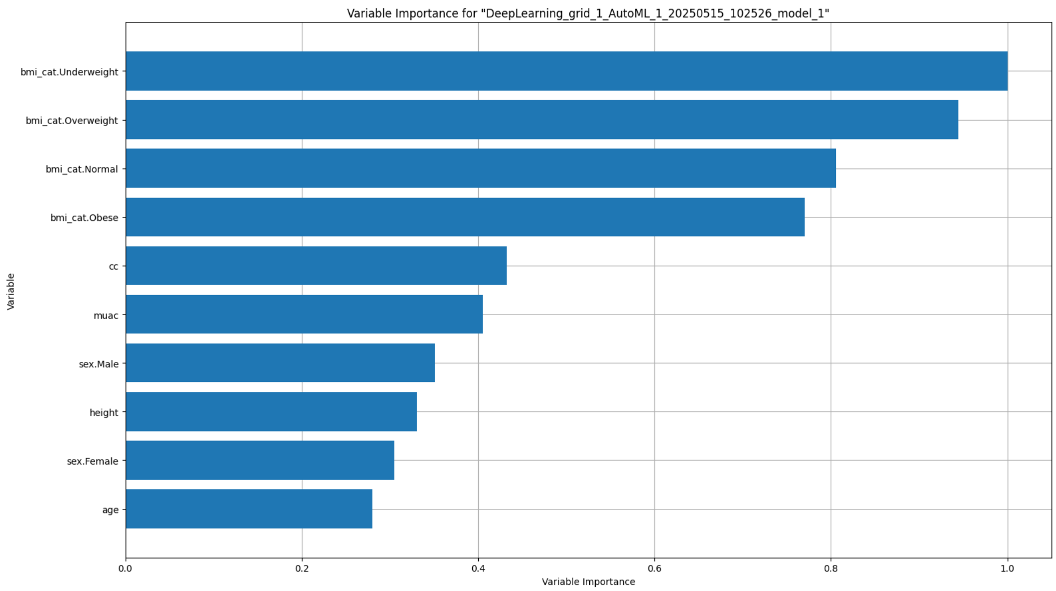

Figure 3: Feature importance

4 Discussion

This study evaluated the predictive performance of three established adult weight estimation methods, namely Kokong [Kokong et al., 2018], Simplified MUAC [Cattermole et al., 2017], and Crandall equations [Crandall et al., 2009], using clinical data from a Ghanaian adult population. In addition, we developed local machine learning models using AutoML, which outperformed the pre-existing methods in our context. Our findings underscore the limitations of applying externally developed equations without local validation and highlight the value of population-specific predictive models for adult weight estimation.

Among the pre-existing methods evaluated, the Kokong equation, while simple and practical, yielded an MAE of 11 kg compared to 3 kg from our local predictive model and a P10 of 43%. This is consistent with prior concerns about its generalisability beyond the population it was derived from [Wells et al., 2022]. In our sample, the correlation between height and weight was weak (r = 0.28), similar to previous study reports in adult populations (r = 0.42) [Cattermole et al., 2017], and much lower than that observed in pediatric populations (r = 0.87). These findings reaffirm the limited utility of height-based equations in adult weight estimation.

The Simplified MUAC equation, previously shown to be more accurate than height-based equations [Wells et al., 2022], also failed to meet performance benchmarks in our context. The correlation between MUAC and weight in our sample (r = 0.78) was strong, though lower than values reported in other adult populations (r = 0.90) [Cattermole et al., 2017, Katherina and Sudiarti, 2020]. Regardless, the performance of the simplified MUAC equation was suboptimal in our cohort (MAE = 15 kg vs 3 kg; P10 = 23% vs 90%), further supporting prior reports on the variability of MUAC-based predictions across populations [Wells et al., 2022].

Interestingly, the Crandall equations, developed specifically for obese adults, performed worst overall, even among participants with obesity in our sample (see Figure 2). This reinforces the need for local validation before applying such equations in distinct demographic and clinical contexts.

Accurate weight estimation is critical in clinical settings, particularly in resource-limited environments where scales may not be available or when patients are immobile or critically ill. Incorrect estimates can lead to sub-optimal treatment, especially in medication dosing and nutrition prescriptions [Wells et al., 2022]. As emphasised by Orlando and LaBond [Orlando and LaBond, 2019], deviation greater than 10% from actual weight may pose life-threatening risks. In our current study, none of the evaluated pre-existing methods met the P10 $\geq$ 70% and P20 $\geq$ 95% criteria proposed by Wells and colleagues [Wells et al., 2017b], indicating that they are not suitable for use in our clinical population without adjustment or recalibration. The superior performance of our AutoML-derived model further demonstrates the importance of context-specific modelling, particularly in African populations where few such tools have been validated or developed.

While our model performed well on internal validation, its generalisability to other populations remains untested. Our model may have generalisability issues in other adult populations, as was the case with the equations evaluated in our current study. External validation in diverse Ghanaian and African populations is essential before widespread deployment. Regardless, our study has provided evidence for the development of local models in a Ghanaian population and is among the limited data in this population. Also, a prototype Shiny application was developed to provide a user-friendly interface for clinicians and frontline health workers in our setting. The app enables weight estimation by simply entering anthropometric inputs from the bedside to facilitate clinical decision-making. Future work will involve usability testing with frontline clinicians to assess integration into routine care and ease of use at the bedside. Also, additional data points will be collected to retrain the models to improve prediction at our study site and other sites accross the country. Existing models exist that utilise MUAC for BMI prediction [Madden and Smith, 2016]. However, their validity has not been tested in our population. Evaluating these models in future works will be essential for improving the usability of our application. Our current study did not evaluate other weight estimation methods, such as Lorenz [Lorenz et al., 2007] , Rabito [Rabito et al., 2006], Chumlea [Chumlea et al., 1988]), owing to the non-availability of WC, HC, skinfold thickness and knee height in our dataset. Also, PAWPER XL MUAC, a specialised tool for weight estimation, was not evaluated due to non-availability in our setting. Future studies will consider evaluating these equations for their predictive performance and usability in our population.

4.1 Conclusion

Weight is an important variable for supporting clinical care decisions such as nutrition prescriptions and drug dosing, but is often not feasible to measure in specific scenarios such as critical illness and immobility, indicating the need for estimations. This study has highlighted the limited applicability of pre-existing adult weight estimation methods in our Ghanaian clinical population. Our findings advocate for the development and validation of population-specific models and urge caution when applying externally derived tools without contextual adaptation.

Dataset and code availability statement

The data and code supporting the findings of this study are openly available in Zenodo, Dataset and GitHub, Notebook, respectively.

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