British Journal of Mathematics & Computer Science
19(5): 1-14, 2016; Article no.BJMCS.28870
ISSN: 2231-0851

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Assessing Infant Mortality in Nigeria Using Artificial Neural Network and Logistic Regression Models

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Authors' contributions

This work was carried out in collaboration between all authors. Authors OBY, AUC and MOJ designed the study. Authors MOJ and SOO performed the data analysis. Authors AUC, JOA and SAA supervised the analysis. Author MOJ wrote the first draft of the manuscript. Authors OBY, JOA and SAA managed the literature searches and edited the manuscript. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/BJMCS/2016/28870
Editor(s):
(1) Xiaodi Li, School of Mathematical Sciences, Shandong Normal University Ji'nan, 250014, Shandong, P. R. China.
Reviewers:
(1) Mika Gissler, National Institute for Health and Welfare, Helsinki, Finland.
(2) Taysseer Sharaf, University of Michigan-Dearborn, USA.
(3) Haresh Chandwani, GCS Medical College, Ahmedabad, Gujarat, India.
Complete Peer review History: http://www.sciencedomain.org/review-history/16819

Original Research Article

Received: 10th August 2016
Accepted: 4th October 2016
Published: 7th November 2016

Abstract

Aim: To examine the suitability of Artificial Neural Network (ANN) in predicting infant mortality and compare its performance with Logistic Regression (LR) model.
Study Design: A cross-sectional population based study was conducted. The 2013 Nigeria Demographic Health Survey (NDHS) data were used.
Place and Duration of Study: The study was conducted in Nigeria and the fieldwork was carried out from February 15, 2013, to May 31, 2013.
Methodology: Data were partitioned into training and testing sets with ratio 7:3. Logistic and ANN models were fitted on the training set and were validated using the testing sample. Akaike Information Criterion (AIC) and Area under curve (AUC) were used as criteria for comparing the two models. The discriminative ability was measured using sensitivity and specificity. Variable importance analysis was also conducted to determine the magnitude of contribution of each predictor to the outcome.
Results: The sensitivity of the classification model was 67% and 76% for the LR and the ANN models

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respectively. Specificity of the prediction was 94% for the two models. Overall accuracy was approximately 81% and 83% for LR and ANN respectively. The AIC values were 9462 and 9614 for ANN model and LR model respectively. Area under curve was 0.621 and 0.637 for the LR model and the ANN model respectively. The variable importance analysis showed that preceding birth interval less than 24 months and not receiving tetanus toxoid injection during pregnancy had the highest positive contribution to infant mortality.

Conclusion: The artificial neural network model had a higher sensitivity than the logistic regression model. Preceding birth interval of less than 24 months and non-reception of tetanus toxoid injection by mothers' during pregnancy were important predictors of infant mortality in Nigeria.

Keywords: Model comparison; classification models; variable importance analysis; infant mortality.

1 Introduction

The most frequently used models in clinical and public health risk estimation are logistic regression and artificial neural network [1]. Over time, medical researchers have conventionally used the logistic regression simply because of the dichotomous nature of study outcome variables.

Logistic regression is a class of generalised linear models and a type of regression model used when the outcome variable is qualitative and has binary indicators. In the current study, the outcome event is infant mortality i.e. the proportion of a cohort of children born in the last five years who had died before their first birthday. The relationship between the independent variables such as socio-demographic, environmental, health facility related and child characteristics can be represented by a logistic regression model of the form; $y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_n X_n$ where y is the response variable (infant mortality) with a status 1 if the child died before reaching one year and 0 if otherwise. The expected value of *y* is the probability that y=1 which makes the range of *y* to be limited between 0 through 1. Logit link function is therefore used to transform the output of a linear regression and present it in form of a probability. Therefore y is expressed as *logit (p)* where *p* is the probability of dying before the age of one. The logit transformation is written as the log odds:

$$logit(p) = \log odds = log\left[\frac{p}{1-p}\right] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_n X_n.$$

Artificial neural networks (ANN) on the other hand are algorithms used to; perform non-linear statistical modelling and provide a new alternative to logistic regression [2]. These algorithms are used to estimate unknown functions that can depend on a large number of inputs. The network is divided into layers namely; the input layer, the hidden layer and the output layer. The hidden nodes in artificial neural networks allow the model to detect complex relationships present between the input variables and infant mortality. In fact, a special ANN with no hidden node has been made known to be identical to a logistic regression model [3]. The ANN produces a variable importance analysis chart that illustrates the contribution of each variable to infant survival status. Artificial neural networks are used as a black box model: a certain number of inputs produce a desired output, the model achieves this result through a self-organizing process which involved: multiplication, summation and activation. At the input level, the inputs are weighted i.e. every input value is multiplied with an individual weight. In the middle section the sum of all weighted inputs and bias is computed. At the final stage, the sum of the previously weighted inputs and bias is passed through a transfer function. Artificial neural network models work in two phases; the Learning phase and the Evaluation phase. In the learning phase, the ANN adapt to the internal parameters.

This study used the artificial neural network with feed-forward topology which has only one condition: information must flow from input to output in only one direction with no back-loops. This network has no limitations neither on number of layers nor the type of transfer function used in individual artificial neuron nor the number of connections between the individual artificial neurons. Successful applications of artificial neural network to predict medical outcomes have been achieved in the past [4-6]. ANN has also been used to predict mortality risk in preterm infants [7].

Studies which compared the model accuracy of ANN and GLM in terms of model accuracy showed that ANN performed better than the GLM [5,8-10]. Green et al. [11] applied the logistic regression and the artificial neural network to predict acute coronary syndrome in electrocardiogram (ECG) data. The finding from this study showed ANN model was at an advantage when the effective odds ratios from the ANN model were compared with the odds ratios obtained from the logistic regression model.

A comparison of ANN and logistic regression was conducted on lung cancer data in Turkey [12] using Area Under the Curve (AUC), sensitivity and specificity criteria. The ANN outperforms logistic regression for all criteria. The ANN also outshines the logistic regression model in terms of performance when the two were applied in predicting mortality among critical care patients. In the prediction of pregnancy using In Vitro Fertilisation (IVF) treatment, logistic regression turned out to be suitable for theoretical interest while ANN was more useful in clinical prediction [13]. However, some research findings have also revealed that both the logistic regression model and the ANN model are capable of achieving accurate results [14-16].

Nigeria is a country with a large population of young people and infant mortality is still an issue of major public health concern. In Nigeria, the infant mortality rate is 68 per 1,000 live birth and the country losses about 2,300 under-five years old children on daily basis [17-19]. A quarter of the deaths among under-five children is accounted for by the death of new-borns which occur mostly within the first week of life [20]. This input makes Nigeria the second largest contributor to the under–five and maternal mortality rate in the world.

Most studies on infant mortality either used logistic regression or Cox-proportional hazard model [21-26] with very few using ANN model. Also information on the comparison of the performance of logistic regression and ANN is still a grey area for research in Nigeria. Therefore, this study compares the performance of ANN and logistic regression in predicting infant mortality in Nigeria. It also applies ANN to infant mortality to check whether the efficient predictive ability of ANN will be maintained in mortality data and to test its ability to detect new factors.

2 Methodology

2.1 Data source

The data used was extracted from the child recode dataset of the Nigeria Demographic Health Survey (NDHS 2013); the dataset was cleaned and variables were recoded to suit the study [27]. The NDHS was a cross-sectional population based study design.The 2013 NDHS sample was nationally representative and covers the entire population residing in non-institutional dwelling units in the country. Data on birth history were collected from women of reproductive age. Specifically, background information about the under-five children were obtained through verbal reporting by their mothers. In addition, measurements were made where possible to get information on nutritional status of the children.

2.2 Study population

The target population were children less than 12 months old i.e. infants.

2.3 Study variables

2.3.1 Outcome variable

The main outcome variable was infant mortality (this was obtained from the survival status of the children from age 0 to 11 months). Each death case was coded as 1 and each non-death (living) case was coded as 0.

2.3.2 Explanatory variables

The choice of the explanatory variables was based on previous studies on factors influencing infant mortality [17,19-22,28-32]

Maternal factors

Age at birth
Educational level
Marital status
Birth interval
Desire for the pregnancy
Wealth index

Child factors

Sex
Size at birth
Birth order

Environmental/Health related factors

Region
Religion
Place of residence
ANC attendance
Tetanus toxoid injection
Place of delivery
Delivery by caesarean section
Delivery assistance
Source of drinking water
Type of toilet facility
Availability of electricity

2.3.3 Akaike information criterion (AIC)

Akaike information criterion (AIC) is a penalized-likelihood criterion which is used for choosing best predictor subsets in regression and often used for comparing non nested models, which ordinary statistical tests cannot do. AIC is an estimate of a relative distance between the unknown true likelihood function of the data and the fitted likelihood function of the model, so that a lower AIC means the model is nearer to the truth. AIC for a model is usually illustrated as $[-2\log l + kp]$, where l is the likelihood function, p is the number of parameters in the model, and $k= 2$.

2.3.4 Receiver operating characteristic

The receiver operating characteristic is mainly used in radiological researches to illustrate the diagnostic accuracy of imaging examinations. The observer's prediction in each case is plotted against the true condition of the case to detect misclassification of cases. One criterion to assess the quality of a classification model is discrimination. The discriminative ability of the logistic regression model and the artificial neural network model was likened using the Receiver's Operating Characteristics (ROC) curve. This is usually plotted as true positive (TP) versus false positive (FP). The ROC curve is an indication of an observer's degree of diagnostic certainty. The area under this curve is commonly used as a global indicator of diagnostic performance.

2.4 Data analysis

Descriptive statistics (proportion for categorical variables) for all independent variables were obtained. A chi-square test was performed to investigate the relationship between the outcome variable (infant mortality) and the independent variables. The dataset was further partitioned into training and testing samples where 70% of the dataset was attributed to training set and the remaining 30% to the testing set [33]. Thereafter the multivariate logistic regression was conducted on the training set using the forward selection method of model building. The significant variables from the chi-square test were added to the model based on the magnitude of their χ^2-statistic. The Hosmer Lemeshow goodness-of-fit test was performed to determine the adequacy of the logistic regression model.

The artificial neural network model was also built on the training sample. The sigmoid activation function with a cross entropy error function was utilised. Both models were validated using the testing dataset. The variable importance analysis from the artificial neural network illustrated the contribution of each predictor on infant mortality. The results from the logistic and the ANN models were compared in terms of predictive and discriminative ability using the Akaike Information Criterion, Sensitivity, Specificity and the Area Under the curve (AUC).

The data was cleaned and weighted using SPSS version 20 and was then exported to the R statistical software which was used to fit the logistic regression and the ANN models. The *neuralnet* package was installed on the R software to help in building the neural network model on the training set.

3 Results

3.1 Background characteristics of infants

Two-third of the infants (67.1%) were from the rural areas and a large proportion (73.5%) was born to mothers between the ages of 20 to 35 years. The mean maternal age at birth was 27.5 years (SD=6.9years) with almost half (46.9%) having no formal education. Islam was the religion practised by most (58.6%) of the mothers and a higher proportion (95.3%) of the mothers were currently married.

Only 8.8% of the mothers did not desire their pregnancy when they became pregnant. Three-quarters of the mothers did not receive tetanus toxoid injection during their pregnancy and 79.0% of mothers never attended antenatal care. Only one–third (36.6%) of the mothers gave birth in a health facility while others gave birth at home (62.4%) or places other than a health facility. Majority (86.5%) of the mothers received no assistance from any health professional or community health worker at time of delivery.

Very few (2.1%) of the infants were delivered by caesarean section compared to normal delivery (96.9%). About 4 out of 10 (43.2%) of the live-births were of large size at birth and only 14.3% were small in size at the time of birth.

Table 1. Percentage distribution of infants according to selected background characteristics

Background characteristics	%(n=31482)
Region	
North Central	14.7
North East	20.7
North West	31.5
South East	8.9
South South	11.9
South West	12.3
Residence	

Background characteristics	**%(n=31482)**
Rural	67.1
Urban	32.9
Religion	
Christianity	40.2
Islam	58.3
Traditionalists and others	1.0
Maternal education	
No education	46.9
Primary education	20.4
Secondary or Higher	32.7
Maternal age	
< 20	12.2
20-35	73.5
>35	14.3
Marital status	
Currently or formerly in a union	95.3
Never in a union	4.7
Sex of child	
Male	49.3
Female	50.7
Size at birth	
Small	14.6
Average	40.3
Large	43.2
Place of delivery	
Home	62.4
Health facility	36.6
Delivered by caesarean section	
Yes	96.9
No	2.1
No delivery assistance	
Yes	86.5
No	12.1
Birth order	
1	19.4
2 or 3	32.0
>3	48.6
Preceding birth interval	
First births	19.6
≤ 24months	21.2
>24 months	59.2
Unwanted pregnancy	
Yes	90.1
No	8.8
No antenatal attendance	
Yes	79.0
No	21.0
Did not receive tetanus toxoid injection	
Yes	75.2
No	24.8
Wealth index	
Poor	45.9
Middle	19.9

Background characteristics	%(n=31482)
Rich	34.1
Source of water	
Improved	57.9
Unimproved	42.1
Type of toilet facility	
Improved	48.2
Unimproved	51.8
Electricity	
Yes	53.7
No	46.3

3.2 Factors affecting infant mortality

3.2.1 Multivariate logistic regression model

A multivariate logistic regression analysis was conducted to determine the factors affecting infant mortality. The model fit was tested with Hosmer Lemeshow-statistic=2.654 (*P*=0.954). A male infant had about 26% (OR= 1.26; 95% CI: 1.13, 1.41) increased risk of experiencing infant mortality compared to a female infant. Infants born to mothers with no formal education were 32% (OR= 1.32; 95% CI: 1.07, 1.62) at higher risk of experiencing infant mortality than those whose mothers had a secondary or tertiary education. Similarly, mothers with primary education were 28% (OR= 1.28; 95% CI: 1.06, 1.53) at higher risk of losing their babies than mothers who had a secondary or tertiary education.

There was approximately 29% (OR=1.29; 95% CI: 1.06, 1.56) higher risk in infant mortality among infants born to mothers who were less than 20 years of age compared to mothers that were between the ages of 20 and 35 years. Similarly, about 23% (OR=1.23; 95% CI: 1.04, 1.45) increased risk in infant mortality was experienced by infants whose mothers were above 35 years of age compared to those with mothers between the ages of 20 and 35 years. Infants from the rural areas were more likely to experience infant mortality than those from the urban areas (OR=1.27; 95% CI: 1.07, 1.50).

Infants with small size at birth were (OR=1.93; 95% CI: 1.65, 2.25) more likely to die at infancy compared to babies with large birth size. Likewise, those with average size were (OR=1.21; 95% CI: 1.06, 1.38) more likely to experience infant mortality compared to large size babies. Mothers that did not receive tetanus toxoid injection during pregnancy had an 11% (OR=1.11; 95% CI: 0.97, 1.26) increase in risk of losing their babies compared with the mothers that received tetanus toxoid injection during their pregnancy (Table 2).

Table 2. Multivariate logistic regression analysis of factors affecting infant mortality

Explanatory variables	OR	95% CI		p-value
		Lower bound	Upper bound	
Region				
North Central	0.87	0.675	1.11	0.519
North East	1.02	0.795	1.32	0.917
North West	1.22	0.940	1.59	0.032
South East	1.12	0.859	1.46	0.037
South	0.74	0.562	0.97	0.022
South West®				
Residence				
Rural	1.27	1.074	1.50	0.001
Urban®				
Religion				
Islam®				
Christianity	1.19	0.987	1.44	0.068

Explanatory variables	OR	95% CI		p-value
		Lower bound	Upper bound	
Traditionalists and others	1.25	0.720	2.02	0.994
Maternal education				
No education	1.32	1.072	1.62	0.002
Primary education	1.28	1.063	1.53	0.003
Secondary or Higher®				
Maternal age				
< 20	1.29	1.059	1.56	0.001
20-35®				
>35	1.23	1.042	1.45	0.031
Marital status				
Currently in a union®				
Formerly or never in a union	1.40	1.087	1.78	0.001
Sex of child				
Male	1.26	1.125	1.41	< 0.001
Female®				
Size at birth				
Small	1.93	1.652	2.25	< 0.001
Average	1.21	1.062	1.38	0.003
Large®				
Place of delivery				
Home	1.06	0.903	1.24	0.189
Health facility®				
Delivered by caesarean section				
Yes	1.56	1.063	2.21	0.002
No®				
No delivery assistance				
Yes	0.91	0.759	1.09	0.362
No®				
Preceding birth interval				
First births	1.25	1.012	1.37	0.034
≤ 24months	1.16	1.040	1.34	0.003
>24 months®				
No antenatal attendance				
Yes	0.59	0.498	0.68	<0.001
No®				
No tetanus toxoid injection received				
Yes	1.11	0.969	1.26	0.353
No®				
Wealth index				
Poor	1.12	0.883	1.41	0.310
Middle	1.04	0.852	1.28	0.546
Rich®				
Source of water				
Improved®				
Unimproved	1.01	0.89	1.15	0.641
Type of toilet facility				
Improved®				
Unimproved	1.08	0.95	1.23	0.068
No electricity				
Yes	1.06	0.91	1.25	0.540
No®				

® Reference category

3.2.2 Variable importance analysis

The result of the ANN showed that the preceding birth interval of an infant had the largest contribution to whether the infant will experience infant mortality or not. The type of toilet facility in the household was the predictor with the lowest contribution to infant mortality relative to all other factors. The size of the child at birth also contributed to the probability of an infant dying at the stage of infancy. Fig. 1 shows the factors according to their contribution to infant mortality.

The logistic regression model and the artificial neural network model were compared using the ROC curve by examining the area under the curve. The area under the curve was 0.646 and 0.637 for the logistic regression model and the artificial neural network respectively. Fig. 2 shows the ROC curve from both models. Table 3 shows the performance of ANN and LR in predicting infant mortality. The sensitivity of the classification model was 67% and 76% for the logistic regression model and the artificial neural network respectively. Specificity of the prediction was 94% for both the logistic regression and the artificial neural network model. The AIC values were 9462 and 9614 for the neural network model and the logistic regression model respectively.

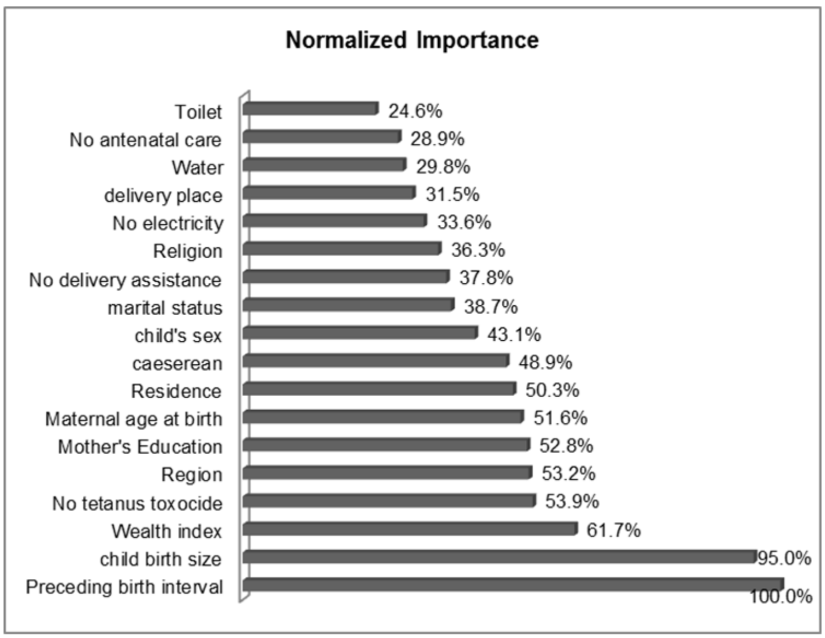

Fig. 1. Percentage contribution of each factor to infant mortality

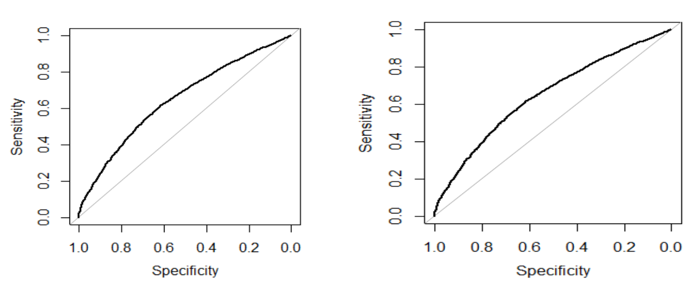

Fig. 2. ROC curve from logistic regression model (left) and neural network model (right)

Table 3. Comparison of ANN and LR models

Performance indices	ANN	LR
Accuracy	83%	81%
Specificity	94%	94%
Sensitivity	76%	67%
AIC	9462	9614
AUC	0.637	0.622

3.3 Topology of the artificial neural network model

The ANN applied was a feed-forward back propagation; multi-layer perceptron (MLP) neural network with three layers which includes the input, the hidden and the output layers. The neural network model was trained using 1, 10, 20, 22 and 24 neurons in the hidden layer. The error of the network models were 4772, 4270, 4008, 3989 and 3989 for 1, 10, 20, 22 and 24 hidden neurons respectively (Table 4). The error reduced up to the model with 22 hidden neurons and there was no effect of adding more neurons on the error.

Table 4. Error across number of hidden neurons

Number of hidden neurons in the model	Error
1	4772
10	4270
20	4008
22	3989
24	3989

4 Discussion

The discriminative ability of a classification model can be assessed using the sensitivity and the specificity of the prediction. In this study, the results of logistic regression model were compared with those of ANN model in the prediction of infant mortality through ROC curve. Research findings revealed that ANN model had better predictive ability than that of logistic regression model. Moreover, ANN model possessed a higher sensitivity than the logistic regression. Many studies have been conducted on the application of ANN for analysing data, and most of them have evaluated the results of the model to be favourable [4,5].

The Artificial neural network also had a higher overall accuracy than the logistic regression model. The overall accuracy was measured as percentage of correct predictions out of total predictions. This higher accuracy is in line with what was discovered in other studies conducted on the comparison of artificial neural network and logistic regression models [6,34]. In fact, neural networks are mostly condemned as 'black-boxes' that gives little or no perception about the causative relationships among variables. Olden and Jackson [35] have addressed this criticism and several approaches have since been developed to 'illuminate the black-box'. Though, the ANN does not give the odds ratio of predictors but it was able to illustrate the contribution of each factor to the risk of infant mortality from the variable importance analysis.

The variance importance analysis was developed by Olden and Jackson [35] to show the magnitude of contribution of each predictor on the outcome. This analysis was able to detect that preceding birth interval of less than 24 months has the largest contribution to infant mortality. Previous studies have also shown that birth interval greater than 24 months reduces the risk of infant mortality [36-39]. Furthermore, non-reception of tetanus toxoid injection by mothers' during pregnancy achieved significance using ANN but not with LR. However, previous studies using Cox regression did not also identify non-reception of tetanus toxoid has a significant factor [29].

ANN had a lower Akaike Information Criterion indicating that ANN model fits the data more than the LR model. This lower AIC can be associated with the hidden layer present in the artificial network model as reported by Rojas [33]; that a neural network model without an hidden layer is similar to the logistic regression model. The model with 22 hidden neurons was suitable enough to minimize the error of the model.

5 Conclusion

Artificial neural network outperformed the logistic regression in terms of accuracy and discriminative ability. Both models (ANN and LR) performed efficiently in their unique way but the artificial neural network was able to detect more true positives than the logistic regression model. The ANN minimizes the error as the number of neurons in the hidden layer increases.

Less than 24 months gap between an infant and the preceding child and non-reception of tetanus toxoid injection by mothers' during pregnancy were important predictors of infant mortality in Nigeria.

Ethical Issues

Authorisation for data usage was sought from the Micro International USA before the data was extracted from their web platform. Informed consent from the study participants was pursued by the data initiators before commencement of the interview after a detailed description of all issues related to the study was addressed. Eligible respondents who did not agree to take part in the study were excluded from the survey. Each consenting participant was made to sign appropriate agreement form before the start of the interview.

Acknowledgement

We express our gratitude to the National Population Commission, Abuja, Nigeria and other partners involved in the NDHS.

Competing Interests

Authors have declared that no competing interests exist.

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