Dependent variable selection in phylogenetic generalized least squares regression analysis under Pagel's lambda model

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Abstract

1. Phylogenetic generalized least squares (PGLS) regression is widely used to analyze evolutionary relationships between two traits. In contrast to the equal treatment of analyzed traits in conventional correlation methods such as Pearson and Spearman's rank tests, we must designate one trait as the independent variable and the other as the dependent variable.
2. We retrieved an empirical dataset containing the optimal growth temperature, minimal doubling time, CRISPR-Cas, and prophage contents of 262 bacteria from a recent publication and conducted 16000 simulations of the evolution of two traits along a binary tree with 100 terminal nodes, using different models and variances. Correlations in these two datasets were examined by PGLS regression using Pagel's λ model.
3. By examining correlations in the empirical dataset, we found that switching independent and dependent variables resulted in conflicting results in 26.3% of cases. PGLS regression analysis of the 16000 simulated data showed that the frequency of conflicting outcomes from switching dependent and independent variables depends on the strength of the relationship between the two analyzed traits. Switching dependent and independent variables would strongly affect the parameter estimation of the PGLS regressions if the two variables differ significantly in their phylogenetic signals. To assess correlations in each simulation, we established a gold standard by analyzing changes in traits along phylogenetic branches. Next, we tested seven potential criteria for dependent variable selection: log-likelihood, Akaike information criterion, R^2, p-value, Pagel's λ, Blomberg et al.'s K, and the estimated λ in Pagel's λ model. We determined that the last three criteria performed equally well in selecting the dependent variable and were superior to the other four.

4. Since Pagel's λ and Blomberg et al.'s K values are indicators of phylogenetic signals, which are commonly calculated at the beginning of phylogenetic comparative studies, we suggest using the trait with a higher λ or K value as the dependent variable for practicality in future PGLS regressions. In analyzing the evolutionary relationship between two traits, we should designate the trait with a stronger phylogenetic signal as the dependent variable even if it could logically assume the cause in the relationship.

Keywords

Akaike information criterion (AIC), evolutionary correlation, dependent variable, phylogenetic comparative methods, phylogenetic generalized least squares (PGLS), phylogenetic signal.

1 | INTRODUCTION

Through mutations, genetic drift, and natural selection, some biological characteristics tend to co-evolve throughout evolution (Felsenstein 1985; Revell & Collar 2009; Goswami *et al.*, 2014; Revell *et al.*, 2022). Analyzing correlations between such traits can reveal the extent and direction of changes in one characteristic in response to evolutionary changes in another, providing supporting evidence or contradictions for hypotheses (Pearman *et al.*, 2014). This in-depth analysis of biological processes contributes to a better understanding and reconstruction of evolutionary history (Bartomeus *et al.*, 2018; Bawa *et al.*, 2019; Suarez-Castro *et al.*, 2020).

The relationship between the two variables is typically assessed by calculating Pearson, Spearman's rank, or Kendall's rank correlation coefficient. Conventional statistical methods, however, have limitations in dealing with evolutionary traits because they violate the

assumption of independence and are interconnected through the evolutionary relationships of the species studied (Felsenstein 1985). Neglecting phylogenetic dependence may lead to distorted trait correlations (Revell 2010; Whitney & Garland 2010). Various techniques, collectively called phylogenetic comparative methods, have been developed to address the issue of phylogenetic non-independence and have become extremely popular over recent years (Felsenstein 1985; Grafen 1989; Lynch 1991; Garamszegi 2014; Cooper *et al.*, 2016). Among them, the phylogenetic generalized least squares (PGLS) approach, first proposed by Grafen (1989) and further refined by Martins and Hansen (1997), Pagel (1997; 1999), and Rohlf (2001), has become the most commonly used method for determining the relationship between multiple traits. Using "phylogenetic generalized least squares" as keywords, we found 33130 papers published in the last ten years (2013-2022) from Google Scholar (https://scholar.google.com/, accessed June 2, 2023). In the last three years, 4137 papers/year indicate that PGLS studies are on the rise.

Both traits occupy the same position in standard correlation analyses, such as Pearson and Spearman's rank tests. However, in a regression model, one trait is designated as the independent variable and the other as the dependent variable. A causal relationship is often assumed in regression analysis (Waugh 1943). For example, when assessing the relationship between GC content and ecological factors, researchers often choose ecological factors as the independent variable and GC content as the dependent variable (Travnicek *et al.*, 2019; Hu *et al.*, 2022), assuming that environmental factors may have driven the evolution of GC content. However, according to statistical principles, regression analysis only examines whether there is a significant positive or negative correlation between the two traits. In standard regression analysis, the independent and dependent variables are interchangeable; switching them will not affect the sign (positive or negative) of the regression coefficient or the significance test results ($p <$ or ≥ 0.05). Therefore, we could arbitrarily select one trait as the independent

variable and designate the other as the dependent variable in standard regression analysis.

In examining the correlations presented in a recent publication (Liu *et al.*, 2023) using Pagel's λ model (Freckleton *et al.*, 2002), we observed that switching independent and dependent variables can significantly impact the results and conclusions of correlation analysis (see Results section). A significant correlation between two traits ($p < 0.05$) can potentially become non-significant ($p \geq 0.05$) after such variable swaps. In these situations, how can we determine which regression model to accept?

Using simulated data, we further assessed the frequency of inconsistent outcomes caused by switching independent and dependent variables in the PGLS analysis. In addition, we compared seven criteria to determine the appropriate designation of independent and dependent variables in the PGLS analysis using Pagel's λ model (Freckleton *et al.*, 2002).

2 | MATERIALS AND METHODS

2.1 | Empirical datasets

A dataset including the empirical minimal doubling times, CRISPR spacer numbers, optimal growth temperature, and prophage numbers of 262 bacteria was extracted from the Supplemental Material Table S1 of Liu et al. (2023). The phylogenetic tree of these 262 bacteria was retrieved from the Genome Taxonomy Database (GTDB; accessed April 8, 2022) (Parks *et al.*, 2022).

2.2 | Simulation data

First, we generated a binary tree containing 100 terminal nodes using the R package ape (Paradis & Schliep 2019). The trait X_1 evolved according to a Brownian motion model (using the R package ape) with a variance rate $\sigma^2{}_{BM} = 4$ along the tree, and then the trait X_2 was simulated according to

$$X_2 = X_1 + \varepsilon, \quad (1)$$

where ε was a normally distributed random noise term with a mean of 0 and a variance of 10^{-4}, 0.01, 1, 4, 16, 64, 256 to 1024. The term ε introduced noise to the dependent variable X_2 and a gradient variance of this noise term (from 10^{-4} to 1024) changed the correlation between X_1 and X_2, from strong to weak. We named this case "BM & BM + Norm."

Then, we simulated the trait X_1 according to a normal distribution with a mean of 0 and a variance of 4. The trait X_2 was simulated according to equation (1), where ε was simulated according to a Brownian motion model with $\sigma^2{}_{BM}$ in a range of 10^{-4}, 0.01, 1, 4, 16, 64, 256, 1024. We named this case "Norm & Norm + BM."

We ran 1000 simulations for each parameter condition, and a total of 16,000 simulations were performed.

2.3 | Software and packages

All PGLS regressions in this study were performed using the R (version 4.0.2) package phylolm (version 2.6.2) (Ho & Ane 2014). The estimated λ ($\hat{\lambda}$), log-likelihood (LLK) (Freckleton *et al.*, 2002), Akaike information criterion (AIC), R^2 of the models, and the *p*-value of the regression coefficients were calculated in the PGLS regression analyses.

The phylogenetic signals (λ and K) were estimated using the R (version 4.0.2) package phytools (version 1.0-3) (Revell 2012).

3 | RESULTS

3.1 | Switching dependent and independent variables in PGLS analyses of empirical data sometimes gave conflicting outcomes

Using a dataset comprising a range of traits from 262 bacteria in a recent publication

(Liu *et al.*, 2023), we analyzed the correlations of empirical minimal doubling time and optimal growth temperature with genomic characteristics. Thirty-eight pairs of traits were re-examined using Pagel's λ model in the PGLS approach. However, switching dependent and independent variables in 10 pairs resulted in conflicting outcomes, leading to different conclusions (Table 1). For instance, when considering the average prophage number as the dependent variable and the optimal growth temperature as the independent variable, the PGLS analysis showed a significant negative correlation between the two traits ($p = 9 \times 10^{-4}$, Table 1). In contrast, switching dependent and independent variables showed no statistically significant correlation ($p = 0.242$, Table 1). Identifying accurate findings rather than conflicting results is necessary. However, the question is how one can determine which one is correct.

Table 1. Switching dependent and independent variables in PGLS may yield conflicting results[a]

Dependent Variable ~ Independent Variable	Slope	p	R^2
EMDT ~ min_CRISPR_spacer	0.010	0.049	0.015
min_CRISPR_spacer ~ EMDT	1.376	0.053	0.014
EMDT ~ mean_prophage_number	0.565	0.013	0.024
mean_prophage_number ~ EMDT	0.008	0.558	0.001
EMDT ~ min_prophage_number	0.622	0.007	0.028
min_prophage_number ~ EMDT	0.011	0.427	0.002
EMDT ~ max_prophage_number	0.448	0.037	0.017
max_prophage_number ~ EMDT	0.005	0.722	5×10^{-4}
OPT ~ min_CRISPR_array	0.308	0.061	0.014

min_CRISPR_array ~ OPT	0.053	8×10^{-5}	0.058
OPT ~ mean_prophage_number	−0.197	0.242	0.005
mean_prophage_number ~ OPT	−0.031	9×10^{-4}	0.042
OPT ~ min_prophage_number	−0.154	0.374	0.003
min_prophage_number ~ OPT	−0.026	0.004	0.031
OPT ~ max_prophage_number	−0.183	0.214	0.006
max_prophage_number ~ OPT	−0.036	4×10^{-4}	0.047
OPT ~ prophage_existence	−1.046	0.182	0.007
prophage_existence ~ OPT	−0.009	8×10^{-4}	0.043
OPT ~ Average_Cas_gene_number	0.197	0.610	0.002
Average_Cas_gene_number ~ OPT	0.023	0.012	0.043

[a]Pagel's λ model was used in these analyses. The dataset containing 262 bacteria was extracted from the Supplemental Material Table S1 of Liu et al. (2023), and the phylogenetic tree used in PGLS analysis was retrieved from the Genome Taxonomy Database (Parks *et al.*, 2022). EMDT, empirical_minimal_doubling_times; OPT, mean_optimal_growth_temperature. The variables before and after "~" are dependent and independent.

3.2 | Prevalence of conflicts resulting from switching dependent and independent variables

In the above survey on correlations within empirical data, we found that switching dependent and independent variables resulted in conflicting outcomes in 26.3% of cases. To evaluate the prevalence of conflicting results from switching dependent and independent variables, we simulated the progression of two traits along a binary tree of 100 species. Different distributions of the traits were simulated. In the case of "BM & BM + Norm", we

constructed the trait X_1 under the Brownian motion model ("BM") and the trait X_2, as "BM + Norm", equals to X_1 plus a noise term "Norm." In the case of "Norm & Norm + BM," the noise term is "BM." To account for varying levels of correlation, we set a gradient of variance in the noise term, with the variance $\sigma^2{}_{Norm}$ varying from 10^{-4}, 0.01, 1, 4, 16, 64, 256, to 1024. For each parameter condition, we simulated 1000 times.

For the data from each simulation, we performed two rounds of PGLS analysis, $X_1 \sim X_2$ and $X_2 \sim X_1$ (representing regressions of X_1 on X_2 and X_2 on X_1, respectively). The results are presented in Table S1 and summarized in Table 2. In 3781 simulations, neither $X_1 \sim X_2$ nor $X_2 \sim X_1$.gave significant correlations ($p \geq 0.05$ for all of them). In 10161 simulations, both $X_1 \sim X_2$ and $X_2 \sim X_1$.gave significant correlations ($p < 0.05$). In each of these 10161 cases, the regression coefficients of $X_1 \sim X_2$ and $X_2 \sim X_1$ have the same sign. In the other 2058 simulations, only one of $X_1 \sim X_2$ and $X_2 \sim X_1$.gave significant correlations ($p < 0.05$ for one and $p \geq 0.05$ for the other). The frequency of conflicting results caused by switching dependent and independent variables in our simulated dataset is 12.9%.

Table 2 shows a relationship between the variance in simulations and the frequency of conflicting results caused by switching dependent and independent variables. When the variance of the noise term is slight (like 10^{-4}, 0.01, 1, and 4), i.e., where there is a strong correlation between X_1 and X_2, switching independent and dependent variables gives almost the same results. As the variance in the term noise increases (i.e., where the correlation between X_1 and X_2 becomes weak), switching independent and dependent variables leads to many conflicting results. In cases where the variance is 16 in "BM & BM + Norm" and 64 in "Norm & Norm + BM," there are even close to 50% of cases with conflicting results. However, as the variance becomes much more pronounced and the correlation between X_1 and X_2 becomes much weaker, the frequency of conflicting results caused by switching dependent and independent variables decreases (Table 2).

Table 2. Frequency of conflicting results caused by switching dependent and independent variables in PGLS analyses using Pagel's λ model

X_1[a]	BM								Norm							
X_2[b]	BM + Norm								Norm + BM							
Noise Term Variance	10^{-4}	0.01	1	4	16	64	256	1024	10^{-4}	0.01	1	4	16	64	256	1024
Simulation times	10^3	10^3	10^3	10^3	10^3	10^3	10^3	10^3	10^3	10^3	10^3	10^3	10^3	10^3	10^3	10^3
$X_1 \sim X_2$ gave $p < 0.05$[c]	10^3	10^3	10^3	982	543	188	68	53	10^3	10^3	10^3	10^3	926	387	134	74
$X_2 \sim X_1$ gave $p < 0.05$	10^3	10^3	10^3	10^3	954	528	171	81	10^3	10^3	10^3	10^3	10^3	844	318	129
Both $X_1 \sim X_2$ and $X_2 \sim X_1$ gave $p < 0.05$	10^3	10^3	10^3	982	534	169	34	14	10^3	10^3	10^3	10^3	926	375	88	39
Both $X_1 \sim X_2$ and $X_2 \sim X_1$ gave $p \geq 0.05$	0	0	0	0	37	453	795	880	0	0	0	0	0	144	636	836
$X_1 \sim X_2$ and $X_2 \sim X_1$ gave conflicting results[d]	0	0	0	18	429	378	171	106	0	0	0	0	74	481	276	125

[a]The trait X_1 evolved according to a Brownian motion (BM) model in the first 8000 simulations, and evolved according to a normal distribution in the other 8000 simulations. For details, see the MATERIALS AND METHODS section.

[b]The trait X_2 was simulated by adding a noise term to X_1. The term noise was normally distributed in the first 8000 simulations and generated according to a Brownian motion model in the other 8000 simulations. For details, see the MATERIALS AND METHODS section.

[c]The variables before and after "~" are dependent and independent, respectively.

[d]When one of $X_1 \sim X_2$ and $X_2 \sim X_1$ gives a $p < 0.05$ result and the other gives a $p \geq 0.05$ result, we define these results as conflicting.

3.3 | Estimated lambda may change according to the choice of the dependent variable

To control the phylogenetic dependence in the data, PGLS assumes that the model residual error is distributed according to the variance-covariance matrix representing the residual variance and the evolutionary relationships among species. In its simplest form, PGLS assumes a Brownian motion model of evolution at a single rate. By parameter estimation and altering the properties of the variance-covariance matrix, PGLS can be extended to various evolutionary models, like Pagel's λ model (Freckleton *et al.*, 2002), Ornstein–Uhlenbeck model (Hansen 1997), and the early burst model (Harmon *et al.*, 2010). We suspect that switching independent and dependent variables in the PGLS analysis may result in inconsistent estimates of the parameters (like Pagel's λ) and so inconsistent correction for the phylogenetic non-independence of the trait values.

For the data of each simulation, we calculated the phylogenetic signal λ of the two traits (X_1 and X_2) and the $\hat{\lambda}$ of $X_1 \sim X_2$ and $X_2 \sim X_1$ using Pagel's λ model.

In the "BM & BM + Norm" case, when the variance of the noise term is slight, both X_1 and X_2 exhibit strong phylogenetic signals with their λ values close to 1, and both $X_1 \sim X_2$ and $X_2 \sim X_1$ give small $\hat{\lambda}$ values (Figure 1). However, with the increase of the variance of the noise term, the λ values of X_2 gradually decrease while those of X_1. remain at their high levels. Together, the $\hat{\lambda}$ values of the $X_1 \sim X_2$ models gradually increase to 1 while those of the $X_2 \sim X_1$ models remain stable at around 0.03 (Figure 1).

In the "Norm & Norm + BM" case, we found a pattern previously reported by Revell (2010), PGLS regression is possible to give a high $\hat{\lambda}$ value even if both traits have very weak phylogenetic signals. When the variance of the BM noise term is slight, both X_1 and X_2 have small λ values but both $X_1 \sim X_2$ and $X_2 \sim X_1$ models yielded high $\hat{\lambda}$ values of about 1 (Figure 1). With the increase of the variance of the noise term, the phylogenetic signals of X_2 gradually become stronger and finally approach one, but that of X_1 remains

weak. Meanwhile, the values of gradually decrease to about 0.03, while those of remain close to 1 (Figure 1).

We could see that the two models, and , generally give similar values when the two variables, and , have similar λ values (Figure 1). That is, switching dependent and independent variables would not dramatically affect the parameter estimation of the PGLS regression analyses when the two analyzed traits have similar levels of phylogenetic signals. However, when the two variables differ strikingly in their phylogenetic signals, the two models give quite different values (Figure 1). In this case, switching dependent and independent variables would dramatically affect the parameter estimation and potentially give conflicting results. In addition, we noticed that the values tend to be close to the phylogenetic signal of the dependent variable.

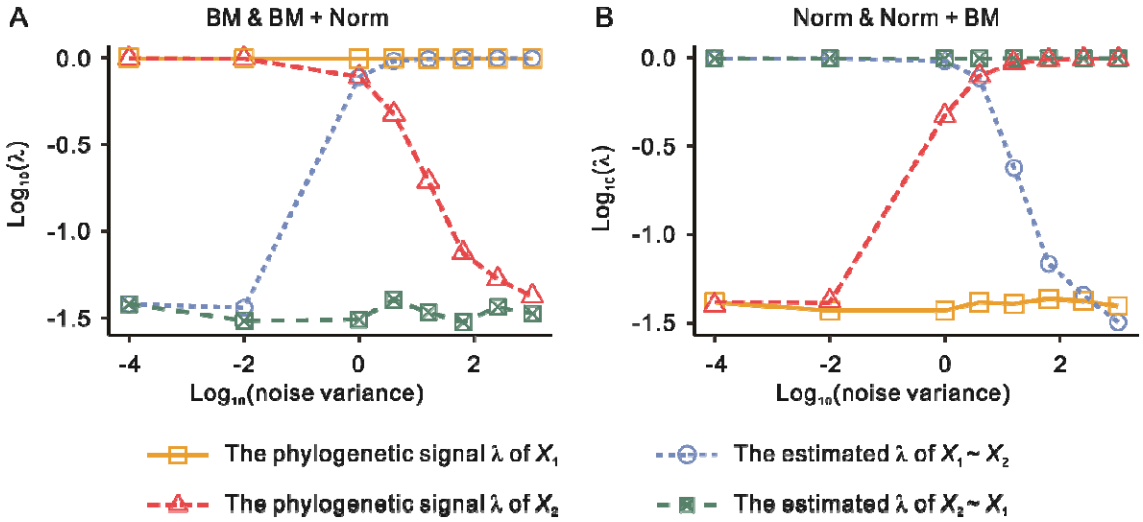

Figure 1 Phylogenetic signals of the variables and the estimated λ of and models under different noise term variances. For each variance gradient, 1000 simulations were conducted. The data points on the graph represent the average value of phylogenetic diagnostics (phylogenetic signals or model estimated λ) of the noise term under a specific variance gradient based on the 1000 simulations. (A) In the "BM & BM + Norm" case,

was simulated according to a Brownian motion (BM) model, while X_2 was simulated based on X_1 plus a normally distributed random noise term. (B) In the "Norm & Norm + BM" case, X_1 was simulated according to a normal distribution, and X_2 was simulated according to X_1 plus a noise term, where the noise term followed a BM model. $X_1 \sim X_2$ and $X_2 \sim X_1$ represent PGLS regressions using X_1 and X_2 as dependent variables, respectively.

3.4 | A golden standard to evaluate the accuracy of PGLS results

When performing PGLS analysis on both empirical and simulated datasets, switching dependent and independent variables leads to a significant frequency of conflicting results. Avoiding arbitrary selection of the dependent variable is essential in PGLS analysis using Pagel's λ model. In order to select a better dependent variable, we will use simulated data to establish a selection criterion.

In empirical phylogenetic data, we only have access to trait values at terminal nodes, and potential correlations between traits can be estimated using methods such as PGLS. In contrast, we can access trait values at internal nodes in simulated phylogenetic data. Since changes along different phylogenetic branches are independent, we can measure the evolutionary correlation between two traits by analyzing their changes along phylogenetic branches using standard statistical methods. First of all, we calculated the changes in the traits X_1 and X_2 along evolutionary branches per unit time, $\Delta X_1/L$ and $\Delta X_2/L$, where L is the length of the branch. Then, we did Shapiro-Wilk test on $\Delta X_1/L$ and $\Delta X_2/L$ to see if they had normal distributions. If both of them satisfy normality, we used Pearson correlation to detect the correlation between $\Delta X_1/L$ and $\Delta X_2/L$. Otherwise, we used Spearman's rank correlation. These analyses revealed significant correlations between the two traits, X_1 and X_2, in 11911 simulations (10988 positives and 923 negatives, $p < 0.05$ for all these cases) but not in the other 4089 simulations ($p \geq 0.05$ for all these cases) (Table S1). These results

provide "golden standards" for judging whether PGLS analyses of trait values on terminal nodes (X_1 and X_2) give correct results.

PGLS analyses of $X_1 \sim X_2$ show that there are significant positive correlations in 10326 simulations ($p < 0.05$ for all these cases), significant negative correlations in 29 simulations ($p < 0.05$ for all these cases), and no significant correlations in 5645 simulations ($p \geq 0.05$ for all these cases) (Table S1). The same analyses of $X_2 \sim X_1$ show that there are significant positive correlations in 12005 simulations ($p < 0.05$ for all these cases), significant negative correlations in 20 simulations ($p < 0.05$ for all these cases), and no significant correlations in 3975 simulations ($p \geq 0.05$ for all these cases) (Table S1). By comparing with the golden standards, we found that PGLS analyses gave correct results for both $X_1 \sim X_2$ and $X_2 \sim X_1$ in 11474 simulations (71.71%) and incorrect results for both $X_1 \sim X_2$ and $X_2 \sim X_1$ in 2468 simulations (15.43%). In 2058 (12.86%) simulations, only one of the two competing models, $X_1 \sim X_2$ or $X_2 \sim X_1$, yielded correct results. Therefore, limited by the performance of PGLS regression analysis, we could at most obtain an accuracy of 84.57% in analyzing the data of our 16000 simulations by PGLS regression. However, if we arbitrarily select one trait (X_1 or X_2) as the independent variable with the worst luck, we could get an accuracy of only 71.71%. In the following attempt to find an accurate criterion for the selection of dependent variables, we hope to perceive more correct cases from the 2058 simulations, where $X_1 \sim X_2$ and $X_2 \sim X_1$ gave conflicting results.

3.5 | Looking for an accurate criterion for dependent variable selection

Referring to the golden standards, we evaluated the potential performance of seven criteria for selecting a better model from $X_1 \sim X_2$ and $X_2 \sim X_1$.

In statistics, the suitability of two competing statistical models is often assessed by calculating each model's log-likelihood (LLK) value. First, we examined whether a higher (or

lower) LLK could give an accurate prediction of the better model between $X_1 \sim X_2$ and $X_2 \sim X_1$. By calculating the LLKs of the two models for the 2058 simulations (Table S1), we found that the models selected from $X_1 \sim X_2$ and $X_2 \sim X_1$ by a lower LLK (denoted as $Model_{LLK,lower}$) have more correct outcomes than the alternative model (denoted as $Model_{LLK,higher}$), 1076 *vs.* 982. A χ^2 test showed a statistically significant difference (p = 3.7×10^{-3}, Table 3).

Akaike information criterion (AIC) is a widely used estimator of the quality of statistical models for a given dataset (Akaike 1974). It balances the excellent fit of the model with the complexity of the model. Calculating the AIC values of the two competing models for the 2058 simulations (Table S1), we found that the models selected with a higher AIC value (denoted as $Model_{AIC,higher}$) had significantly more correct outcomes than the alternative model (denoted as $Model_{AIC,lower}$), 1076 *vs.* 982, $p = 3.7\times 10^{-3}$ (Table 3).

R^2 describes the proportion of total variation in the dependent variable explained by independent variables in the regression model, and the p-value of the regression coefficient is the probability of observing the test statistic value under the assumption that the null hypothesis is true, where the regression coefficient equals 0. These two parameters are widely used indicators of the suitability of regression models. The models selected by a higher R^2 (denoted as $Model_{R^2,higher}$) and a lower p-value (denoted as $Model_{p,lower}$) have significantly more correct outcomes than the alternative models ($p = 2.7\times 10^{-4}$ for both cases, Table 3).

The phylogenetic signal measures how much phylogenetic structure influences species trait values. Pagel's λ and Blomberg et al.'s K are the most commonly used indicators of the phylogenetic signal (Pagel 1999; Blomberg *et al.*, 2003). The estimated λ ($\hat{\lambda}$) is a parameter in Pagel's λ model (Pagel 1997) that measures the relatedness of the regression residuals with the phylogenetic structure. We found that the models that use the trait with a higher λ value or

a higher K value as the dependent variable (denoted as $Model_{\lambda_y,higher}$ and $Model_{K_y,higher}$, respectively) have significantly more correct outcomes than the alternate models (denoted as $Model_{\lambda_y,lower}$ and $Model_{K_y,lower}$, respectively) ($p < 2.2 \times 10^{-16}$ for both case Table 3). And the model chosen by a higher $\hat{\lambda}$ (denoted as $Model_{\hat{\lambda},higher}$) also had significantly more correct results than the alternative model (denoted as $Model_{\hat{\lambda},lower}$) ($p < 2.2 \times 10^{-16}$, Table 3).

Table 3. Differences in the performance of models selected by seven criteria.

Criteria	Models	Correct	Incorrect	χ^2	p^a
LLK	$Model_{LLK,higher}$	982	1076	8.405	3.7×10^{-3}
	$Model_{LLK,lower}$	1076	982		
AIC	$Model_{AIC,higher}$	1076	982	8.405	3.7×10^{-3}
	$Model_{AIC,lower}$	982	1076		
R^2	$Model_{R^2,higher}$	1088	970	13.30	2.7×10^{-4}
	$Model_{R^2,lower}$	970	1088		
p	$Model_{p,higher}$	970	1088	13.30	2.7×10^{-4}
	$Model_{p,lower}$	1088	970		
λ_y	$Model_{\lambda_y,higher}$	1734	324	1929	$< 2.2 \times 10^{-16}$
	$Model_{\lambda_y,lower}$	324	1734		
K_y	$Model_{K_y,higher}$	1734	324	1929	$< 2.2 \times 10^{-16}$
	$Model_{K_y,lower}$	324	1734		
$\hat{\lambda}$	$Model_{\hat{\lambda},higher}$	1734	324	1929	$< 2.2 \times 10^{-16}$
	$Model_{\hat{\lambda},lower}$	324	1734		

[a]The minimal significance value that the R environment (version 4.1.0) gives is 2.2×10^{-16}. Llk, log-likelihood; AIC, Akaike information criterion. When the χ^2 tests were extended to all 16000 simulations, λ_y, K_y, and $\hat{\lambda}$ are also the best criteria (Table S2).

In addition, we defined a virtual criterion where one model was randomly selected from the two competing models, $X_1 \sim X_2$ and $X_2 \sim X_1$. The results of the models selected by this virtual criterion ($Model_{rc}$) were compared with the better models selected by the above seven criteria. Although the better models selected by the above seven criteria consistently have more correct results than $Model_{rc}$ (Table 4), none of $Model_{LLK,lower}$, $Model_{AIC,higher}$, $Model_{R^2,higher}$, and $Model_{p,lower}$ is significantly different from $Model_{rc}$ ($p > 0.100$ for all four cases), but the differences of $Model_{\lambda_y,higher}$, $Model_{K_y,higher}$, and $Model_{\hat{\lambda},higher}$ with $Model_{rc}$ are highly significant ($p < 2.2 \times 10^{-16}$ for all the three cases).

Table 4. Comparing the performance of seven criteria with random selection.

Criteria	Models	Correct	Incorrect	χ^2	p[a]
$\hat{\lambda}$	$Model_{\hat{\lambda},higher}$	1734	324	532.3	$< 2.2 \times 10^{-16}$
	$Model_{rc}$	1039	1019		
K_y	$Model_{K_y,higher}$	1734	324	532.3	$< 2.2 \times 10^{-16}$
	$Model_{rc}$	1039	1019		
λ_y	$Model_{\lambda_y,higher}$	1734	324	532.3	$< 2.2 \times 10^{-16}$
	$Model_{rc}$	1039	1019		
LLK	$Model_{LLK,lower}$	1076	982	1.260	0.262

	$Model_{rc}$	1039	1019		
AIC	$Model_{AIC,higher}$	1076	982	1.260	0.262
	$Model_{rc}$	1039	1019		
R^2	$Model_{R^2,higher}$	1088	970	2.242	0.134
	$Model_{rc}$	1039	1019		
p	$Model_{p,lower}$	1088	970	2.242	0.134
	$Model_{rc}$	1039	1019		

[a]The minimal significance value that the R environment (version 4.1.0) gives is 2.2×10^{-16}. LLK, log-likelihood; AIC, Akaike information criterion.

From Tables 3-4 and S2, we can see three distinct groups of criteria: LLK and AIC, R^2 and p-value, and Pagel's λ, Blomberg et al.'s K, and $\hat{\lambda}$. Within each group, the criteria gave the same results. Among the three groups, Pagel's λ, Blomberg et al.'s K, and $\hat{\lambda}$ seem to be the best criterion for dependent variable selection. For a quantitative evaluation of these impressions, we performed the χ^2 tests to compare Pagel's λ with Blomberg et al.'s K, $\hat{\lambda}$, LLK, AIC, R^2, and p-value using the 2058 simulations where $X_1 \sim X_2$ and $X_2 \sim X_1$ gave conflicting results. As shown in Table 5, the equivalency among Pagel's λ, Blomberg et al.'s K, and $\hat{\lambda}$ and the superiority of λ to LLK, AIC, R^2, and p-value have been statistically confirmed.

Table 5. Comparing the performance of λ_y with other criteria for dependent variable selection

Criteria	Models	Correct	Incorrect	χ^2	p[a]
λ_y *vs.* $\hat{\lambda}$	$Model_{\lambda_y,higher}$	1734	324	0	1

	$Model_{\hat{\lambda},higher}$	1734	324		
λ_y *vs.* K_y	$Model_{\lambda_y,higher}$	1734	324	0	1
	$Model_{K_y,higher}$	1734	324		
λ_y *vs.* LLK	$Model_{\lambda_y,higher}$	1734	324	484.1	$< 2.2 \times 10^{-16}$
	$Model_{LLK,lower}$	1076	982		
λ_y *vs.* AIC	$Model_{\lambda_y,higher}$	1734	324	484.1	$< 2.2 \times 10^{-16}$
	$Model_{AIC,higher}$	1076	982		
λ_y *vs.* R^2	$Model_{\lambda_y,higher}$	1734	324	468.9	$< 2.2 \times 10^{-16}$
	$Model_{R^2,higher}$	1088	970		
λ_y *vs.* p	$Model_{\lambda_y,higher}$	1734	324	468.9	$< 2.2 \times 10^{-16}$
	$Model_{p,lower}$	1088	970		

[a]The minimal significance value that the R environment (version 4.1.0) gives is 2.2×10^{-16}. LLK, log-likelihood; AIC, Akaike information criterion.

In summary, Pagel's λ, Blomberg et al.'s K, and $\hat{\lambda}$ are the best criteria for dependent variable selection. Of the 2058 simulations that $X_1 \sim X_2$ and $X_2 \sim X_1$ gave conflicting results, these criteria led to correct results in 1734 simulations. Combined with the 11474 simulations where both $X_1 \sim X_2$ and $X_2 \sim X_1$ gave correct results, PGLS analysis was able to achieve 82.55% accuracy when the trait with a stronger phylogenetic signal was selected as the dependent variable.

4 | DISCUSSION

In the PGLS correlation analysis of an empirical dataset (Liu *et al.*, 2023), we found that switching dependent and independent variables could lead to a significant incidence of

conflicting results. To investigate this further, we simulated the evolution of two traits (X_1 and X_2) along a binary tree with 100 terminal nodes, using different models and variances for 16000 iterations. Our PGLS analyses of these simulated data showed that the frequency of conflicting results caused by switching dependent and independent variables depends on the strength of the relationship between the analyzed traits. Furthermore, we showed that switching dependent and independent variables leads to different parameter estimations in PGLS regression analysis of two traits that have quite different phylogenetic signals. Using simulation, we established a golden standard for whether the two traits, X_1 and X_2, are correlated in each simulation by conventional correlation analysis of the changes of the two traits along the branches of the phylogenetic tree. With this golden standard, we can tell which model, $X_1 \sim X_2$ or $X_2 \sim X_1$, is correct. Seven potential criteria for dependent variable selection, LLK, AIC, R^2, *p*-value, Pagel's λ, Blomberg et al.'s *K*, and $\hat{\lambda}$, have been compared. The last three criteria are equivalent in selecting dependent variables and have shown their superiority over the other four criteria. Pagel's λ and Blomberg et al.'s *K* values are generally calculated at the beginning of the phylogenetic comparative analysis, so they are already known before the PGLS analysis. If we can choose the trait with a higher λ or *K* value as the dependent variable, two rounds of PGLS analysis, like the $X_1 \sim X_2$ and $X_2 \sim X_1$, are not required. Considering the practical convenience, Pagel's λ and Blomberg et al.'s *K* are superior to $\hat{\lambda}$.

As suggested by some previous publications, like Cooper et al. (2016), Paterno et al. (2018), and Uyeda et al. (2018), PGLS regression is not a perfect method for phylogenetic correlation analysis. In our 16000 simulations, PGLS regression analyses yielded incorrect results for 2468 cases, regardless of which trait is designated as the dependent variable. In 2058 simulations, the two competing models, $X_1 \sim X_2$ or $X_2 \sim X_1$, gave conflicting results: one is right and the other is wrong. That is, PGLS regression analyses of 16000 simulations

with arbitrarily selected dependent variables could yield correct results in the range of 71.79% to 84.57%. By selecting the trait with a strong phylogenetic signal as the dependent variable, we could obtain an accuracy of 82.55%. As this accuracy is still 2.02% below the upper limit of PGLS regression using Pagel's λ model, a better criterion may be found in the future. PGLS regression analysis itself should also be improved.

It is important to note that independent and dependent variables are potentially misleading when used in evolutionary correlation studies. These terms should not be interpreted literally. In a PGLS regression analysis, the independent variable does not necessarily mean the causes of changes in the dependent variable. This analysis replaces conventional correlation methods in phylogenetic comparative studies, such as Pearson and Spearman's rank tests. When selecting a dependent variable for PGLS regression analysis, focusing on an accurate perception of the relationship is critical. For a trait that seems to be the cause in its relationship with another trait, we should still designate it as the dependent variable if it has a stronger phylogenetic signal.

This study primarily focuses on the issue of dependent variable selection in PGLS analyses using Pagel's λ model (Freckleton *et al.*, 2002). We also performed PGLS analysis of the 16000 simulations using the Brownian motion model, with X_1 and X_2 successively used as dependent variables (Table S1). For all 16000 simulations, the results of $X_1 \sim X_2$ and $X_2 \sim X_1$ are consistent in terms of significance (*p* value) and the sign on the coefficient (positive or negative). Arbitrary choosing a dependent variable does not affect correlation results in models (such as Brownian motion) that do not require parameter estimation. However, in other models involving parameter estimation, such as Ornstein–Uhlenbeck (Hansen 1997) and the early burst model (Harmon *et al.*, 2010), switching independent and dependent variables may result in different estimations of their respective parameters and potentially give conflicting results. Further research is needed to establish criteria for

selecting the dependent variable in these models.

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CONFLICT OF INTEREST STATEMENT

The author declares no conflict of interest.

AUTHOR CONTRIBUTIONS

Deng-Ke Niu and Zheng-Lin Chen conceived the idea and designed the general methodology; Zheng-Lin Chen designed the simulations; Zheng-Lin Chen and Hong-Ji Guo implemented the simulations and data analysis; Deng-Ke Niu led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

STATEMENT ON INCLUSION

Our study was a global review and was based on a meta-analysis of secondary data rather than primary data. As such, there was no local data collection. We recognize that more could have been done to engage local scientists with our research as our project developed, and to embed our research within the national context and research priorities. We are planning to address these caveats in future research.

DATA AVAILABILITY STATEMENT

Supplementary Tables S1-S2 and code to simulate the data are available through the Dryad Digital Repository

(https://datadryad.org/stash/share/3iSNk-gOZ6qftpYetca8Mn0qJTBppF2Ml4OFlwqwuCc).

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