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Applying Classical Regression and Robust Multi-level Regression to Analyze the Impact of Educational Policies in Iraqi Universities on Academic Achievement

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Abstract

Multi-level regression models provide a robust framework for analysing hierarchical data characterised by nested structures and mixed effects. These data are commonly available in many fields, including education, social sciences, and others. This research aims to compare the performance of classical regression models and robust multilevel regression models in analysing educational data, and to identify the most effective ones for addressing statistical challenges such as nested data, non-normal distributions, and outliers. A multi-level hierarchical regression model was constructed by conducting exploratory and confirmatory analyses of the latent variables, based on which the hierarchical model was developed across three levels: student level (academic achievement), professor level (incentives, teaching quality), and university level (educational programs). The hypothesised model was estimated using two methods: the restricted maximum likelihood method and the robust design adaptive scale method. The study examines the impact of incentives, teaching quality, and academic programs on student achievement in Iraqi universities. Both methods were applied to data taken from a sample of Iraqi universities, comprising 540 responses. The results showed that the robustly estimated model outperformed the classical method, reducing the impact of outliers and providing more accurate estimates. It was also concluded that developing academic programs and incentives, along with improving the quality of teaching, are key drivers of raising educational achievement and reducing disparities between universities.

1. Introduction

Multi-level hierarchical regression models are models used to analyse data that are hierarchically structured or have mixed effects. They are widely available across many fields, including education, the social sciences, psychology, and agriculture. These models estimate the relationship between a dependent variable and several explanatory variables (independent) at different levels of statistical units, such as students within classes, university classrooms, and universities within educational systems. Many writers and researchers have focused on regression models in general and, in particular, on multilevel hierarchical regression models. Classical regression models assume that the response variable depends on a set of explanatory variables. These variables can be continuous or count data, whereas hierarchical regression models depend on variables at multiple levels. Educational, medical, and environmental research data indicate that many study communities exhibit hierarchical structures. Multilevel hierarchical models are an extension of classical regression models in that their data are organised into groups, and their coefficients can vary across groups. Theoretically, there is no maximum number of levels in this hierarchical system, but in practice, societies with more than four levels are rare.

Many social science researchers seek to explain or interpret individual behaviour and attitudes, and the extent to which this behaviour or attitude is influenced by the social factors in which they live, as well as the group to which they belong (such as the family, educational institutions, such as schools or universities, and the workplace). To increase the accuracy of interpreting this behaviour and attitude, researchers have used statistical models such as general or simple linear regression and analysis of variance (ANOVA) to analyse these data. The real problem with using the aforementioned statistical models is that they focus only on the first level, which refers to the individual or the phenomenon being studied, while neglecting the influence of social factors and groups to which the individual belongs, which refer to the higher level. Therefore, we find that multi-level hierarchical models restore balance by focusing on both the individual and other factors present in the society in which they live, which affect their behaviour and attitudes. It is noted that the most common use of statistical hierarchical models is to explain or describe the effect that occurs in the response variable in relation to the change that occurs in one or more explanatory variables [1]. The hierarchical linear model is a statistical method for analysing hierarchically structured and nested data. A data set is said to be hierarchically organised when lower-level observations are nested within higher-level observations. For example, educational assessment researchers seek to study the effects of classroom assessment practices on student achievement. Data are collected in classrooms, which may include variables describing students (e.g., marital status and academic achievement), variables that infer student performance, and explanatory variables that describe the classroom. Some data, by their very nature, require analysis that accounts for factors at each level of the hierarchy. Usually, this type of model has been analysed by neglecting common variance when evaluating hierarchical data, typically using simple linear regression techniques. This approach was followed before the development of Hierarchical Linear Modelling (HLM), as an algorithm was developed in the early 1980s to estimate covariance components for imbalanced data. This development enables wide-ranging applications of this model for multilevel data analysis [2].

2. Research Objectives

This paper tries to evaluate the impact of various educational policies on academic achievement in Iraqi universities, Compare the performance of classical regression models and multilevel robust regression models in analyzing educational data, and identify the best ones for dealing with statistical challenges such as interacting data, non-normal distributions, and outliers, Finally, identify the factors that significantly influence academic achievement in Iraqi universities.

3. Multi-level Models

Multi-level models are among the most essential modern statistical tools, gaining increasing prominence in educational research for their ability to handle hierarchical data. Data are often collected at overlapping levels, such as the student level within classrooms, the classroom level within a university, and the university within the general education system. The use of classical single-level models neglects this overlap among units, leading to biased or misleading estimates. Multilevel models, on the other hand, allow for the separation of variance across levels and the estimation of both fixed and random effects, providing a more accurate and comprehensive understanding of the factors influencing achievement and educational outcomes. Therefore, these models have become a suitable methodological option for studying complex educational

phenomena and for formulating more effective educational policies through an integrated analysis of variables [3]. For example, if we have the regression equation below and want to construct a hierarchical system consisting of several levels, the steps would be as follows:
The first step is to build a regression equation with different parameters as follows:

$$Y_{ijk} = \alpha_{0jk} + \beta_{1jk} x_{ijkl} + \varepsilon_{ijk} \quad (1)$$

The second step is to create a regression model for the same parameters, since the parameters (α_{0jk}) are considered random variables, meaning that:

$$\alpha_{0jk} = \gamma_{00k} + u_{0jk} \quad (2)$$

$$\alpha_{1jk} = \gamma_{10k} + u_{1jk} \quad (3)$$

Where: u_{0jk} , $u_{1jk}$is the level-2 random effect.
As these effects follow a normal distribution with a mean and variance as follows:

$$u_{0jk}, u_{1jk} \sim N(0, \sigma^2)$$

When building a third level, its indicators are as follows:

$$\gamma_{0jk} = \delta_{000} + r_{0jk} \quad (4)$$

$$\gamma_{1jk} = \delta_{100} + r_{1jk} \quad (5)$$

Whereas: $\delta_{000}, \delta_{100}$: Intercepts Parameters.
If we have more than three levels, the regression model includes more indicators, depending on the number of levels, which is the general case for the multi-level regression model, also called the hierarchical regression model.

3.1 Methods for Estimating a Multilevel Hierarchical Model

3.1.1 Restricted Maximum Likelihood Method

The restricted maximum likelihood (REML) method is one of the most prominent methods for estimating parameters in random-effects hierarchical regression models, due to its ability to provide unbiased estimates of variance components compared to classical methods. This method relies on maximising the likelihood function after excluding fixed-parameter components, thereby reducing bias in variance estimation. The process involves first identifying the appropriate model, then iteratively estimating the random variance and fixed parameters to maximise the likelihood function within the imposed constraints. Despite the computational complexity, REML provides accurate estimates and relatively reliable standard errors [4]. The mathematical equation that expresses this method is as follows [5].

$$\ell_{REML}(\theta) = -\frac{1}{2}\left[(n-p)\ln(2\pi) + \ln|V| + \ln\left|X' V^{-1} X\right| + \left(y - X\hat{\beta}\right)' V^{-1}(y - X\hat{\beta})\right] \quad (6)$$

The part $(n-p)\ln(2\pi)$, where n represents the number of observations, p represents the number of fixed parameters. The part $\ln|V|$ represents ln the variance matrix of the residuals, and the part $\ln\left|X' V^{-1} X\right|$, where X represents the matrix of explanatory variables for the constants. The last part is $\left(y - X\hat{\beta}\right)' V^{-1}(y - X\hat{\beta})$, where y represents the response variable, and $X\hat{\beta}$ the predicted values from the model (the fixed estimates).

3.1.2 The Design Adaptive Scale Method (DAStau)

The adaptive scale design method is a recent extension of parameter estimation within the framework of robust regression. This method addresses heteroskedasticity caused by leverage points in the design matrix. In classical linear models, the variances of the residuals associated with these leverage points are typically adjusted by dividing by the square root of 1-leverage [6]. In the context of robust regression, this correction has been generalised by the DAStau method, which replaces the classical residual-squared function with a weight function specifically designed to enhance robustness. This method relies on residuals being rescaled using a dispersion measure based on the effect size, thereby reducing the contribution of outliers as residuals increase and maintaining stable estimates. Accordingly, this technique provides a balanced equation that accounts for both the design structure and the model's robustness, thereby improving the efficiency and accuracy of estimates relative to classical methods. The equation that expresses this method can be written as follows [6]:

$$\sum_{i=1}^{n} \tau_i^2\, w\left(\frac{r_i}{\tau_i \hat{\sigma}_D}\right)\left[\left(\frac{r_i}{\tau_i \hat{\sigma}_D}\right)^2 - K_D\right] = 0 \tag{7}$$

τ_i: Scale factor that reflects the variation of variance across observations. w: Weight function. $\hat{\sigma}_D$: Variance of the estimation parameter. K_D: Constant associated with the estimation method to adjust for consistency. r_i: Residuals are the errors estimated from the model.

4. Model efficiency standards

4.1 Akaike Information Criterion

The AIC criterion is one of the criteria used to evaluate and compare classical hierarchical models. It balances the model's goodness-of-fit with its complexity. This criterion assumes that errors follow a normal distribution and that the data are free of outliers. The equation for this criterion can be expressed as follows [19]:

$$AIC = -2.\ln(L) + 2k \tag{8}$$

In robust hierarchical models, the classical probability function is not relied upon, but somewhat alternative loss functions, such as the Huber loss function, are used, and its equation can be expressed as follows:

$$AIC = D_{DAStau}(\hat{\theta}) + 2k \tag{9}$$

4.2 Bayesian Information Criterion

The BIC criterion is one of the criteria used to evaluate mixed models. This criterion relies on the classical likelihood function to balance goodness-of-fit with model complexity. The equation expressing this criterion can be written as follows [20]:

$$BIC = -2.\ln(L) + k.\ln(n) \tag{10}$$

In robust mixed models, the classical deviation component is replaced by a robust deviation component that uses loss functions to reduce the influence of outliers. Its equation can be written as follows:

$$BIC = D_{DAStau}(\hat{\theta}) + k\ \ln(\mathrm{n}) \tag{11}$$

5. Robust Models

Robust models are statistical techniques that aim to reduce the impact of outliers and prevent them from affecting the accuracy of analysis results. Robust models are characterised by their ability to provide more accurate and realistic estimates than classical models, especially when data deviate from basic assumptions such as normality and homogeneity of variance. The primary goal of these models is to provide stable and reliable estimates even when data are imperfect, making them more suitable for scientific applications [7]. One of the fundamental goals of robust models is to reduce the impact of outliers so that they do not significantly affect the final results. This, in turn, improves the efficiency and accuracy of statistical estimates. Relying on robust models is an effective way to overcome the statistical challenges associated with outliers, thereby enhancing the reliability of analysis and the accuracy of results [14].

6. Exploratory Factor Analysis (EFA)

Exploratory factor analysis (EFA) is a statistical tool that aims to reduce the number of measurement variables to a smaller set of latent variables while preserving as much of the original information as possible. It is used to identify the latent structure of relationships between items, grouping them into key dimensions that explain common variance, revealing the factors that most influence sample responses, and distinguishing important and unnecessary factors. The number of factors to be retained is typically determined by criteria such as a latent root greater than one, with factor rotation techniques applied to achieve a simple structure, in which each factor is strongly associated with a specific set of items and weakly related to other factors. One of the most prominent methods for extracting factors is principal components analysis (PCA), which is the default method in many statistical programs such as SPSS and SAS and has contributed to its widespread adoption among researchers [8].

6.1 Factor Rotation Methods

There are two methods for applying factor rotation: the orthogonal rotation method, which assumes factors remain independent after rotation, and the oblique rotation method, which allows for correlations among factors. In this study, the orthogonal rotation method was applied using the Varimax method, as follows:

6.1.1 Varimax Method

The Varimax method aims to simplify the saturations of variables on each factor by maximising the variance within each factor, such that some values appear high, others low, and others close to zero, consistent with the simple structure hypothesis. This method is the most common in factor analysis and is used by default in most factor analysis programs. It provides the rotated saturation matrix, along with the calculated variance for each factor [21]. The equation for this method can be written as follows [9]:

$$V=\frac{1}{p}\sum_{j=1}^{k}\sum_{i=1}^{p}\frac{l_{ij}^4}{h_i^4}-\frac{1}{p^2}\sum_{j=1}^{k}\left(\sum_{i=1}^{p}\frac{l_{ij}^2}{h_i^2}\right)^2 \tag{12}$$

7. Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) is a method used in multilevel structural equation modelling. This type of analysis aims to confirmatory construct validation of concepts across different levels, including the individual level (within groups) and the group level (between groups). It aims to identify correlations between observations and the dimensions they represent, as well as between latent variables, thereby assessing the suitability of the hypothetical model to the sample model. Confirmatory factor analysis complements exploratory factor analysis [10]. The CFA model is also called a measurement model, as it aims to verify the properties of tests and measures by analysing the factor saturations of items on latent factors after excluding the effect of measurement error. This contributes to assessing the model's quality by isolating and consolidating measurement errors, thereby providing strong evidence of construct validity and reliability [11].

7.1 Estimation Methods in Confirmatory Factor Analysis

There are several estimation methods used in confirmatory factor analysis, including the maximum likelihood method, the generalised least squares method, the free-scaled least squares method, the free-scaled asymptotic estimation method, and the unweighted least squares method, which was used in this study due to its handling of non-normally distributed data compared to the methods mentioned above. These methods will be explained in detail below:

7.1.1 Unweighted Least Squares (ULS)

Unweighted least squares (ULS) is a classical least squares (OLS) estimation method that minimises the sum of squared differences between the sample correlation matrix and the model's expected correlation matrix. It provides unbiased parameter estimates when using random samples [12]. It differs from the maximum likelihood method in that it does not assume a normal distribution of the data, nor does it require the matrix to be positive-definite, making it suitable for generating initial values for subsequent model or data analysis [13]. Furthermore, this method does not assume that sampling errors are correlated with model errors; therefore, the magnitudes of errors are independent of the correlation coefficients [15]. The mathematical equation for this method can be written as follows:

$$F_{ULS}=\frac{1}{2}tr\{\left[S-\sum(\theta)\right]\}^2 \tag{13}$$

Where tr denotes the trace matrix, S represents the sample covariance matrix, $\sum(\theta)$ the population covariance matrix, θ is the parameter vector with dimension (t×1). The sum of squares of each element in the matrix in the residual matrix $[S - \sum(\theta)]$ Is minimised using the matching function F [16].

7.2 Goodness-of-fit indices for confirmatory factor analysis

7.2.1 Chi-Square Index (CMIN/df)

It is the Chi-square ratio. χ^2 to the degrees of freedom df. There are three limitations to this indicator: it is moderately sensitive to sample size, the degrees of freedom are not related to sample size, and it lacks clear-cut-off points to determine the model's fit. If the value of this indicator is less than 2, it indicates a complete fit to the model; if it is less than 5, it indicates an acceptable fit [17].

$$CMIM/df = \frac{\chi^2}{df} \tag{14}$$

7.2.2 Root Mean Square Residuals (RMR)

The root mean square of the residuals index is a statistical measure in structural equation models (SEM) that quantifies the discrepancy between the observed and model-predicted covariance matrices. The RMR index is the square root of the mean squared residual between the observed and estimated matrices. The equation that expresses its value can be written using the following formula:

$$RMR = \sqrt{\frac{\sum_{ij} (\hat{\sum}_{ij} - \sum_{ij})^2}{\left(\frac{p(p+1)}{2}\right)}} \tag{15}$$

Where: $\hat{\sum}_{ij}$: represents the estimated Covariance Matrix between variables i and j. $\sum_{ij}$ represents the observed variance-covariance between i and j. p: represents the number of observed variables.

RMR provides a direct measure of the average amount of variation for each element of the variance-covariance matrix between the model-predicted values and the observed values. Lower RMR values indicate a higher goodness of fit, meaning that the model adequately represents the variance structure of the data [18].

7.2.3 Goodness of Fit Index-GFI

The goodness-of-fit index is an indicator that compares the extent to which the hypothesized model matches the basic model. The value of this index ranges between (0-1), where high values that are close to one indicate a better quality of fit. According to the guidelines, if the GFI value is equal to or greater than 0.95, it indicates an excellent fit for the model. If the GFI value is between (0.90-0.94), it indicates an acceptable fit, while if the value is less than 0.90, it indicates a weak fit for the model. It is calculated using the following formula: [18].

$$GFI = 1 - \frac{tr(S - \sum(\hat{\theta}))^2}{tr(S^2)} \tag{16}$$

Where: S: The sample covariance matrix. $\sum \theta$: The covariance matrix estimated from the model. tr: The trace matrix, which is the sum of its diagonal elements.

7.2.4 Adjusted Goodness of Fit Index-AGFI

The Adjusted Goodness-of-Fit Index (AGFI) is a modification of the Goodness-of-Fit Index (GFI) in structural equation modelling (SEM). It accounts for model complexity and parameter count, providing a more conservative measure of goodness of fit. The GFI is modified by introducing degrees of freedom into the model, thereby reducing the index's value in models with many parameters. It can be calculated using a standard mathematical formula:

$$AGFI = 1 - \frac{\frac{(p \times (p+1)}{2} - df}{\frac{(p \times (p+1)}{2} \times (1 - GFI)} \tag{17}$$

Where: p: Number of variables. df: Degrees of freedom for the model. GFI: Goodness-of-fit index.

This index ranges from 0 to 1, with higher values indicating a better fit. An AGFI equal to or greater than 0.90 indicates a better fit, while an AGFI equal to 0.85 indicates an acceptable fit, and a lower value indicates a poor fit. An AGFI equal to 1 indicates a perfect fit [18].

7.2.5 Parsimony Adjusted (PGFI)

The modified econometric goodness-of-fit index (GFI) is a measure of goodness-of-fit in structural equation models (SEMs). It is used to adjust the GFI to account for model complexity. The PGFI modifies the classical GFI by simplifying complex models by introducing a correction factor that depends on the number of estimated parameters. This modification aims to promote parsimony, rewarding models that achieve a good fit using fewer parameters. The equation expressing this index can be written as:

$$PGFI = \frac{\chi^2_{model}}{df_{model}} \tag{18}$$

χ^2_{model}: is the chi-square of the hypothesised model. df_{model}: is the degrees of freedom of the hypothesised model.

The PGFI value ranges from (0-1), with values closer to 1 indicating a better fit to the hypothesised model [18].

7.2.6 The Normed Fit Index (NFI)

It is one of the measures used to assess the fit of a model in confirmatory factor analysis. This index was proposed by Bentler and Bonett (1980) and later developed by Hu and Bentler (1995). This index is defined as the ratio of the difference between the value of the null model (χ^2_{null}) and the value of the hypothetical model (χ^2_{target}) to the value of the null model. It is calculated according to the following formula [18]:

$$NFI = \frac{\chi^2_{null} - \chi^2_{target\ model}}{\chi^2_{null} - \chi^2_{target\ model}} \tag{19}$$

Whereχ^2_{null}: represents the chi-square value for the null model. Andχ^2_{target}: represents the chi-square value for the hypothetical model.

The NFI reflects the proportion of variance explained by the variables in the target model relative to the null model. Its value ranges from 0 to 1; 0.95 indicates an excellent model fit, 0.90 an acceptable fit, less than 0.90 a poor fit, and 1 a perfect fit. However, the index suffers from several limitations, most notably its sensitivity to sample size and its limited ability to detect model misfits [18].

7.2.7 Relative Fit Index -RFI

The relative fit index (RFI) is a goodness-of-fit index used in structural equation models (SEMs). It is similar to the standard fit index, which compares the fit of the hypothesised model to the baseline model, taking into account the degrees of freedom. The RFI measures the relative improvement in the goodness-of-fit of the hypothesised model over the null model, while accounting for the degrees of freedom used. It indicates how well the hypothesised model fits the data compared to a more complex model. The mathematical equation for this index can be written as follows:

$$RFI = \frac{\chi^2_{null\ model} - \chi^2_{model}}{\chi^2_{null\ model}} \tag{20}$$

χ^2_{model}: represents the Chi-square of the hypothesised model. $\chi^2_{null\ model}$: represents the chi-square of the null model.

The value of this index ranges from 0 to 1. An RFI value of 0.95 indicates a best fit, while an RFI of 0.90 indicates an acceptable fit. A value less than 0.90 indicates a poor fit, while an RFI value of 1 indicates a perfect fit. This index is affected by two main factors: sample size and the estimation method used [18].

7.2.8 Parsimony Ratio -PRATIO

This indicator measures the simplicity of the proposed model relative to the number of degrees of freedom. This indicator helps evaluate models that contain a large number of parameters. The equation that expresses this indicator can be written as follows [13]:

$$PRATIO = \frac{df_{model}}{df_{null}} \tag{21}$$

The value of this indicator is between (0-1), and the closer it is to (1), the simpler the model is.

7.2.9 Parsimony Normed Fit Index -PNFI

This index is one of the statistical tools used to compare alternative structural models in factor analysis. It modifies the value of the standardised fit index (NFI) to account for model complexity by incorporating a correction factor based on degrees of freedom and estimator parameters. This modification aims to reinforce the principle of simplicity, rewarding models that achieve a good fit using fewer parameters. The mathematical equation for this index can be written as follows:

$$\text{PNFI} = \frac{NFI \times df_{null\ model}}{df_{model}} \tag{22}$$

Where: NFI: Standardised Fit Index. $df_{null\ model}$: Degrees of freedom for the null model. df_{model}: Degrees of freedom for the hypothesised model.

This index takes values between (0-1), such that a value greater than 0.90 indicates a good fit for the model [18].

8. Real Data Analysis

In this paper, the hierarchical regression method was applied in R, AMOS, and SPSS, using both traditional and robust procedures, to data collected from a stratified sample within the university (8 students, 16 faculty members, and three administrators). A questionnaire containing 34 items was distributed across three axes (levels). The questionnaire included 540 respondents from 20 Iraqi universities across the three levels, as described above (students, faculty members, and staff). The final model was reached after the researcher conducted a series of preliminary analyses, including traditional questionnaire analysis, exploratory and confirmatory analyses, and principal components analysis and axis rotation. This resulted in a set of key factors influencing the student level, drawn from the 34 items within the axes, upon which the final model was built. The variables used in the analysis are:

Table (1): Questions and topics of the questionnaire

First axis: at the student level		
	No	**The question**
Academic achievement	S11	Educational policies set standards that contribute to raising the academic level of students.
	S21	The curricula help develop students' skills on the theoretical level.
	S31	The curricula help develop students' skills on a practical level.
	S41	The Ministry provides adequate support to students to achieve their academic ambitions.
Skills	S51	Educational policies encourage the development of students' skills for independent decision-making.
	S61	Educational policies contribute to encouraging universities to hold training workshops aimed at developing students' professional skills.
	S71	Current educational policies help raise students' academic research writing skills.
Study satisfaction	S81	Educational policies contribute to providing an educational environment that encourages creativity and innovation.
	S91	There is a satisfactory level of quality of education that students receive at universities.
	S101	The university provides the necessary technological requirements for study (computers, internet, educational platforms, laboratories, etc.)

Future trends	S111	The university's educational policies help determine the future career path.
	S121	Educational policies encourage students to consider studying abroad to gain new experiences.
	S131	The university works to prepare students comprehensively to enhance their ability to contribute effectively to the development of the private sector and achieve leadership in it.
The second axis: at the teacher level		
Quality of teaching	T12	The Ministry's educational policies support the development of teachers' teaching skills.
	T22	There is interest from the Ministry in providing the necessary resources to improve the quality of teaching.
	T32	Educational policies encourage teachers to use innovative teaching methods that keep pace with modern developments.
Incentives	T42	The Ministry provides incentives to academics to encourage them to put in more effort.
	T52	The efforts of the professors in teaching and scientific research are appreciated by the university administration and the ministry.
	T62	Academic promotion instructions are clear, fair, and encourage academic excellence.
Academic independence	T72	The annual evaluation system is fair and accurately reflects the performance of professors.
	T82	The professor has sufficient freedom to make decisions related to his teaching or research work.
	T92	The university professor has the freedom to choose teaching methods that suit the nature of the subject and the students.
The third axis: at the university level		
Academic programs	C13	The university's academic programs keep pace with scientific and cognitive developments.
	C23	Academic programs prepare graduates for the job market.
	C33	Educational policies seek to achieve a balance between theoretical and practical aspects in academic programs.
Scientific research	C43	The university supports scientific research and provides the necessary resources for it.
	C53	Educational policies support research cooperation between Iraqi universities and international scientific institutions.
	C63	Educational policies support initiatives that encourage the publication of scientific research in prestigious scientific journals.
Partnerships	C73	Educational policies encourage the university to build partnerships with international academic institutions.
	C83	The university cooperates with other institutions (industrial, governmental, etc.) to serve the community.
	C93	Educational policies contribute to motivating the university to sign partnerships with private companies to implement joint projects that contribute to improving the quality of education.
infrastructure	C103	The university provides a stimulating educational environment that encourages creativity and innovation.
	C111	The university library provides sufficient knowledge resources to support scientific research and study.
	C121	The university's internet networks are fast and reliable.

9. Test for detecting outliers for independent study variables

Table (2): Number of outliers detected in the data

Residuals Statistics		
Method	**Mahalanobis Distance-MD**	**Robust Mahalanobis Distance-RMD**
No.	**59**	**91**

Table (2) above shows the number of outliers in the data for the independent variables (response rates on the questionnaire axes). The two methods were compared based on the chi-square distribution at a significance level of (0.05), and degrees of freedom (3), which equals the number of independent variables, where the tabular value equals ($\chi^2_{(3,0.05)} = 7.83$). The results show that using the traditional Mahalanobis distance (MD) revealed 59' outliers. The robust Mahalanobis distance (RMD) identified 91 outliers, underscoring the need to use a robust method for hierarchical model estimation.

10. Testing the measurement model for the study levels and dimensions after the rotation process.

Table (3): Standardised Regression Weighted (SRW) coefficient values (loadings) for the results of confirmatory factor analysis for the study levels after factor rotation

Questions	Relationship direction	Dimensions	Estimate	SRW	Lower	Upper	P-Value
S21	<---	Academic achievement	1.00	.738	.690	.771	.010
S31	<---		.860	.657	.606	.700	.010
S41	<---		.884	.610	.550	.661	.010
S51	<---		.805	.621	.567	.672	.010
S61	<---		.618	.507	.442	.565	.010
S71	<---		.949	.665	.612	.711	.010
S81	<---		1.062	.741	.708	.773	.010
S91	<---		.778	.619	.557	.665	.010
S101	<---		.861	.546	.480	.604	.010
S111	<---		.913	.694	.652	.732	.010
S121	<---		.822	.588	.531	.636	.010
S131	<---		.943	.663	.617	.710	.010
T12	<---	Quality of teaching	1.000	.622	.551	.685	.010
T22	<---		.791	.529	.446	.685	.010
T32	<---		1.373	.712	.638	.775	.010
C13	<---	Academic programs	1.000	.727	.685	.761	.010
C23	<---		1.197	.730	.691	.767	.010
C33	<---		1.034	.734	.693	.771	.010
C53	<---		1.015	.683	.630	.723	.010
C63	<---		.973	.626	.559	.673	.010
C73	<---		.857	.610	.549	.664	.010
C83	<---		.915	.616	.558	.667	.010
C93	<---		1.032	.656	.596	.705	.010
C103	<---		1.154	.749	.699	.795	.010
C113	<---		.912	.593	.529	.652	.010
C123	<---		1.279	.633	.589	.685	.010
T42	<---	Incentives	1.000	.713	.664	.760	.010
T52	<---		.924	.740	.686	.785	.010
T62	<---		.851	.566	.506	.624	.010
T72	<---		.904	.616	.564	.670	.010
S11	<---		.914	.785	.745	.824	.010
C43	<---		1.065	.767	.722	.801	.010

Table (3) above shows the process of confirmatory factor analysis for all study variables after conducting exploration and rotation processes for the latent variables, based on what was explained in paragraph (6) for confirmatory factor analysis from the theoretical side, and in paragraph (7.1.1), for the unweighted least squares method, where all saturation values for all variables measured on the dimensions appeared greater than (0.30), which represents the minimum for accepting saturation of the items on the latent variables. The value (P-value) also seemed less than 0.05 for all values, thus being statistically significant.

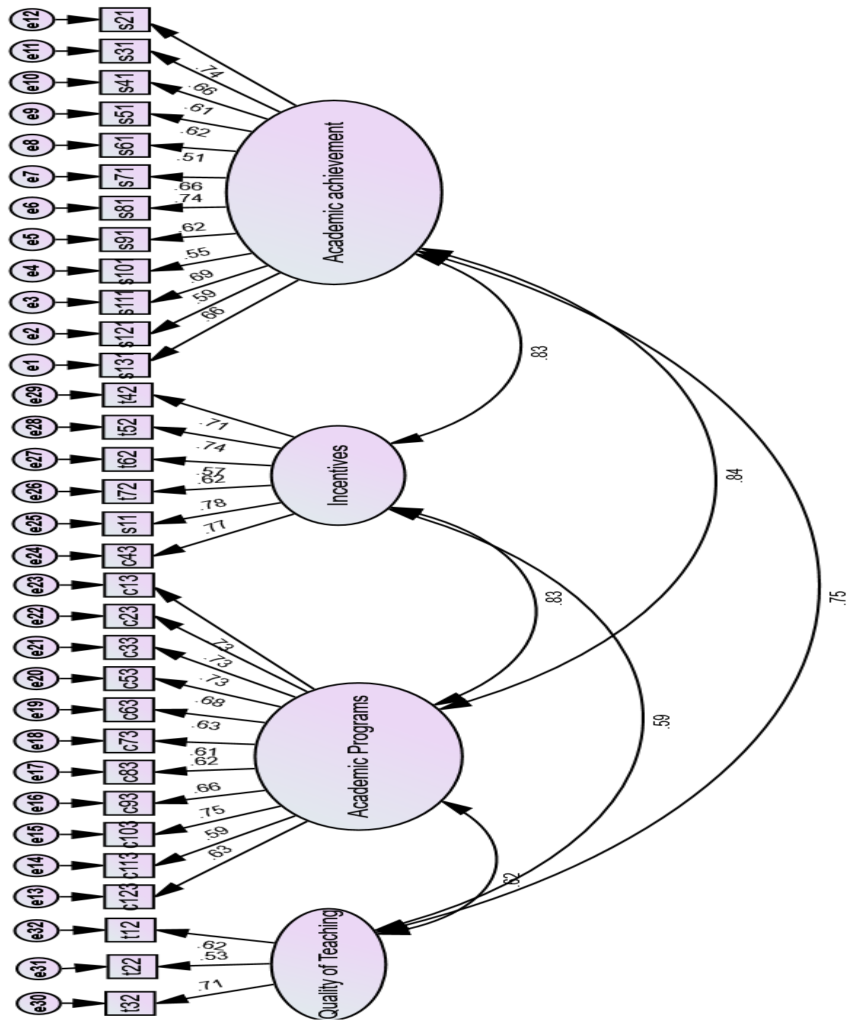

Figure (1): Structural model for confirmatory factor analysis of the total study levels after the rotation process

Figure (1) above shows the Factor Loading values of the correlation of the observed or measured variables (questions) with the variables that indicate them (latent) and are related to the study variables, the values of which are shown on the single-headed arrow between the question and the latent variable, in addition to the correlation values between each pair of latent variables, the values of which are shown on the double-headed arrow. The figure above shows the model's simplicity compared to the overall model of levels before the rotation process is carried out**.**

Table (4): Goodness-of-fit indices of confirmatory factor analysis of the hypothesized model for the four study levels after rotation.

No.	Standard indicators	Acceptance limits	Model indicators	Matching result
1	Standard chi-square (CMIN/df)	CMIN/df < 2 Exact Match. CMIN/df < 5 Accept the form.	1.423	**match**
2	Root mean square residuals index (RMR)	The RMR value is equal to 0.08, and the closer it is to zero, the better the model fits.	0.045	**match**
3	Goodness of Fit Index (GFI)	GFI > 0.90 Model quality GFI < 0.90 weak match	0.988	**match**
4	Corrected goodness-of-fit index (AGFI)	AGFI > 0.85 Acceptable Match AGFI = 1 exact match AGFI > 0.90 Best Match	0.986	**match**
5	Economic Conformity Quality Index (PGFI)	The closer it is to (1), the better the fit of the .model	0.857	**match**

6	Standard Conformity (NFI) Index	NFI = 1 Exact Match NFI > 0.90 Best Match	0.985	**match**
7	Relative Conformity (RFI) Index	RFI > 0.90 Data matching with the model RFI > 0.95 Best Match	0.984	**match**
8	Relative Model Simplicity Index (PRATIO)	0=<PRATIO<=1 The closer it is to (1), the simpler the model is.	0.923	**match**
9	Economic Standard Conformity Index (PNFI)	Its value ranges from (0-1), such that a value that exceeds (0.90) indicates a good fit to the model.	0.910	**match**

11. Estimating hierarchical model parameters using the restricted maximum likelihood (REML) method

Table (5): REML mixed linear regression model

Fixed effects					
Parameters	**Estimates**	**standard error**	**t-value**	**P-value**	**Interpretation**
Intercept	0.27617	0.10882	2.538	0.001	The overall mean of the dependent variable (academic achievement) is represented when all values of the independent variables are equal to zero.
Incentives	0.24741	0.02876	8.604	0.001	It indicates that a one-unit increase in the variable (incentives) leads to an increase in the dependent variable by 0.24.
Quality of teaching	0.27089	0.03145	8.613	0.001	It indicates that a one-unit increase in the variable (quality of teaching) leads to an increase in the dependent variable by 0.27.
Academic programs	0.38874	0.03576	10.871	0.001	It represents the most influential variable, as a one-unit increase in the variable (academic programs) leads to an increase in the dependent variable by 0.38.

Random effects			
Levels	**Variance**	**standard deviation**	**Interpretation**
Differences between individuals in universities	0.00234	0.04837	It indicates that there are differences between the responses of one individual and another within universities, but they are slightly less than the differences between universities.
The difference between universities	0.00310	0.05571	It indicates that there are differences between individuals' responses from one university to another, which are relatively greater than the differences between one individual and another.
Residuals	0.14994	0.38722	The unexplained variance in the dependent variable (academic achievement) is much larger than the random variances, indicating that most of the variance comes from individual factors.

Table (5) above shows the results of the mixed regression model analysis, which indicates that all independent variables (incentives, teaching quality, and academic programs) had positive and statistically significant effects at a significance level of $p<0.001$, indicating that these variables play an essential role in explaining the variance in the dependent variable (academic achievement). The effect of the independent variable (educational programs) was the largest among the other independent variables, followed by (teaching quality) and (incentives). At the random-effects level, the results showed that the differences between universities were equal (0.0031) and those within universities (0.0023) contributed to a limited extent to the total variance, compared with the residuals (0.1499). This suggests that the most significant part of the variance is due to unmeasured individual factors rather than institutional differences. Hence, the hierarchical nature of the data under study is highlighted.

12. Estimating hierarchical model parameters using the Design Adaptive Scale (DAStau) method

Table (6): Mixed linear regression model using the DAStau method

Fixed effects					
Parameters	**Estimates**	**standard error**	**t-value**	**P-value**	**Interpretation**
Intercept	0.23896	0.10625	2.249	0.001	The overall mean of the dependent variable (academic achievement) is represented when all values of the independent variables are equal to zero.
Incentives	0.23845	0.02820	8.455	0.001	It indicates that a one-unit increase in the variable (incentives) leads to an increase in the dependent variable by 0.23.
Quality of teaching	0.24467	0.03094	7.908	0.001	It indicates that a one-unit increase in the variable (quality of teaching) leads to an increase in the dependent variable by 0.24.
Academic programs	0.43741	0.03513	12.451	0.001	It represents the most influential variable, as a one-unit increase in the variable (academic programs) leads to an increase in the dependent variable by 0.43.
Random effects					
Levels	**Variance**	**standard deviation**	**Interpretation**		
Differences between individuals in universities	0.00000	0.00000	It indicates that there are no differences between the responses of one individual and another in universities.		
The difference between universities	0.00233	0.04827	It indicates that there are differences between individuals' responses from one university to another.		
Residuals	0.13949	0.37348	The unexplained variance in the dependent variable (academic achievement) is much larger than the random variances, indicating that most of the variance comes from individual factors.		

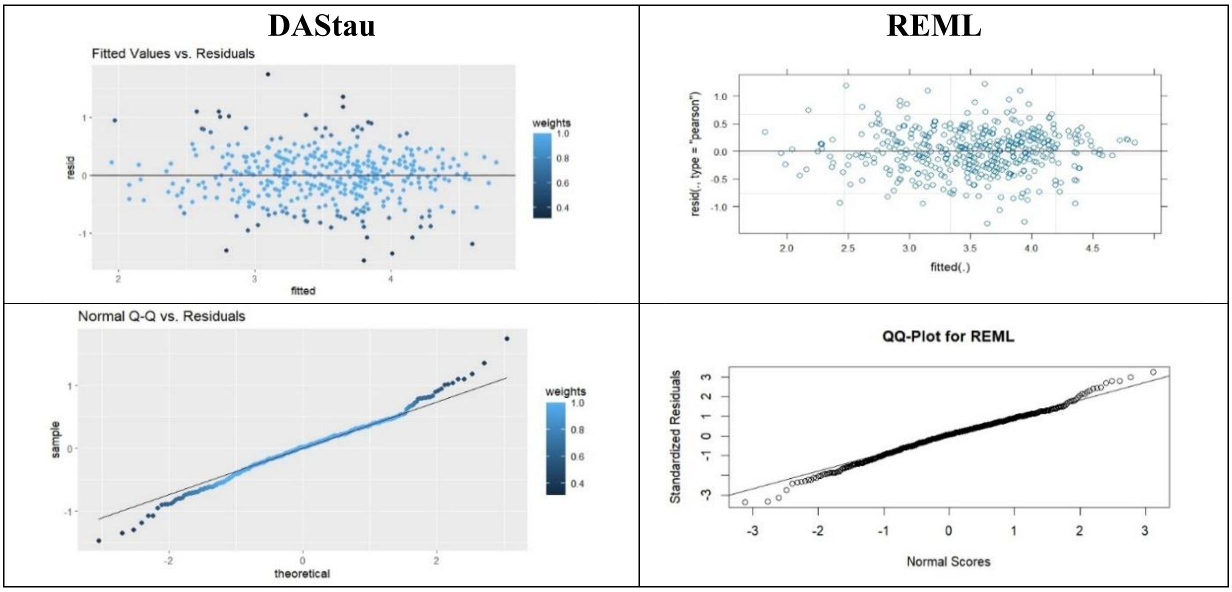

Figure (2): Comparison results between REML and DAStau estimation methods

Figure (2) above shows the results of comparing the regular REML and robust estimation methods (DAStau). The REML model shows a stable residual pattern, but it may be affected by outliers. The robust estimation method (DAStau) demonstrates greater ability to detect and handle data with skewed and non-normal distributions, thereby providing the estimated model with greater flexibility in parameter estimation.

Table (7): Results of comparison criteria between REML and DAStau estimation methods

Model	AIC	BIC
REML	555.032	585.073
DAStau	52.646	78.395

Table (7) above, which compares the results of the two models estimated using the Restricted Maximum Likelihood (REML) method and the Design Adaptive Measure (DAStau) method, indicates a difference in the fit and accuracy indices. The model estimated using the robust method (DAStau) showed significantly lower values for both (AIC=52.646) and (BIC=78.395) compared to the model estimated using the regular method (REML), which recorded higher values (AIC=555.032) and (BIC=585.073). Therefore, it can be said that the model estimated using the robust method (DAStau) outperforms the model estimated using the regular method (REML) in terms of fit criteria (AIC, BIC), due to its ability to handle data outliers.

13. Conclusion

We conclude from the results of the two models that all independent variables (incentives, teaching quality, and academic programs) have impacts on students' academic achievement at highly statistically significant levels. The results showed that academic programs represent the most influential factor in improving achievement, reflecting the role of the organised academic structure in formulating quality educational outcomes. At the random-effects level, the REML model revealed variance within and between universities, and the majority of the unexplained variance was due to individual factors outside the scope of the intervening variables. Meanwhile, the results of the DAStau model showed no variance among individuals within universities, with differences limited to the university level, suggesting that academic achievement is more affected by institutional differences than by individual differences. Comparing the two models, it becomes clear that the inclusion of the independent variables in the second model reduced the amount of random variance, especially at the individual level, reflecting the model's accuracy and explanatory power. Therefore, it can be concluded that developing academic programs and incentives, along with improving teaching quality, represent a fundamental lever for raising academic achievement and reducing disparities between universities.

14. Recommendations

Based on the results obtained, the study concluded the following:

1- The study recommends applying hierarchical models to various fields due to their ability to represent differences between levels and provide a more accurate and comprehensive picture of the influencing factors compared to traditional regression models.
2- Expanding the scope of the study in the future to include more than three different levels not included in the current study.
3- Using different estimation methods to analyse hierarchical data that take this hierarchical structure into account, such as the robust Bayes method and other robust methods.
4- Focusing on updating curricula and courses to keep pace with scientific and technological developments and enhance students' ability to integrate into the labour market.
5- Investing in continuous training for faculty members and encouraging them to adopt modern teaching methods based on interaction, participation, and the use of educational technologies.

15. Supplementary material

(None).

16. Author's Contributions

Faris Isaak Mohamoud: Writing, editing, and conducting the analyses. Bashar A. Al-Talib: Designed and planned the research and interpreted the results.

17. Funding

(None).

18. Data availability statement

The research data were collected by distributing a questionnaire to a sample of professors, students, and administrators at Iraqi universities to analyse the impact of the Ministry of Higher Education and Scientific Research's educational policies.

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20. Conflict of interest

The authors declare no conflict of interest.

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تطبيق الانحدار التقليدي والانحدار الحصين متعدد المستويات لتحليل تأثير السياسات التعليمية في الجامعات العراقية على التحصيل الأكاديمي

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المستخلص

تعد نماذج الانحدار متعدد المستويات إطارًا قويًا لتحليل البيانات الهرمية التي تتميز بالهياكل المتداخلة والتأثيرات المختلطة، حيث تتوفر هذه البيانات بشكل شائع في مجالات عدة منها التربية، والتعليم، والعلوم الاجتماعية، وغيرها من المجالات. يهدف البحث الى مقارنة أداء نماذج الانحدار التقليدي والانحدار الحصين متعدد المستويات في تحليل البيانات التعليمية، وتحديد أفضلها للتعامل مع التحديات الإحصائية مثل البيانات المتداخلة والتوزيعات غير الطبيعية والقيم الشاذة في البيانات. تم بناء نموذج انحدار هرمي متعدد المستويات من خلال الاعتماد على اجراء تحليلات استكشافية وتوكيدية للمتغيرات الكامنة التي على اساسها تم بناء النموذج الهرمي لثلاثة مستويات: (مستوى الطالب: التحصيل الأكاديمي، مستوى الأستاذ: الحوافز، جودة التدريس. ومستوى الجامعة: البرامج الأكاديمية)، حيث تم تقدير النموذج المفترض بطريقتين طريقة الإمكان الأعظم المقيدة Restricted Likelihood Method، وطريقة تقدير التصميم الحصين للمقياس المكيف Robust Design Adaptive Scale Method ، وتناولت الدراسة تأثير الحوافز، وجودة التدريس، والبرامج الاكاديمية، على التحصيل الأكاديمي للطلبة في الجامعات العراقية، تم تطبيق الطريقتين على بيانات مأخوذة من عينة من الجامعات العراقية، شملت 540 استجابة، حيث أظهرت النتائج أن النموذج المقدر بالطريقة الحصينة يتفوق على النموذج المقدر بالطريقة التقليدية من خلال تقليل تأثير القيم الشاذة على البيانات وإعطاء مقدرات أكثر دقة. كما تم الاستنتاج أن تطوير البرامج الاكاديمية، والحوافر الى جانب تحسين جودة التدريس يمثل دافع أساسي لرفع مستوى التحصيل الأكاديمي وتقليل التباينات بين الجامعات

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