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Modeling Monthly Internet Data Package Expenditures Using the Numerical Method of Inverse Matrices

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Abstract

Mobile data has become a routine monthly expense for many university students, yet few studies have modelled this expense, and fewer still show the linear algebra behind such a model. In this study we built a model of monthly internet data package expenditure using the matrix inverse method. Fourteen students from the 2023 cohort of the Mathematics Education Study Program at Universitas Kristen Indonesia completed a short questionnaire on the quota they bought each month (GB) and the amount they paid for it (thousand IDR). We arranged these responses as a design matrix, formed the normal equations, and solved them with the inverse of X^TX. After checking the arithmetic, we evaluated the model with the coefficient of determination, *F*- and *t*-tests, residual analysis, and the mean absolute percentage error (MAPE). The model obtained was $\hat{Y} = -7.271 + 2.250X$, so every extra gigabyte added roughly IDR 2,250 to a student's monthly spending. Quota accounted for 93.6% of the variation in expenditure ($F(1, 12) = 175.02$, $p < 0.001$), and the predictions missed the actual amounts by 12.60% on average. The negative constant was not significant, which means the model should only be used between 10 and 50 GB. The 30 GB packages deviated most from the line because they cost more per gigabyte than the others. For students, the model offers a quick way to budget for data; for lecturers, it is a worked example of the matrix inverse applied to data that students produced themselves.

Keywords: mathematical modeling, internet data package, inverse matrix, linear regression, numerical method

1. Introduction

Studying at university today is hard to imagine without an internet connection, and in most cases, it is the students themselves who pay for it. In Indonesia, the internet became students' largest

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spending need after the shift to online learning (59%, ahead of consumption and transportation) (Wibawa & Pauzy, 2022), and technical and financial barriers kept many students offline (Simamora & Nababan, 2024). Data costs also affect learning: subsidised quota contributed 49% to students' learning motivation (Sugiyarto et al., 2022), and similar cost burdens have been reported for university and teacher-education students in other countries (Amoah et al., 2026; Jaca, 2022). Knowing how much each additional unit of data costs is therefore practical information for students' financial planning.

Previous studies have modelled student expenditure with regression, for example the additional data cost of online learning (Amoah et al., 2026), the effect of digital payments ($R^2 = 0.832$; Fathoni et al., 2025), pocket money and QRIS use ($R^2 = 0.189$; Wulandari et al., 2026), and online shopping ($R^2 = 0.113$; Widiawati et al., 2025). Closer to the present topic, Al Mustofa and Nurmalitasari (2023) regressed package price on quota size and other package attributes, and Rahman (2023) reported that most students used 11–20 GB of data per month. Matrix methods have also been applied to everyday economic data, including Gaussian elimination and Cramer's rule for a multiple regression on ornamental-plant sales data (Bagaswara & Astuti, 2025), the matrix inverse for a bakery's production data (Amanda et al., 2026), and a comparison of Gauss–Jordan and cofactor–adjoint inversion on small-business data (Melani et al., 2026). However, the expenditure studies obtained their parameters with statistical software, and the matrix studies did not examine the conditioning or numerical accuracy of their solutions, even though Bagaswara & Astuti (2025) reported different prediction errors for two solvers of the same system (MAPE of 21% and 40%).

In mathematics teacher education, modelling is a core professional competence (Wiegand & Borromeo Ferri, 2023), and pre-service teachers are the most frequently studied group in recent modelling research (32%) (Mahe & Kharisudin, 2026). Yet modelling difficulties appear from school onwards (Putriani et al., 2025); prospective teachers struggle to design realistic and open modelling tasks (Hwang & Han, 2025) and to solve real-world problems (Parandrengi & Hiltrimartin, 2023; Winarni et al., 2025); and undergraduates who learned linear systems through modelling did not validate their results (Ramírez-Montes et al., 2021). In linear algebra, students report a gap between theory and application (Ali & Avivor, 2026) and considerable anxiety (Maimunah et al., 2026), while Indonesian studies have mainly described how students translate realistic problems into mathematical representations (Putri & Zukhrufurrohmah, 2022).

Two gaps therefore emerge. First, studies of student internet spending estimate regression models with software, without exposing the matrix computation or examining the numerical quality of the solution. Second, studies of modelling and linear algebra in teacher education rarely use authentic data drawn from the students' own lives. This study addresses both gaps by modelling the monthly data package expenditure of mathematics education students with the matrix inverse applied to the normal equations, reporting every computational step, verifying the solution numerically, and evaluating the model's fit, accuracy, and range of validity. Its novelty lies in combining a student-generated contextual dataset with a fully transparent numerical procedure, which yields both a practical budgeting estimate and a reproducible example for numerical methods and linear algebra courses. Our aim was to model the monthly internet data package expenditure of mathematics education students from the 2023 cohort with the matrix inverse method and to see how accurately the resulting model describes their spending.

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2. Methods

2.1 Research Design and Procedure

We used a descriptive quantitative design. A mathematical model was built from the students' data, and its parameters were estimated directly by applying the matrix inverse to the normal equations of least-squares regression. The research was carried out in six operational stages, as shown in Figure 1: (1) identifying the problem and reviewing related studies to establish the state of the art and the research gap; (2) preparing the questionnaire; (3) collecting the data and checking their accuracy; (4) formulating the model in scalar and matrix form; (5) estimating the parameters by computing X^TX, its determinant, its inverse, and the parameter vector; and (6) evaluating and interpreting the model.

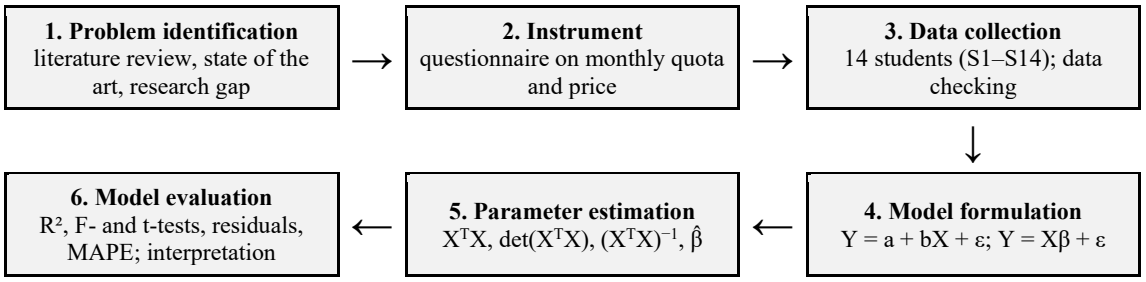


Figure 1. Research procedure

2.2 Participants

The population was the 2023 cohort of the Mathematics Education Study Program, Faculty of Teacher Training and Education, Universitas Kristen Indonesia. The sample consisted of the 14 students who voluntarily completed the questionnaire (convenience sampling). Data were collected in 2026, and each respondent is identified only by a code (S1–S14) to protect their privacy.

2.3 Instrument and Data Collection

Data were collected with a short questionnaire. The questionnaire asked each student to report (a) the data quota of the internet package purchased in a typical month, in gigabytes (GB), and (b) the price paid for that package, in rupiah (IDR). Two variables were derived from the responses: monthly data quota (X, in GB) as the independent variable and monthly package expenditure (Y, in thousand IDR) as the dependent variable. Expenditure was expressed in thousands of rupiah so that the entries of the matrices remained of manageable magnitude.

2.4 Data Analysis

We modelled the link between data quota and expenditure with simple linear regression, as written in Equation (1). Here a is the constant, b is the regression coefficient, and ε_i is the random error for the i-th student.

$$Y_i = a + bX_i + \varepsilon_i, \quad i = 1,2,\dots,n \tag{1}$$

Stacking the n observations gives the matrix form in Equation (2). The design matrix $\mathbf{X}$ has n rows and two columns, and its first column is filled with ones so that the constant can be estimated.

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$$\mathrm{Y} = \mathrm{X}\beta + \varepsilon, \quad \mathrm{X} = \begin{bmatrix} 1 & X_1 \\ 1 & X_2 \\ \vdots & \vdots \\ 1 & X_n \end{bmatrix}, \quad \mathrm{Y} = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix}, \quad \beta = \begin{bmatrix} a \\ b \end{bmatrix} \tag{2}$$

The parameters were estimated by solving the normal equations of least squares with the matrix inverse (Montgomery et al., 2021) in five steps: (a) arranging the data into X and Y; (b) computing $\mathrm{X^TX}$ and $\mathrm{X^TY}$; (c) computing det ($\mathrm{X^TX}$) to confirm invertibility; (d) computing $(\mathrm{X^TX})^{-1}$; and (e) computing the parameter vector and writing the final model. The model was then evaluated with the coefficient of determination (R^2), the *F*-test of overall significance, *t*-tests and 95% confidence intervals for each parameter, residual analysis including the Shapiro–Wilk normality test, and the mean absolute percentage error (MAPE). The numerical quality of the solution was examined through the condition number of $\mathrm{X^TX}$. All hand calculations were verified with Python 3 (NumPy and SciPy).

3. Results and Discussion

3.1 Description of the Data

Before the model was constructed, the responses of the 14 students were summarised to describe the range and spread of each variable and to check whether expenditure was proportional to data quota. For this purpose, the unit price (*Y*/*X*), the expenditure per gigabyte, was derived from the two research variables. The resulting summary is given in Table 1.

Table 1. Descriptive statistics of the research variables (n = 14)

Variable	Unit	Minimum	Maximum	Mean	SD
Monthly data quota (*X*)	GB	10	50	27.07	13.90
Monthly package expenditure (*Y*)	thousand IDR	15	100	53.64	32.34
Unit price (*Y*/*X*)	thousand IDR/GB	1.43	2.50	1.88	0.39

Note. SD = standard deviation.

Based on Table 1, the quota bought each month varied from 10 to 50 GB (mean 27.07 GB), and monthly spending varied from IDR 15,000 to IDR 100,000 (mean about IDR 53,640). Most purchases clustered around a handful of package sizes; 20, 30, and 50 GB were each bought by three students. This is to be expected, since operators sell data in fixed bundles rather than by the gigabyte. What stands out more is the unit price. Students paid anywhere from IDR 1,430 to IDR 2,500 per GB, so spending does not rise in strict proportion to quota. A model with a constant term is needed, and whether a straight line fits these data well has to be checked rather than assumed.

3.2 Constructing the Matrix System

Minimising the sum of squared errors in Equation (2) gives the normal equations in Equation (3). As long as $\mathrm{X^TX}$ is non-singular, they have exactly one solution, shown in Equation (4).

$$\mathrm{X}^T\mathrm{X}\,\beta = \mathrm{X}^T\mathrm{Y} \tag{3}$$

$$\hat{\beta} = (\mathrm{X}^T\mathrm{X})^{-1}\mathrm{X}^T\mathrm{Y} \tag{4}$$

Writing the data of the 14 students in their original order (S1–S14) gives the transposed design matrix in Equation (5) and the expenditure vector in Equation (6).

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$$\mathrm{X}^{T} = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 20 & 50 & 50 & 14 & 30 & 30 & 10 & 14 & 25 & 50 & 20 & 16 & 20 & 30 \end{bmatrix} \quad (5)$$

$$\mathrm{Y}^{T} = [35 \quad 100 \quad 100 \quad 20 \quad 75 \quad 75 \quad 15 \quad 20 \quad 41 \quad 100 \quad 35 \quad 25 \quad 35 \quad 75] \quad (6)$$

Equation (7) is obtained by multiplying X^{T} by X and by Y.

$$\mathrm{X}^{T}\mathrm{X} = \begin{bmatrix} n & \sum X_i \\ \sum X_i & \sum X_i^2 \end{bmatrix} = \begin{bmatrix} 14 & 379 \\ 379 & 12{,}773 \end{bmatrix}, \quad \mathrm{X}^{T}\mathrm{Y} = \begin{bmatrix} \sum Y_i \\ \sum X_i Y_i \end{bmatrix} = \begin{bmatrix} 751 \\ 25{,}985 \end{bmatrix} \quad (7)$$

Each entry in Equation (7) can be read directly from the data. $\mathrm{X}^{\mathrm{T}}\mathrm{X}$ holds the number of students (n = 14), the total quota (ΣX = 379 GB), and the sum of squared quotas (ΣX^2 = 12,773). $\mathrm{X}^{\mathrm{T}}\mathrm{Y}$ holds the total expenditure (ΣY = 751 thousand IDR) and the cross-product ΣXY = 25,985. The fourteen observations have thus been reduced to just two linear equations, $14a + 379b = 751$ and $379a + 12{,}773b = 25{,}985$. Because this system is square, it can now be solved with a matrix inverse.

3.3 Inverse Matrix and Parameter Estimation

The inverse of a 2 × 2 matrix can be found from its determinant and adjoint (Equation 8). For our data, the determinant of $\mathrm{X}^{\mathrm{T}}\mathrm{X}$ is computed in Equation (9).

$$(\mathrm{X}^{T}\mathrm{X})^{-1} = \frac{1}{\det(\mathrm{X}^{T}\mathrm{X})}\,\mathrm{adj}(\mathrm{X}^{T}\mathrm{X}), \quad \det(\mathrm{X}^{T}\mathrm{X}) \neq 0 \quad (8)$$

$$\det(\mathrm{X}^{T}\mathrm{X}) = (14)(12{,}773) - (379)^2 = 178{,}822 - 143{,}641 = 35{,}181 \quad (9)$$

The determinant is not zero, so $\mathrm{X}^{\mathrm{T}}\mathrm{X}$ can be inverted and the normal equations have a single solution. Equation (10) shows the inverse obtained from Equation (8).

$$(\mathrm{X}^{T}\mathrm{X})^{-1} = \frac{1}{35{,}181}\begin{bmatrix} 12{,}773 & -379 \\ -379 & 14 \end{bmatrix} \approx \begin{bmatrix} 0.363065 & -0.010773 \\ -0.010773 & 0.000398 \end{bmatrix} \quad (10)$$

We then substituted Equations (7) and (10) into Equation (4). This gives the parameter vector in Equation (11) and the fitted model in Equation (12), where $\hat{Y}$ is in thousand IDR and X is in GB.

$$\hat{\beta} = \frac{1}{35{,}181}\begin{bmatrix} (12{,}773)(751) - (379)(25{,}985) \\ -(379)(751) + (14)(25{,}985) \end{bmatrix} = \frac{1}{35{,}181}\begin{bmatrix} -255{,}792 \\ 79{,}161 \end{bmatrix} \approx \begin{bmatrix} -7.271 \\ 2.250 \end{bmatrix} \quad (11)$$

$$\hat{Y} = -7.271 + 2.250X \quad (12)$$

We checked these results in two ways. Multiplying $\mathrm{X}^{\mathrm{T}}\mathrm{X}$ by the inverse in Equation (10) gave back the identity matrix, with off-diagonal entries below 3×10^{-15}, and recomputing the regression with a standard least-squares routine reproduced the same estimates to at least ten decimal places. The condition number of $\mathrm{X}^{\mathrm{T}}\mathrm{X}$ was about 4.65×10^3, the square of the condition number of X (about 68.2). With only two parameters, the precision lost in double-precision arithmetic is negligible. The situation changes when a model has many predictors or strongly correlated ones. Squaring the condition number then makes the normal equations sensitive to small errors, which is why QR decomposition of X, which never forms $\mathrm{X}^{\mathrm{T}}\mathrm{X}$, has been proposed for regression (Dorokhov et al., 2022); the accuracy of least-squares solvers is known to depend on conditioning (Meier et al., 2024). A simpler step for classroom use is to centre the predictor ($X_i - \bar{X}$). This turns $\mathrm{X}^{\mathrm{T}}\mathrm{X}$ into a diagonal matrix, so its inverse no longer has off-diagonal terms.

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3.4 Model Fit and Accuracy

With the parameters in hand, the next question was whether each coefficient differs significantly from zero and how well the model fits the data overall. Table 2 lists the estimates, their significance tests, and the goodness-of-fit statistics.

Table 2. Parameter estimates and goodness of fit of the regression model

Parameter	Estimate	Standard error	$t(12)$	p-value	95% confidence interval
a (constant)	−7.271	5.137	−1.415	0.182	[−18.464, 3.923]
b (data quota)	2.250	0.170	13.230	< 0.001	[1.880, 2.621]
$R^2 = 0.936$; adjusted $R^2 = 0.930$; $F(1, 12) = 175.02$, $p < 0.001$; standard error of estimate = 8.526 thousand IDR; MAPE = 12.60%					

Note. Estimates in thousand IDR; MAPE = mean absolute percentage error.

Based on Table 2, the slope $b = 2.250$ is clearly significant ($t(12) = 13.230$, $p < 0.001$), and its 95% confidence interval does not include zero. Put simply, one more gigabyte per month goes with about IDR 2,250 more in spending, and the true marginal cost probably lies between IDR 1,880 and IDR 2,620 per GB. Quota alone explains 93.6% of the variation in expenditure ($R^2 = 0.936$), and the overall model is significant ($F(1, 12) = 175.02$, $p < 0.001$). The constant tells a different story. At $a = -7.271$ it is not significantly different from zero ($p = 0.182$), and its confidence interval spans zero.

These statistics describe the fit with single numbers, but they cannot show where the line fits well and where it does not. For that, Figure 2 plots the observed data against the fitted regression line.

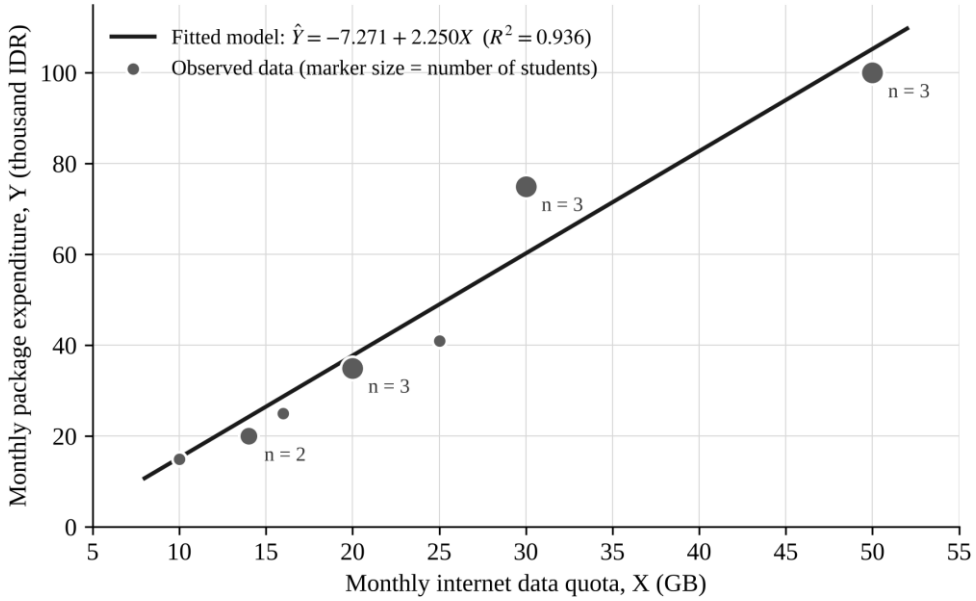


Figure 2. Observed monthly expenditure and the fitted regression line

As Figure 2 shows, the points stay close to the line across the whole range, so the positive linear trend is easy to see. The scatter around the line is not random, though. The three students who bought 30 GB packages sit well above it, while those who bought 14–25 GB and 50 GB packages fall slightly below. Table 3 puts numbers on these deviations for each quota level.

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Table 3. Observed and predicted monthly expenditure by data-quota level (thousand IDR)

Quota X (GB)	Students (n)	Observed Y	Predicted $\hat{Y}$	Residual ($Y - \hat{Y}$)	Absolute percentage error (%)
10	1	15	15.230	−0.230	1.54
14	2	20	24.231	−4.231	21.15
16	1	25	28.731	−3.731	14.92
20	3	35	37.731	−2.731	7.80
25	1	41	48.982	−7.982	19.47
30	3	75	60.232	14.768	19.69
50	3	100	105.235	−5.235	5.23
MAPE (weighted by the number of students) = 12.60%; root mean squared error = 7.894 thousand IDR					

Table 3 shows that the model predicts best at 10 GB (1.54% error) and 50 GB (5.23%) and worst at 14, 25, and 30 GB, where the error reaches about 19–21%. At every quota level except 30 GB the model overestimates spending; at 30 GB it falls short by about IDR 14,770. The 30 GB packages had the highest price per gigabyte in the sample (IDR 2,500), and they pull the fitted line upward and make it steeper. A MAPE of 12.60% means the estimate is off by roughly one-eighth of the actual amount on average. That is good enough for planning a monthly budget, but not for predicting what a particular package will cost. The residuals were also not normally distributed (Shapiro–Wilk $W = 0.700$, $p < 0.001$), which is not surprising when prices come in a few fixed steps set by operators. For this reason, the p-values in Table 2 should be treated as a guide rather than as exact probabilities.

3.5 Discussion

For this group of students, monthly quota turned out to be a strong linear predictor of what they spend on data, at a marginal cost of about IDR 2,250 per GB. This figure is higher than the average unit price in Table 1 (IDR 1,880 per GB). The reason is that bigger packages in our sample were not cheaper per gigabyte. Students paid IDR 2,500 per GB for 30 GB and IDR 2,000 per GB for 50 GB, but only IDR 1,430–1,750 per GB for packages of 10–20 GB. One would normally expect the opposite, a discount for buying more. The difference may come from the choice of operator, the validity period, or extra quota for specific applications, none of which we recorded.

The negative constant should not be read as a negative price. Because the estimate is not significantly different from zero and the smallest observed quota is 10 GB, the constant only positions the line within the observed range; the model reaches zero expenditure at about 3.2 GB, well outside the data. The model is therefore valid for interpolation within 10–50 GB (for example, it estimates that a 40 GB package costs about IDR 82,700) but not for extrapolation to very small or very large quotas. Making this range of validity explicit is part of the validation step of the modelling cycle, the step that undergraduates in the study by Ramírez-Montes et al. (2021) did not take.

The strength of the relationship found here ($R^2 = 0.936$) is much higher than that of regression models of broader student consumption, such as $R^2 = 0.189$ for pocket money and QRIS use (Wulandari et al., 2026) and $R^2 = 0.113$ for online shopping (Widiawati et al., 2025), and is closer to the $R^2 = 0.832$ reported for digital payments (Fathoni et al., 2025). The difference is reasonable: the present model relates a price to the quantity purchased, which is largely fixed by operators' tariffs, whereas consumption models involve behavioural factors such as impulsive buying. Our

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finding that quota size drives the price is in line with Al Mustofa & Nurmalitasari (2023), who likewise used quota size to predict package price, although they also added speed, region, and active period to their model. The quota levels in this study (10–50 GB, most often 14–30 GB) are consistent with Rahman (2023), in which most students used 11–20 GB and about 23% used 31–45 GB per month. Where Amoah et al. (2026) estimated how much extra online learning cost students, our model gives the price of each additional gigabyte, a figure students can use straight away when budgeting.

From a numerical standpoint, the results agree with Amanda et al. (2026) that the matrix inverse gives accurate solutions whenever the coefficient matrix is non-singular, while for larger systems Melani et al. (2026) found Gauss-Jordan inversion faster and more stable than the cofactor–adjoint method used here for the 2 × 2 case. Unlike the different errors that Bagaswara & Astuti (2025) reported for two solvers of the same system, the inverse-based solution in this study matched an independent least-squares routine to at least ten decimal places, which shows that a correctly implemented direct method yields the unique least-squares solution. As models grow, however, the normal-equations route squares the condition number, which is why QR decomposition has been proposed to overcome multicollinearity in regression (Dorokhov et al., 2022) and why the stability of newer least-squares solvers is judged against QR-based direct methods (Epperly et al., 2026; Meier et al., 2024). Reporting the condition number, as done here, is therefore a simple safeguard that applied studies of matrix methods can adopt.

For mathematics teacher education, this study walks through a full modelling cycle using data the students produced themselves. A familiar situation was simplified, written as a linear system, solved with a matrix inverse, and then interpreted and checked against reality. Working with real data of this kind helps with something pre-service teachers often find hard, making modelling tasks realistic and open (Hwang & Han, 2025), and it narrows the gap between theory and application reported in linear algebra (Ali & Avivor, 2026). Doing the calculation by hand also shows what software usually keeps out of sight: the entries of X^TX are simply sums of the data, and the stability of the solution depends on the condition number. This adds a computational side to the qualitative account of how students translate realistic problems into matrix representations (Putri & Zukhrufurrohmah, 2022). Pairing hand calculation with a software check also follows the recommendation to combine real contexts with technology when teaching pre-service teachers (Nopriyanti et al., 2025).

The main strength of this study is that nothing is hidden: every step from the raw data to the final model can be redone by hand, and the results were checked numerically. It also has clear limitations. The sample is small and was drawn by convenience from a single cohort, there is only one predictor, the data are self-reported, and the residuals are not normal because prices come in fixed steps. The model should therefore be read as a description of this group, not of Indonesian students in general. Within these limits, students get a simple rule of thumb of about IDR 2,250 for each extra gigabyte between 10 and 50 GB, and lecturers of numerical methods and linear algebra get a ready-made example that links normal equations, determinants, and matrix inverses to their students' own data.

4. Conclusion

We modelled the monthly internet data package expenditure of 14 mathematics education students with the matrix inverse method and obtained $\hat{Y} = -7.271 + 2.250X$. Each additional gigabyte adds about IDR 2,250 to monthly spending. Quota explained 93.6% of the variation in expenditure and

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the average prediction error was 12.60%, so the model can serve as a first estimate for budgeting, but only within the observed range of 10–50 GB. The matrix inverse gave an exact solution that can be traced step by step, although it becomes more sensitive as the condition number of X^TX grows. Further work should use larger and more varied samples, add predictors such as operator, validity period, and Wi-Fi access, and compare the inverse-matrix solution with QR or Cholesky factorisation and with non-linear pricing models.

5. Acknowledgments

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