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Modelling Bologna System Student Satisfaction: An Probit and Logistic Regression Analysis of Kurdistan Region Universities

Sarween A. Othman [1], Chnar Smko Abdullah [2], Kurdistan I. Mawlood [3]

[1,2,3] *Dep.of Statistics& Information-College of Administration and Economics/Salahaddin University Erbil, Erbil, Iraq*

sarween.a.othman@su.edu.krd [1], Chnar.abdullah@su.edu.krd [2], kurdistan.mawlood@su.edu.krd [3]

Abstract: The main goal of this study is to compare two statistic models, the Binary Logistic Regression model and the Probit Regression model, to find the most important things that impact how happy students are with bologna system. The study included survey data from 234 students attending four universities in the Kurdistan Region: Salahuddin University, Erbil Polytechnic University, Raparin University, and Soran university. The dataset included 20 explanatory variables related to the bologna systems academic, administrative, and financial aspects/ the binary logistic regression model identified five significant predictors of satisfaction, whereas the probit regression model identified six. We utilized the Akaike information Criterion (AIC) and the Bayesian information criterion (BIC) to compare the models. The findings demonstrated that the binary logistic regression model displayed a somewhat better fit than the probit regression model; however, both models provided valuable insights into the factors influencing student satisfaction. This work contributes to the limited research on assessing higher education reform in the Kurdistan region by demonstrating the comparative efficacy of two limited dependent variable models based on empirical evidence. The findings offer guidance for improving openness, recognition of qualifications, and institutional support within the bologna process. All analyses were conducted using SPSS V26 and MATLAB.

Keywords: Bologna System, Binary Logistic Regression Model probit Regression Model, Student satisfaction, AIC.

نمذجة رضا الطلاب عن نظام بولونيا: تحليل الانحدار اللوجستي والبروبيت في جامعات إقليم كردستان

م.م. سروين أسعد عثمان [١]، م.م. جنار سمكو عبدالله [٢]، أ.د. كوردستان إبراهيم مولود [٣]

[١،٢،٣] *قسم الاحصاء والمعلوماتية-كلية الادارة والاقتصاد/جامعة صلاح الدين-أربيل، أربيل، العراق*

sarween.a.othman@su.edu.krd [1], Chnar.abdullah@su.edu.krd [2], kurdistan.mawlood@su.edu.krd [3]

المستخلص: تهدف هذه الدراسة إلى مقارنة نموذجين إحصائيين، هما نموذج الانحدار اللوجستي الثنائي ونموذج انحدار بروبيت، لتحديد أهم العوامل المؤثرة على رضا الطلاب عن نظام بولونيا. شملت الدراسة بيانات استبيان من ٢٣٤ طالبًا يدرسون في أربع جامعات في إقليم كردستان: جامعة صلاح الدين، وجامعة أربيل التقنية، وجامعة رابارين، وجامعة سوران. تضمنت مجموعة البيانات ٢٠ متغيرًا تفسيريًا متعلقًا بالجوانب الأكاديمية والإدارية والمالية لنظام بولونيا. حدد نموذج الانحدار اللوجستي الثنائي خمسة مؤشرات تنبؤية مهمة للرضا، بينما حدد نموذج انحدار بروبيت ستة مؤشرات. استخدمنا معيار معلومات أكايكي (AIC) ومعيار معلومات بايز (BIC) لمقارنة النموذجين. أظهرت النتائج أن نموذج الانحدار اللوجستي الثنائي كان أكثر ملاءمةً من نموذج انحدار بروبيت؛ ومع ذلك، قدم كلا النموذجين رؤى قيّمة حول العوامل المؤثرة على رضا الطلاب. تُسهم هذه الدراسة في إثراء البحوث المحدودة حول تقييم إصلاح التعليم العالي في إقليم كردستان، وذلك من خلال إظهار فعالية نموذجين محدودين للمتغيرات التابعة، استنادًا إلى أدلة تجريبية. وتقدم النتائج إرشادات لتحسين الانفتاح، والاعتراف بالمؤهلات، والدعم المؤسسي ضمن عملية بولونيا. وقد أُجريت جميع التحليلات باستخدام برنامجي SPSS الإصدار ٢٦ وMATLAB.

الكلمات المفتاحية: نظام بولونيا، نموذج الانحدار اللوجستي الثنائي، نموذج الانحدار البروبتي، رضا الطلاب، AIC.

Corresponding Author: E-mail: sarween.a.othman@su.edu.krd

Introduction

This study investigates the implementation of the bologna process in higher education institutions in the Kurdistan region and evaluates student's satisfaction and perceptions of efficacy the Bologna framework seeks to harmonize higher education institutions via standardized degree cycles the implementation of ECTS to facilitate student mobility and enhanced quality assurance measures. The study used two types of limited dependent variable models to evaluate these aspects binary logistic regression and probit regression. The logistic model assesses the probability of student satisfaction using logistic link function, while the probit model is based on a laten construct related to the variables through the standard normal cumulative distribution, both models are calculated utilizing maximum likelihood estimation (MLE), guaranteeing consistent and robust parameter estimation. The performance of models is evaluated by AIC and BIC to identify the predictors that most significantly influence student's satisfaction with the bologna system. This analysis identifies a significant deficiency in regional literature and offers evidence-based recommendations for university leadership and higher education authorities to enhance the execution of bologna reforms the examination of prior studies provides crucial conceptual foundation for the current research, facilitating a more precise interpretation of results.

1st: Statement of the Problem

This study provides valuable empirical insights into factors influencing student's satisfaction with bologna process. Its findings help universities and educational authorities' pinpoint areas that require improvement particularly in relation to transparency, curriculum organization and the allocation of academic and administrative resources.

2nd: Importance of the Study

This study offers significant empirical insights into the determinates affecting student's satisfaction with the bologna process. The findings assist universities and educational authorities in identifying areas necessitating enhancement, especially with openness, curriculum structure, and the distribution of academic and administrative resources

3rd: Objectives

- To assess student satisfaction with the bologna process in Kurdistan universities.
- To identify the significant predictors of satisfaction using logistic and probit regression.
- To compare to performance and fit of both models using AIC and BIC.
- To provide recommendation for enhancing the implementation of the bologna process.

4th: Models for Limited Dependent Variables

When the dependent variable is categorical instead of continuous, the assumptions of conventional linear regression is breached. Consequently, models specifically tailored for constrained dependent variables are utilized methods, the binary logistic regression and probit regression models are among the most commonly utilized methods, both estimating event probabilities using maximum likelihood techniques. The fundamental distinction between the two resides in the selection of the link function the logistic distribution, whereas the probit model utilizes the cumulative standard normal distribution.

1- Binary Logistic Regression Model

Binary logistic regression is extensively employed to model the likelihood of a binary outcome based on a collection of explanatory variables. The dependent variable assumes only two possible values typically represented as 0 and 1 and logistic regression addresses the constraints of traditional linear regression when managing categorical response commonly referred to as the logit model, it is the most widespread kind of logistic modeling, despite the existence of variants for multinomial the ordinal data. Its applications typically encompass two categories analyzing the relationship between variables or developing predictive models [2]. A primary advantage of logistic regression is its lack of stringent assumptions, such as linearity between predictors and outcomes, normally distributed errors, or homoscedasticity. This renders it especially appropriate for many fields that engage with binary outcomes. The logistic distribution supports several predictor types quantitative, qualitative, mixed ordinal, or binary demonstrating its analytical versatility. Its uncomplicated execution, limited assumptions, and resilience across various sampling methodologies enhance its widespread application as a fundamental technique in applied statistical analysis.

The response variable Y is binary, with the probability P (Y = 1) being influenced by a vector of predictor variables $= x$. The objective is to create a model (1) for this relationship.

$$p = P(Y = 1 \mid X = x) = \frac{e^{\beta_1+\beta_0 x}}{1+e^{\beta_1+\beta_0 x}} \quad \dots (1)$$

This relationship produces an S-shaped curve, reflecting its inherent non-linearity. In the context β denotes the coefficient associated with the predictor variable x in the regression framework. When extended to include several explanatory variables, the expression is reformulated into the standard logistic regression model, which preserves linearity in the predictors and is generally considered more practical and informative than the basic logistic response from (2).

$$p = P\left(Y = 1 \mid X = x_1, \dots, X_p = x_p\right) = \frac{e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_p x_p}}{1+e^{\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_p x_p}} \quad \dots(2)$$

Where p (x_1, ..., x_k) represents the explanatory variables, p(x) lies within range of [0,1] or meets the probability condition. By transforming p(x), we derive another function (3). [3]

$$log\left(\frac{p(\bar{x})}{1-p(\bar{x})}\right) = \beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p \quad \dots (3)$$

The logistic regression model utilizes maximum likelihood estimation (MLE) to determine the relationship between a binary dependent variable and independent variables (continuous or categorical). MLE finds the parameters that maximize the likelihood of observing the given data, which can be expressed through the likelihood function (4).

$$f(y \mid \beta) = \prod_{i=1}^{n} \frac{n_i!}{y_i!(n_i-y_i)!} p_i^{y_i} (1-p_i)^{n_i-y_i} \quad \dots (4)$$

Probability of success in the ithith trial. By transforming the likelihood function into a log-likelihood function (5)

$$l(\beta) = \sum_{i=1}^{n} \left(y_i \ln p_i + (1-y_i) \ln(1-p_i)\right) \quad \dots (5)$$

We derive the conditions for maximizing the likelihood by taking the derivative with respect to the coefficient β and setting them to zero. This results in a system of nonlinear equations that can be solved using the Newton-Raphson method. The iterative approach allows convergence to the maximum likelihood estimates, while the second derivatives provide the variance-covariance matrix of the estimates.

2- Probit Regression Model

The probit model is a nonlinear regression method developed for binary response variables, where the dependent variable takes the values zero or one. It is based on the assumption of an unobserved latent variable defined as $y_i^* = I_i = \alpha + \beta x_i$, where x_i is observed while y_i^* is not directly measurable. The observed outcome is determined by the rule $y_i = 1$ if $y_i^* > 0$, and $y_i = 0$ otherwise. This latent variable framework allows a probabilistic interpretation of the relationship between predictors and outcomes.
To ensure probabilities remain in the valid interval [0,1], the probit model assumes that the error term follows a standard normal distribution. This leads to the use of the standard normal cumulative distribution function $\Phi(\cdot)$, to define the probability in the equation (6):

$$P(y_i = 1) = 1 - \Phi\left(\frac{-\alpha-\beta x_i}{\sigma}\right),\ P(y_i = 0) = \Phi\left(\frac{-\alpha-\beta x_i}{\sigma}\right) \quad \dots (6)$$

Equivalently, the model may be expressed as($F^{-1}(P_i) = F^{-1}(I_i) = \alpha + \beta x_i$), which connects the probability with the linear predictor through the inverse cumulative distribution function. This nonlinear specification circumvents the primary limitation of the linear probability model, which can produce fitted values beyond the unit interval and enforces an implausible linearity on the conditional probability function.

The coefficients of the probit model are estimated by maximum likelihood. For binary outcomes y_t, the likelihood function (7) takes the form.
with the log-likelihood function (8):

$$L = \prod_{t=1}^{T} [\Phi(\beta' x_t)]^{y_{t+h}}[1 - \Phi(\beta' x_t)]^{1-y_{t+h}} \quad \dots (7)$$

$$ln\ L = \sum_{t=1}^{T} \left[y_{t+h} ln\ \Phi(\beta' x_t) + (1 - y_{t+h}) ln\left(1 - \Phi(\beta' x_t)\right)\right] \quad \dots (8)$$

Under conventional regularity conditions, maximum likelihood estimators are consistent and asymptotically normal, ensuring their statistical validity and efficiency. While weighted least squares can serve as an approximation substitute, it typically exhibits inferior performance compared to maximum likelihood. A unique feature of the probit model is the interpretation of its coefficients. A one-unit change in a predictor influences the latent variable linearly; nevertheless, the transition from this latent index to the observed binary outcome is nonlinear, as it involves the cumulative normal distribution. Consequently, the coefficients are not inherently apparent. Consequently, marginal effects are commonly reported, as they elucidate how fluctuations in an explanatory variable correspond to alterations in the anticipated likelihood. These marginal effects offer a more lucid and interpretable assessment of each variable's impact in the context of binary response data.

3- Evaluating the Significance of Model Predictions

A. Pearson's statistic and Deviance

In regression models for categorical outcomes estimated by maximum likelihood, such as logistic and probit models, the goodness-of-fit is often evaluated using Pearson's Chi-square statistic and Deviance. In addition, both measurements should be minimum, while their associated significance values should be large, a p-value greater than (0.05) indicates that the null hypothesis of good fit cannot be rejected, suggesting that the model adequately represents the data. For computation, the observed frequencies of cases are denoted as O_{ij} and the expected frequencies as E_{ij}, across a table with p rows and q columns, the formulas (9)(10):

$$\chi^2 = \sum_{i=1}^{p} \sum_{j=1}^{q} \frac{(O_{ij}-E_{ij})^2}{E_{ij}} \quad \ldots (9)$$

$$D = 2\sum_{i=1}^{p} \sum_{j=1}^{q} O_{ij} \ln\left(\frac{O_{ij}}{E_{ij}}\right) \quad \ldots (10)$$

The degrees of freedom are given by $(p-1)(q-1)$, adjusted for marginal totals.

B- Wald Test

The Wald test is characterized by the ratio of the maximum likelihood estimate to its standard deviation. The Wald statistic is calculated using the formula (11):

$$W = \frac{\hat{\beta}_j}{S{\cdot}E(\hat{\beta}_j)} \quad \ldots (11)$$

For large samples, W follows a standard normal distribution with mean 0 and variance 1. The hypotheses are:

$H_0: \beta_j = 0$

$H_1: \beta_j \neq 0.$

If the absolute value of W surpasses the threshold $\lambda_{\alpha/2}$, we can reject the null hypothesis at the chosen significance level α. Additionally, the Wald statistic can be represented as function (12):

$$W_k^2 = \left[\frac{b_k}{S{\cdot}E(b_k)}\right]^2 \quad \ldots (12)$$

Where b_k denotes the coefficient of the variable and S.E. refers to the standard error involved in estimating this coefficient. This statistic is asymptotically distributed as a chi-squared distribution and adheres to a standard normal distribution when considering a single variable (i.e., W_1). The Wald statistic evaluates how each predictor individually contributes to the model, where a statistically significant Wald statistic suggests that the variable should be kept in the model.

C- Cox and Snell R² and Nagelkerke R² are measures for assessing the goodness of fit

The formulas for the Cox and Snell R² and Nagelkerke R² statistics for dichotomous variables are as follows:

$$Nagelkerke\ R^2 = \frac{\left[1-\left(\frac{D_0}{D_1}\right)^{\frac{2}{N}}\right]}{\left[1-(D_0)^{\frac{2}{N}}\right]} \quad \ldots (13)$$

In this equation (13), N is the total amount of cases; if the model accurately fits the data, the anticipated value for both statistics would be 1. However, the Cox-Snell R^2 statistic does not reach this maximum value, while the Nagelkerke R^2 statistic modifies the Cox-Snell R^2 to achieve a maximum of 1. Both statistics are useful for assessing the strength of the relationship between dependent and independent variables.

4- Model Selection

An alternate model selection methodology employs probabilistic measures to evaluate both dataset performance and model complexity. The optimal model is generally selected based on its performance on a hold-out test dataset. Examples encompass the Akaike Information Criterion and the Bayesian Information Criterion.

A. Akaike's Information Criterion

The Akaike Information Criterion (AIC), initially in traduced by Akaike in 1974 is a widely utilized method for evaluation statistical models. It provides an estimation of prediction error and facilitates the evaluating of the comparative performance of rival models applied to the identical dataset. AIC represent a balance between goodness of fit and model complexity, with lower values signifying a more suitable and parsimonious model.

The AIC is calculated using the formula: AIC = –2 log (maximized likelihood) + 2 × (number of estimated parameters).

The term -2 log (maximum likelihood) denotes the deviation, indicating the lack of fit, whereas the subsequent term enforces a penalty for the inclusion of more parameters. To facilitate a comprehensive comparison among many model forms, the AIC can be expressed as a generic function (14):

$$AIC = -2\log(likelihood) + 2(p + k) \quad \ldots (14)$$

K is the complete number of model parameters, which includes both the variables in the model and the intercept. The log-likelihood serves as a metric for model fit, typically derived from statistical output.

B. Bayesian Information Criterion

The Bayesian Information Criterion (BIC) is a prominent and extensively utilized instrument in statistical model selection. Its appeal stems from its computational simplicity and successful performance across several modeling frameworks, including Bayesian applications where prior distributions may be difficult to ascertain. The criterion was established by Schwarz (1978) as an asymptotic estimate for a transformation of the Bayesian posterior probability of a candidate model, is the one that produces the lowest BIC value. The general formula for BIC is expressed as a function (15):

$$BIC = -2\, loglikelihood + \log N^* k \quad \ldots (15)$$

Where it relies on log-likelihood (L), the number of parameters (k), and the total number of observations (N).

5th: Results and Discussion:

This section employed two limited dependent variable models' logistic regression and probit regression to analyze the data about the implementation and impact of bologna system in higher education following the presentation of the empirical findings, the efficacy of the two models was evaluated using the Akaike information criterion and the Bayesian information criterion to ascertain the best appropriate model for the dataset. The analyses were conducted utilizing SPSS (Version 23) and MATLAB.

1- Data Collection

This research investigates student satisfaction on the implementation of the bologna system in higher education at four universities in the Kurdistan region: Salahuddin University, Erbil polytechnic University, Raparin University, and soran university. The analysis is derived from 234 verified questionnaires. The survey included 20 independent variables that represented demographic data, including gender, age, and level of study, alongside students' assessments on academic, administrative, and financial aspects of the bologna framework.

Table (1): Data Description

Variable names	Symbol	Categorization	N
-Overall, are you satisfied with the implementation of the Bologna system in your field of study	Y	0=No	٨٩
		1=Yes	١٤٥
Gender	X1	1=Male	١٣١
		2=Female	١٠٣
Age	X2	1=19-22	١٣٨
		2=23-26	٢١
		3=27-30	٢١
		4=31-34	١١
		5=35-38	١٥
		6=39+	٢٨
Level of learning	X3	1=Bachelor	١٤٧
		2=Higher Diploma	٢٧
		3=Master	٣٣
		4=Doctorate	٢٧
How familiar are you with the Bologna system and its principles	X4	1= I'm very familiar	١٦٧
		2= I'm fairly familiar	٢٥
		3= I'm not familiar with it at all	٤٢
Do you understand the goals and principles of the Bologna system	X5	1=Yes	49
		2= Yes, to some extent	122
		3=No, to some extent	18
		4=No	45
Do you think Bologna will be fully implemented in your education system	X6	1=Yes	32
		2= Yes, to some extent	80
		3=No, to some extent	122
		4=No	0
How do you assess the impact of the information about the Bologna system available at your university on the quality of your education	X7	1=Good	41
		2= Relatively good	100
		3= Relatively bad	37
		4=Bad	56
Do you think the Bologna system has improved the comparison and recognition of academic degrees in Kurdistan universities	X8	1=Yes	48
		2= Yes, to some extent	69
		3= I don't know	60
		4= No, to some extent	31
		5= No	26
The European Credit Transfer and Accumulation System (ECTS) is effective in facilitating student mobility	X9	1=Yes	37
		2= Yes, to some extent	95
		3= I don't know	53
		4= No, to some extent	24
		5= No	25
Do you think the Bologna system addresses the issue of graduate employment well	X10	1=Yes	41
		2= Yes, to some extent	69
		3= I don't know	53
		4= No, to some extent	45
		5= No	26
Do you think the Bologna system has increased competition and cooperation between Kurdistan universities	X11	1=Yes	54
		2= Yes, to some extent	88
		3= I don't know	45
		4= No, to some extent	21
		5= No	26
How would you assess the overall transparency and comparability of qualifications under the Bologna system	X12	1=Yes	40
		2= Yes, to some extent	92
		3= I don't know	50
		4= No, to some extent	28
		5= No	24
Is the Bologna system effective in promoting interdisciplinary and multidisciplinary programs	X13	1=Yes	41
		2= Yes, to some extent	98
		3= I don't know	29
		4= No, to some extent	39
		5= No	27

Do you think the Bologna system has led to a greater focus on student-centered learning and teaching methods	**X14**	1=Yes 2= Yes, to some extent 3= I don't know 4= No, to some extent 5= No	43 89 40 41 21
In your opinion, does the Bologna system deal well with the issue of research and innovation in higher education	**X15**	1=Yes 2=Yes, to some extent 3= I don't know 4= No, to some extent 5= No	34 92 48 36 24
Has the implementation of the Bologna system been equal in Kurdistan universities	**X16**	1=Yes 2=Yes, to some extent 3= I don't have any information 4= No, to some extent 5= No	18 37 106 39 34
Has the student's financial situation created obstacles to implementing the Bologna system in your studies	**X17**	1=Yes 2=Yes, to some extent 3=No, to some extent 4=No	38 58 109 29
In your opinion, is this system fair at all levels among students	**X18**	1=Yes 2=Yes, to some extent 3= I don't know 4= No, to some extent 5= No	31 73 46 40 44
Has the lack of adequate college facilities and services prevented the full implementation of the Bologna system	**X19**	1=Yes 2=Yes, to some extent 3= I don't know 4= No, to some extent 5= No	65 69 36 35 29
What additional comments or suggestions do you have about the impact of the Bologna system on your field of study	**X20**	1=It promotes greater transparency around academic programs 2=It encourages flexibility and adaptability in the education system 3=Supports interdisciplinary program development. 4=Greater emphasis on employability and skills development 5=Further coordination of quality assurance is required for the continued implementation of reforms 6=Allow for continuous curriculum improvement 7=I have no additional comments or suggestions	17 69 26 19 28 47 28

Table (1) shows the study variables, their coding structure, and the distribution of participants among the specified groups. The dependent variable Y represents total student satisfaction with the bologna system, coded as 0 for "No" and 1 for "Yes." The independent variables (X1-X20) encompass several elements, such as student's awareness of bologna principles, clarity of institutional information, degree recognition, financial obstacles, and the sufficiency of university resources. The results indicate that the majority of participants were undergraduate students, with 138 individuals aged between (19 and 22) years. The sample comprised (131 male and 103 females) participants. Ninety-eight people conveyed satisfaction with the system. A considerable number of students demonstrated familiarity with the bologna framework and its objectives; nonetheless, perspectives differed concerning its efficacy in augmenting employability, facilitating degree recognition, and ensuring uniform implementation across universities. Moreover, numerous respondents identified financial hardships and insufficient facilities as persistent issues.

2- Model Fitting

This research employed two limited dependent variable models. Binary Logistic Regression and probit regression, to evaluate the implementation of the bologna system. The dependent variable (Yi) represents student's overall satisfaction, classified as a binary outcome. The logistic model assessed satisfaction probability based on demographic characteristics and perception-based variables, whereas the probit model provided a different approach via a latent-response framework based on the cumulative normal distribution. Both models were estimated by maximum likelihood ratio test, facilitating a thorough evaluation of model adequacy and prediction accuracy.

A. Result for Binary Regression Model

In table (2) the wald statistics and its significant level were used to assess the effect of each factor on satisfaction with thr bologna system, Exp(*B*)=0.050), X7 (impact of university-provided information, Exp(*B*)=0.121), X8 (perceived improvement in degree recognition, Exp(B)=0.220), X17 (financial situation as a barrier, Exp(*B*)=0.293), and X20 (additional comments or suggestions, Exp(*B*)=0.357). All had odds ratios below 1, indicating that less favorable responses in these areas markedly reduced satisfaction. For examples, lower familiarity decreased the odds of satisfaction by about %95, and poorer ratings of information quality reduced them by %88. Variables X9, X13, and X19 approached significance, while the remaining predictors (X1, X2, X3, X5, X6, X10, X11, X12, X14, X15, X16, X18) were not significant in this model.

Table (2): Binary Regression Model

Variables in the Equation						
Variables	**B**	**Std. Error**	**Wald**	**df**	**Sig.**	**Exp(B)**
X1	.712	1.007	.499	1	.480	2.038
X2	.045	.448	.010	1	.919	1.047
X3	-.027	.885	.001	1	.976	.973
X4	-3.003	1.130	7.062	1	.008	.050
X5	-.251	.609	.170	1	.680	.778
X6	-1.103	.751	2.156	1	.142	.332
X٧	-2.114	.565	14.015	1	.000	.121
X٨	-1.515	.654	5.365	1	.021	.220
X9	1.170	.682	2.944	1	.086	3.221
X10	.334	.513	.425	1	.515	1.397
X11	.356	.451	.625	1	.429	1.428
X12	-.863	.493	3.063	1	.080	.422
X13	-.787	.407	3.734	1	.053	.455
X14	-.572	.614	.868	1	.351	.564
X15	.593	.501	1.396	1	.237	1.809
X16	-.773	.567	1.863	1	.172	.461
X17	-1.227	.599	4.198	1	.040	.293
X18	.000	.362	.000	1	.999	1.000
X19	.678	.356	3.623	1	.057	1.970
X20	-1.030	.306	11.302	1	.001	.357
Constant	22.590	4.802	22.129	1	.000	6466848978.567

The prediction equation (16) with significant predictors is:

$$\hat{y} = 22.590 - 3.003(X4) - 2.114(X7) - 1.515(X8) - 1.227(X17) - 1.030(X20)$$

These results suggest that improving familiarity, information quality, recognition of qualifications, and reducing financial barriers are key to enhancing satisfaction with Bologna System implementation in Kurdistan universities.

B. Result for Probit Regression Model

Table (٣) presents the results of the probit regression analysis, including the coefficients and significance tests for all independent variables. 6 variables were statistically significant at ($p < 0.05$), familiarity with the Bologna System and its principles (X4 = 1.566, p = .005), perceived impact of Bologna-related information (X7 = 1.061, p < .001), recognition of academic degrees across Kurdistan universities (X8 = 0.761, p = .024), financial situation as an obstacle (X17 = 0.633, p = .037), adequacy of college facilities and services (X19 = –0.379, p = .047), and students' additional comments or suggestions (X20 = 0.541, p < .001). Positive coefficients indicate that Higher predictor values correlate with an augmented likelihood of a positive opinion of the Bologna System, whereas negative coefficients signify a diminished probability. Two variables, overall transparency and comparability of qualifications (X12 = 0.496, p = .057) and effectiveness in promoting interdisciplinary programs (X13 = 0.419, p = .057), neared significance, indicating a possible impact on the outcome. The other factors, especially (Gender, Age, level of learning, and opinions of student-centered learning, research, and innovation) were not statistically significant, suggesting they do not substantially enhance the model.

Table (3): Probit Regression Model

Variables in the Equation						
Variables	**B**	**Std. Error**	**Wald**	**df**	**Sig.**	**Exp(B)**
X1	-.432	.4806	.807	1	.369	.649
X2	-.011	.2419	.002	1	.964	.989
X3	.048	.4700	.011	1	.918	1.050
X4	1.566	.5563	7.925	1	.005	4.787
X5	.165	.3306	.248	1	.618	1.179
X6	.504	.3948	1.630	1	.202	1.655
X7	1.061	.2704	15.391	1	.000	2.889
X8	.761	.3369	5.106	1	.024	2.141
X9	-.542	.3340	2.630	1	.105	.582
X10	-.233	.2742	.720	1	.396	.792
X11	-.156	.2403	.420	1	.517	.856
X12	.496	.2606	3.621	1	.057	1.642
X13	.419	.2206	3.612	1	.057	1.521
X14	.289	.3190	.821	1	.365	1.335
X15	-.356	.2630	1.828	1	.176	.701
X16	.347	.2977	1.361	1	.243	1.415
X17	.633	.3040	4.335	1	.037	1.883
X18	.022	.1980	.013	1	.910	1.023
X19	-.379	.1907	3.946	1	.047	.685
X20	.541	.1505	12.901	1	.000	1.717
Constant	-11.524	2.1756	28.059	1	.000	9.888E-6

The results of probit regression analysis, the prediction equation (17) using the significant variables is as follows:

$$\hat{y} = \Phi(-11.524 + 1.566X_4 + 1.061X_7 + 0.761X_8 + 0.633X_{17} - 0.379X_{19} + 0.541X_{20})$$

These results indicate that familiarity with the Bologna System X4, the perceived impact of Bologna-related information X7, recognition of academic degrees across Kurdistan universities X8, financial obstacles X17, adequacy of college facilities and services X19, and students' additional comments or suggestions X20 are key predictors of satisfaction with the Bologna System.

Table (4): Goodness of Fit

Probit Regression Model			
	Value	**Df**	**P Value**
Deviance	59.551	190	.313
Pearson Chi-Square	131.786	190	.694
Log Likelihood	-29.775		
Likelihood Ratio Chi-Square	251.309	21	.000

Table (4) indicates that the probit regression model has a significantly superior fit compared to the intercept only model, as evidenced by the likelihood ratio test (χ^2_{21} = 251.309, $p < 0.001$). This important result verifies that the included predictors together meaningfully account for changes in the outcome variable. The goodness of fit statistics additionally corroborates the model's adequacy. The Pearson Chi-square statistics is 131.786, accompanied by a p-value of 0.694; the Deviance statistics is 59.551, with a p-value of 0.313. Given that both p-value above (0.05), there is no significant difference between the observed and predicted frequencies. This signifies that the model aligns well with the real data and adeptly represents its primary structural patterns, showing a robust and dependable overall fit.

C. Model Comparison Using AIC and BIC

AIC and BIC are used in statistical model selection to compare models based on goodness-of-fit and penalize complexity. The model with the lowest AIC or IC is preferred, indicating a better balance between accuracy and simplicity.

Table (5): comparing models with AIC, BIC

Models	N. of Parameters	-2 Log Likelihood	AIC	BIC
Binary Logistic Regression	20	58.735	98.735	167.835
Probit Regression	20	59.551	99.551	168.651

Table (5) indicates that, based on the comparative statistics, the Binary logistic regression model demonstrates a marginally superior performance relative to the probit regression model. Despite both models being estimated with an identical number of parameters (20) and the same sample size (N = 234), the logistic regression model resulted in lower AIC (98.735 vs. 99.551) and BIC adequacy, these findings imply that the logistic regression model offers a more suitable representation of the factors influencing student satisfaction with the Bologna System.

D. Model Adequacy and Fit

In the process of implementing binary logistic regression, we obtained the following outcomes and interpretations:

Table (6): Model Summary and Hosmer–Lemeshow Goodness-of-Fit Test

−2 Log Likelihood	Cox & Snell R^2	Nagelkerke R^2	Hosmer–Lemeshow χ^2	df	Sig.
58.735	0.660	0.897	2.258	8	0.972

In table (6) the adequacy of the binary logistic regression model was evaluated using the Model Summary statistics and the Hosmer and Lemeshow goodness-of-fit test. The Model Summary indicated a (-2 Log Likelihood) value of 58.735, with a Cox & Snell R^2 of (0.660) and a Nagelkerke R^2 of (0.897), suggesting that the model explains a substantial proportion of the variance in the dependent variable.

For the Hosmer and Lemeshow Test, the hypotheses were:
H_0 **:** the model adequately fits the data.
H_1 **:** the model does not adequately fit the data.
The test produced a Chi-square statistic of 2.258, having (8) degrees of freedom and a significance level of 0.972. Since ($p > 0.05$), there is insufficient evidence to reject the null hypothesis, suggesting that the model adequately fits the observed data.

E. Distribution of Standardized Residuals Relative to Predicted Probabilities

A scatterplot was utilized to evaluate the suitability of the logistic regression model by analyzing the relationship between standardized residuals and projected probabilities. Figure (1) illustrates the distribution pattern of these residuals about the models anticipated values.

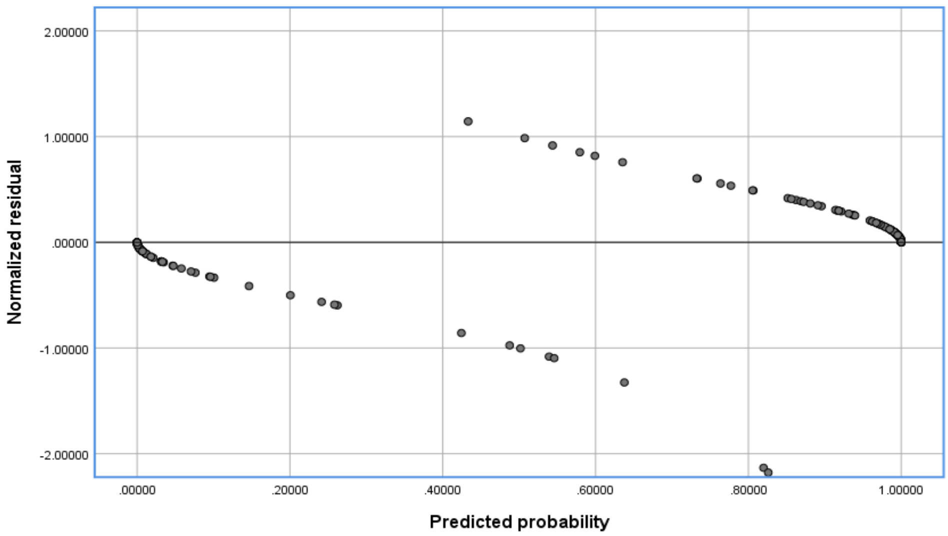

Figure (1): Scatterplot of standardized residuals versus predicted probabilities

The scatterplot indicates that the logistic regression model well fit data, as the residuals are randomly distributed about zero, exhibiting no dissemble trend or significant outliers.

6th: Conclusions

The principle finding of the study about the Bologna process, based on a model calculated from 234 students, was that:

- The majority of responders were undergraduates, predominantly aged between 19 and 22 years, comprising 131 males and 103 females.
- Descriptive statistics indicated that around 62% of students conveyed a favorable evaluation of the Bologna system: however, financial and administrative challenges emerged as significant concerns.
- The results of binary logistic regression were utilized to determine the primary predictors of satisfaction: familiarity with the Bologna system, clarity of institutional information, recognition of degrees, financial challenges. and the student's supplementary remarks.
- Probit regression showed the same main predictors of student satisfaction with the addition of quality teaching and quality of support from faculty.
- Both AIC and BIC indicated that the binary logistic regression model (AIC = 98.735; BIC = 167.835) provided a superior fit for the data compared to the probit model (AIC = 99.551; BIC = 168.651), consequently both models possessed a same number of parameters and sample size.
- The primary factors influencing student satisfaction included familiarity with the Bologna System, transparency of information, degree recognition, and financial challenges, highlighting the

necessity for enhanced communication to academic students, improved academic support quality, and alleviation of student's financial burdens.

➢ The distribution of standardized residuals indicates that this logistic regression model adequately fits the data, exhibiting no dissemble systemic bias or outlier patterns.

7th: Recommendation

➢ Improve student comprehension of the Bologna process with more explicit communication and direction
➢ Ensure transparency and fairness in the recognition of academic qualifications.
➢ Reduce financial barriers that affect student's engagement with the system.
➢ Provide continuous training for academic and administrative staff.
➢ Strengthen coordination among universities to ensure consistent implementation

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