Overcoming Overdispersion on Direct Mathematics Learning Model Using the Quasi Poisson Regression

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ABSTRACT

The study aims to overcome the overdispersion in the final exam score of Calculus subject. The occurrence of a gap in the score is inseparable from the influence of internal factors and external factors. The internal factors are factors that originate within students themselves. In contrast, external factors are factors that exist outside of students that can affect students' success or failure, such as learning environment, the physical environment where the exam takes place, infrastructure and facility that are owned and used by students, and their condition during the exam. The connection of these factors to the gap in final exam scores can be approached with Poisson regression analysis because Poisson Regression assumes a Poisson distribution of response variables with equidispersion. It is necessary to conduct a research to find out the factors that cause the diversity of the final score in order to overcome, that is by implementing direct learning. The results obtained show that with the application of direct mathematics learning, there is no overdispersion, while the low score of the final exam results in an increase, resulting in the variance of final exam results to be smaller than the average score.

Keywords: Overdispersion, quasi-Poisson regression, Direct Math learning, Calculus subject.

1. INTRODUCTION

The significant goal of lecturers for teaching in the class is helping students to enrich the learning goals [1]. In the class of mathematics teaching, the students will get the wide range of information in the form aspects of math from the lecturers [2–4]. The direct mathematics learning strategy through a variety of active knowledge is a way to introduce students to the taught subject matter [5]. This method is suitable for all class sizes with any subject matter. When applying the mathematics learning model directly, the lecturer must demonstrate the knowledge or skills that will be trained step by step to the students [6]. In learning, because the role of lecturers is very dominant, they are demanded to become attractive models for the students [7]. If the role of a lecturer is not dominant, then, in the evaluation of the final grade of the subject, in this case one of the basic subject, namely calculus, it turns out that the

scores obtained show great diversity among students' grades, the solution is needed to avoid the occurrence of variance greater than average score; this is called overdispersion.

Quasi-Poisson regression analysis is included in non-linear regression whose, response variable is modelled as a Poisson distribution. Poisson regression represents equidispersion, which is a condition in which the mean and response variance are the same. However, there is sometimes an overdispersion phenomenon in the data modeled by Poisson regression. Overdispersion means that the variance is greater than the mean [8]. To overcome the case of data overdispersion, several models have been developed such as the negative binomial, quasi-Poisson, generalized Poisson, and zero inflated Poisson models. Quasi-Poisson and negative binomials are used more often due to the fact that they are readily available in the software and generalized

easily into Poisson cases. Quasi-Poisson in certain counts is more accurate than negative binomials [9–11] [9].

Based on the description above, the author shall analyse the data on the final exam scores of students participating in the Calculus subject at one of the state tertiary institutions in Makassar city, Indonesia, using the direct mathematics learning model with the quasi-Poisson approach, related to external factors that influence resulting in a large diversity of values.

2. LITERATURE REVIEW

2.1. *Direct Learning model*

The Direct Mathematics Learning Model is a learning model emphasizing on the mastery of concepts and behavioral changes by prioritizing a deductive approach with the following characteristics: (1) transformation and direct skills; (2) learning is oriented towards specific goals; (3) structured learning material; (4) structured learning environment; and (5) structured by lecturers [12]. The lecturer acts as a conveyor of information, and in this case the Lecturer should use a variety of suitable media, such as films, tape recorders, pictures, demonstrations, and so on [13]. The information conveyed can be in the form of procedural knowledge (i.e. knowledge of how to do something) or declarative knowledge, (i.e. knowledge of something which can be in the forms of facts, concepts, principles, or generalizations) [14]. Critics on using this model include that this model cannot be used all the time and not for all learning purposes and for all students [15]. In the direct learning model, there are five very important phases. The lecturer starts the lesson with goals and background of learning, and prepares students to accept the lecturer's explanation [16].

This preparation and motivation phase is then followed by a presentation of the teaching material being taught or demonstration on certain skills [17]. This lesson also includes providing opportunities to the students to do exercises and providing feedback on student success. In the exercises and providing certain feedback phase, the Lecturer always needs try to provide opportunities to the students to apply the knowledge or skills learned to real life situations. The summary of the five phases can be seen in Table 1.

Table 1. Syntax of Direct Math Learning models

Phases	Lecturer's Behavior
PHASE 1 Conveying goals and preparing students	The lecturer conveys the objectives, background information on the lesson, the importance of this lesson, thus preparing students for learning
PHASE 2 Demonstrating knowledge and skills	The lecturer demonstrates the right skills or presents information, step by step
PHASE 3 Guiding exercise	The lecturer plans and provides initial exercise guidance
PHASE 4 Checking understanding and providing feedback	Checking whether students have successfully completed the task and providing feedback
PHASE 5 Providing exercise opportunities for advanced exercise implementation	The lecturer prepares the opportunity to carry out further exercise with special attention to the application of more complex situations and everyday life.

Source : [18]

Direct mathematics learning requires careful planning and implementation on the part of the Lecturer [19]. To be effective, Direct Mathematics Learning requires that each skill or content detail be carefully defined. Demonstrations and exercise schedules must also be planned and carried out carefully. Although learning objectives can be planned together by the Lecturer and students, this model is mainly centered on the Lecturer [20]. The learning management system conducted by the Lecturer must ensure the involvement of students, especially through planned attention, listening, and recitation. This does not mean that learning is authoritarian, cold, and humorless. This means that the environment is task oriented and the members have high expectations for the students to achieve good learning outcomes [21].

The steps of the direct teaching model basically follow the general learning patterns. These cover the following stages [22]: (1) *Preparing and motivating students*, the purpose of this initial step is to attract and focus students' attention as well as motivating them to participate in the lesson. (2) *Conveying objectives*, students need to know clearly why they are participating in a particular lesson and they need to know what they should be able to do after completing their participation in the lesson. (3) *Presentation and Demonstration*, this is the second phase of direct teaching. Lecturer delivers presentations or demonstrations of knowledge and skills. The success key for these activities are the level of clarity of the demonstrated information and adherence to effective demonstration patterns. (4) *Achieving clarity*, research results consistently show that the ability of Lecturers to provide clear and specific information to students has a positive impact on the teaching and learning process. (5) *Demonstrating,* direct teaching holds fast to the assumption that most of what is learned (learning outcomes) come from observing others. Learning by imitating behaviour of others can save time and take students away from learning through "trial and error."(6) *Achieving understanding and mastery*, to ensure that students observe the right behaviours and not the opposite, Lecturer needs to really pay attention to what happens at each stage of the demonstration; this means that, if necessary, the Lecturer needs to strive so that everything that is demonstrated is also true. (7) *Practicing***,** to be able to demonstrate something properly requires intensive exercise and paying attention to important aspects of the skills or concepts that are demonstrated. (8) *Providing guided exercise*, one of the important stages in direct teaching is the way the Lecturer prepares and implements "guided exercise." Active student involvement in an exercise can increase retention, make learning take place with actors, and enable students to apply concepts/skills to new situations.

2.2. Overdispersion

Poisson regression model requires equi-dispersion; a condition where the mean and variance of the response variable are same [10]. However, there is sometimes an overdispersion phenomenon in the data modeled by Poisson distribution. Overdispersion means that the variance is greater than the mean. This indicates that the Poisson regression model is not suitable for the data [23].

The phenomenon of overdispersion [24] can be written as:

$$Var(Y) > E(Y) \qquad (1)$$

Overdispersion can be caused by a positive correlation between independent variables or due to a large variance in independent variables. Overdispersion can also be caused by a tendency to the data, i.e. an initial event that affects the next event. The impact of overdispersion in Poisson regression modeling is a variable that can appear as a significant parameter when in fact it is not significant [25].

Hypothesis testing on overdispersion cases is carried out as follows:

$$H_0 = \theta = 0 \text{ (without overdispersion)}$$

$$H_1 = \theta \neq 0 \text{ (with overdispersion)}$$

The test statistic used is :

$$X^2 = \sum_{i=1}^{n} \frac{(y_i - \hat{\mu}_i)^2}{\hat{\mu}_i} \sim \chi^2_{(n-p)}$$

(2)

with disperse ratio :

$$\phi = \frac{X^2}{df}$$

(3)

The test criteria are reject H_0 if the value of $X^2 > \chi^2(n-p)$ or *p-value < α.* Disperse estimation is measured by the value of the deviation or Pearson's Chi-Square divided by degrees of freedom; if the division results in a value greater than 1, it can be concluded that the data is overdispersed.

2.3. Quasi-Poisson Regression

The Quasi-Poisson regression model is one of the generalization models to overcome the case of overdispersion. The Quasi-Poisson model does not require knowing the shape of the distribution of the response variables; it only requires assumptions on the first two moments. Quasi-Poisson regression parameter estimation uses the quasi-likelihood estimation method [26].

Derives some traits from quasi-likelihood, but it should be noted that this theory assumes that ϕ is known [27]. With this assumption, it is seen that quasi-likelihood is the actual log likelihood if and only if the response *yi* comes from an exponential family model with parameter-one (GLM family with $\phi = 1$) [28]. The algorithm for estimating Quasi-Poisson regression parameters can be expressed as the iterative weighted least square (IWLS). This estimation can be used as Gauss-Newton algorithm to solve the estimation [29].

3. METHOD

This study uses primary data on the final exam scores in Basic Mathematics subject and the factors affecting the final grade. The data was taken from the Basic Mathematics learning class of 2019 new students of the undergraduate degree program in Civil Engineering, Faculty of Engineering of the Hasanuddin University in Makassar city, Indonesia.

The variables used in this study are one response variable (Y) and 4 predictor variables (X). Response variable is the final exam score of Basic Mathematics subject. While the predictor variables are the factors affecting the final exam scores in the Basic Mathematics subject. The variables used in this study are:

Table 2. Research Variables

Variables	Proxies
Y	Final exam scores in Basic Mathematics
X_1	Learning environment
X_2	Physical environment where the test takes place
X_3	Facilities / infrastructure and facilities
X_4	Conditions during the exam

Application of Direct Teaching Method in learning Basic Mathematics subjects for undergraduate degree students in first semester on odd semester period of the academic year of 2019/2020. The phases of applying the math direct learning is according to the table 1, consists of the syntax of direct math learning models.

4. RESULT AND DISCUSSION

This study uses the final exam score in the Basic Mathematics subject with the independent variables as shown in Table 3 below:

Table 3. Data on Final Exam score of Basic Mathematics subject

Description	Amount (%)	Average Score
Learning environment	18	55
Physical environment where the test takes place	21	77
Facilities / infrastructure and facilities	32	63
Conditions during the exam	29	35

Source: 2020 processed data

Table 3 shows the basic mathematics scores students in 2019 related to independent variable representation learning environment (18%), Physical environment where the test takes place (21%), facilities infrastructure (32%) and facilities and conditions during the exam (29%).

As a preliminary description, a descriptive analysis of basic mathematics score data and the factors that are suspected to cause it are carried out. This direct learning strategy is designed to introduce students to subjects in order to build interest, arouse curiosity, and stimulate thinking. Students cannot do anything if they are spoon-fed by the lecturer. Many Lecturers make teaching mistakes, that is, before the students feel involved and are mentally ready; Lecturer spoon-feeds subject matter.

After the direct learning model is applied by following the steps of direct learning, the lecturer begins by conveys the objectives, background information on the lesson, the importance of this lesson, thus preparing students for learning. Next, the lecturer demonstrates the right skills or presents information step by step, plans and provides initial exercise guidance, and checks whether students have successfully completed the task, then giving feedback. Finally, the lecturer prepares the opportunity to carry out further exercise with special attention to the application of more complex situations and everyday life. The results are shown in Table 4 below:

Table 4. Statistical description of score after applying the Direct Math Learning

Varia-bles	Mean	Std. Deviation	Minimum	Maximum
Y	68.4667	33.1425	41.88	86.54
X1	65.3158	12.1584	58.22	74.88
X2	74.7147	4.3205	56.99	81.35
X3	31.0812	8.9319	13.18	55.00
X4	74.8297	8.3920	62.53	88.99

Source: 2020 processed data

Based on Table 4, it appears that the average score of the final exam in basic mathematics is 68.4667. The lowest basic mathematics score is 41 and the maximum score is 86.54

4.1. Multicollinearity test

One of the conditions that must be met in the formation of a regression model with several predictor variables is that there are no cases of multicollinearity. The detection of multi-linearity cases is carried out using VIF (Variable Inflation Factor) criteria. Using SAS 9.2 application, the results of muliticollinearity testing are obtained as shown in Table 5 below:

Table 5. Multicollinearity Test

Variables	X_1	X_2	X_3	X_4
VIF	1.2181	1.1456	1.0920	1.4337

Source: 2020 processed data

Based on Table 5, it is shown that the VIF value of each predictor variable is smaller than 10; it is safe to conclude that there is no multicollinearity of the tested data so it is feasible to be included in the formation of the regression model.

4.2. Poisson Regression analysis

Estimated parameters of the Poisson regression model using the maximum likelihood estimation method.

Table 6. Estimated parameters of the Poisson Regression model

Para-meter	Estima-tion	Standard Error	df	Wald	P-Value
β_0	3.2041	0.2306	53	193.07	*0.0001
β_1	-0.0045	0.0012	53	13.32	*0.0003
B_2	-0.0078	0.0019	53	17.59	*0.0001
B_3	0.0338	0.0025	53	179.69	*0.0001
B_4	0.0016	0.0016	53	1.00	0.3167

Source: 2020 processed data

Based on Table 6 it can be seen that the parameters of the Poisson regression model for the Basic Mathematics final exam score data for the Basic Mathematics subject have scores $W \geq \chi^2_{(\alpha,1)} = 3.7915$ or $P_{value} < \alpha (0.05)$, except β_4 having score $W = 1.00$ and $P_{value} = 0.3167$. This shows that each parameter is significant to the model except parameters β_4 (conditions during the exam), which shows that the conditions during the exam does not affect the final grade of the basic mathematics exam.

4.3. Overdispersion test

The overdispersion assumption on the final exam data of the Basic Mathematics subject can be seen to be based on the Pearson Chi Square value and the deviation divided by the degree of freedom that is more than 1. Table 7 shows the results of the overdispersion test using Pearson Chi Square values and deviations.

Table 7. Deviation Value and Pearson Chi Square Poisson Model

Criteria	df	Score	Score/DF
Deviation	53	239.4724	4.5372
Pearson Chi Square	53	229.8607	4.3559

Source: 2020 processed data

Table 7 shows that the deviation value of the Poisson regression model is 239.4724; if such value is divided by the value of the free degree, it will produce a value of 4.5372. Similarly, the Pearson Chi Square value is 229.8607; if it is divided by the degree of freedom, it will produce a value of 4.3559. This means that both values are greater than 1; it can be concluded that the response data is overdispersed. Continue testing the dispersion ratio with the following hypothesis:

H_0 : α = 1 (without overdispersion)

H_1 : α > 1 (with overdispersion)

Table 7 shows the Deviation value of 240.4724, with α = 5% obtained a value of $\chi^2_{(0.05,db)} = 7.935$. Result: deviation value of 240.4724 > table value of 7.935; the decision to accept H_0 which indicates that the Poisson regression model does not overdisperse anymore after direct learning. This means that the average test score is greater than the average variance.

4.4. Quasi-Poisson Regression analysis

Estimated parameters of the Poisson regression model using the quasi-likelihood estimation method.

Table 8. Estimated parameters of the Poisson-Quasi Regression model

Para-meter	Esti-mation	Standard Error	df	T-stat	P-Value
β_0	3.1941	0.4813	53	6.66	*0.0001
β_1	-0.0050	0.0026	53	-1.75	*0.0002
β_2	0.0079	0.0068	53	1.17	*0.0009
β_3	-0.0034	0.0034	53	-1.00	*0.0001
β_4	-0.0078	0.0039	53	-2.01	0.0498

Source: 2020 processed data

Table 8 shows that the parameters of the Quasi Poisson regression model for the data of the significant Basic Mathematics subject score are β_1, β_2, and β_3, because it has a value $|t_{count}| \geq t_{0.025:56} (2.0032)$ or $P_{value} < \alpha (0.05)$. This means that the Quasi-Poisson regression model of the data has a significant predictor variable namely X_1, X_2 dan X_3 (learning environment, physical environment where the test takes place, facilities / infrastructure and facilities),

except X_4 (conditions during the exam). The formed Quasi-Poisson regression model is:

$$\hat{\mu}_i = \exp(3.1941 - 0.0050\,x_1 + 0.0079x_2 - 0.0034x_3 - 0.0078x_4)$$

(4)

The interpretation of the Quasi Poisson regression model that is produced, the value $exp(3.1941)$, is a constant value indicating that there are no factors of X_1, X_2, X_3, and , then the average score of the Basic Mathematics subject with $exp(3.1941) = 25.0333 \approx 25$. The X_4 shows that X_4 of by one percent will increase Y (Final Grade Final Examination in Basic Mathematics) by $\exp(-0.0078) = 1.0078$.

4.5. Selection the Best Model

The best model is one with the smallest AIC. The AIC value of the model can be seen in the following Table 9.

Table 9. Selection of the best regression model

Criteria	Poisson Regression	Quasi-Poisson Regression
AIC	704.6164	148.8873

Source: 2020 processed data

Table 9 explains that the AIC value of the Quasi-Poisson regression is smaller than the AIC value of the Poisson regression. This shows that Quasi-Poisson regression is better in modeling data, indicating that Quasi-Poisson regression is able to overcome the overdispersion occurring in Poisson regression.

5. CONCLUSION

Direct Learning Model can increase the value of Basic Mathematics subject examinations, thereby reducing the value of diversity, so there is no overdispersion, as seen from the Quasi-Poisson regression model of the data has a significant predictor variable, namely X_1, X_2 and X_3 (learning environment, physical environment where the test takes place, facilities / infrastructure and facilities), except X_4 (conditions during the exam) of one percent will increase Y (Basic Mathematics Test Score) $\exp(-0.0078) = 1.0078$.

The Quasi-Poisson regression model is as follows:

$$\hat{\mu}_i = \exp(3.1941 - 0.0050\,x_1 + 0.0079x_2 - 0.0034x_3 - 0.0078x_4)$$

(5)

The minimum AIC value obtained from the Quasi-Poisson regression is 148,8873. This proves that Quasi-Poisson regression is able to overcome the overdispersion that occurs in Poisson regression. It means that it can overcome the gap in the value of Basic Mathematics with diversity value smaller than the average value so that the overdispersion is no longer found.

AUTHORS' CONTRIBUTIONS

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REFERENCES

[1] Tinungki GM, Nurwahyu B. The Implementation of Google Classroom as the E-Learning Platform for Teaching Non-Parametric Statistics during COVID- 19 Pandemic in Indonesia. Int J Adv Sci Technol. 2020;29(4):5793–803.

[2] Nurwahyu B, Tinungki GM, Mustangin. Students' Concept Image and Its Impact on Reasoning towards the Concept of the Derivative. Eur J Educ Res. 2020;9(4):1723–34.

[3] Nurwahyu B, Tinungki GM. Concept image and its influence on beliefs: Case study on undergraduate engineering students in solving of calculus concept problems. Int J Adv Sci Technol. 2020;29(5):2227–43.

[4] Tinungki GM. Zone Proximal Development Gives a New Meaning To the Students' Intelligence in Statistical Method Lesson. J Honai Math. 2019;2(2):129–42.

[5] Hausberger T. Structuralist Praxeologies as a Research Program on the Teaching and Learning of Abstract Algebra. Int J Res Undergrad Math Educ. 2018;4(1):74–93.

[6] Bowman-Perrott L, Burke MD, Zhang N, Zaini S. Direct and collateral effects of peer tutoring on social and behavioral outcomes: A meta-analysis of single-case research. School Psych Rev. 2014;43(3):260–85.

[7] Coimbra MT, Cardoso T, Mateus A. Augmented Reality: An Enhancer for Higher Education Students in Math's Learning? Procedia Comput Sci [Internet]. 2015;67(Dsai):332–9. Available from: http://dx.doi.org/10.1016/j.procs.2015.09.277

[8] Smith DM, Faddy MJ. Mean and variance modeling of under- and overdispersed count data. J Stat Softw. 2016;69.

[9] Seyoum A, Ndlovu P, Zewotir T. Quasi-Poisson versus negative binomial regression models in identifying factors affecting initial CD4 cell count change due to antiretroviral therapy administered to HIV-positive adults in North-West Ethiopia (Amhara region). AIDS Res Ther. 2016;13(1):1–10.

[10] Tinungki GM. Orthogonal iteration process of determining K value on estimator of Jackknife ridge regression parameter. J Phys Conf Ser. 2019;1341(9).

[11] Tinungki GM. The analysis of partial autocorrelation function in predicting maximum wind speed. In: IOP Conference Series: Earth and Environmental Science. Institute of Physics Publishing; 2019.

[12] Noah Ekeyi D. Effect of Demonstration Method of Teaching on Students' Achievement in Agricultural Science. World J Educ. 2013;3(6):1–7.

[13] Dole S, Bloom L, Kowalske K. Transforming Pedagogy : Changing Perspectives from Teacher-Centered to Learner-Centered The Interdisciplinary Journal of Problem-based Learning Transforming Pedagogy : Changing Perspectives from Teacher-Centered to Learner-Centered. Interdiscip J Probl Learn [Internet]. 2015;10(1). Available from: at: https://doi.org/10.7771/1541-5015.1538

[14] Ewing B. Direct instruction in mathematics: Issues for schools with high indigenous enrolments: A literature review. Aust J Teach Educ. 2011;36(5):64–91.

[15] Al-Makahleh AAA. The Effect of Direct Instruction Strategy on Math Achievement of Primary 4th and 5th Grade Students with Learning Difficulties. Int Educ Stud. 2011;4(4):199–205.

[16] Buchori A, Setyosari P, Wayan Dasna I, Ulfa S. Developing character building learning model using mobile augmented reality on elementary school student in Central Java. Glob J Pure Appl Math. 2016;12(4):3433–44.

[17] Wenno H. Direct Instruction Model to Increase Physical Science Competence of Students as One Form of Classroom Assesment. Int J Eval Res Educ. 2014;3(3):1–6.

[18] Munroe L. Observations of classroom practice … Using the Open Approach to teach mathematics in a grade six class in Japan. 2015;(May):347–55.

[19] Neugebauer J, Ray DG, Sassenberg K. When being worse helps: The influence of upward social comparisons and knowledge awareness on learner engagement and learning in peer-to-peer knowledge exchange. Learn Instr [Internet]. 2016;44:41–52. Available from: http://dx.doi.org/10.1016/j.learninstruc.2016.02.007

[20] Schleyer GK, Langdon GS, James S. Peer tutoring in conceptual design. Eur J Eng Educ. 2005;30(2):245–54.

[21] Khoo GH, Low C, Leong FL, L.K K, Phua PL, Siah SY. Learning to Assess, Assess for Learning. In: GH Khoo & H Galistan (Eds), The Art & Craft of Teaching. 2nd ed. Singapore: East Zone Centre of Excellence for Teaching and Learning; 2016. p. 162–70.

[22] Collins AGE, Frank MJ. Cognitive control over learning: Creating, clustering, and generalizing task-set structure. Psychol Rev. 2013;120(1):190–229.

[23] Topping KJ, Peter C, Stephen P, Whale M. Cross-Age Peer Tutoring of Science in the Primary School: Influence on scientific language and thinking. Educ Psychol. 2004;24(1):57–75.

[24] McCullagh P, Nelder JA. Generalized Linear Models. 2nd ed. Chapman and Hall. London: Chapman & Hall; 1989. 1–511 p.

[25] Hilbe JM. Modelling Count Data. Cambridge University Press. New York: Cambridge University Press; 2014. 1–294 p.

[26] Gabrielli A, Richman R, Wüthrich M V. Neural network embedding of the over-dispersed Poisson reserving model. Scand Actuar J. 2019;1–29.

[27] Sáez-Castillo AJ, Conde-Sánchez A. A hyper-Poisson regression model for overdispersed and underdispersed count data. Comput Stat Data Anal [Internet]. 2013;61:148–57. Available from: http://dx.doi.org/10.1016/j.csda.2012.12.009

[28] Grover G, Vajala R, Swain PK. On the assessment of various factors effecting the improvement in CD4 count of aids patients undergoing antiretroviral therapy using generalized Poisson regression. J Appl Stat. 2015;42(6):1291–305.

[29] Handley MA, Lyles CR, McCulloch C, Cattamanchi A. Selecting and Improving Quasi-Experimental Designs in Effectiveness and Implementation Research. Annu Rev Public Health. 2018;39(1):5–25.