Zero : Jurnal Sains, Matematika, dan Terapan
E-ISSN : 2580-5754; P-ISSN : 2580-569X
Volume 9, Number 1, 2025
DOI: 10.30829/zero.v9i1.24602
Page: 37-45

Choosing the Right Tool: Practical Considerations for GLMM and GEE in Longitudinal Studies, with a Focus on Data Challenges

[1] **Pardomuan Robinson Sihombing**
School of Data Science, Mathematics and Informatics, IPB University, Indonesia

[2] **Erfiani**
School of Data Science, Mathematics and Informatics, IPB University, Indonesia

[3] **Khairil Anwar Notodiputro**
School of Data Science, Mathematics and Informatics, IPB University, Indonesia

[4] **Anang Kurnia**
School of Data Science, Mathematics and Informatics, IPB University, Indonesia

Article Info

Article history:

Accepted, 28 May 2025

Keywords:

GEE;
GLMM;
Literature;
Longitudinal;
Panel

ABSTRACT

The proposed research systematically reviews the comparative issues between GLMM and GEE for longitudinal data. The review discusses the competing arguments regarding the practical strengths and weaknesses of the two arrests. Empirical evidence demonstrates that GLMM generally provides subject-specific estimates and performs better than GEE in hierarchical and individual variance. In contrast, GEE provides resilient population-level findings, which are crucial for policy. The choice of method depends on the data structure and scope of inference. GLMM is consistently better when characterizing individuals, for example, in studies where we assume random effects are drawn from a complex distribution. GEEs shine most brightly in large datasets, obtaining robust population-level estimates even when the working correlation is misspecified. Finally, the results provide hands-on recommendations for researchers from various domains who apply statistical models to longitudinal studies to select solid, context-fitting statistical models for long-term studies.

Corresponding Author:

Pardomuan Robinson Sihombing,
School of Data Science, Mathematics and Informatics, IPB University, Indonesia
IPB University, Indonesia
Email: robinsonpardomuan@apps.ipb.ac.id

1. INTRODUCTION

1.1. Context and Challenges of Longitudinal Data Analysis

The last few decades have seen growth in longitudinal research, especially in health, economics, and social sciences. Longitudinal panel data is gathered from the same entity multiple times, making it possible to study change and the interdependencies among variables over time. Longitudinal data analysis, however, faces specific challenges due to the correlation between observations, which can lead to parameter estimation bias if proper measures are not taken. Models based on Generalized Linear Models (GLM), which are widely employed in data analysis—particularly for non-normally distributed data—are often insufficient because they do not correctly address these correlations.

The Generalized Linear Mixed Model (GLMM) and Generalized Estimating Equation (GEE) models are among the most widely used methods for handling correlation problems in longitudinal or panel datasets. GLMM is an extension of GLM, which includes random effects to account for within-subject correlation, allowing for inferences at the subject level. It handles complex data systems, including non-normal distributions, and is derived from maximum likelihood estimation [1][2][3]. Therefore, GLMM is more effective in obtaining accurate and efficient estimates of model parameters, particularly in cases with strong correlations among observations. This result has made it possible to apply GLMMs in clinical settings, where they have been used to longitudinally model the progression of various diseases while considering diverse patient's individual-level and treatment effects [4][5].

In contrast, GEE employs a quasi-likelihood theory and does not rely on a particular distribution for response variables. This result permits greater adaptability for both discrete and continuous data. With GEE, one can also model the correlation structure for the observations using a working correlation matrix, which permits a flexible choice of correlation structure appropriate for the data under analysis [4][5][6]. An important example of applying GEEs is in large-scale public health studies, such as evaluating community-based health interventions where the objective is to estimate the health impact on population groups, not on the individual longitudinal patient data [6].

The GLMM model gives subject-specific parameter estimates, which aid in analyzing individual differences [7]. GEE provides population-averaged estimates, making it more suitable for public health and policy studies [8]. The GLMM model is usually assessed with AIC and BIC based on likelihood [9]. GEE uses QIC for model selection and a modified AIC for quasi-likelihood models [4]. The GLMM model handles complex data systems with hierarchies and absent data points more efficiently [10] [11]. GEE is more robust against incorrectly defining the correlation structures and is easier to use with bigger datasets [10]. Regarding computational complexity, the integration of random effects makes GLMM more straining. GEE is computationally simpler and faster than other systems, making it more useful for larger datasets [12].

1.2. Distinctions, Strengths, and Research Contribution

Prior studies have demonstrated a balance of advantages and disadvantages for both GLMM and GEE. For example, GLMM provides a more transparent interpretation of the parameters since it models random effects but requires some assumptions regarding the distribution of the response variables. On the other hand, GEE is more accommodating regarding the types of data it can process since it has no restrictions on distribution assumptions. However, interpreting the parameters is more complicated due to them being marginal. This study aims to assess the advantages of GLMM and GEE in analyzing longitudinal panel data for the accuracy, efficiency, and estimation of the parameters, along with the covariate correlations between the observations. This study also intends to assist other researchers in determining the best model suited for their longitudinal data analysis.

This research will review the literature applying GLMM and GEE for longitudinal data analysis to synthesize their findings and draw conclusions. Thus, this study aims to help understand the merits and demerits of each model as well as aid researchers in making informed choices when selecting appropriate analysis models relevant to their studies.

2. RESEARCH METHOD

In this study, we conduct a systematic literature review to identify and examine published articles that apply generalized linear mixed models (GLMM) and generalized estimating equations (GEE) to longitudinal data. A systematic review is a rigorous, pre-planned method that searches, evaluates, and combines all relevant evidence on a given question in a transparent and reproducible manner. The aim is to produce a trustworthy and thorough summary for researchers to explore this analytic approach in panel studies.

Scope and Selection Criteria: To ensure quality, we applied tight screening rules to include only studies of clear relevance and high methodological rigor. Papers were judged on three core features: their publication status as peer-reviewed articles, the robustness and transparency of their results, and the conclusions' soundness.

Research Questions: Our review explicitly targets head-to-head comparisons of the efficiency, flexibility, and suitability of GLMM versus GEE within longitudinal or panel frameworks. Search strategy: We crafted a search string that combined terms like Generalized Linear Mixed Model, GLMM, Generalized Estimating Equation, GEE, longitudinal data, and panel data. Multiple databases ran This string across titles, abstracts, and keywords.

- Selection of Database: Scopus served as the primary source, chosen for its extensive coverage of peer-reviewed journals across the relevant fields.
- Time frame: Articles were restricted to work published between 2011 and 2025 to capture the latest methodological developments and relevant comparisons.
- Inclusion criteria: Only peer-reviewed papers in English were considered. Articles had to examine GLMM and GEE side by side, explicitly assessing them on longitudinal or panel data. Studies addressed applications, theoretical insights, or empirical tests comparing the two frameworks.
- Exclusion criteria: Conference abstracts lacking a complete manuscript, book chapters, theses, and any material not subjected to peer review were set aside. Without direct contrast, papers investigating a single model, GEE or GLMM, were removed. Broad narrative reviews that did not center on methods were also excluded.

The SLR process involves a sequence of well-defined steps: first, researchers search relevant databases and grey literature; then, they judge each paper's relevance and quality; next, they extract key data; thereafter, they synthesize that evidence; and finally, they interpret the findings in light of the guiding questions [13]. Each study was rated against a set checklist that zeroed in on issues central to comparative statistics, such as whether the work was a simulation or an empirical trial, the nature of its data, the precision of its models, the scrutiny of its assumptions, the openness of its reporting, and the strength of its inferential techniques. The checklist covered design, data, specification, and transparency, ensuring no critical aspect was overlooked. By applying this approach, the review delivers a fair and thorough summary of the evidence and, at the same time, highlights what is known, where holes remain, and what future studies should address [14]. This way, the work aims to minimize bias and provide a clear platform for other scholars to follow, replicate, or expand [15].

The article database used for analysis was obtained from the Scopus website using GLMM and GEE Comparison. In this study, only a database of journal articles was used, excluding proceedings, systematic reviews, book reviews, and book chapters, so that the database quality could be better for analysis. There were 25 articles, but only 19 were open access to download PDF files for further analysis. The study used the Vosviewer application. The Vosviewer application looks at the relationship between researchers and the themes of the studied articles. In addition, further analysis was carried out using Sciscape to summarize research from existing databases. Furthermore, an analysis of the relationship between articles was carried out. There was no statistical test in this study.

3. RESULT AND ANALYSIS

Table 1 shows a list of journal databases obtained from the Scopus database. The information obtained includes the author's name, article title, year of publication, and journal.

Table 1. Scopus Article Database with GLMM and GEE keywords

Authors	Title	Year	Source Journal
Samur A.A.; Coskunfirat N.; Saka O. [16]	Comparison of predictor approaches for longitudinal binary outcomes: Application to anesthesiology data	2014	PeerJ
Wang J.; Cao J.; Zhang S.; Ahn C. [17]	A flexible sample size solution for longitudinal and crossover cluster randomized trials with continuous outcomes	2021	Contemporary Clinical Trials
Pardo M.C.; Pérez T. [18]	Analysis of housing prices by GEE and GLMM methodologies: A longitudinal study	2013	Applied Stochastic Models in Business and Industry
Lin T.; Zhao R.; Tu S.; Wu H.; Zhang H.; Tu X.M. [19]	On modeling relative risks for longitudinal binomial responses: implications from two dueling paradigms	2023	General Psychiatry
Li Y.; Feng D.; Sui Y.; Li H.; Song Y.; Zhan T.; Cicconetti G.; Jin M.; Wang H.; Chan I.; Wang X. [20]	Analyzing longitudinal binary data in clinical studies	2022	Contemporary Clinical Trials
Mittal M.; Harrison D.L.; Thompson D.M.; Miller M.J.; Farmer K.C.; Ng Y.-T.[21]	An evaluation of three statistical estimation methods for assessing health policy effects on prescription drug claims	2016	Research in Social and Administrative Pharmacy
Hamzah N.; Shaik Abdullah F.Z. [7]	Analyzing longitudinal data by using population-averaged and subject-specific approaches	2024	AIP Conference Proceedings
Sihombing P.R.; Notodiputro K.A.; Sartono B.[9]	Comparison of GEE and GLMM Methods for Longitudinal Data (Case Study: Determinants of the Percentage of Poor People in Indonesia, 2015-2019)	2022	AIP Conference Proceedings
Jiang H.; Kulkarni P.M.; Mallinckrodt C.H.; Shurzinske L.; Molenberghs G.; Lipkovich I.[22]	Adjusting for Baseline on the Analysis of Repeated Binary Responses with Missing Data	2015	Statistics in Biopharmaceutical Research
Zhang H.; Xia Y.; Chen R.; Gunzler D.; Tang W.; Tu X.[1]	Modeling longitudinal binomial responses: Implications from two dueling paradigms	2011	Journal of Applied Statistics
Fouks Y.; Vaughan D.A.; Neuhausser W.; Cohen Y.; Penzias A.S.; Sakkas D.[23]	Intra-patient analysis of individual weight gain or loss between IVF cycles: cycle nowãnd transfer later	2024	Human Reproduction

Authors	Title	Year	Source Journal
Hallgren K.A.; Atkins D.C.; Witkiewitz K.[11]	Aggregating and analyzing daily drinking data in clinical trials: A comparison of Type I errors, power, and bias	2016	Journal of Studies on Alcohol and Drugs
Ali M.W.; Talukder E.[24]	Analysis of longitudinal binary data with missing data due to dropouts	2005	Journal of Biopharmaceutical Statistics
Zhang H.; Yu Q.; Feng C.; Gunzler D.; Wu P.; Tu X.M.[2]	A new look at the difference between the GEE and the GLMM when modeling longitudinal count responses	2012	Journal of Applied Statistics
Tantular B.; Faidah D.Y.; Indrayatna F.[25]	Quasi Likelihood On Linear Mixed Effect Of Binary Response In Longitudinal Data	2025	Communications in Mathematical Biology and Neuroscience
Satty A.; Mwambi H.; Molenberghs G.[26]	Different methods for handling incomplete longitudinal binary outcomes due to missing at random dropout	2015	Statistical Methodology
Bell M.L.; Grunwald G.K.[27]	Small sample estimation properties of longitudinal count models	2011	Journal of Statistical Computation and Simulation
Sutradhar B.C.[28]	Two Stage Cluster Sampling Based Asymptotic Inferences in Survey Population Models for Longitudinal Count and Categorical Data	2021	Sankhya A
Alencar A.P.; Singer J.M.; Rocha F.M.M.[8]	Competing regression models for longitudinal data	2012	Biometrical Journal

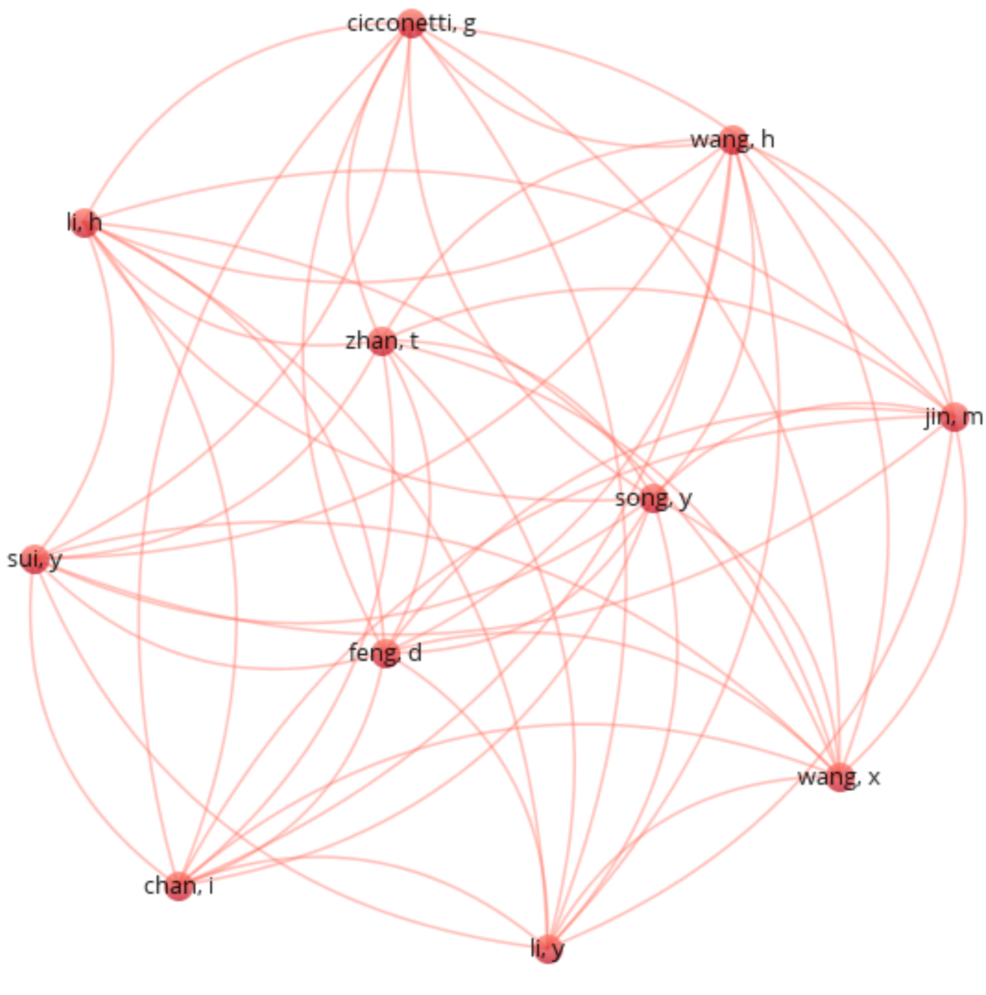

Figure 1. Relationship Between Author with VosViewer

In Figure 1, we can see the co-authorship network of researchers working on comparing GLMM and GEE models. In this case, each author is a network node, and the edges are the co-authorship ties denoting actual partnerships in publications. The graphic shows clear groups of closely linked authors, indicating strong collaborative ties within specific subdisciplines or themes. For example, the cluster with authors like Cicconetti, g, li, h, zhan, t, sui, y, Feng, d, song, y, wang, h, wang, x, Jin, m, and Chan, I, shows that these individuals form a substantial collaborative nexus. The number of connections, their density, and the presence of distinct clusters, within and across boundaries, testify to the interdisciplinary rich character of the research and the active circulation of ideas among the best scholars in the field. Such collaboration is important in refining techniques and widening the use of GLMM and GEE models for longitudinal data analysis. Some of the culprits are interrelated and collaborative. This result indicates that this type of modeling is of considerable interest to scholars.

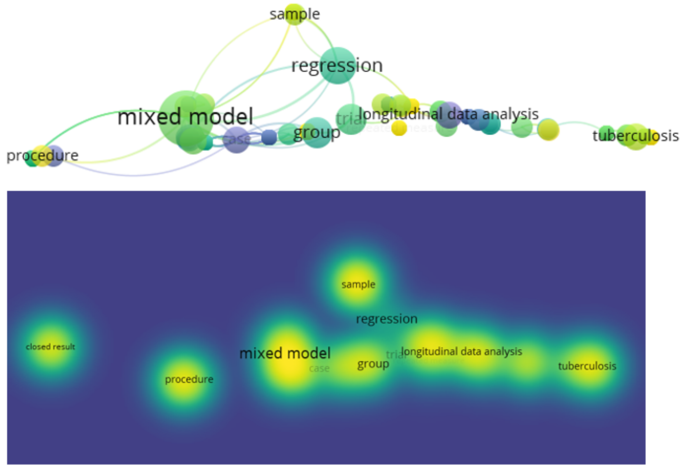

Figure 2. Network Visualisation With VosViewer

The Network Visualization Figure 2 reveals the relationships among keywords and concepts extracted from the research papers. Each node's size correlates with the frequency or prominence of terms such as "tuberculosis," "trial," "case," "mixed model," "longitudinal data analysis," "regression," "sample," "group," and "procedure" showcases their prominence as do the lines (edges) alongside them, indicating thematic relationships. The clustering of "mixed model" and "longitudinal data analysis" suggests primary areas of discussion and methodological focus within the domain. Significantly, the "mixed model" having the central position and size underscores its foundational significance in this literature. Methodologically, "mixed model," "regression," and "longitudinal data analysis" demonstrate core discourse. Moreover, "tuberculosis" and "procedure" suggest applying statistical models in clinical or practical fields.

Next, the research activity concerning certain key concepts is illustrated by Density Visualization, which accompanies the network map. Warmer colors like bright yellow indicate closely related terms. In addition to these keywords, the visualization depicts dense regions around "mixed model" and "longitudinal data analysis," which illustrates their importance in the field. Fields such as "procedure" and "tuberculosis" demonstrate significant density, illustrating their strong linkage to the fundamental statistical techniques in applied research. This form of visualization offers an overview of the more traditional topics of research as well as the developing trends in the comparison of GLMM and GEE models.

Furthermore, the discussion will be based on the research results from the existing literature review.

The literature analysis comparing Generalized Linear Mixed Models (GLMMs) and Generalized Estimating Equations (GEEs) in longitudinal studies reveals several key research clusters focusing on mixed models, longitudinal data analysis, and related procedures. The identified studies provide profound insights into these two methods' relative strengths and weaknesses across various application contexts.

A fundamental difference lies in the inferential focus of each model. GLMMs tend to provide *subject-specific* parameter estimates, allowing researchers to understand individual-level variation, as highlighted by Hamzah and Shaik (2024) [7], even if accompanied by sometimes larger standard errors compared to GEE (Samur et al., 2014) [16]. In contrast, GEEs provide *population-averaged* estimates, which are more relevant for policy and public health inference, underscoring their utility in delivering robust population-level estimates (Mittal et al., 2016) [21]. Alencar et al. (2012) [8] add that while population-averaged results from GLMM and GEE can be similar, GEE-based models might be superior in managing unique data properties, such as a non-constant coefficient of variation.

Regarding distributional assumptions and flexibility, GEEs are often considered more adaptive. Lin et al. (2023) [19] state that GEEs do not impose strict distributional assumptions on the response variable, offering greater flexibility than GLMMs, which require explicit modeling of *within-subject* correlations via random effects. Zhang et al. (2011) [1] and (2012) [2] further criticize GLMMs, arguing that they can yield marginal models with complex, unrecognizable distributions and introduce artifacts that lead to difficult-to-comprehend overdispersion. Conversely, GEEs, according to them, disregard these layers of distributional assumptions, providing consistent estimates regardless of the data distribution or correlation structure complexity.

Both models offer distinct approaches to handling correlation and missing data. GLMMs utilize random effects to account for *within-subject* correlation and can manage missing data, particularly under the Missing At Random (MAR) assumption (Li et al., 2022) [20]. However, Jiang et al. (2015) [22] note that GLMMs surprisingly showed bias with MAR data, while Multiple Imputation (MI) remained unbiased. On the other hand, GEEs prove more efficient in handling missing data (Wang et al., 2021) [17] and are more robust to misspecification of the working correlation structure (Tantular et al., 2025) [25]. Ali and Talukder (2005) [24] demonstrate how Weighted GEE (WGEE) and GLMM can correct for potential GEE bias (under MCAR) for missing data. Nevertheless, Tantular et al. (2025) [25] also note that GEE estimators can be biased and inefficient in small samples, though their performance improves and becomes more robust in large samples. Satty et al. (2015) [26] found that MI-GEE consistently outperformed WGEE and GLMM in efficiently handling incomplete longitudinal binary data with MAR dropout.

Concerning predictive performance and accuracy, results vary across studies. For instance, in a specific case study focusing on the percentage of poor people in Indonesia, Sihombing et al. (2022) [9] found that the GLMM model outperformed the GEE model, evidenced by lower RMSE and AIC values. This result suggests GLMM's superior capability in representing that particular dataset. However, it is crucial to recognize that, while valuable, such a finding represents a specific application within a unique socio-economic context and may not be universally generalizable. The performance of these models can be susceptible to the specific data characteristics, model specification choices, and the underlying social dynamics being studied. Other studies also contributed to this comparison: Pardo and Pérez (2013) [18] found that GLMMs provided better forecasts for house prices despite higher residual variability. Conversely, Hallgren et al. (2016) [11] found that Type I error rates could slightly increase in both models with an exchangeable correlation structure, and GLMM power might decrease when modeling disaggregated data. Bell and Grunwald (2011) [27] specifically found Type I error rates to be too high for GEE (with sandwich standard errors) and too low for GLMM, although the type I error rate generally decreased with an increasing number of subjects.

Several studies also highlighted other specific issues. Sutradhar (2021) [28] discussed that existing GEEs based on longitudinal correlations could fail to produce consistent estimates in two-stage cluster survey designs, proposing WGQL (Weighted Generalized Quasi-Likelihood) and WML (Weighted Maximum Likelihood) estimators as consistent alternatives. Fouks et al. (2024) [23] provided an application example of both models in the context of intra-patient analysis for weight changes and IVF outcomes, finding small positive correlations for some variables in both models.

The literature confirms that no single model is universally superior in all conditions. The choice between GLMM and GEE heavily depends on the research question, data structure, and tolerance for the underlying assumptions of each respective model.

4. CONCLUSION

As most literature indicates, GLMMs and GEEs have particular advantages and disadvantages. The GLMM model integrates random effects with within-subject correlation for hierarchical or nested data structures, thus providing subject-specific parameter estimates critical for individual-level differences. On the other hand, in the GEE model, without having to model random effects explicitly, a working correlation structure for repeated measures is defined to estimate population-averaged effects, which are more appropriate for overall population inference. Also, although GLMM may induce artifacts in marginal models for binomial responses, which could limit its utility for some types of binary data, the GEE model is preferred for binary and count data because it is robust to strong dependence between observations without requiring stringent distributional assumptions.

Hence, the decision between GLMM and GEE is more about the research problem and the relationships within the data framework. For studies focusing on variability at the individual level, bespoke predictions tied to subjects, or dealing with intricate nested structures, particularly where the distribution of underlying random effects is not too far off from reality (for instance, if random intercepts and slopes are normally distributed), GLMM would have marked advantages. On the other hand, if the aim is to derive robust population-averaged conclusions, particularly with large datasets and weaker distributional assumptions or with potentially misspecified correlation structures (notably for binary or count data), GEE becomes more beneficial. Careful consideration of these differences is essential for selecting the appropriate model, as invalid and impactful conclusions could otherwise be drawn.

5. REFERENCES

[1] H. Zhang, Y. Xia, R. Chen, D. Gunzler, W. Tang, and X. Tu, "Modeling longitudinal binomial responses: Implications from two dueling paradigms," *J. Appl. Stat.*, vol. 38, no. 11, pp. 2373–2390, 2011, doi: 10.1080/02664763.2010.550038.

[2] H. Zhang, Q. Yu, C. Feng, D. Gunzler, P. Wub, and X. Tu, "A new look at the difference between the GEE and the GLMM When Modeling Longitudinal Count Modeling Longitudinal Count Responses," *J. Appl. Stat.*, vol. 39, no. 9, pp. 2067–2079, 2017.

[3] M. B. M. B. K. Gawarammana and M. R. Sooriyarachchi, "Comparison of methods for analyzing binary repeated measures data: A simulation-based study (comparison of methods for binary repeated measures)," *Commun. Stat. Simul. Comput.*, vol. 46, no. 3, pp. 2103–2120, 2017, doi: 10.1080/03610918.2015.1035445.

[4] J. Cui, "QIC program and model selection in GEE analyses," *Stata J.*, vol. 7, no. 2, pp. 209–220, 2007, doi: 10.1177/1536867x0700700205.

[5] S. Lipsitz and G. Fitzmaurice, "Generalized estimating equations for longitudinal data analysis," in *Longitudinal Data Analysis*, Division of General Medicine, Brigham and Women's Hospital, Boston, MA, United States: CRC Press, 2008, pp. 43–78. doi: 10.1201/9781420011579.ch3.

[6] J. E. Overall and S. Tonidandel, "Robustness of Generalized Estimating Equation (GEE) tests of significance against misspecification of the error structure model," *Biometrical J.*, vol. 46, no. 2, pp. 203–213, 2004, doi: 10.1002/bimj.200210017.

[7] N. Hamzah and F. Z. Shaik Abdullah, "Analyzing longitudinal data by using population-averaged and subject-specific approaches," in *AIP Conference Proceedings*, Y. Z., A. N.A.M., G. N., M. W.Z.A.W., A. B. N.A., Z. W.M.K.A.W., D. W.S.W., O. N., S. S.B.M., K. F., A. Y. Y.N., and B. B., Eds., School of Medical Sciences, Universiti Sains Malaysia, Kubang Kerian, Kota Bharu, Kelantan, 16150, Malaysia: American Institute of Physics, 2024. doi: 10.1063/5.0225236.

[8] A. P. Alencar, J. M. Singer, and F. M. M. Rocha, "Competing regression models for longitudinal data," *Biometrical J.*, vol. 54, no. 2, pp. 214–229, 2012, doi: 10.1002/bimj.201100056.

[9] P. R. Sihombing, K. A. Notodiputro, and B. Sartono, "Comparison of GEE and GLMM Methods for Longitudinal Data (Case Study: Determinants of the Percentage of Poor People in Indonesia, 2015-2019)," in *AIP Conference Proceedings*, A. L., R. null, P. R., P. G.E., and S. T.Y., Eds., BPS-Statistics Indonesia, Jl. Salemba Tengah No.36, RT.2/RW.4, Paseban, Senen, Daerah Khusus Ibukota, Jakarta, 10440, Indonesia: American Institute of Physics Inc., 2022, pp. 2015–2019. Doi: 10.1063/5.0103254.

[10] M. B. de Melo, D. Daldegan-Bueno, M. G. Menezes Oliveira, and A. L. de Souza, "Beyond ANOVA and MANOVA for repeated measures: Advantages of generalized estimated equations and generalized linear mixed models and its use in neuroscience research," *Eur. J. Neurosci.*, vol. 56, no. 12, pp. 6089–6098, 2022, doi: 10.1111/ejn.15858.

[11] K. A. Hallgren, D. C. Atkins, and K. Witkiewitz, "Aggregating and analyzing daily drinking data in clinical trials: A comparison of type I errors, power, and bias," *J. Stud. Alcohol Drugs*, vol. 77, no. 6, pp. 986–991, 2016, doi: 10.15288/jsad.2016.77.986.

[12] S. An, Y. Zhang, and Z. Chen, "[Analysis of binary classification repeated measurement data with GEE and GLMMs using SPSS software].," *Nan Fang Yi Ke Da Xue Xue Bao*, vol. 32, no. 12, pp. 1777–1780, 2012, [Online]. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84884175455&partnerID=40&md5=4f344c04f2925be5f6a8b16a6b56efed

[13] S. Bawadi *et al.*, "Pemahaman Konsep Matematika dengan Teknik Scaffoldıng: Systematic Literature Review," *MethodsX*, vol. 14, no. 1, p. 100777, 2023, doi: 10.30653/003.202391.2.

[14] A. Widjiseno and A. Eliyana, "Systematic Literature Review of Knowledge Management Strategy for Optimization Budgeting Function on Indonesian Local Legislative Council," *Inf. Knowl. Manag.*, 2019, doi: 10.7176/ikm/9-4-04.

[15] C. F. Durach, A. Wieland, and J. A. D. Machuca, "Antecedents and dimensions of supply chain robustness: a systematic literature review," *Int. J. Phys. Distrib. Logist. Manag.*, vol. 45, pp. 118–137, 2015, doi: 10.1108/ijpdlm-05-2013-0133.

[16] A. A. Samur, N. Coskunfirat, and O. Saka, "Comparison of predictor approaches for longitudinal binary outcomes: Application to anesthesiology data," *PeerJ*, vol. 2014, no. 1, 2014, doi: 10.7717/peerj.648.

[17] J. Wang, J. Cao, S. Zhang, and C. Ahn, "A flexible sample size solution for longitudinal and crossover cluster randomized trials with continuous outcomes," *Contemp. Clin. Trials*, vol. 109, 2021, doi: 10.1016/j.cct.2021.106543.

[18] M. C. Pardo and T. Pérez, "Analysis of housing prices by GEE and GLMM methodologies: A longitudinal study," *Appl. Stoch. Model. Bus. Ind.*, vol. 29, no. 5, pp. 552–563, 2013, doi: 10.1002/asmb.1940.

[19] T. Lin, R. Zhao, S. Tu, H. Wu, H. Zhang, and X. M. Tu, "On modeling relative risks for longitudinal binomial responses: implications from two dueling paradigms," *Gen. Psychiatry*, vol. 36, no. 2, pp. 1–5, 2023, doi: 10.1136/psych-2022-100977.

[20] Y. Li *et al.*, "Analyzing longitudinal binary data in clinical studies," *Contemp. Clin. Trials*, vol. 115, 2022, doi:

10.1016/j.cct.2022.106717.
[21] M. Mittal, D. L. Harrison, D. M. Thompson, M. J. Miller, K. C. Farmer, and Y.-T. Ng, "An evaluation of three statistical estimation methods for assessing health policy effects on prescription drug claims," *Res. Soc. Adm. Pharm.*, vol. 12, no. 1, pp. 29–40, 2016, doi: 10.1016/j.sapharm.2015.03.004.
[22] H. Jiang, P. M. Kulkarni, C. H. Mallinckrodt, L. Shurzinske, G. Molenberghs, and I. Lipkovich, "Adjusting for Baseline on the Analysis of Repeated Binary Responses With Missing Data," *Stat. Biopharm. Res.*, vol. 7, no. 3, pp. 238–250, 2015, doi: 10.1080/19466315.2015.1067251.
[23] Y. Fouks, D. A. Vaughan, W. Neuhausser, Y. Cohen, A. S. Penzias, and D. Sakkas, "Intra-patientãnalysis of individual weight gain or loss between IVF cycles: cycle nowãnd transfer later," *Hum. Reprod.*, vol. 39, no. 1, pp. 93–101, 2024, doi: 10.1093/humrep/dead244.
[24] M. W. Ali and E. Talukder, "Analysis of longitudinal binary data with missing data due to dropouts," *J. Biopharm. Stat.*, vol. 15, no. 6, pp. 993–1007, 2005, doi: 10.1080/10543400500266692.
[25] B. Tantular, D. Y. Faidah, and F. Indrayatna, "QUASI LIKELIHOOD ON LINEAR MIXED EFFECT OF BINARY RESPONSE IN LONGITUDINAL DATA," *Commun. Math. Biol. Neurosci.*, vol. 2025, pp. 1–13, 2025, doi: 10.28919/cmbn/9025.
[26] A. Satty, H. Mwambi, and G. Molenberghs, "Different methods for handling incomplete longitudinal binary outcome due to missing at random dropout," *Stat. Methodol.*, vol. 24, pp. 12–27, 2015, doi: 10.1016/j.stamet.2014.10.002.
[27] M. L. Bell and G. K. Grunwald, "Small sample estimation properties of longitudinal count models," *J. Stat. Comput. Simul.*, vol. 81, no. 9, pp. 1067–1079, 2011, doi: 10.1080/00949651003674144.
[28] B. C. Sutradhar, "Two Stage Cluster Sampling Based Asymptotic Inferences in Survey Population Models for Longitudinal Count and Categorical Data," *Sankhya A*, vol. 83, no. 1, pp. 26–69, 2021, doi: 10.1007/s13171-019-00170-7.