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Intervention treatment for progressed learners at selected secondary schools in the Pietermaritzburg district, KwaZulu-Natal province, South Africa

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Abstract
In this article we outline an application of the causal TRT procedure and missing data methods to a dataset of progressed pupils (pupils who moved to the subsequent grade although they did not meet the promotional criteria in their current grade) in poor school communities. The technique approximates the contributing effect of binary treatment on a continuous or discrete outcome. With the application of the procedure in this study, we aimed to approximate the contributing effect of the intervention treatment, specifically extra classes for progressed learners on their learning outcomes as suggested by the policy on progression. Inverse probability weighting (IPW) and multiple imputation (MI) were employed to address the missing data. A sample of 828 learners from 4 schools in the Pietermaritzburg district was selected for this study. Our findings indicate that the causal treatment had a positive effect on these learners' results. Moreover, multiple imputation proved to be a better method for imputing missing data over the inverse probability weighting. We recommend the use of monitored extra classes to improve progressed learners' results. Additionally, we recommend the use of multiple imputation over inverse probability weighting when the missing data is less than 5%.

Keywords: augmented inverse probability weighting; CAUSALTRT; inverse probability weighting; missing data; multiple imputation; progression

Introduction
Education is a fundamental right that empowers individuals and promotes socio-economic development. By providing extra classes for progressed learners as an additional learning opportunity in poor school communities, we address educational inequalities, thus ensuring that every pupil gets a fair chance to reach their full potential. Progressed learners are those learners who were allowed to move to the next grade despite not meeting the advancement criteria for the current grade (Mogale & Modipane, 2021). Using the causal TRT procedure and missing data methods to analyse the dataset of progressed learners allows us to accurately assess the impact and effectiveness of these extra classes (Lam, Ardington & Leibbrandt, 2011). The CAUSALTRT procedure is a method used to estimate the average causal effect of a binary treatment on a continuous or discrete outcome. By implementing extra classes as an intervention, we can improve the learning ability of learners within their existing instructional environment. The South African Education Department has been striving to improve learners' learning skills by introducing and adopting policies that aim to change the educational system. The responsibility for putting these educational policies into practice at school level rests with the senior management teams (SMTs) and teachers. One of the biggest challenges that teachers face is adapting to these ever-changing programmes and policies, given that some of the teachers are underqualified and some are newly graduated (Du Plessis & Letshwene, 2020). The country's education system, however, is overwhelmed with challenges and as a result, more still needs to be done to achieve the required improvement (Maarman & Lamont-Mbawuli, 2017).

From the available research on the application of the progression policy within the South African school framework, no research has been designed and carried out to study the implementation of the suggested examples of support measures mentioned in the progression policy guidelines for poor school communities. Awareness of the erratic application of the progression policy (Nkosi & Adebayo, 2021) and the lack of research studies on the implementation of the proposed support mechanisms for mitigating challenges faced by progressed learners in poor school communities, gave rise to this research study. To combat this problem and to achieve the desired academic achievements, we explored an intervention treatment in the form of extra classes. The data collected for this study had missing values due to learners withdrawing from the study. Missing data in this case refers to learner results that were meant to be collected but were not collected.

Analysing a dataset with missing values without taking missing data into account could potentially lead to incorrect results because of minimised data sizes (Dong & Peng, 2013). Several approaches are available for handling incomplete data that may produce reliable conclusions under specific conditions (Dong & Peng, 2013). Since less than 5% of the data was missing from our dataset, we considered inverse probability weighting (IPW) and multiple imputation (MI) to augment the incomplete data and compare the results to those of the traditional complete case analysis (CCA). The focus of the study was to answer two questions:

(i) Was the supervised study group intervention treatment successful in assisting struggling, progressed learners in the four Pietermaritzburg district secondary schools to achieve better results?
(ii) As less than 5% of the data for progressed learners was missing, would the application of CCA produce sufficient estimates?

Literature Review

The increasing number of learner dropouts over the years is a matter of great concern for the South African Department of Education. The biggest contributor to learner dropout is the retention of over-aged learners in schools (Lam et al., 2011). According to Reddy, Visser, Winnaar, Arends, Juan and Prinsloo (2016), in comparison to their age-appropriate peers, the performance of over-aged learners is lower. Repeating a grade more than once may increase the likelihood of some learners dropping out of the schooling system (Mabungane, Ramroop & Mwambi, 2023). In 2022 alone the South African schooling system suffered a 10% increase in learner dropouts compared to 2019 (Masson, 2023). The high learner dropout rate from the education system is very concerning since less than 60% of the youth below the ages of 20 years had completed Grade 12 (Department of Basic Education [DBE], Republic of South Africa [RSA], 2018). Statistics on the issue indicate that nearly 40% of all learners enrolled in Grade 1 drop out of the system before completing Grade 12 (Hartnack, 2017). However, the Department of Education attempts to encourage learners to remain in the schooling system. In 2013, the Department of Education endorsed the implementation of a progression policy in the Further Education and Training (FET) band, however, the policy was only fully implemented in 2014 (DBE, RSA, 2016). The introduction of the policy was aimed at allowing learners who did not meet promotional requirements but met the progression criteria, to be promoted (Mabungane et al., 2023). The progression criteria are as follows:

i. The learner must have failed either Grade 10 or Grade 11 and must have repeated either of the grades.
ii. The learner must have passed at least four of the seven subjects offered.
iii. The learner must have attended school regularly, and
iv. The learner must have fulfilled the prescribed school-based assessment (SBA) requirements for every subject offered.

Progression refers to a condition where learners move up to the following grade even though they did not meet the promotional requirements (George, 2019). The progression policy aims to keep learners in the system by minimising the dropout rates and limiting repetition. Furthermore, the policy suggests that learners are provided with additional support to minimise their chances of failing again and improve their chances of passing.

Available data on progressed learners indicate that a small proportion of these learners pass Grade 12. These poor results can be attributed to not adhering to the suggested implementation phase of the progression policy (Mogale & Modipane, 2021). Using the 2015 statistics, the Department had enrolled 644,536 full-time candidates and 70.7% of them passed (DBE, RSA, 2016). Of the 644,536 full-time candidates, 65,671 were progressed learners and only 22,060 (37.6%) passed (DBE, RSA, 2016). The class of 2015 registered a decrease in the pass rate compared to the class of 2014, and this might be attributed to the application of this policy. The global community has also experienced challenges with progressing learners. For example, in Estonia, a country in Northern Europe, the progression policy did not achieve the expected outcome in terms of students' operational skills (Mogale & Modipane, 2021).

The drafters of the progression policy in South Africa established a series of approaches for supporting progressed learners to cope and succeed in their new grades. These approaches include additional learning opportunities, regular, informal, short testing, additional time and adequate practice worksheets (DBE, RSA, 2017). The implementation of this policy places a burden on under-resourced schools, in particular lower quintile schools (no fee-paying public schools often found in low-income communities) since these schools are already faced with challenges of scarce resources (Stott, Dreyer & Venter, 2015). Lower quintile schools also suffer from classroom overcrowding, previously disadvantaged socio-economic backgrounds and poor school infrastructure (Stott et al., 2015). As a result, progressed learners do not always receive the much-needed assistance, which contributes to increased levels of depression (Stott et al., 2015). These challenges increase the likelihood of erratic implementation of the policy resulting in ineffective support mechanisms implemented in these schools. Progressed learners are thus most likely to continue struggling from grade to grade (Munje & Maarman, 2016). Progressing learners without proper support mechanisms may result in frustrated learners (Reddy, Hannan, Zuze-Wilcox & Juan, 2016). According to Mabungane et al. (2023), specialised support should be provided to progressed learners as this equips them with the skills required in the new grades. The Department of Education does provide some form of support to struggling learners, however, statistical evidence on progressed learners indicates that much still needs to be done in schools with poor resources if progressed learners are to achieve the desired outcomes (DBE, RSA, 2017). Smith and Loock (2019) report that two schools in a residential camp in Gauteng provided support to progressed learners resulting in increased pass rates of 67% and 79% for progressed learners in the respective schools. The support provided by the residential camp included comfortable accommodation that was ideal for learning, specialised teachers, classrooms equipped with electronic learning (e-learning) resources and designated mentors (Smith & Loock, 2019). Many schools in rural South Africa do not have the resources necessary for such achievements. For example, progressed learners from poor school communities usually do not have access to libraries, internet and computers and, therefore, cannot participate in online learning.

Problem Statement

Despite evidence on the application of the progression policy in South African schools, no research studies have been done on such implementation. We proposed an intervention treatment in the form of supervised extra classes for progressed learners as supportive measure.

Conceptual Framework

The intervention treatment for progressed learners was the basic concept of this study. The aim with the intervention treatment was to assist struggling progressed learners to improve their results and to determine the outcomes of the implementation thereof. We proposed a binary treatment effect (T) for these learners, which was to place them in an intense study group with supervision (experimental group) and a flexible study group with no supervision (control group). The treatment effect was designed in such a way that 1 indicated learners in the control group (studying on their own, studying their sets of questions, no prescribed setting, teachers only available on request) and 0 indicated learners in the experimental group (prescribed sets of questions for every session and a formal study timetable, teachers monitoring the sessions and providing support and answers). Learners in this control group were given more challenging problems every day accompanied by difficult tests every Fridays. This was done so that they can be competitive and match promoted learners in the experimental group and in some cases outperform them. The primary objective of this study was to investigate whether having struggling progressed learners in the intense study group with forced supervision would have a positive effect on these learners' results. We also aimed at providing mitigating strategies to struggling progressed learners for reaching their potential to become more competitive in their new grades. These learners were allowed an opportunity to choose a study group that suited their needs based on their results (PROG or promoted) from their previous grades. The study was designed so that there would be no randomisation. During the study, the learner's attendance and school performance were monitored throughout the terms. Upon collection of the data, some learners did not receive any results as they had dropped out of the study – thus the missing values in the data set

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Methodology

Data Collection

The office of the Head of Department of Education (HOD) granted us consent to conduct research in institutions of the KwaZulu-Natal (KZN) Department of Education (DoE). The data set comprised four variables (result, study, gender and age) from a sample of 828 Grade 11 and Grade 12 secondary school learners. The data were collected from four selected secondary schools in the Pietermaritzburg district of the KwaZulu-Natal province of South Africa. These learners were followed over the four school terms (Term 1 to Term 4). About 63% of these learners were at risk of failing their examinations since they had been progressed the previous year. To address this problem, intervention groups were designed for these learners. For data collection, designed mark sheets were used for the purposes of recording learners' marks after weekly written tests. The data on whether learners passed or failed the term were collected from the school administration clerk at the beginning of a new term. In our longitudinal study, learner's results were missing because of the following reasons:

(i) Learners might have been nervous that they might fail.
(ii) The possibility that learners felt under pressure because their peers were in other study groups or were doing better than them.
(iii) Since the study was done after school hours, some learners who used scholar transportation might not have had enough money for bus fare.
(iv) Some learners dropped out of the study because they changed schools.

Assumptions about Missing Data

Incomplete data analysis requires the user to make assumptions about the missing data. The statistical literature discusses three distinct assumptions about missing data: missing not at random (MNAR), missing at random (MAR), and missing completely at random (MCAR) (Sterne, White, Carlin, Spratt, Royston, Kenward, Wood & Carpenter, 2009). Since learners who had been progressed presented more chances of experiencing challenges and dropping out of the study compared to their counterparts, the data was assumed to be MAR.

Complete case analysis (CCA)

When analysing a data set that has incomplete information, it is worthwhile to choose an appropriate method for dealing with the missing values. CCA is the most widely used technique for handling missing data, in which any case with missing values is excluded from the study (Pigott, 2001). CCA is likely to yield less biased estimates when a data set is presumed to be MCAR and has fewer cases with missing values (Pigott, 2001). Computationally, the method is used as a default in most standard statistical software, including the Statistical Package for Social Sciences (SPSS), SAS, and Stata (Pigott, 2001).

Inverse probability weighting (IPW)

When data are collected in research studies, the data often contain missing values. The use of traditional approaches like the CCA that eliminates all subjects with missing information may result in wrong conclusions. The solution to this problem might be the use of the IPW method. This method is one of several methods of reducing bias caused by a CCA estimator when the weighting is correctly specified (Seaman, White, Copas & Li, 2012). In contrast to simple surveys with predetermine weights, IPW uses observed data to estimate weights (Satty & Mwambi, 2012). To understand this concept better, we consider a complete dataset as displayed in Table 1:

Table 1 Weight estimation for complete data

Group	X	Y	Z
Response	555	666	777

This data has no missing values; therefore, its average response variable is 6 and is unbiased. But, if the same data were incomplete, the result would be as displayed in Table 2:

Table 2 Weight estimation for incomplete data

Group	X	Y	Z
Response	5??	666	?77

Since the data shown above are incomplete, the average response is biased and can be calculated as $\frac{37}{9}$. Since X has only one observation, its calculated probability is $\frac{1}{3}$ in group Y and $\frac{2}{3}$ in group Z. The weighted average then is:

$$\frac{5\times\frac{3}{1}+(6+6+6)\times 1+(7+7)\times\frac{3}{2}}{\frac{3}{1}+1+1+1+\frac{3}{2}+\frac{3}{2}}$$

The calculated weighted average adds up to 6, which is equal to the average response of 6. From this we may conclude that the IPW has rectified the bias produced by the incomplete data. Furthermore, the IPW estimate is unbiased for the population average treatment effect (Liu, Miao, Sun, Robins & Tchetgen Tchetgen, 2020). By appropriately weighting each observation based on its propensity score, the inverse probability weighted estimator accounts for selection bias and produces an unbiased estimate of the average treatment effect (Austin & Stuart, 2017).

Augmented inverse probability weighting (AIPW)

An alternative method to IPW for handling missing data is an improved augmented inverse probability weighted (AIPW) approach (Robins, Rotnitzky & Zhao, 1994). This method has been proven to be more efficient than the traditional IPW and possesses a double robustness property (Robins et al., 1994). This property is said to provide consistent estimators when the regression propensity score or the regression model for the outcome variable is correctly specified (Qin, Zhang & Leung, 2017). According to Kurz (2022), the initial step when applying the AIPW estimator involves fitting a propensity score model, followed by fitting two outcome models under different conditions. The result of step 1 is then applied to each outcome of step 2, resulting in a weighted average (Kurz, 2022).

Multiple imputation (MI)

When participants are lost from a study, researchers are often faced with difficulty when analysing and drawing conclusions because of the incomplete data. Multiple imputation (MI) is the most prevalent technique for handling missing data and has been widely used in randomised controlled trials due to its flexibility (Kleinke, Stemmler, Reinecke & Lösel, 2011). The technique fills missing values with not just one value but with a set of reasonably estimated values (Kleinke et al., 2011). In statistical analysis, the technique has been proven to be the most trustworthy technique since it is known to produce efficient parameter estimates (Yamaguchi, Ueno, Maruo & Gosho, 2020). MI has been argued to provide unbiased parameter estimates under the MAR assumption for the general missing data setting. Furthermore, MI in randomised controlled trials can provide unbiased estimates of the treatment effect when the imputation and analysis models are correctly specified (Yamaguchi et al., 2020).

Results

The CAUSALTRT Procedure

The CAUSALTRT procedure offers a variety of estimators which are useful in statistical analysis. In this section, we apply the CAUSALTRT procedure to analyse the dataset. The CAUSALTRT procedure is used to estimate the average causal effect of a binary (0–1) treatment on a continuous or discrete outcome (Lam et al., 2011). With this procedure, a researcher can estimate the causal effect of a treatment decision by specifying a model for the treatment variable or by specifying a model for the outcome variable or both models (Glynn & Quinn, 2010; Lam et al., 2011). Specifying both models would result in an estimator that has a doubly robust property (Glynn & Quinn, 2010). This estimator may yield unbiased estimates for the treatment effect even if one of the models is not correctly specified (Lam et al., 2011).

Since there was no randomisation in the study, simply comparing the outcomes between the two treatments would not have yielded an unbiased estimate of the average treatment effect (ATE). Using the treatment effect approach in our problem we attempted to assess whether the treatment, T (intense study group with supervision), had a positive effect on learners' results. The binary treatment variable, T, represents exposure to a condition (exposing learners to an intense study group with supervision vs a flexible study group with no supervision). Since the CAUSALTRT procedure can be used to estimate two types of causal effects, i.e. the ATE and the ATE for the treated, our focus was on the application of the ATE to the dataset. The CAUSALTRT results after the application of the IPW method and the AIPW to the dataset are displayed in Table 3.

Table 3 Potential outcome means (POM) and average treatment effect (ATE) estimates

Analysis of causal effect					
		IPW		AIPW	
Parameter	Treatment level	Estimate	Robust *SE*	Estimate	Robust *SE*
POM	0	0.6510	0.0137	0.6510	0.0118
POM	1	0.6238	0.0140	0.6238	0.0120
ATE		0.02721	0.0195	0.02721	0.0137

The availability of empirically supported poor Grade 12 results, primarily in poorer community schools, highlights the significance of providing an intervention treatment to secondary school progressed learners. One of the objectives with this study was to provide struggling progressed learners with coping mechanisms to build their ability to become more competitive in their new grades. The CAUSALTRT results of the effect of implementing the binary treatment representing an intervention on progressed learners are displayed in Table 3. The IPW and AIPW estimates for the POM and the ATE are displayed in rows 1, 2 and 3 of Table 3 respectively. The ATE estimate of 0.02721 for both methods indicates that treatment 0 (experimental group) was 0.02721 more effective on average than treatment 1 (control group) for improving the learners' pass rate. These results indicate that the additional support provided to struggling progressed learners had a positive contribution to their results. Therefore, having struggling progressed learners in a control group with supervision leads to positive results. Furthermore, comparing the standard error estimates for the ATE between the two methods, the IPW method yielded larger standard error values compared to the AIPW method. Furthermore, the IPW method yielded higher standard errors for the potential means outcomes for both treatment levels. The AIPW method, on the other hand, yielded smaller standard errors for the potential means outcomes for both treatment levels. These findings are consistent with those of Lamm and Fung (2017) who report that the IPW methods resulted in higher standard errors compared to the AIPW method signalling inconsistency in the IPW methods. Furthermore, Qin et al. (2017) also report that their results showed that the AIPW method yielded smaller standard error estimates on average compared to the IPW method. Therefore, we confirm that the AIPW method is more constant than the IPW method.

Imputation of Missing Data (CCA, IPW and MI)

The assessment of incomplete data values in our dataset was carried out using CCA, IPW and MI. When missing data proportions are less than about 5%, CCA can be employed as the main data analysis (Jakobsen, Gluud, Wetterslev & Winkel, 2017). IPW was chosen because of its ability to reduce bias caused by CCA estimators when the weighting is correctly specified, However, if the missing data are assumed to be MAR, IPW normally fails to produce a valid inference (Jakobsen et al., 2017). The MI approach was chosen since it has been proven to be an effective generic approach for addressing missing data for a variety of data types. Furthermore, the approach has been argued to provide unbiased parameter estimates when the assumption about missing data is MAR (Yamaguchi et al., 2020). Also, the technique can provide unbiased estimates of the treatment effect when both the imputation and analysis models are correctly specified (Yamaguchi et al., 2020).

Table 4 The comparison of CCA, IPW and MI for missing data

	Complete case (CCA)		Multiple imputation (MI)		Inverse probability weighting (IPW)	
Variable	*SE*	Pr > |t|	*SE*	Pr > |t|	*SE*	Pr > |Z|
Intercept	0.06867	< .0001	0.069394	< .0001	7.1746	< .0001
Gender	0.01389	0.4153	0.013998	0.3799	0.2819	0.2688
Age	0.00363	< .0001	0.003670	< .0001	0.4002	< .0001
study	0.01389	0.0505	0.013851	0.0401	0.2813	0.2198

The results obtained using a regression model on a dataset with incomplete data values using CCA, IPW and MI under the MAR assumption, are presented in Table 4. We expected MI and IPW to achieve superior results than CCA for this dataset since these methods yield improved estimates than CCA when data are assumed to be MAR (Seaman et al., 2012). These results indicate that the standard errors of IPW and MI were not similar. All three variables in the IPW method had higher standard errors than those in MI. The smaller standard errors in MI suggest that these estimates are superior to the

IPW estimates. A study by Perkins, Cole, Harel, Tchetgen Tchetgen, Sun, Mitchell and Schisterman (2018), shows that the IPW standard errors were larger while the MI standard errors were the smallest – as the results in our study. The results indicate that CCA produced efficient results when the dataset had fewer than 5% missing data values, which was confirmed by MI.

Discussion

With this article we aimed to answer two research questions. Based on the first research question we sought to test whether the intervention treatment of the supervised study group had any positive effect on improving the results of progressed learners. The results in Table 3 indicate that the intervention treatment yielded a positive effect on the results of progressed learners. Houtveen and Van de Grift (2007) found that poorly performing learners who had received support in the form of organised instructions, showed improved results. In a study by Berlinski, Busso and Giannola (2023), the intervention treatment proved to be effective in improving the learning skills through academic support of low performing students in a class with higher performing students. Liswaniso (2023) found that effective intervention treatment can improve reading progress for weaker, older learners in a grade. We argue that having progressed learners in supervised study groups improved their academic performance. It must be noted that without a monitoring plan and support for progressed learners, the progression policy may not yield effective results (Muedi, Kutame, Ngidi & Uleanya, 2021). Munje and Maarman (2016) found that learners were struggling with their work because they were not receiving the individual and additional support they required. Individual support would be the academic knowledge and the academic requirements they had failed to obtain in their former grades (Munje & Maarman, 2016). Moreover, the progression policy does not prescribe that teachers provide additional support to progressed learners (Muedi et al., 2021; Munje & Maarman, 2016). Using the intervention treatment to shrink the gap between the results of struggling progressed learners and promoted learners we noted that promoting undeserving learners who needed additional support made it difficult for them to cope with the subject content of the new grade if such additional support was not provided.

Based on the second research question, we sought to test whether applying CCA to a dataset with fewer than 5% missing data could produce efficient estimates. When CCA was applied to the dataset it reduced the sample size from 828 to 794 amounting to about 4% of lost data. This amount of lost data may seem small, but it could have had a negative impact on the analysis of the dataset. Comparing the CCA results with those obtained from the IPW and MI, the MI and CCA yielded similar results. The study variable was only not significant in the case of CCA but was significant in the case of MI, while the IPW method yielded different results to these methods. Also, the IPW method produced higher standard errors while the CCA and MI methods produced similar but smaller standard errors. Seaman and White (2008) argue that introducing weights in the data could result in an increase in the standard errors. Furthermore, when estimating the ATE, IPW would sometimes yield imprecise estimates due to over-estimation of the weights (Kostouraki, Hajage, Rachet, Williamson, Chauvet, Belot & Leyrat, 2024). The results of our study also show that the introduction of weights in the form of IPW resulted in higher standard errors when compared to CCA and MI for the dataset. The extremely reduced standard errors (IPW standard errors) by the MI method could mean that very little information was needed in the data. Regarding the missing values in the dataset, we noticed that 4% was very little, thus resulting in CCA results close to those of full data. The use of CCA is recommended only when small proportions of missing values are present in the data (Gad & Abdelkhalek, 2017). Our dataset had 4% missing values; therefore, it may infer that using CCA on our data provided acceptable results complemented by the MI results. We, therefore, recommend the use of CCA and MI over IPW for dealing with smaller proportions of missing data. According to Lydersen (2022), analysing a dataset with small proportions of missing data (less than 5% or 10%) is not problematic – consistent with the results of our study.

Conclusion

We investigated the effect of an intervention treatment on a sample of 828 Grade 11 and Grade 12 learners from four secondary schools in the Pietermaritzburg district. The results show that the intervention treatment for the sampled learners had effectively improved their academic achievement. Based on these results, we recommend that support mechanisms in the form of extra classes be put in place for progressed learners in Grade 11 and Grade 12. The academic support may be provided by the schools while the DBE provides support and monitoring assistance. In relation to handling smaller amounts of missing data, using CCA and MI over IPW is recommended due to the simplicity and straightforwardness of CCA and MI, while the use of IPW adds unnecessary complications and more computational time to compute weights. Intervention treatment for primary school learners – Grade 7 learners in particular – should be the subject of future studies.

Limitations

One limitation of our study was that learners were not randomly assigned to the experimental and control groups. This meant that learners were allowed to choose a study group (control or experimental) and learners with higher chances of passing were choosing to study together due to their academic potential.

Authors' Contributions

SM collected and analysed the data and wrote the manuscript. SR performed the analysis, did proofreading of the manuscript and recommended reviewers. HM assisted with proofreading of the manuscript and recommended international reviewers. All authors reviewed the final manuscript.

Notes

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