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ARIMA Forecasting of Ordinary Level Mathematics Pass Rates: A 13-Year Case Study from a Zimbabwean High School

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Abstract

This study applies time series analysis and ARIMA forecasting to the Ordinary Level Mathematics results of one high school in Bulawayo, Zimbabwe, for the period 2010 to 2022—a period following the 2008–2009 emigration of qualified teachers that was anticipated to disrupt mathematics performance. Secondary results data were smoothed and analyzed in R Studio to identify the underlying trend through regression analysis, and an ARIMA model was fitted to forecast the school's future pass rate. To explain the observed pattern face-to-face interviews were conducted with all ten qualified mathematics teachers at the school. The pass rate followed a repeating cycle of a fall in one year being usually followed by an improvement in the next two years and both the fitted ARIMA (1,1,1) model and trend line suggested a small improvement by the sixteenth year of the series, 2025. Interview evidence linked this cycle chiefly to the rotation of teachers between examination and non-examination classes. The study recommends that the school deploy teachers with a demonstrated record of improving pass rates to examination classes, allocate more revision time, and introduce performance-based incentives while extending this line of research to the district and provincial level.

Keywords: Time Series Analysis; ARIMA Model; Forecasting; Ordinary Level Mathematics; ZIMSEC Results

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1. Introduction

The pass rate a school achieves in Ordinary Level Mathematics is far more than an administrative statistic; it is treated by parents, prospective learners, and school authorities as a proxy for institutional quality and as a gatekeeping credential for further study (Deogratias et al., 2025). In Zimbabwe, a pass in mathematics at the ordinary level is a formal prerequisite for admission into science and engineering programs, including electrical and automotive engineering, a requirement that the National University of Science and Technology enforces uniformly across its faculty of science (Ariyo et al., 2020). The stakes attached to this single subject were heightened by the emigration of qualified teachers between 2008 and 2009, when a large share of Zimbabwe's education workforce left the profession in search of higher salaries elsewhere, leaving many schools understaffed and their mathematics results vulnerable to disruption (Makonye, 2017). Parents and other stakeholders at one high school in Bulawayo have repeatedly asked whether the school's mathematics pass rate is improving and whether any improvement can be expected to continue, questions that cannot be answered responsibly by impression alone and that require a defensible quantitative evidence base.

Time series analysis and forecasting supply exactly this kind of evidence base across a wide range of applied domains. In finance, the technique is used to anticipate stock prices and currency movements (Ramos et al., 2017), in public health, it supports outbreak monitoring (Zareie et al., 2024), and in education (Rosman et al., 2024), it has been used to project learner and system-level performance, most relevantly in the Zimbabwean context. What unites these applications, as McCarville (2026) observes, is the underlying assumption that the past encodes information about the future and that the central problem of time series analysis is deciding how that information should be extrapolated. Box and Jenkins, whose autoregressive integrated moving average (ARIMA) framework remains the discipline's methodological backbone, trace this assumption to early twentieth-century econometric work, later formalized through the computational advances that made ARIMA estimation practical (Aljandali, 2017).

Within this methodological lineage, a body of work has clarified when ARIMA should be preferred over the simpler ARMA specification. Rizvi (2024) shows that ARMA models are best suited to short-horizon prediction, while ARIMA's differencing step allows it to model non-stationary, trending data over considerably longer horizons. Mills (2015) makes the same distinction more formally: because ARMA requires stationarity and ARIMA does not, ARMA is properly understood as a special case of the broader ARIMA family. More recently, attention has turned to model transparency, with Sahlaoui et al., (2021) adapting explainability techniques such as SHAP to make forecasting models more interpretable to non-technical decision-makers, precisely the audience of parents and school administrators this study is written for.

Two recent studies illustrate both the maturity of the field and the specific gap this study addresses. Kolambe & Arora (2024) offers a broad, application-spanning analysis of time series and forecasting techniques, but its scope is general rather than applied: the work does not situate the methods within a systematic review of prior literature, nor does it demonstrate the underlying mathematics or computational implementation that a practitioner would need in order to reproduce the analysis. George et al., (2017) by contrast, are methodologically rigorous, using worked examples and computer-generated output to compare competing forecasting algorithms, and conclude that Long Short-Term Memory (LSTM) models achieve the best predictive accuracy for the data sets tested. Yet, the study is algorithm-comparison research rather than an applied case addressing a concrete institutional decision problem (Siami Namini et al., 2018). Neither study, nor the broader literature surveyed above, combines a formally validated ARIMA specification with qualitative triangulation to explain a single institution's multi-year secondary mathematics performance in a low-resource, Sub-Saharan African setting, where staffing volatility, curriculum consistency, and data infrastructure differ materially from the contexts in which ARIMA has typically been demonstrateds (Surur et al., 2026). This gap matters because forecasting accuracy alone is insufficient for decision-making in schools; findings must be anchored in a theory of what drives achievement in the first place. The study therefore draws on the theory of educational assessment, which treats measurement as inseparable from instructional practice and policy decision-making (Shepard, 2000), and on the argument advanced by Suleiman et al., (2024) that predictive statistical models, including regression and time series approaches, should be used to identify the determinants of academic performance so that resource-constrained schools can address disparities more equitably. Positioned against Machimbidza & Mutula (2020) and Anyigulile (2026), the present study corroborates their broader finding that ARIMA can meaningfully forecast Zimbabwean examination outcomes but extends it in three respects: it formally tests the stationarity of the series with the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test rather than assuming it; it triangulates the resulting quantitative forecast with qualitative interview evidence from the school's entire mathematics teaching staff to explain the mechanisms behind observed trends rather than merely describing the trends themselves; and it operates at the single-school level, where the resulting forecast can be attached directly to an actionable managerial decision, such as the deployment of teachers to examination classes, rather than to system-wide policy alone.

With this positioning, the study aims to analyze the trend and pattern of this school’s ordinary-level mathematics results from 2010 to 2022 and develop an ARIMA forecasting model that can predict future results while identifying factors that plausibly explain the pattern through teacher interviews. The study aimed to: (1) plot a time series of the ordinary level mathematics pass rate for the period 2010-2022 and determine if it follows a discernible pattern; (2) determine the trend line of the series using regression analysis in R Studio; (3) obtain qualitative evidence from the mathematics teachers to help explain any observed trend; and (4) use R Studio to fit an ARIMA model that forecasts the school’s future pass rate. These objectives translate into four research questions: What pattern, if any, does the Ordinary Level Mathematics pass rate follow between 2010 and 2022? What does the fitted trend line or curve reveal about the direction of that pattern? What pass rate is the school likely to record in future years, for example, the sixteenth year of the series, 2025? And is the interview data collected from teachers useful in interpreting the trend depicted by the pass rate figures?

2. Method

Time series analysis and forecasting techniques use historical data to predict the future behavior of a variable; in this study, the dependent variable was the Ordinary Level Mathematics pass rate, and the independent variable was time (Mema & Zela, 2024). The research design combines a quantitative ARIMA and trend-line analysis of secondary examination data with a qualitative interview component. Pass-rate data were obtained from the results-analysis file of one high school in Bulawayo, Zimbabwe, for the period 2010 to 2022, covering results issued by the Zimbabwe Schools Examinations Council (ZIMSEC). Grades A, B, and C, and, under current grading conventions, D and E, are counted as passing grades, while F and U are recorded as fail grades. Data were analyzed in R Studio, with the goal of fitting an ARIMA model capable of forecasting the school's future pass rate.

The theoretical framework of the study adheres to Anderson et al., (1978) the autoregressive (AR) element predicts future values based on historical values of the series; the moving average (MA) element anticipates future values from previous forecast errors (residuals); and the ARIMA model integrates both elements with a differencing phase to address non-stationary data. These principles form the foundation of the model-fitting methodology detailed in the Results and Discussion section.

ARIMA was preferred over ARMA for four reasons. First, ARIMA is more flexible than ARMA and can accommodate non-stationary data or data with a trend component. Second, its parameters are more directly interpretable. Third, it supports forecasting over a longer horizon than ARMA. Fourth, it is more robust to outliers and extreme values in the series. The specific diagnostic evidence supporting this choice for the present data set is reported in the Result and Discussion section. Primary data were collected through face-to-face interviews with all ten Mathematics teachers at the school, using total sampling; this qualitative evidence was used to explain, rather than establish, the trends identified in the quantitative series. Secondary data, comprising the school's Ordinary Level Mathematics results for 2010 to 2022, was drawn from the school's results-analysis file, an approach consistent observation that institutional examination records are a cost-effective and readily available data source. The secondary data were processed in four steps: cleaning, to identify and remove missing values, outliers, and inconsistencies; normalization in RStudio, by centering the data to a mean of zero and scaling it to a standard deviation of one so that all observations were placed on a comparable scale; trend-line identification, using regression analysis in RStudio; and forecasting of future values based on the fitted trend.

The ARIMA modeling procedure followed six steps, conducted principally in R Studio: model identification, based on the autocorrelation and partial autocorrelation functions of the series, parameter estimation, using maximum likelihood or least squares, model validation, using goodness-of-fit measures such as the Akaike Information Criterion and Theil's inequality coefficient, model modification, adjusting the model order or estimation method where performance was inadequate, forecasting of future values once the model was validated and forecast evaluation, using mean absolute error or mean squared error (Hyndman & Athanasopoulos, 2021).

The research instrument for the qualitative component was a structured face-to-face interview schedule developed by the researchers, administered individually to each of the ten mathematics teachers, and recorded separately. The interview asked whether time series analysis was a useful tool for understanding performance trends and invited teachers to suggest factors that might explain the trends the quantitative analysis revealed.

The school had 1,742 learners and 78 members of staff, of whom ten were qualified mathematics teachers: five held a Bachelor of Science Honours degree in mathematics, two held a Bachelor of Science Honours degree in mathematics and statistics, and three held a Diploma in Education majoring in applied and pure mathematics. Because this represented the entire population of mathematics teachers at the school, a total sampling (purposive) technique was used for the interviews; non-mathematics staff were excluded given the technical, subject-specific nature of the interview content. Two limitations follow from this design. First, responses may be affected by social desirability bias, as teachers may have reported what they believed was expected of them rather than their unfiltered views. Second, the single-school scope limits the statistical generalisability of the findings; the results are nonetheless interpretable as an in-depth single-case study, and the triangulation of quantitative and qualitative evidence strengthens confidence in the conclusions drawn within that scope.

Table 1. ZIMSEC Ordinary Level Mathematics pass rates for the school under study, 2010-2022 (%)

Year	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
Pass rate (%)	10.5	8.3	11.7	19.0	13.1	14.1	15.8	21.3	17.4	12.0	14.1	18.7	9.8

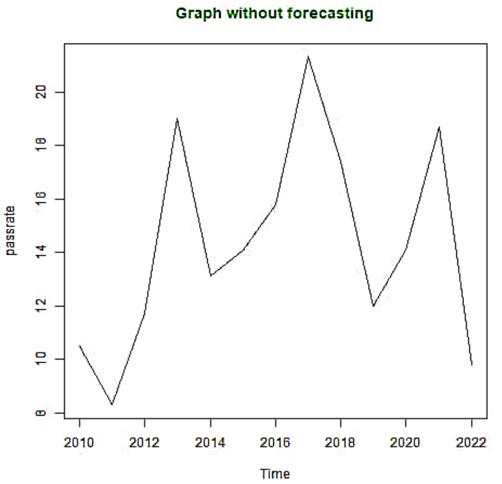

Figure 1. Time series plot of the school's ordinary level mathematics pass rate, 2010-2022.

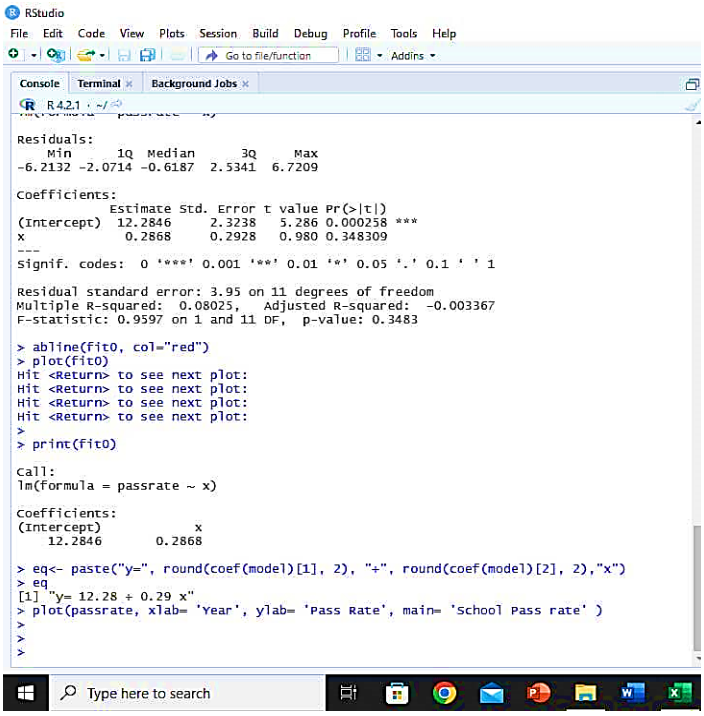

Figure 2. R Studio output showing the fitted linear regression trend line for the school's ordinary level mathematics pass rate, 2010-2022.

3. Results and Discussion

The Ordinary Level Mathematics pass rates recorded by the school between 2010 and 2022 are presented in Table 1 and analysed below, first through a time series plot and fitted trend line in R Studio, and then through a validated ARIMA model. The section closes with the qualitative interview findings and a discussion that reads the quantitative and qualitative evidence together.

The plotted series shows a recurring pattern: whenever the pass rate fell each year, it tended to rise over the following two years, a pattern evident for 2011-2012, 2014-2015, and 2019-2020, while declines followed the years 2012-2013, 2016-2018, and 2021-2022. Read against this pattern, the pass rate for 2025 and 2026 would be expected to exceed that recorded in 2022 shown in Figure 1.

The fitted trend was specified as linear because linear models are commonly assessed using the coefficient of determination (R^2) as a goodness-of-fit measure, with higher R^2 indicating that more variance is explained by the model (Piepho, 2019, 2023). The estimated trend line was $y = 12.28 + 0.29x$, where y is the pass rate and x is the year index, with 2010 as year 1. Substituting $x = 16$ for the sixteenth year of the series, 2025, gives a projected pass rate of approximately 16.9%. This projection is consistent with the pattern identified in Figure 2: because the pass rate fell to 9.8% in the thirteenth year, 2022, the model implies an improvement by the sixteenth year. Figure 3 reports the ARIMA (1,1,1) forecast generated in R Studio.

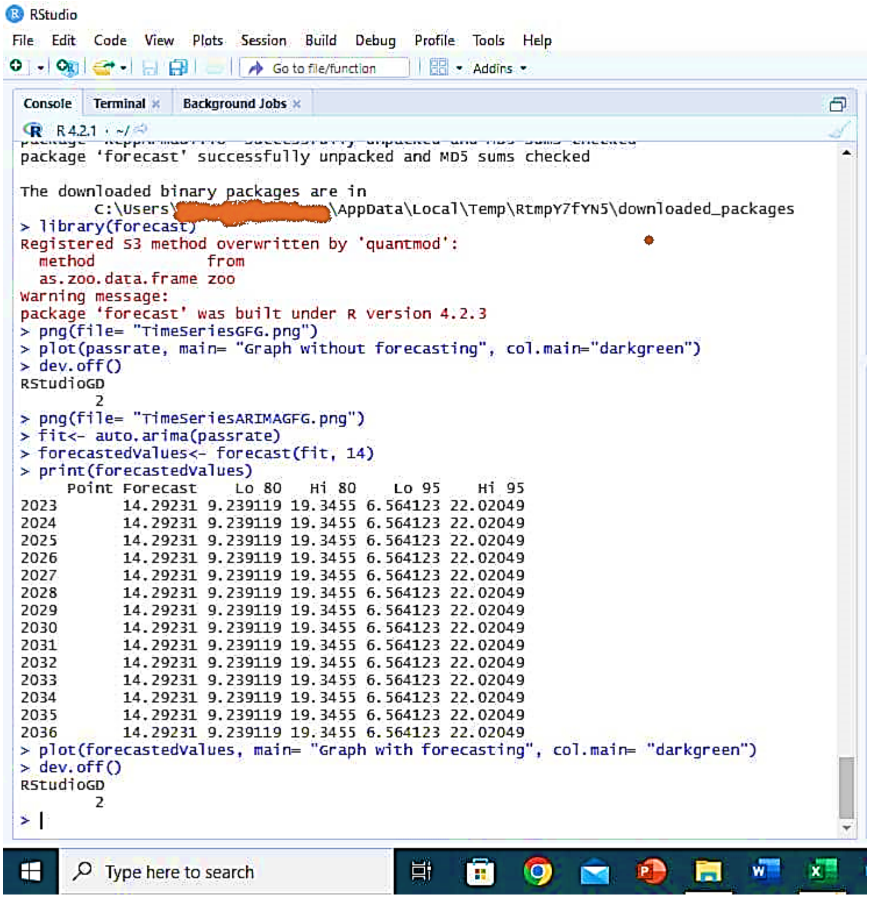

Figure 3. ARIMA(1,1,1) forecast of the school's Ordinary Level Mathematics pass rate generated in R Studio, with 95% confidence intervals.

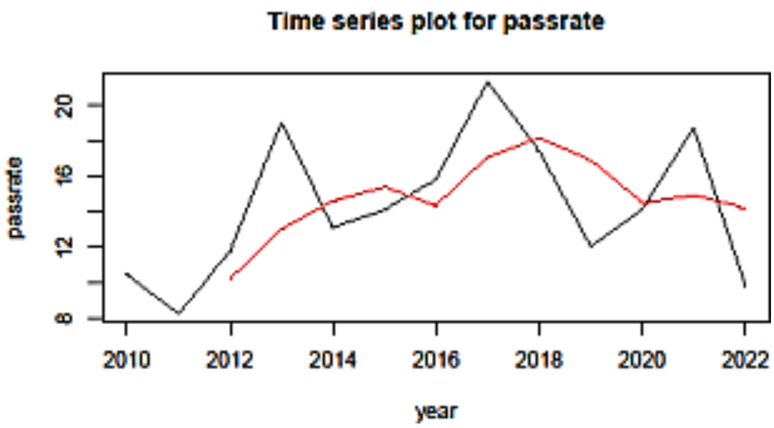

Figure 4. Original and 3-point-moving-average-smoothed Ordinary Level Mathematics pass rate series, 2010-2022, with forecast values.

In Figure 4 compares the original series against the forecast values after smoothing with a three-point moving average. The three-point moving average preserves more of the underlying data than higher-order moving averages and, as shown in red in Figure 4, highlights an overall upward trend in the forecast values. ARIMA was preferred over ARMA for this data set for three specific reasons. First, the series is non-stationary, in that its mean and variance change over time; ARIMA's differencing step (the 'I' in ARIMA) addresses this directly. Second, the series shows both trends, for example, the general increase in pass rates between 2010 and

2017, and irregular year-to-year fluctuations that ARIMA, unlike ARMA, is equipped to capture. Third, the series exhibits a degree of memory, in that past values influence future values, which ARIMA's integration component accounts for explicitly. An ARMA specification alone would not adequately capture these features and would be expected to produce less accurate forecasts and a mis-specified model.

Before fitting the ARIMA model, the series was tested for stationarity using the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, under the null hypothesis that the pass rate series is stationary against the alternative that it is non-stationary (Kwiatkowski et al., 1992). The mean of the series and its partial sums were first calculated, giving a long-run variance term of 792.663 over T = 12 observations and a KPSS statistic of 0.335. Because this value is below the 5% critical value of 0.463, the null hypothesis could not be rejected, indicating that the series may be stationary around a constant level or deterministic trend.

With stationarity established, the auto-ARIMA procedure in R Studio selected a differencing order of d = 1, reflecting the trend evident in the raw series and its stationarity after first differencing, and identified p = 1 and q = 1 from the autocorrelation and partial autocorrelation functions, yielding an ARIMA(1,1,1) specification. The autoregressive term, AR(1) = 0.45, indicates that roughly 45% of the previous year's change in pass rate carries over into the current year; because the coefficient is positive, an increase tends to be followed by further, smaller increases. The moving average term, MA(1) = -0.72, indicates that the model corrects strongly for the previous year's forecast error, adjusting the current forecast downward by about 0.72 percentage points for every percentage point by which the prior forecast overshot the actual value. The differencing order, d = 1, means the model is fitted to year-on-year change rather than to the level of the pass rate directly, which was necessary because an Augmented Dickey-Fuller test on the raw series indicated non-stationarity, in contrast to the KPSS result reported above; this discrepancy suggests that further diagnostic testing or additional data cleaning would strengthen confidence in the stationarity conclusion in future work. Finally, the estimated drift term of 0.85 indicates a mild average yearly increase in the pass rate after differencing, consistent with the positive trend identified through the regression analysis.

Read together, the quantitative and qualitative results tell a coherent story. The time series and its three-point moving average show that the pass rate rises and falls in a repeating short cycle rather than declining structurally, and the ARIMA (1,1,1) forecast implies that the pass rate for the sixteenth year of the series, 2025, having fallen to 9.8% in the thirteenth year, 2022, is likely to improve, consistent with the trend-line projection reported above. This finding is in line with (Mastellos et al., 2018) and (Machimbidza & Mutula, 2020b) who similarly found that ARIMA models can meaningfully forecast Zimbabwean examination outcomes.

The interview evidence helps explain why the cycle exists. Most teachers regarded time series analysis as a useful diagnostic tool: by revealing whether a trend is favorable, it allows corrective action to be taken before results deteriorate further. The clearest explanatory theme concerned the rotation of teachers between examination and non-examination classes: a teacher typically follows a cohort from Form One to Form Four before returning to take a new Form One class, and the pass rate tended to improve while a stronger teacher held the examination class and to fall when that teacher rotated back to junior forms.

Table 2. Themes emerging from interviews with the school's Mathematics teachers

Theme	Illustrative quote	Analysis
Utility of time series analysis in Mathematics education	"Time series analysis is a very useful tool that can help in identifying trends followed by the data and one can have a clear picture of how the pass rate, as a variable, is most likely to behave in the future" (6 teachers).	Most teachers regard time series analysis as useful for identifying trends and predicting future pass rates.
Impact of technology on data analysis	"Time series has helped so much in analysing data, and one major advantage is that technology can analyse data with great speed and accuracy" (6 teachers).	Most teachers see technology as having made data analysis faster and more accurate.
Knowledge and application of time series analysis	"I always use it to evaluate how my learners are performing, and this helps me to change my teaching strategies accordingly" (6 teachers).	Most teachers use time series analysis to evaluate learner performance and adjust their teaching strategies.
Importance of pass-rate trends	"Knowledge of these trends is very important to all the stakeholders because an investigation into the causes of the trends can help the school improve its pass rate" (4 teachers).	Teachers vary in how much importance they attach to understanding pass-rate trends for school improvement.
Factors contributing to pass-rate trends	"There are so many factors that contribute to the fluctuations in the pass rate; one of the factors is that there are some teachers who have a history and a record of improving the pass rate whenever they take examination classes" (6 teachers).	Teachers identify teacher deployment and teaching strategy as key contributors to pass-rate trends.
Strengths and weaknesses of time series analysis	"Strengths are that it is easy to calculate the moving averages and to get the trend line; it is also easy to understand." The drawback is that smoothing with a larger n-point moving average risks losing data (90% of teachers).	Teachers recognise both the ease of use and the data-loss trade-off inherent in time series smoothing.
Use of standardised tests	"Standardised tests are good to use as they give a fair analysis of the results, and comparison will not be a problem when tests are standardised" (all teachers).	All teachers agree standardised testing is important for meaningful trend comparison.
Assessing teacher and school performance using time series	"Time series should be used to assess or evaluate the performance of teachers and schools so that corrective action can be taken; however, not all teachers are keen on using it, so there could be a need to train them" (7 teachers).	Most teachers see value in using time series to assess performance but note a need for further teacher training.

Teachers linked this pattern to limited time and effort available for revision with examination classes, a finding consistent with Hanushek et al., (2011) evidence that teacher effort is an important determinant of student achievement. Notably, only about half of the teachers interviewed were consciously aware that the pass rate followed this pattern; the other half attributed year-to-year variation to differences in the examination and the learner cohort rather than to a systematic rotation effect, and several were reluctant to be associated with a low pass rate, a reluctance consistent with Fuller & Ladd, (2013) observation that teachers less concerned with pass-rate trends tend to be associated with lower-performing students.

In terms of methodology, the trend line was the simplest way of achieving a future projection, requiring relatively little computation, and reinforces the observation by Hyndman & Athanasopoulos, (2021) that trend lines are a simple model for forecasting. However, (Taylor, 2003) points out that more complicated models such as ARIMA and exponential smoothing can be superior to simple trend lines in terms of forecast accuracy, and the present results, in that the ARIMA and trend-line forecasts converge on a similar improvement for 2025, support the use of the two methods in tandem as opposed to one or the other. The identified drivers of pass-rate fluctuation, particularly teacher deployment and instructional constraints, are also consistent with evidence from Zimbabwean rural secondary schools showing that teacher turnover, low teacher qualification or motivation, unfavorable teacher-pupil ratios, weak teaching methods, and limited resources are associated with persistently low mathematics pass rates (Marongedza et al., 2023).

4. Conclusion

This study examined trends in Ordinary Level mathematics pass rates at a Bulawayo high school from 2010 to 2022 and successfully developed an ARIMA model to forecast future performance, meeting both of its main objectives. After smoothing the data with a three-point moving average to reveal the underlying pattern, the study used a regression-based trend line alongside a validated ARIMA (1,1,1) model to estimate that pass rates will likely remain within a near-term range of about 14% to 22%, providing useful planning information for parents, school leaders, government, and policymakers who need to respond to the school's broader trajectory rather than a single year's result. Even so, the forecast should be interpreted cautiously, since ARIMA estimates depend heavily on the quality of the underlying data and cannot account for external influences such as curriculum reforms or changes in teaching practice. In light of the teacher-rotation pattern identified in the interviews, the study recommends that the mathematics department and school leadership plan for ongoing fluctuation in pass rates, monitor performance trends routinely, assign examination classes where possible to teachers with stronger records of improving results, and support junior-form teachers to maintain the same level of effectiveness across all forms. It also suggests that performance-based recognition may help spread improvement across the department, while future research should expand the analysis beyond one school to district and provincial levels, examine additional explanatory factors beyond those captured in time-series models, and reduce social desirability bias in interviews through more anonymous or independently administered data collection.

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AI Declaration Statement	:	Claude (Anthropic) was used to assist with synthesizing prior literature, restructuring and strengthening the Introduction section, and reformatting the manuscript into this journal's template. All AI-assisted text was reviewed, edited, and approved by the authors, who take full responsibility for the accuracy, originality, and integrity of the final manuscript.

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