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FORECASTING THE NUMBER OF ROAD ACCIDENTS IN POLAND IN 2024-2030 – A COMPARATIVE ANALYSIS OF CLASSICAL METHODS, NEURAL NETWORKS, AND FORECASTS GENERATED BY AI SYSTEMS

Piotr **Gorzelańczyk** [1,*]

[1] Department of Transport. Stanislaw Staszic State University of Applied Sciences in Pila, Podchorazych 10 Street, 64-920 Pila, Poland, piotr.gorzelanczyk@ans.pila.pl, https://orcid.org/0000-0001-9662-400X

* Corresponding author

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Abstract – The article presents a comparative analysis of forecasts of the number of road accidents in Poland in 2024–2030, developed using classical methods, artificial neural networks, and artificial intelligence (AI) tools. Based on historical data from 1990 to 2023, the accuracy, stability, and reliability of the forecasts were assessed using the mean absolute percentage error (MAPE) as the main evaluation metric. The results show that neural networks and exponential smoothing methods are characterized by the highest accuracy and stability of forecasts, while high-degree polynomial regression models and forecasts automatically generated by AI are characterized by greater variability and lower reliability. The forecasts indicate that the number of road accidents in Poland in the analyzed horizon is likely to remain stable at around 20,000–22,000 per year. The study emphasizes the importance of controlled modeling and conscious selection of forecasting methods in predicting road safety trends.

Key words – road accidents, forecasting, neural networks, artificial intelligence, classical methods.

JEL Classification – C22, C45, C53, R41, R4

INTRODUCTION

Road safety remains one of the key socio-economic problems in Poland. Despite a marked improvement in the situation over the last two decades, the number of road accidents remains at a level that generates significant social, economic, and health costs. Effective planning of preventive, infrastructural, and legislative measures requires reliable forecasts of future trends in the number of road accidents.

An analysis of historical data from 1990 to 2023 indicates significant changes in the dynamics of the phenomenon under study. After a period of increase in the number of accidents in the 1990s, there was a long-term downward trend, particularly pronounced after 2007. In addition, the years 2020–2021 saw a sharp decline in the number of accidents due to mobility restrictions during the COVID-19 pandemic. These phenomena mean that the time series is characterized by non-linearity, structural changes, and a possible flattening of the trend in recent years.

Forecasting the number of road accidents is the subject of numerous scientific studies, which use both classical statistical methods (regression, exponential smoothing, ARIMA models) and, increasingly, methods based on artificial neural networks. At the same time, the dynamic development of publicly available artificial intelligence tools has led to forecasts being generated automatically by AI systems, often without full methodological control and without analysis of the quality of the results obtained.

However, there is a lack of literature that systematically compares forecasts obtained using classical forecasting methods and neural networks with forecasts generated by popular AI tools. Empirical assessments of the accuracy of such forecasts using uniform error measures are particularly rare.

Research on forecasting the number of road accidents is developing in several main areas: classical time series models, neural networks (including hybrids with classical models), and more broadly, AI systems used for accident prediction.

Trend models and classical time series dominate the literature on Poland. Gorzelańczyk, analyzing annual data from 2000 to 2021, used trend models to forecast the number of accidents in Poland until 2031, showing that trend methods are still the most commonly used, despite the lack of a comprehensive approach that takes into account other classes of methods and factors affecting traffic safety [1]. In another article, the same author forecasted the number of accidents broken down by day of the week using various time series models in the Statistica environment [2].

Another study concerning Poland deals with the optimization of forecasting methods – multi-criteria optimization was used here to select the "best" time series method for accident forecasts, drawing attention to the limitations of classical models (autocorrelation of residuals, lack of exogenous variables, problems with assessing the accuracy of long-term forecasts) [3]. A separate paper analyzed the time horizon of forecasts and showed that, based on Polish monthly and annual data, it makes sense to forecast up to about 6 years ahead [4].

A strong research trend is neural models that forecast the number or frequency of accidents. For road sections outside built-up areas, deep neural networks (DNN) outperformed regression models and gene expression programming in terms of RMSE and correlation coefficient, better capturing the nonlinear relationships between road geometry, traffic, and the number of events [5]. In a study on accident trend forecasting in Turkey, ANN, ARIMA, state models, and CNN+LSTM and Attention+GRU hybrids were compared; all produced acceptable errors, but state models proved to be the most stable, and hybrids were competitive with the classics [6].

The share of complex AI models in international literature is growing. Deep models (DNN, CNN, graph networks) are used to predict the number of accidents at intersections, assess risk, and analyze environmental factors [5, 7]. Review papers on hybrid and explainable models (ASTMGCN, RFCNN, CNN–BiLSTM–Attention with SHAP) emphasize that models with attention layers and XAI tools achieve better accuracy than traditional methods and facilitate the interpretation of key risk factors [8].

In the area of time series forecasting, solutions based on Transformers and multimodal large language models (LLMs) are emerging, where results are compared with ARIMA and Prophet; research indicates the potential of Transformer models in predicting traffic events and the use of LLM/VLM for real-time intervention in autonomous driving systems [9,10]. Multimodal frameworks combining ARIMA, XGBoost, and CNN highlight the possibility of integrating classic time series forecasting with accident severity classification and image analysis [11].

There are studies directly comparing different model "streams": negative binomial, SARIMA-X (ML on series), MLP – where classical models proved to be the best on average, but MLP performed better with data on variable accident intensity scales 7. Other studies indicate the superiority of Random Forest and logistic regression over ANN and Naive Bayes in accident severity classification [12], while in various contexts, ANN achieve higher accuracy than linear regression and other methods [13, 14]. A systematic review by Chai et al. synthesizes these results, pointing to the growing role of ML/DL and hybrids in predicting accident frequency, risk, and severity [15].

Taking into account the above literature review, the aim of this article is to conduct a comparative analysis of forecasts of the number of road accidents in Poland from 2024 to 2030 obtained using selected statistical methods, artificial neural networks, and forecasts generated by artificial intelligence systems. The study aims to evaluate the effectiveness of individual forecasting approaches and identify limitations resulting from the automatic generation of forecasts without an in-depth analysis of the time series structure.

1. RESEARCH HYPOTHESES

Based on an analysis of the literature on the subject and preliminary observation of empirical data, the following research hypotheses were formulated:

H1. Exponential smoothing methods and artificial neural networks are characterized by higher accuracy in forecasting the number of road accidents in Poland compared to classical regression models with a high degree of complexity.

H2. High-degree polynomial regression models lead to unstable long-term forecasts, including values that are unrealistic from the point of view of the phenomenon under study.

H3. Forecasts of the number of road accidents generated automatically by artificial intelligence tools are significantly less accurate than forecasts developed as part of a controlled forecasting modeling process.

H4. In the analyzed forecast horizon for 2024–2030, a further dynamic decline in the number of road accidents in Poland should not be expected, but rather a stabilization of the phenomenon under study.

H5. Simple forecasting models, correctly selected for the characteristics of the time series, can provide comparable or higher quality forecasts than more complex models, including those generated automatically by AI systems.

2. MATERIALS AND METHODS

The analysis used annual data on the number of road accidents in Poland in 1990–2023, presented in Table 1, Figure 1. These data come from official statistical sources and include both accidents caused by drivers and pedestrians. The number of observations is 34, which allows for the use of time series and various forecasting methods, both classical and AI-based. Analysis of historical data identified a significant downward trend in the number of accidents, particularly evident after 2007, as well as significant fluctuations related to mobility restrictions during the COVID-19 pandemic in 2020-2021. Figure 1 shows a comparison of MAPE values for all methods, allowing for quick identification of the most accurate forecasting approaches.

Forecasts of the number of road accidents for the period 2024–2030 were developed using three main groups of methods, described in detail in Table 2 and 3. The first group consisted of methods based on artificial neural networks. For this purpose, a multilayer perceptron neural network (MLP) was used, in which different proportions of training, test, and validation data sets were tested in the range of 90–5–5 to 80–10–10. The aim was to check how changes in data distribution affect the quality of forecasts. Network parameters, including the number of hidden layers, activation functions, and the number of training epochs, were selected experimentally in such a way as to minimize prediction error. The forecasts obtained using neural networks in Table 2 show relatively stable values, in many variants remaining at around 21,322 accidents per year.

The second group of methods consisted of classical statistical models. Within this group, linear, logarithmic, power, and second to sixth degree polynomials were used. Various variants of exponential smoothing were also used, including simple exponential smoothing (SES), Holt's model with a linear trend, Holt's model with a damped trend, and Winters' seasonal model. In addition, moving averages covering 2, 3, and 4 points were used. The forecasts obtained using these methods, presented in Table 2, showed varying accuracy, and models with a high degree of polynomial generated negative or extremely unrealistic values in some cases, indicating the risk of extrapolation in overly complex methods. The parameters of all classical models were selected in such a way as to minimize the mean absolute percentage error (MAPE) on the test set. The best results were obtained with simple exponential smoothing and moving average methods, where MAPE ranged between 1% and 3%. MAPE was chosen because it is a relative measure that allows for comparison of forecast accuracy between different methods, regardless of the scale of the data values. MAPE - mean absolute percentage error

$$\mathrm{MAPE}=\frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}\frac{\left|\mathrm{Y_i}\text{-}\mathrm{Y_p}\right|}{\mathrm{Y_i}} \tag{1}$$

where:

n – length of forecast horizon;

Y – observed value of road accidents;

$\mathrm{Y_p}$ – projected value of road accidents.

The third group consisted of forecasts generated by artificial intelligence tools, presented in Table 3. In this case, popular AI systems such as ChatGPT (free and paid versions), Gemini, Grok, and Perplexity were used. As of December 30, 2025. These forecasts included both simple methods built into the tools, such as linear regression, quadratic regression, moving averages, exponential smoothing, as well as methods based on ARIMA models and “naive” forecasts, which take the last observed value or the average of historical data. The accuracy of the forecasts, the stability of the values, and their consistency with the historical trend were analyzed using MAPE as the main evaluation metric. The analysis showed that in many cases, AI generated forecasts that deviated significantly from actual values, especially in the case of simple methods that did not take into account the downward trend in historical data. AI tools such as ChatGPT and Gemini do not allow full control of model parameters, which may limit the accuracy of forecasts for historical data with a non-linear trend.

The assessment of forecast quality in the study was based primarily on the mean absolute percentage error (MAPE). This measure allows for the comparison of the accuracy of different forecasting methods in relation to actual data and is particularly useful in time series analysis. In addition, the stability of the forecasts, the presence of unrealistic values such as negative numbers, and the sensitivity of the models to changes in the proportions of training, test, and validation sets were evaluated.

Three main aspects were taken into account in the comparison of all methods: the accuracy of the forecasts, the stability of the forecast values, and the methodological control of the forecasting process. This approach allowed for a systematic comparison of classical statistical models, neural networks, and forecasts generated automatically by AI in a single coherent research framework. This made it possible to draw conclusions about the usefulness of individual methods in the practice of forecasting the number of road accidents in Poland in the 2024–2030 period.

Table 1. Number of road accidents in Poland in 1990–2023 [16]

Year	**Traffic accidents**	Year	**Traffic accidents**
1990	50432	**2007**	49536
1991	54038	**2008**	49054
1992	50990	**2009**	44196
1993	48901	**2010**	38832
1994	53647	**2011**	40065
1995	56904	**2012**	37046
1996	57911	**2013**	35847
1997	66586	**2014**	34970
1998	61855	**2015**	32967
1999	55106	**2016**	33664
2000	57331	**2017**	32760
2001	53799	**2018**	31674
2002	53559	**2019**	30288
2003	51078	**2020**	23540
2004	51069	**2021**	22816
2005	48100	**2022**	21322
2006	46876	**2023**	20936

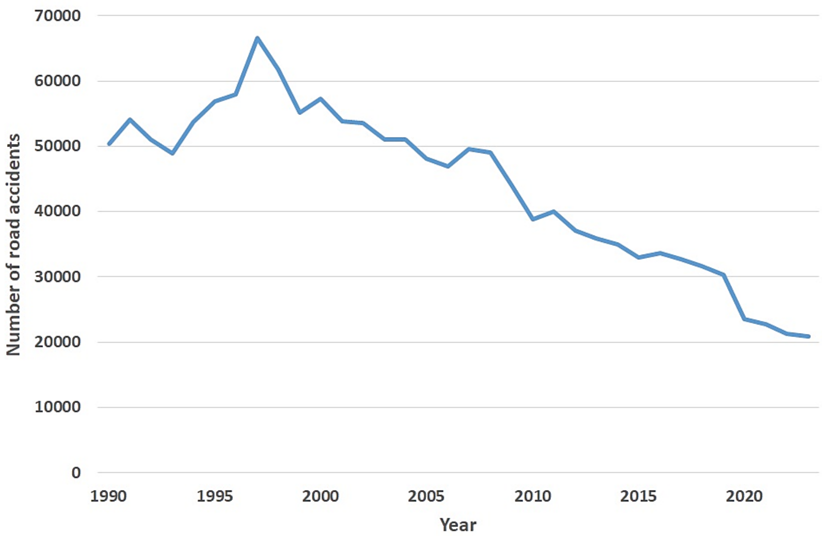

Fig. 1. Number of road accidents in Poland between 1990 and 2023 [16]

Table 2. Results of forecasting the number of road accidents in 2024–2030 – author's data [1, 17–20]

Year		2024	2025	2026	2027	2028	2029	2030	MAPE
Neural networks	Number of random samples: Training, test, validation: 90-5-5	21322	21322	21322	21322	21322	21322	21322	**3.38%**
	Number of random samples: Training, test, validation: 10-45-45	19044.13	18622.45	18412.72	18310.54	18261.27	18237.63	18226.31	**4.63%**
	Number of random samples: Training, test, validation: 20-40-40	23540	23540	23540	23540	23540	23540	23540	**5.68%**
	Number of random samples: Training, testing, validation: 30-35-35	21322	21322	21322	21322	21322	21322	21322	**7.38%**
	Number of random samples: Training, testing, validation: 40-30-30	21322	21322	21322	21322	21322	21322	21322	**4.85%**
	Number of random samples: Training, testing, validation: 50-25-25	21322	21322	21322	21322	21322	21322	21322	**5.34%**
	number of random samples: training, testing, validation: 60-20-20	27641.37	29340.6	30527.26	31371.16	31979.03	32420.93	32744.3	**4.96%**
	number of random samples: training, testing, validation: 70-15-15	24045.18	24422.76	24615.49	24716.88	24771.06	24800.23	24816.01	**5.74%**
	number of random samples: training, testing, validation: 80-10-10	20518.96	20352.69	20260.2	20209.17	20181.14	20165.79	20157.39	**5.99%**
Linear regression	linear model	27925	26402	24880	23357	21835	20312	18789	**33.92%**
	exponential model	28467	27379	26331	25324	24356	23424	22528	**35.17%**
	logarithmic model	32095	31555	31040	30548	30077	29625	29191	**172.93%**
	2nd degree polynomial model	27631	25944	24239	22516	20774	19015	17237	**27.51%**
	3rd degree polynomial model	27633	25845	24005	22109	20154	18136	16052	**27.01%**
	4th degree polynomial model	28038	25801	23144	19965	16148	11571	6099	**23.06%**
	5th degree polynomial model	-19103	-46062	-83083	-132635	-197533	-280964	-386507	**135.08%**
Exponential smoothing	6th degree polynomial model	-1462	-15393	-32396	-52395	-75066	-99771	-125494	**141.85%**
	power model	31850	31427	31029	30653	30298	29961	29641	**84.18%**
	Moving average method 2-points,	35409	33969	33316	33212	32217	30981	26914	**39.06%**
	Moving average method 3-points,	35954	34595	33867	33130	32699	31574	28501	**40.55%**
	Moving average method 4-points,	36982	35208	34362	33590	32766	32097	29566	**41.73%**
	Exponential smoothing no trend seasonal component: none,	22816	22816	22816	22816	22816	22816	22816	**2.47%**
	Exponential smoothing no trend seasonal component: additive,	21027	22027	22371	22877	21440	19802	21027	**2.49%**
	Exponential smoothing no trend seasonal component: multiplicative,	22877	23487	23310	22816	23355	22345	22877	**2.43%**
	Exponential smoothing linear trend seasonal component: none HOLTA,	20574	19683	18792	17901	17011	16120	15229	**4.48%**
	Exponential smoothing linear trend seasonal component: additive,	18495	18673	18193	17875	15615	13153	13554	**3.02%**
	Exponential smoothing linear trend seasonal component: multiplicative WINTERSA,	21118	20841	19851	18614	18219	16632	16210	**3.12%**
	Exponential smoothing exponential seasonal component: none,	18060	16706	15454	14296	13224	12233	11316	**2.55%**
	Exponential smoothing exponential seasonal component: additive,	16705	16411	15556	14954	12492	9905	10253	**2.55%**
	Exponential smoothing exponential seasonal component: multiplicative,	18716	17943	16628	15197	14526	12977	12406	**1.68%**
	Exponential smoothing fading trend seasonal component: none,	21092	20508	19931	19362	18798	18242	17693	**2,85%**
	Exponential smoothing fading trend seasonal component: additive,	20779	21779	22123	22628	21192	19554	20778	**2,97%**
	Exponential smoothing fading trend seasonal component: multiplicative)	22848	23455	23269	22805	23307	22328	22848	**1,08%**

Table 3. Results of forecasting the number of road accidents in 2024–2030 – data generated by AI [21–24]

	Year	2024	2025	2026	2027	2028	2029	2030	MAPE
Chat GPT	Simplest naive (last value)	20936	20936	20936	20936	20936	20936	20936	35.60%
	Average of historical data	44050	44050	44050	44050	44050	44050	44050	103.50%
	Drift method (linear trend)	20042	19148	18255	17361	16467	15573	14679	26.50%
	Linear regression (trend)	24531	23416	22300	21185	20070	18954	17839	34.50%
	Single exponential smoothing (SES)	20938	20938	20938	20938	20938	20938	20938	35.60%
	Holt's method (additive trend)	19132	17554	15977	14399	12822	11245	9667	21.50%
	Holt's method (suppressed)	19471	18106	16754	15416	14091	12780	11482	22.60%
	ARIMA(3.1.2) model	20730	20792	20920	20778	20787	20887	20806	32.90%
Chat GPT paid version	Moving average (3 years)	21 691	21 316	21 315	21 441	21 357	21 371	21 390	9.30%
	Weighted moving average	21 428	21 259	21 245	21 286	21 268	21 269	21 272	8.10%
	Exponential smoothing (SES)	20 938	20 938	20 938	20 938	20 938	20 938	20 938	6.00%
	Holt's method (linear trend)	19 132	17 554	15 977	14 399	12 822	11 245	9 667	5.30%
	Linear regression	24 531	23 416	22 300	21 185	20 070	18 954	17 839	9.50%
	Quadratic regression (degree 2)	14 850	12 075	9 207	6 248	3 196	53	0	6.00%
	ARIMA (0.1.0) with drift	20 042	19 148	18 255	17 361	16 467	15 573	14 679	5.20%
Grok	Naive	20936	20936	20936	20936	20936	20936	20936	29.49%
	Linear	24531	23416	223	21185	2007	18954	17839	32.33%
	Quadratic	1485	12075	9207	6248	3196	53	0	57.40%
	Holt	19317	17821	16339	14872	13419	11982	10558	8.15%
	ARIMA	2106	20999	21029	21014	21022	21018	2102	29.33%
Gemini	Linear regression	19850	18715	17580	16445	15310	14175	13040	11.40%
	Naive method	20936	20936	20936	20936	20936	20936	20936	14.10%
	Average growth (-2.6% y/y)	20392	19862	19346	18843	18353	17876	17411	8.20%
	Holt model (trend)	19650	18360	17070	15780	14490	13200	11910	5.80%
Perplexity	Linear regression	20742	20563	20384	20205	20026	19847	19668	8.42%
	Polynomial degree 2	20512	20277	20042	19807	19572	19337	19102	7.56%
	Polynomial degree 3	20324	20027	19727	19424	19118	18809	18496	7.45%
	Polynomial degree 4	20203	19821	19435	19043	18646	18243	17833	7.89%
	Polynomial degree 5	20156	19732	193	18859	18408	17946	17473	8.21%
	Exponential regression	20586	20486	2039	20297	20206	20118	20031	9.87%
	Power Law	20421	20187	19954	19721	19488	19255	19022	10.12%
	5L Moving Average	21066	21066	21066	21066	21066	21066	21066	11.23%
	10L Moving Average	22008	22008	22008	22008	22008	22008	22008	15.34%
	Smoothing α=0.2	21227	21227	21227	21227	21227	21227	21227	12.45%
	Smoothing α=0.3	21094	21094	21094	21094	21094	21094	21094	13.67%
	LOESS Trend	20936	20936	20936	20936	20936	20936	20936	11.89%
	Naive Method	20936	20936	20936	20936	20936	20936	20936	14.56%
	Naive Seasonal	2085	20736	20622	20508	20394	2028	20166	13.34%
	Linear Drift	20936	20756	20576	20396	20216	20036	19856	14.12%

3. Discussion

An analysis of historical data presented in Table 1 shows that the number of road accidents in Poland between 1990 and 2023 shows a clear downward trend. After peaking in 1997, when 66,586 accidents were recorded, the number of incidents steadily declined, reaching 20,936 in 2023. There were clear disruptions to this trend in 2020–2021, which was a consequence of the mobility restrictions introduced during the COVID-19 pandemic. The time series therefore exhibits characteristics of non-linearity, seasonality, and structural variability, which makes forecasting over a period of several years challenging.

The forecasts prepared as part of our own research, presented in Table 2, show the varying effectiveness of different methods. Neural networks, regardless of the division of training, test, and validation sets, generated relatively stable forecasts, remaining at around 21,322–21,664 accidents per year. The mean absolute percentage error (MAPE) for neural networks was 3.38%, which indicates high accuracy and stability of forecasts in relation to actual historical data.

In the case of classical regression and polynomial models, significant variability in forecasts was observed. Linear regression models and lower-degree polynomials were moderately accurate, while high-degree polynomials generated negative or unrealistically high values in some years, leading to MAPE values of up to several hundred percent. This is a clear example of over-extrapolation in overly complex models and indicates the need for caution when using high-degree polynomials in long-term forecasts.

The most effective forecasting methods were exponential smoothing and moving averages, including both classic simple smoothing and the Holt and Winters variants. The MAPE values for these methods ranged from 1.08% to 3.12%, making them the most reliable tools for predicting the number of road accidents in the 2024–2030 period. These methods were also characterized by forecast stability, without generating unrealistic values.

The forecasts generated by artificial intelligence systems, presented in Table 3, showed greater variability and often lower accuracy. In the case of simple naive forecasting methods or historical averages, the MAPE exceeded 100%, indicating their low practical usefulness. AI systems such as ChatGPT, Gemini, and Grok generated forecasts that varied in terms of the method used: linear regression and single exponential smoothing had a MAPE of between 5% and 35%, while more complex models, such as ARIMA or Holt's methods, achieved better accuracy (MAPE 5%–22%). Compared to forecasts obtained using proprietary methods, AI forecasts were less stable and deviated more often from the expected downward trend, indicating the limitations of automatic forecast generation without a full analysis of the time series structure.

Comparing the results of all methods, it can be concluded that proprietary forecasts based on neural networks and exponential smoothing were characterized by the highest accuracy and stability, while at the same time lacking unrealistic values. Classic models with a high degree of complexity and forecasts generated automatically by AI were characterized by greater variability and often lower reliability. These results suggest that when forecasting the number of road accidents in Poland, the best results are achieved by using proven statistical methods that take into account the characteristics of the time series, while at the same time making controlled use of neural networks.

In summary, all methods indicate that in 2024–2030, the number of road accidents in Poland will most likely remain at around 20,000–22,000 per year, which means stabilization rather than a further dynamic decline observed in previous years. A comparative analysis of our own forecasts and those generated by AI leads to the conclusion that conscious, controlled modeling still outperforms automatic artificial intelligence tools in terms of the accuracy and reliability of forecasts.

The analysis of the results obtained in this study allows us to draw both methodological and practical conclusions. Historical data show a clear downward trend in the number of road accidents in Poland since the late 1990s, with fluctuations in 2020–2021 caused by mobility restrictions during the COVID-19 pandemic. This phenomenon highlights the need to take into account both the long-term trend and structural points when making forecasts.

The results of our own forecasts, based on neural networks and exponential smoothing methods, confirm hypothesis H1, that these approaches are more accurate than classic regression models with a high degree of complexity. Neural networks generated stable forecasts of around 21,000–22,000 accidents per year, and exponential smoothing methods achieved the lowest MAPE values, within the range of 1–3%. These results show that a well-chosen, simple model can outperform more complex solutions in terms of forecast quality, which further confirms hypothesis H5.

In contrast, high-degree polynomial regression models showed significant instability and in some years generated unrealistic values, including negative ones, which clearly confirms hypothesis H2. Excessive model complexity over a long forecasting horizon leads to extrapolation and large errors, which is clearly evident in MAPE reaching hundreds of percent.

Forecasts generated automatically by AI tools such as ChatGPT, Gemini, Grok, and Perplexity, although readily available, were characterized by significantly greater variability and often lower accuracy compared to proprietary models, confirming hypothesis H3. The worst results were obtained for naive or historical average-based methods (MAPE >100%), while more advanced AI-embedded approaches, such as linear regression or ARIMA, achieved moderate accuracy (MAPE 5–35%). These results indicate that AI forecasts can serve as exploratory support, but cannot replace a conscious and controlled forecasting modeling process.

An analysis of the entire forecast horizon indicates that the number of road accidents in Poland from 2024 to 2030 is likely to remain at around 20,000–22,000 per year, which means stabilization rather than a further sharp decline. These observations are consistent with hypothesis H4, which states that a significant decline in the number of accidents should not be expected in the forecast period, but rather a stabilization of the phenomenon under study.

In summary, the results of the study show that conscious, controlled modeling using classical methods or neural networks provides the best accuracy and stability of forecasts, while forecasts automatically generated by AI are less reliable. At the same time, it has been confirmed that a simple model tailored to the characteristics of the data can outperform complex models, and that excessive complication does not guarantee an improvement in the quality of forecasts. These conclusions suggest that institutions responsible for road safety should use proven statistical methods and neural networks instead of relying solely on forecasts generated automatically by AI.

CONCLUSIONS

An analysis of forecasts for the number of road accidents in Poland in 2024–2030 allows us to draw several important conclusions. First, forecasts based on neural networks and exponential smoothing methods were the most accurate and stable. These results confirm that such methods outperform classic regression models with a high degree of complexity.

Second, the use of high-degree polynomials led to unstable and, in some cases, unrealistic forecasts, which shows that excessive model complexity does not guarantee better forecast quality.

Thirdly, forecasts generated automatically by artificial intelligence tools were less accurate and deviated more often from the historical trend compared to our own forecasts. This indicates that AI tools can only play a supporting role and cannot replace conscious, controlled forecasting modeling.

Fourth, all forecasts indicate that the number of road accidents in Poland in 2024–2030 will remain stable at around 20,000–22,000 per year. This means that a further sharp decline in the number of accidents should not be expected, but rather a stabilization of the phenomenon.

Finally, the analysis showed that well-chosen, simple statistical methods can provide forecasts that are as accurate or more accurate than more complex models. This means that when forecasting the number of accidents, it is crucial to consciously match the method to the characteristics of the time series, rather than automatically using the most complex solutions.

In summary, the results of the study emphasize the importance of controlled and thoughtful modeling in road accident forecasting. Forecasts based on proven classical methods and neural networks provide the greatest reliability, while forecasts generated by AI should be treated only as an auxiliary tool. The stabilization of the number of accidents in the coming years suggests that preventive measures and investments in road safety should focus on maintaining current trends rather than expecting a further sharp decline in the number of incidents. A limitation of the study is that it does not take into account seasonal data and possible legislative changes, which suggests the need for further analysis to consider additional factors affecting the number of road accidents.

Moreover, the presented forecasting methods may serve as practical decision-support tools for improving road safety management and policy planning. Reliable medium-term forecasts of the number of road accidents enable public authorities to formulate evidence-based strategies, adjust national road safety programs, and set realistic operational targets consistent with the projected stabilization trend. In the case of Poland, where all applied models indicate stabilization at approximately 20,000–22,000 accidents annually in 2024–2030, forecasting results provide a quantitative reference point for strategic planning rather than relying on assumptions of further automatic decline.

Accurate forecasts also support more rational allocation of financial and organizational resources. Estimating the expected scale of accidents allows for better planning of expenditures related to emergency services, road infrastructure modernization, intelligent transport systems, enforcement activities, and preventive educational campaigns. In this context, forecasting models function as a tool for optimizing public spending and increasing the efficiency of road safety investments.

In addition, systematic comparison of observed values with forecast trajectories enables early identification of structural changes, unexpected increases in accidents, or the measurable effects of newly introduced legal regulations and safety interventions. Forecasts can therefore serve as a baseline (counterfactual scenario) for evaluating the effectiveness of implemented road safety measures, strengthening the analytical foundations of policy assessment.

The study also demonstrates that transparent and well-calibrated statistical and neural network models are more suitable for supporting public decision-making than automatically generated AI forecasts, as they ensure methodological control, parameter verification, and interpretability. This is particularly important in the context of public administration, where accountability, reproducibility, and clarity of analytical procedures are essential.

Consequently, the proposed forecasting framework should be treated not only as a comparative methodological analysis but also as a practical instrument supporting long-term road safety improvement and evidence-based policymaking in Poland.

PROGNOZOWANIE LICZBY WYPADKÓW DROGOWYCH W POLSCE W LATACH 2024–2030 – ANALIZA PORÓWNAWCZA METOD KLASYCZNYCH, SIECI NEURONOWYCH I PROGNOZ GENEROWANYCH PRZEZ SYSTEMY AI

Artykuł przedstawia analizę porównawczą prognoz dotyczących liczby wypadków drogowych w Polsce w latach 2024–2030, opracowanych przy użyciu metod klasycznych, sztucznych sieci neuronowych oraz narzędzi sztucznej inteligencji (AI). Na podstawie danych historycznych z lat 1990–2023 oceniono dokładność, stabilność i wiarygodność prognoz, stosując jako główny wskaźnik oceny średni bezwzględny błąd procentowy (MAPE). Wyniki pokazują, że sieci neuronowe i metody wygładzania wykładniczego charakteryzują się najwyższą dokładnością i stabilnością prognoz, natomiast modele regresji wielomianowej wysokiego stopnia i prognozy generowane automatycznie przez AI charakteryzują się większą zmiennością i mniejszą wiarygodnością. Prognozy wskazują, że liczba wypadków drogowych w Polsce w analizowanym horyzoncie czasowym prawdopodobnie utrzyma się na stabilnym poziomie około 20 000–22 000 rocznie. Badanie podkreśla znaczenie kontrolowanego modelowania i świadomego doboru metod prognozowania w przewidywaniu trendów w zakresie bezpieczeństwa ruchu drogowego.

Słowa kluczowe: wypadki drogowe, prognozowanie, sieci neuronowe, sztuczna inteligencja, metody klasyczne.

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