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ANALYSIS OF TRAFFIC ACCIDENT TIME SERIES IN THE KARLOVY VARY REGION AND PREDICTION OF THEIR DEVELOPMENT

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Abstract

Road traffic accidents represent a long-term social issue influenced by various temporal, regional and behavioural factors. The aim of this study was to identify the trend and seasonal components of road traffic accidents in the Karlovy Vary Region in the period 2015–2024, to evaluate their development and to verify the possibilities of predicting future accident rates using a selected time series model. The study was based on secondary data on road traffic accidents processed through content analysis. Descriptive statistics and time series methods were applied to evaluate accident development, while the ARIMA model was used for short-term prediction. The results showed that the development of road traffic accidents in the Karlovy Vary Region cannot be described by a clear long-term increasing or decreasing trend, but rather by significant variability over time and recurring seasonal fluctuations. Furthermore, men were consistently more frequently involved in traffic accidents than women, although the development dynamics of both groups were similar. The predictive model achieved an acceptable level of accuracy for short-term forecasting and indicated a continuation of the existing development pattern without major structural changes. The main limitation of the study is the use of aggregated monthly data, which does not allow for a detailed assessment of accident causes or severity. Future research could focus on more detailed accident characteristics, regional comparisons or the application of alternative predictive models.

Keywords: Road traffic accidents, time series analysis, seasonal fluctuations, traffic accident forecasting, ARIMA model, Karlovy Vary Region

Introduction

Traffic accidents are a significant part of road traffic. In many cases, they can lead not only to damage to vehicles and property, but also to serious injuries or even death of road users. The prevalence of traffic accidents and related mortality in a given country is an important indicator of the sophistication of that country and its population (Andrejiova, 2024). Traffic accidents result in lost productivity and healthcare costs (Bertoli & Grembi, 2021). Safe traffic is an important part of sustainable transport. Traffic accidents cause a large number of casualties and property losses every year (Zeng et al., 2024). The development of road transport infrastructure is progressing rapidly in both developed and developing countries. However, the number of deaths caused by traffic accidents continues to rise (Hermawan et al., 2024). Traffic accident risk analysis and prediction are considered prerequisites for road safety management, which directly affects the accuracy and effectiveness of road safety decisions (Zhao et al., 2023).

Purkrábková et al. (2021) addressed the current issue of classifying traffic accident risks in urban environments. In connection with the increase in traffic in the Czech Republic, a higher probability of traffic excesses can be expected in the future. In the event of a traffic excess in a city, the goal is to propose a meaningful traffic management solution that minimizes social losses. Gorzelanczyk et al. (2024) argue that there has been a decline in the number of reported traffic accidents in the Czech Republic and worldwide each year. Although these figures have been affected by recent pandemic-related trends, the overall rate remains significant.

Real-time traffic accident prediction helps identify and prevent traffic accidents. For many years, various real-time traffic accident prediction models have been studied to provide effective information for proactive traffic management (Lei et al., 2021). The causes of traffic accidents vary, including weather, road conditions, road design, and psychological factors. With the development of information technology, large amounts of traffic accident data can be collected and analyzed more easily than before (Yang et al., 2024). Demographic factors such as age and gender significantly influence the causes of traffic accidents, which is essential for ensuring effective prevention and road safety (Reznicek & Kovac, 2025).

The aim of this study is to identify the trend and seasonal components of traffic accident development in the Karlovy Vary Region in the period 2015–2024, evaluate their development, and verify the possibilities of predicting future accident rates using a selected time series model. In connection with this aim, the following research questions are set:

The prices of selected commodities have a significant impact on the economy and the standard of living of the population. This research question allows for a better understanding of the development of these commodities over a longer period of time and an assessment of the main trends in their prices over the last seven years.

RQ1: What is the long-term trend in traffic accidents in the Karlovy Vary Region between 2015 and 2024?

The first research question focuses on determining the long-term trend in traffic accidents in the Karlovy Vary Region between 2015 and 2024. Its aim is to find out whether the number of accidents is showing an upward, downward, or stable trend, and thus to assess the overall development of road safety in the region.

RQ2: What are the differences in the involvement of men and women in traffic accidents in the Karlovy Vary Region in the period 2015–2024?

This research question focuses on analyzing the differences in the involvement of men and women in traffic accidents in the Karlovy Vary Region in the period 2015–2024. The aim is to quantify the proportions of each gender among traffic accident participants and monitor their development over time.

RQ3: How accurate is the prediction model in estimating future traffic accident trends in the region?

The third research question deals with the accuracy of the created prediction model in estimating future traffic accident trends. Its purpose is to verify the reliability of the selected time series model and assess its usability for predicting accident trends on a regional scale.

Literary research

Author Getahun (2021) focused on modeling trends in injury, fatal, and total traffic accidents based on monthly regional data, using ARIMA time series models to analyze and predict accident trends; The results indicated a continuing, unabated trend in traffic accidents in the predicted period and pointed to the need for systematic preventive measures. The importance of using time series in assessing accident trends is also confirmed by other studies that focus on a broader geographical and methodological context. Authors Khasawneh et al. (2022) focused on the development of predictive models of traffic accidents, injuries, and deaths in developing countries with the aim of supporting planning and improving road safety measures, with predictive models created using time series analysis broken down into trend, cyclical, seasonal, and irregular components; The results showed that this approach explained a significant part of the variability of the monitored variables, as evidenced by relatively acceptable values of the coefficient of determination (R^2). Similarly, time series analysis was also used to evaluate long-term trends in traffic accidents at the national level, identifying a downward trend in accidents and fatalities in the Slovak Republic between 2009 and 2022 based on the ETS exponential smoothing method (Andrejiova, 2024). Kovač et al. (2025) analyzed over 90,000 traffic accidents from the Czech national accident register (10/2022–10/2023) and confirmed a statistically significant increase in accident frequency during sunrise and sunset periods. Although the correlation between sunrise/sunset timing and accident frequency was weak, it remained statistically significant, indicating that sunlight glare represents a relevant risk factor for road safety.

The results of this study also confirmed the importance of the trend and seasonal components of the time series and enabled a five-year forecast of further developments. At the macro level of traffic accident development, there are further studies that, in addition to time dynamics, also take into account the influence of selected explanatory factors, with a combination of correlation and regression analysis with the ARIMA time series model demonstrating a statistically significant influence of demographic and traffic characteristics on accident development (Cincikaite & Meidute-Kavaliauskiene, 2023)

The authors Sekadakis et al. (2021) focused on predicting the number of traffic accidents and related losses by combining the classic ARIMA time series model with a backpropagation neural network. The results showed that the hybrid ARIMA-BP model achieved a lower prediction error rate than the ARIMA model alone, but at the cost of higher methodological and computational complexity, which the authors identify as the main limitation of this approach. Using the same data set, the authors further evaluated the impact of extraordinary events on the development of traffic accidents by analyzing the impact of the COVID-19 pandemic on the development of traffic accidents, deaths, and injuries in Greece using monthly data for the period 2010–2020. Using the SARIMA seasonal time series model, they compared actual developments with a counterfactual prediction without the pandemic, with the results showing an overall decline in accidents but also a relative deterioration in road safety during the lockdown period due to the disproportion between traffic volume and the number of accidents. The use of time series models to predict traffic accidents at the national level is also followed up by studies focusing on the urban environment and a more detailed spatial context. The study focused on the development and frequency of traffic accidents on London's A-class roads with the aim of identifying factors influencing accident rates and creating a short-term estimate of their future development. Descriptive statistics and ARIMA and SARIMAX time series models were used to process the data. The results showed that the ARIMA model achieved higher predictive accuracy and enabled the identification of key factors influencing the frequency of traffic accidents (Balawi & Tenekeci, 2024).

The impact of pandemic measures on specific transport segments was examined by Islam et al. (2025), who focused on analyzing the effects of restrictions against the spread of COVID-19 on accident rates and mortality. To process the data series from 2016–2023, the authors used the ARIMA time series prediction model in combination with boxplot analysis, which allowed them to compare real data with the expected development. The results showed that while the first wave and lockdowns led to a significant decrease in accidents compared to the prediction, the third wave saw a sharp increase in all monitored variables, confirming the significant but time-varying impact of crisis measures on safety trends. The issue of interventions in the transport system is also addressed in studies focusing on targeted state interventions outside the pandemic context. Delavara et al. (2024) analyzed the impact of government interventions on road traffic fatalities and injuries, specifically the effects of two waves of fuel price increases and stricter penalties for traffic violations. They used a method of interrupted time series analysis to evaluate three specific intervention points. The results showed that although the overall accident rate (RTM) was declining, this decline was not uniform across all provinces. A key finding was that while both waves of fuel price increases correlated with a decline in accidents, the second wave had an impact in fewer provinces than the first, suggesting that repeated interventions of the same type lose their effectiveness. Furthermore, it was shown that increasing fines was an effective tool only in a limited number of regions. In a geographically similar context, Tutka et al. (2025) analyzed the impact of stricter traffic laws and increased financial penalties in Poland in 2022. The aim of the study was to estimate the impact of these legislative changes on road safety. The authors chose interrupted time series analysis as their primary methodological tool and compared the results with data from neighboring countries. The model demonstrated a statistically significant impact of the reforms, with the authors estimating a decrease in the number of accidents by approximately 6–8% and a decrease in the number of deaths by up to 22% as a result of the measures introduced.

Billah et al. (2022) assumed that the frequency of traffic accidents, the severity of injuries, and driver behavior differ according to gender, and analyzed differences in accident rates between men and women based on ten years of data from a traffic accident database. The study focused on selected types of risky driver behavior, particularly inattentive driving, speeding, lane departure, and drunk driving, and their relationship to injury severity. The results showed that men were more often involved in accidents related to speeding, driving under the influence of alcohol, and lane departure, while women were more often involved in accidents caused by inattentive driving, with time and environmental factors also playing a significant role. Studies focusing exclusively on drunk driving provide a more detailed breakdown of gender differences in specific risk behaviors. Khasawneh et al. (2022) focused on analyzing traffic accidents related to drunk driving in order to identify differences in accident severity between men and women. Based on single-vehicle accident data, a logit model with random parameters was created, which allowed for separate assessment of factors influencing injury severity by gender, taking into account driver, vehicle, road condition, and environmental characteristics. The results showed significant gender differences in the severity of injuries in accidents caused by drunk driving and confirmed that the likelihood of serious injury increases significantly even at lower blood alcohol levels.

Authors Wang et al. (2023) analyzed risk factors affecting the severity of traffic accidents with regard to the responsibility of the perpetrator and the characteristics of the built environment. Based on traffic accident data from 2018–2020, they used the RF-SHAP method to identify key factors affecting accident severity, including the season, road type, mode of travel, driver age, and density of points of interest (POI) at the accident site. The results showed that the significance of individual risk factors varies depending on whether motor vehicle drivers or vulnerable road users are responsible for the accident, with seasonality and the nature of the built environment playing a significant role, especially in serious and fatal accidents.

The studies mentioned above show that research into traffic accidents in professional literature is most often based on quantitative processing of secondary data using descriptive statistics, time series analysis, and regression approaches. These methods make it possible to capture long-term accident trends, identify changes in trends, and assess the impact of selected factors such as extraordinary events, legislative interventions, or demographic characteristics of drivers.

Based on the literature review, content analysis will be used for data collection in this work. Descriptive statistics and time series methods will be used for data processing, which will allow us to describe the development of traffic accidents over time, assess changes in long-term trends, and create a short-term estimate of future developments using the ARIMA time series model. This approach builds on previous research, but is applied in the regional context of the Karlovy Vary Region and to a specific data set.

Data and methods

This chapter focuses on defining the data base and methodological procedure used in the application part of the thesis. Its aim is to present the data used, the analytical methods applied, and to describe the procedure used to obtain the results that serve to fulfill the objective of the thesis and answer the research questions set.

The data base of the thesis consists of secondary data on traffic accidents in the Karlovy Vary Region. The data was obtained from a publicly available database of traffic accidents administered by the Transport Research Centre of the Czech Republic via the internet portal nehody.cdv.cz. Content analysis of the data source was used for data collection, with the aim of selecting relevant indicators and verifying their consistency. The data used covers the period from January 2015 to December 2024, is processed on a monthly basis, and the unit of observation is one calendar month. The database includes the total number of traffic accidents in the Karlovy Vary Region and the number of participants in traffic accidents by gender.

Descriptive statistics and time series analysis methods were used to analyze the data. Descriptive statistics were used to provide a basic description of the database and a clear presentation of the development of traffic accidents over time. Time series analysis was used to capture the development of values on a monthly basis, identify fluctuations over time, and recurring seasonal fluctuations. These methods were applied in particular to answer research questions focused on the development of traffic accidents and differences in the involvement of men and women in traffic accidents.

An ARIMA (AutoRegressive Integrated Moving Average) time series model was used to predict future trends in traffic accidents. The ARIMA model combines an autoregressive component, an integration component, and a moving average and can be generally expressed by the equation (Box et al., 2015):

$$\phi(B)(1-B)^d y_t = \theta(B)\varepsilon_t(1$$

where:

- $y_t$represents the value of the time series at time
- t [number],
- B is the delay operator,
- d is the degree of differentiation,
- $\phi(B)$ is the autoregressive polynomial,
- $\theta(B)$ is the moving average polynomial
- ε_t is a random component of the model.

The prediction model was estimated using monthly data for the period from January 2015 to December 2023. To verify its predictive ability, validation was performed for the year 2024, when the predicted values were compared with the actual recorded values of traffic accidents.

The accuracy of the model was evaluated using the standard error indicators MAE, RMSE, and MAPE.

The Mean Absolute Error (MAE) indicator is defined by the relationship (Hyndman and Athanasopoulos, 2021):

$$MAE = \frac{1}{n}\sum_{t=1}^{n} | y_t - \hat{y}_t |$$

where:

- y_t = represents the actual value of the time series at time
- t = [number],
- $\hat{y}_t$ = is the predicted value [number]
- n = is the number of observations.

The RMSE (Root Mean Squared Error) indicator is expressed by the following equation: (Hyndman and Athanasopoulos, 2021):

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}$$

where the individual variables have the same meaning as in the MAE indicator.

The relative accuracy of the prediction was evaluated using the MAPE (Mean Absolute Percentage Error) indicator, which is defined by the following equation (Hyndman and Athanasopoulos, 2021):

$$MAPE = \frac{100}{n}\sum_{t=1}^{n} | \frac{y_t - \hat{y}_t}{y_t} |$$

where MAPE expresses the average relative deviation of predicted values from reality in percent.

Basic data processing, descriptive statistics, and the creation of graphical outputs related to research questions VO1 and VO2 will be performed in Microsoft Excel. Statistical software R (RStudio) will be used for time series modeling, ARIMA prediction model estimation, validation of its accuracy, and the creation of related graphical outputs within the framework of research question VO3.

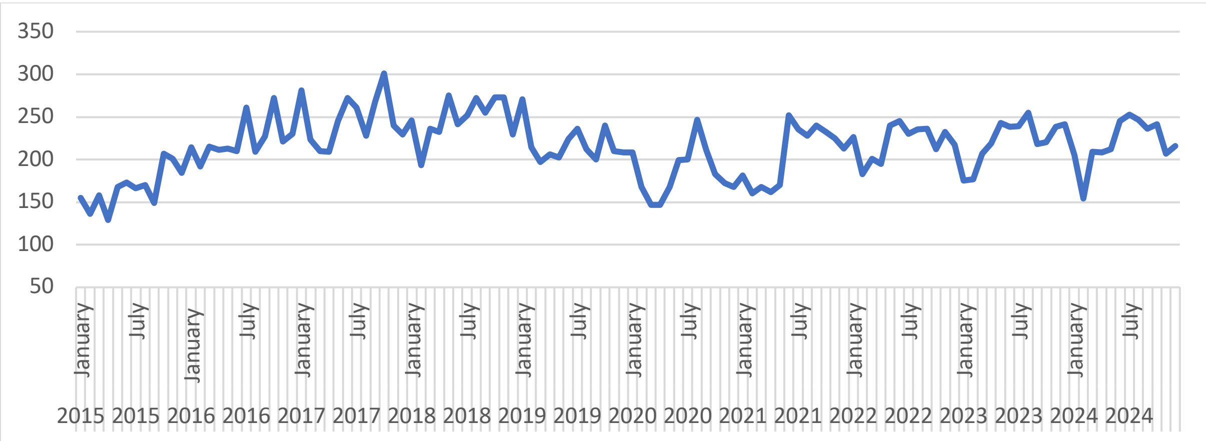
Based on the verified prediction model, a prediction of the development of traffic accidents in the Karlovy Vary Region for the period from January 2025 to December 2026 will then be created. The prediction will be processed on a monthly basis and supplemented with confidence intervals that will express the uncertainty of future developments and serve as a basis for interpreting the results in the following chapter of the thesis.

Results

This section presents the results of an analysis of the development of the total number of traffic accidents in the Karlovy Vary Region between January 2015 and December 2024. The results are based on monthly data on traffic accidents obtained from the database of the Transport Research Centre of the Czech Republic and were processed in accordance with the methodological procedure described in the previous chapter.

Chart 1 shows the development of the total number of traffic accidents in the Karlovy Vary Region on a monthly basis. The chart shows that the number of traffic accidents during the period under review fluctuates and shows recurring fluctuations over time. The values for individual months range from approximately 130 to 300 traffic accidents. The time series indicates the presence of regular seasonal fluctuations, with differences in the absolute accident rate between individual years.

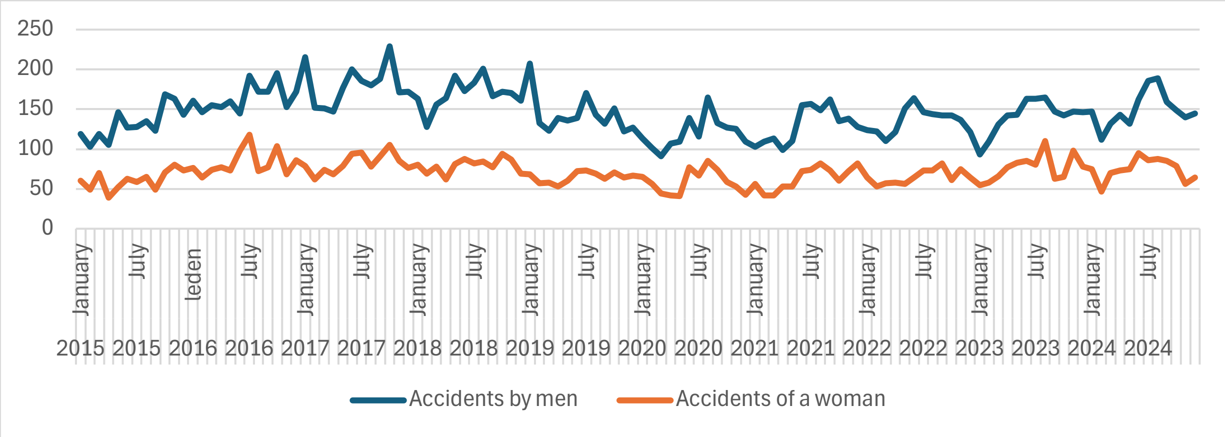
Figure 1: Development of the total number of traffic accidents in the Karlovy Vary Region



Source: Own processing based to nehoda.cdv.cz.

At Chart 2 shows the development of the number of participants in traffic accidents by gender in the Karlovy Vary Region in the period from January 2015 to December 2024. The graph shows that throughout the entire period under review, the number of men involved in traffic accidents exceeded the number of women. This difference is evident in all the years under review and does not show any significant changes over time. The development of both time series shows similar dynamics, characterized by fluctuations over the years and recurring seasonal fluctuations. Higher and lower values for the number of traffic accident participants for both sexes occur in similar time periods. The absolute numbers of traffic accident participants for men range from approximately 100 to 180 persons in most months, while for women the values most often range from approximately 50 to 100 participants per month. The graph also shows that differences between the numbers of traffic accident participants by gender are evident throughout the period under review, with their magnitude varying slightly from month to month depending on the total number of recorded traffic accidents.

Figure 2: Development of the number of traffic accidents by gender in the Karlovy Vary Region (2015–2024)



Source: Own processing based to nehoda.cdv.cz.

To verify the accuracy of the prediction model, validation was performed on a known period. The ARIMA model was first estimated on monthly data for the period January 2015 to December 2023, followed by the creation of an annual prediction for the period January 2024 to December 2024. This prediction was compared with the actual values recorded in 2024. The accuracy of the model was evaluated using standard error indicators MAE, RMSE, and MAPE, which allow the deviation of the prediction to be expressed both in absolute values and relatively in percentages.

Table 1: Error indicators of the ARIMA prediction model (verification for 2024)

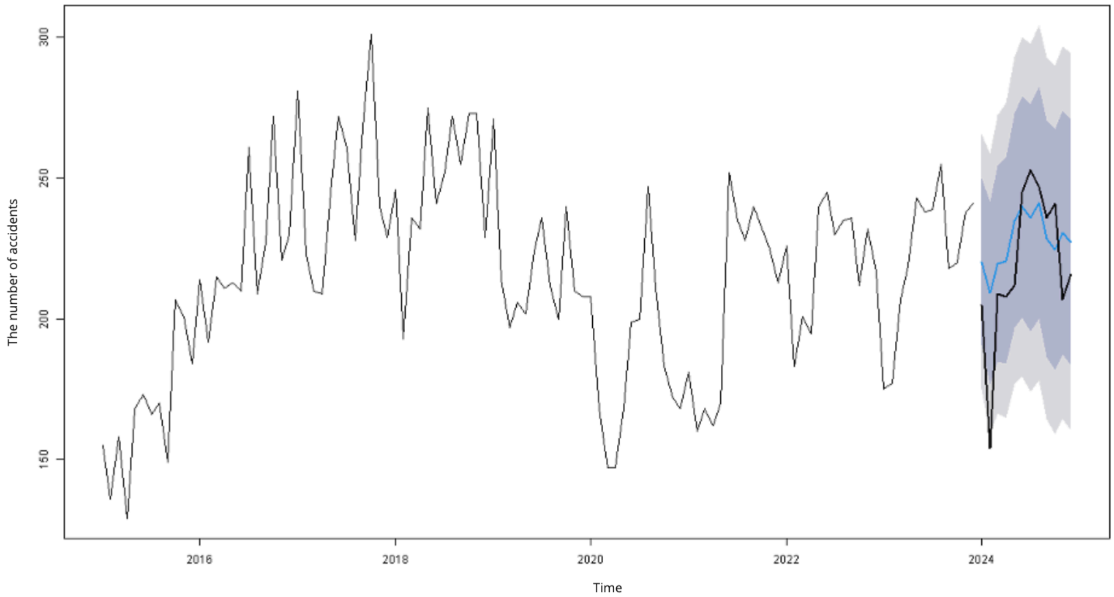
MAE	RMSE	MAPE
16,92	**21,26**	**8,57 %**

Source: Own processing based to nehoda.cdv.cz.

Table 1 shows the values of the error indicators of the ARIMA prediction model when verified for 2024. The MAE and RMSE indicators express the magnitude of the absolute deviation of the predicted values from reality, while MAPE expresses the relative deviation of the prediction in percent.

For a clear assessment of the estimated values, a visual comparison of the actual development and the prediction for 2024 was performed. Graph 3 shows the actual monthly values of the number of traffic accidents in the Karlovy Vary Region in 2024 and, at the same time, the values predicted by the ARIMA model created on the basis of historical time series. The display also includes prediction confidence intervals, which define the expected range of values at the selected probability level.

Figure 3: Actual and predicted total number of traffic accidents in the Karlovy Vary Region (ARIMA), 2024

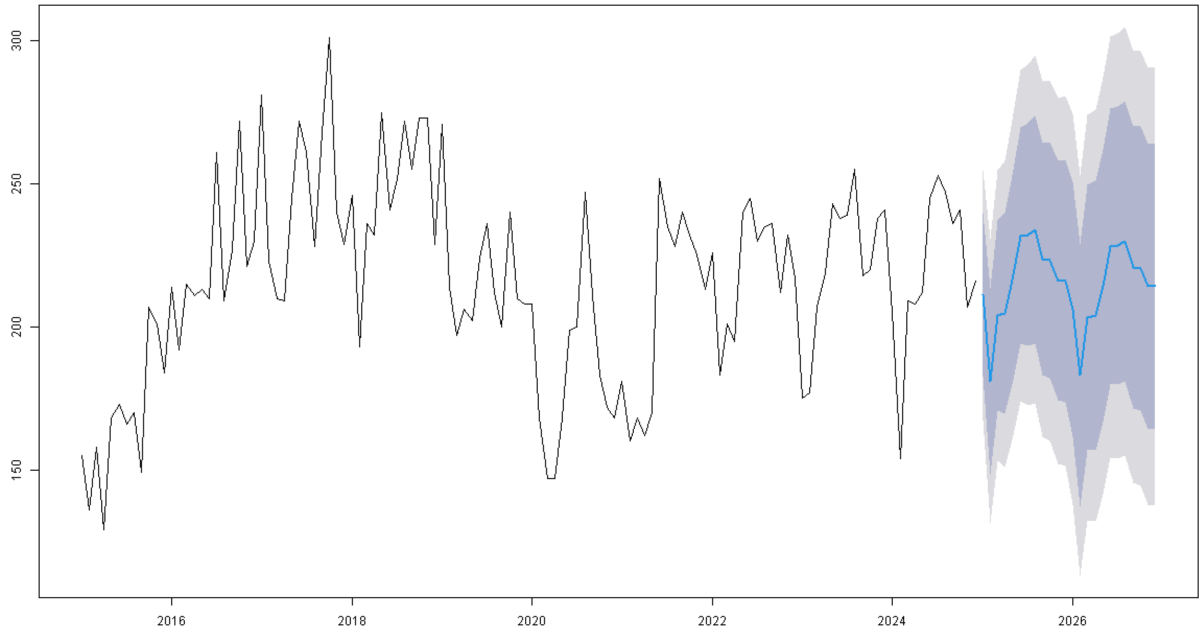


Source: Own processing based to nehoda.cdv.cz.

Chart 3 shows that the predicted time series captures the monthly development of the number of traffic accidents in 2024. The actual values for each month are close to the predicted trajectory. The confidence intervals shown define the range of values within which the actual values for each month lie, given the level of uncertainty of the model.

After verifying the predictive power of the model for 2024, the model was then applied to the entire available time series for the period from January 2015 to December 2024. Based on this model, a prediction of traffic accidents in the Karlovy Vary Region for the period from January 2025 to December 2026 was created. Graph 4 shows the historical development of the number of traffic accidents and the corresponding point prediction supplemented by confidence intervals.

Figure 4: Prediction of the monthly number of traffic accidents in the Karlovy Vary Region for 2025–2026 (ARIMA model)



Source: Own processing based to nehoda.cdv.cz.

Chart 4 shows that the model provides a prediction of future traffic accident trends on a monthly basis and also illustrates the uncertainty of the estimate through confidence intervals. The point prediction represents the mean estimate of future trends, while the confidence intervals define the lower and upper limits of expected values at the selected probability level. The prediction is processed on a monthly basis with a frequency of 12, which corresponds to the nature of the input database.

The specific numerical values of the point prediction and confidence intervals for individual months of 2025 and 2026 are listed in the appendix to this work.

Discussion of results

RQ1: What is the long-term trend in traffic accidents in the Karlovy Vary Region between 2015 and 2024?

The observed trend in traffic accidents in the Karlovy Vary Region indicates that the long-term trend cannot be characterized as clearly increasing or decreasing, but rather as variable with significant seasonal fluctuations. This may be due to a combination of several factors, including fluctuations in traffic intensity throughout the year, the influence of weather conditions, and the specifics of the regional transport infrastructure. The marked seasonality suggests that traffic accident rates are strongly influenced by short-term changes in traffic behavior and external conditions rather than by a stable long-term trend.

The conclusions of this study are consistent with the study by Getahun (2021), who, using ARIMA time series models, pointed out the unstable nature of traffic accident trends and emphasized the importance of the trend and seasonal components of the time series. At the same time, however, the results suggest differences from the conclusions of Andrejiová (2024), who identified a long-term downward trend in traffic accidents at the national level. This difference can be interpreted as meaning that aggregated national data may obscure regional specifics and local fluctuations, which are more pronounced at the level of individual regions. From an interpretative point of view, it can therefore be assumed that regional analysis provides a more detailed view of the development of traffic accidents and allows us to capture dynamics that may not be reflected in national averages. The results thus support the hypothesis that conclusions based on national-level analyses cannot be automatically transferred to the level of individual regions without further generalization.

RQ2: What are the differences in the involvement of men and women in traffic accidents in the Karlovy Vary Region in the period 2015–2024?

The differences found in the involvement of men and women in traffic accidents in the Karlovy Vary Region indicate a long-term stable imbalance between the sexes, with men systematically more frequently involved in traffic accidents than women. The stability of this difference over time may indicate that it is a structural characteristic of traffic accidents rather than a short-term or random phenomenon. The fact that the development of male and female participation shows similar temporal dynamics also suggests that both groups respond to the same seasonal and temporal factors affecting overall accident rates. This result is consistent with the conclusions of the professional literature, which has long pointed to the existence of gender differences in traffic accidents. Billah et al. (2022) link the higher representation of men among traffic accident participants primarily to different patterns of traffic behavior and a higher degree of risky behavior. Although this work does not directly assess the causes of traffic accidents or their severity, the results support the general assumption that gender is a significant factor in the differentiation of participation in traffic accidents.

From an interpretative point of view, however, it is necessary to emphasize that the data used reflect participation in traffic accidents, not responsibility for their occurrence. The differences found cannot therefore be interpreted as differences in the degree of fault between men and women, but rather as differences in their exposure to traffic and in the way they are involved in the transport system. This view is consistent with approaches in the professional literature, which points to the need to distinguish between participation, behavior, and responsibility when assessing the gender aspects of traffic accidents.

RQ3: How accurate is the prediction model in estimating future traffic accident trends in the region?

The prediction of traffic accident trends in the Karlovy Vary Region for the period 2025–2026 suggests that future trends are likely to continue along the same lines as before, with no significant changes in the trend. It can therefore be assumed that the short-term development of traffic accidents will continue in a similar pattern to that observed in previous years. Confidence intervals express the natural uncertainty of the prediction and show the possible range of future values, not the exact scenario of development.

Verification of the prediction model over a known period showed that the selected model provides sufficiently reliable estimates for the short-term outlook. From a practical point of view, it can be said that the ARIMA model is able to capture basic development trends and recurring seasonal fluctuations in traffic accident data well. This confirms its usefulness, especially at the regional level, where the goal is to provide an indicative estimate of future developments rather than an accurate prediction of individual values.

The findings of this work correspond to the conclusions of the professional literature, which considers ARIMA models to be a suitable tool for short-term prediction of traffic accidents when working with monthly time series. Getahun (2021) and Khasawneh et al. (2022) point out that these models are able to capture the basic structure of accident development and provide a meaningful estimate of future developments. Compared to more methodologically complex approaches, such as hybrid models combining ARIMA with neural networks (Sekadakis et al., 2021), the chosen approach has the advantage of simpler interpretation of results.

In the context of this work, the ARIMA model can therefore be considered a suitable compromise between accuracy and simplicity. This approach allows for a clear description of the expected development of traffic accidents and provides a clear basis for basic orientation in future developments at the regional level.

Conclusion

The aim of the study was to identify trend and seasonal components in the development of traffic accidents in the Karlovy Vary Region in the period 2015–2024, to evaluate their development, and to verify the possibilities of predicting future accident rates using a selected time series model. This objective was achieved within the scope of the study.

Based on the synthesis of the results and their discussion, it can be stated that the development of traffic accidents in the Karlovy Vary Region is characterized by significant temporal variability and regularly recurring seasonal fluctuations. These fluctuations point to the fact that traffic accident rates are strongly influenced by short-term factors such as changes in traffic intensity, climatic conditions, or the seasonal behavior of road users. At the same time, the results suggest that at the regional level, accident trends cannot be clearly interpreted through a simple long-term trend, which confirms the importance of regionally focused analyses in assessing traffic safety.

Another important finding of the study is that the differences in the involvement of men and women in traffic accidents in the Karlovy Vary Region have remained stable over the long term. During the period under review, men were systematically more frequently involved in traffic accidents than women, with both groups showing similar trends over time. This suggests that gender differences in accident rates are more structural in nature and are not the result of short-term fluctuations. The findings are consistent with the conclusions of the professional literature and support the view that gender is an important aspect that should be taken into account when interpreting traffic accident data.

The study also included verification of the possibilities for predicting future trends in traffic accident rates at the regional level. Discussion of the results showed that short-term predictions based on historical trends make it possible to create realistic and comprehensible estimates of future accident dynamics. The predictive approach thus appropriately complements the view focused on past developments and provides a framework for considering future developments in traffic safety in the region. The significance of prediction lies not in the accurate estimation of individual values, but primarily in the identification of the expected direction of development and its possible variability.

The main limitations of the study include the use of aggregated monthly data, which does not allow for a detailed assessment of the causes of traffic accidents, their severity, or the responsibility of individual participants. The prediction is also based on the assumption of continuity of current developments and does not take into account possible future changes in transport infrastructure, legislative measures, or the occurrence of extraordinary events. Further research could therefore focus on working with more detailed data, extending the analysis to include causal factors, or comparing the results with other regions of the Czech Republic. The findings could serve as a basis for further specialist research and contribute to a deeper understanding of the development of traffic accidents at the regional level.

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Attachments

Appendix 1 - Point prediction of traffic accident trends

Date	Point prediction	Lower limit of 80%	Upper limit 80%	Lower limit of 95%	Upper limit of 95%
01/2025	211	183	240	168	255
02/2025	181	149	213	131	231
03/2025	204	171	237	153	255
04/2025	205	170	240	151	258
05/2025	216	180	253	161	272
06/2025	232	194	270	174	290
07/2025	232	193	271	173	292
08/2025	234	194	274	173	295
09/2025	224	183	264	162	286
10/2025	223	182	264	160	286
11/2025	216	174	258	152	280
12/2025	216	174	258	151	281
01/2026	206	162	251	138	275
02/2026	183	137	229	113	253
03/2026	203	157	250	132	274
04/2026	204	157	251	132	276
05/2026	214	167	262	141	287
06/2026	228	180	276	154	302
07/2026	228	180	277	154	303
08/2026	230	181	279	155	305
09/2026	221	172	270	145	296
10/2026	220	171	270	145	296
11/2026	214	164	264	138	290
12/2026	214	164	264	138	291

Source: Own processing based to nehoda.cdv.cz.

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THE IMPACT OF THE CURRENT CRISIS IN THE AUTOMOTIVE INDUSTRY ON CORPORATE STRATEGIES OF COMPANIES IN THE CZECH REPUBLIC

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Abstract

The aim of this study was to clarify how recent crises and structural changes in the automotive industry affected the strategic decision-making of companies in the Czech Republic and their ability to adapt to changing market conditions. To achieve this aim, quantitative methods were employed, specifically correlation analysis, regression modeling, and input share analysis using data from selected companies for the period 2019-2023. The results revealed a strong relationship between production volume and corporate profitability, while the short-term impact of foreign input shares was limited, manifesting rather as a long-term structural risk. The contribution of this study lies in enhancing knowledge of strategic adaptation in the Czech automotive industry and identifying factors that support its resilience and competitiveness., regional comparisons or the application of alternative predictive models.

Keywords: Automotive industry, crisis, structural changes, competitiveness, Czech Republic.

Introduction

The automotive industry is one of the most important and complex sectors of the European economy. By its very nature, it connects an extensive network of suppliers, manufacturing companies, logistics services, and research institutions, and contributes significantly to gross domestic product and employment. The automotive industry is a key sector for the Czech economy and has a significant impact on employment, exports, and the overall added value of industry. Motor vehicle production in the Czech Republic is among the most significant in the European Union, accounting for 8.1% of total EU production (Heryán, Rucková, and Cerulli, 2024). It is therefore an important segment of the economy, highlighting the strategic importance of this sector for the national economy.

In recent years, however, the industry has undergone a fundamental structural transformation as a result of both external crisis factors and long-term trends related to technological and environmental transformation. According to Britsch and Fekete (2024), the European automotive industry is facing growing instability in supply chains, caused, among other things, by global geopolitical risks, raw material shortages, and the increasing complexity of international relations. This situation is leading to a re-evaluation of traditional production and distribution management models, with an emphasis shifting to building the resilience and adaptability of businesses. The automotive industry is thus in a period where the ability to respond strategically to changing conditions is a key factor in its long-term competitiveness.

Although the automotive industry remains a long-term focus of attention for experts, most studies to date have concentrated primarily on technological transformation within the European Union or on its macroeconomic impacts. However, the strategic adaptation of Czech companies to the current crisis conditions has been examined only marginally, particularly in the context of global challenges such as deglobalization, the digitization of production, and the transition to sustainable energy sources. This fact is further confirmed by Procházka and Černá (2023), who point out that for effective strategic decision-making, it is necessary to conduct a more in-depth analysis of the relationships between structural changes in the automotive industry and corporate strategies in the Czech Republic.

The aim of this thesis is to clarify the ways in which the current crisis and structural changes in the automotive industry are influencing the strategic direction and decision-making processes of companies operating in the Czech Republic, with a particular emphasis on their ability to adapt to changing market conditions and supply chains. The thesis also includes an assessment of approaches that could strengthen the resilience and competitiveness of the Czech automotive industry in the future in the context of ongoing global changes.

Based on the stated objective of the thesis, the following research questions are formulated:

RQ1: How do current crises and external pressures affect strategic decision-making by companies operating in the Czech automotive industry?

RQ2: What approaches can strengthen their ability to adapt to changing market conditions and supply chain disruptions?

RQ3: How can companies leverage current changes to strengthen their long-term competitiveness?

Literary research

In recent years, the automotive industry has faced a series of crises that have fundamentally affected its structure, production models, and strategic direction. The following sections summarize the findings of studies examining the impacts of individual crises and the transformation of corporate strategies in response to them.

The COVID-19 pandemic was one of the first major factors to significantly disrupt global supply chains, with the automotive industry being one of the most affected sectors. A study by Pató, Herczeg, and Csiszárik-Kocsir (2022) shows that, particularly during the second and third waves of the pandemic, production processes were severely affected by restrictions on the supply of raw materials and components from Asia, leading to a significant slowdown in production and the need for companies to quickly reevaluate their strategic decisions. The authors also identify that companies with greater resilience and adaptability were better able to respond to supply chain disruptions, underscoring the importance of strategies focused on flexibility and crisis management.

This factor also had a significant impact on the European Union, which was forced to respond to rapidly changing global economic, political, environmental, and technological conditions. Gräf and Topuria (2025) report that, as part of its crisis management, the EU launched massive state interventions aimed at supporting digital transformation and green transition. The main tool was a program called NGEU with a total allocation of EUR 750 billion, with member states required to allocate 20% of the funds to digital transformation. These funds support the automotive industry's transition to electromobility, complemented by legislative measures such as strict CO_2 emission reduction targets for new cars by 2030 and 2035. In addition, the EU has launched an initiative that sets digital targets for 2030 and supports multinational projects in the field of low-cost processors and IT services. At the same time, projects focused on breakthrough research and the first industrial deployment of new technologies, for example in microelectronics, batteries, cloud infrastructure, and hydrogen, have become an important strategic tool for implementing the new industrial policy, through which the EU is attempting to ensure long-term sectoral transformation and strengthen Europe's strategic autonomy.

From a microeconomic perspective, the pandemic has caused fundamental changes at the level of individual companies, with the adaptation of business models playing a key role. A study by Dobrowolska and Sliż (2023) shows that most Polish car dealerships were forced to rethink their relationships with customers and key partners, with the most significant changes affecting individual clients and corporate customers, while competition was perceived less critically. The main transformation measures included expanding the range of services, digitizing vehicle and parts sales, and using IT tools for online sales. Companies also implemented rapid organizational changes, including the introduction of remote working and flexible process adaptation to ensure business continuity and financial stability during the crisis. This resulted in a shift in the main source of profit from new vehicle sales to service and warranty services, which also strengthened customer focus and the ability to respond to current customer needs.

In the Czech context, the COVID-19 pandemic had a similarly strong impact. According to Kučera and Tichá (2022), Czech automotive manufacturers in 2020 faced a decline in profitability, rising indebtedness, and temporary production shutdowns caused by government measures as well as disruptions to supply chains. Škoda Auto a.s. recorded a year-on-year decline in profit of CZK 9.9 billion and a reduction in return on sales of 2%, while its indebtedness increased to 58%, i.e. by 3% more than in 2019. Hyundai Motor Manufacturing Czech reported a decline in profit of CZK 3.18 billion and a similar 2% decrease in return on sales, whereas Toyota Motor Manufacturing Czech Republic faced a decline in profit of CZK 40 million and an increase in indebtedness of 6%. The authors also note that the second wave of the pandemic at the beginning of 2021 brought about a global shortage of semiconductors, which further constrained production in the European and Czech automotive sectors. Overall, the pandemic led to a reduction in profitability and an increase in the financial burden on companies, with its effects also reflected in rising automobile prices as a result of lower production and increasing costs.

This implies that the COVID-19 pandemic forced automotive companies to rapidly adapt their strategies and business models in order to overcome production disruptions and disturbances in supply chains. Dragos-Marian (2024) further adds that, alongside the crisis, an opportunity emerged to leverage new market trends and changes in demand to strengthen resilience and the long-term competitiveness of firms. This idea is also supported by a study focusing on government stimulus programs in the automotive industry during the COVID-19 pandemic in France and Germany (Lechowski, Krzywdzinski, and Pardi, 2023). The authors state that both countries introduced extensive programs supporting changes and technological transformations of the sector; however, the nature of these measures was rather structurally conservative. This means that they primarily supported existing manufacturers and established structures, rather than radically transforming the industry. The conclusion points out that even within crisis management, strategies tend to ensure stability and continuity of firms rather than a revolutionary transformation of their business models.

After the stabilization of the consequences of the COVID-19 pandemic, the conflict between Russia and Ukraine escalated, once again significantly affecting the functioning of firms and national economies. The disruption of complex global supply chains revealed the insufficient preparedness of companies and the need to adapt business processes. Lazic, Grujic, and Skoric (2025) emphasize that such disruptions represent a long-term risk for firms, especially in a period of high globalization, as supply chains are typically complex and lengthy. Insufficient preparedness and the absence of alternatives subsequently lead to significant changes in business processes and supply structures, which may affect the overall financial situation of companies.

One of the major problems for the global economy became the price of strategic raw materials. Since the outbreak of the conflict, the price of Brent crude oil, which is considered the benchmark of the international oil market, rose to USD 139 per barrel, reaching a new maximum since 2008. This represents an increase of approximately 45% within one week. Such a sharp rise in international oil prices was reflected in gasoline prices in most countries. Liu, Chen, and Zhang (2023) state that, for example, in China gasoline prices were adjusted eight times between March 4, 2022 and June 15, 2022, with seven of these adjustments being price increases. The authors also add that this development had a significant impact on the subsequent increase in electric vehicle sales in China.

Financial market analyses show that overall the automotive industry was strongly affected by this crisis. Companies worldwide recorded an average decline in market value between −4.9% and −6.4% at the onset of the war, with more than 70% of firms experiencing a negative stock market reaction. These data reflect not only the impact on automobile and component manufacturers themselves, but also on the broader global economy, as disruptions in supply chains spill over into other industries and markets (Kim et al., 2025).

Growing pressure on automotive companies represents a significant structural and financial factor influencing their strategic decisions. An analysis of 48 automotive firms in the EU and the United Kingdom up to 2022 shows that while in the United Kingdom there is a positive relationship between the quality of environmental reporting and corporate profitability, in the European Union this obligation, by contrast, reduces profitability. This difference suggests that stricter European regulations strengthen corporate social responsibility, but at the same time increase costs and the strategic burden on firms (Lanzalonga, Likavec, and Biancone, 2025). Another major structural pressure on corporate strategies arises from the regulatory decision of the European Union to end the sale of vehicles with internal combustion engines by 2035, despite the fact that electric vehicles accounted for only 2.2% of the EU vehicle fleet in 2022. A comparative study of nearly four thousand respondents from Italy, France, Germany, and Denmark shows that consumers' willingness to shift to electromobility is influenced primarily by socio-psychological factors, with perceived usefulness increasing purchase intention, while the need to change established mobility habits significantly reduces it (Augurio et al., 2025).

An important factor driving changes in strategies is also the deep integration of the European automotive sector into global value chains. Campos-Romero, Rodil-Marzábal, and Pérez (2024) explain that participation in these chains is associated with a higher environmental burden, with Central European economies focusing more on higher value-added activities, while less developed countries remain dependent on emission-intensive production. An additional factor is the ownership structure of firms. Heryán, Rucková, and Cerulli (2024) found that companies with dispersed ownership are more sensitive to liquidity issues, whereas firms with a dominant owner react more strongly to macroeconomic conditions, which is reflected in different approaches to financial management and strategic decision-making. Alongside these factors and increasing pressures for change, automotive firms are also beginning to orient themselves toward hydrogen technologies. Analyses show that the hydrogen fuel cell is perceived as a promising alternative powertrain, the development of which is, however, in its initial phases strongly dependent on public support and long-term research funding. In countries with a developed automotive industry, state investment programs are therefore being established to reduce the technological and financial risks associated with the introduction of these innovations (Carrera-Rivera et al., 2024).

In the Czech context, the automotive industry has a key impact primarily on the economies of former industrial regions. Koutsky, Novák, and Holub (2025) state that automotive manufacturers significantly contribute to the reindustrialization of these areas, with evaluations based on the indicator of value added per employee confirming a high concentration of industry at the microregional level. Various factors influence the dynamics of this process, suggesting that corporate strategies must reflect both regional conditions and the need to adapt to structural changes in the sector. Given that motor vehicle manufacturing in the Czech Republic accounted for around 10.2% of total industrial production in 2023, corresponding to a value of CZK 1,732 billion, this sector should be considered key not only within these regions but also for the national economy as a whole (Czech Statistical Office, 2025).

From the perspective of international linkages, the Czech automotive industry is characterized by a substantial dependence on foreign inputs, particularly from China. The analysis shows that the overall dependence of the Czech automotive industry on Chinese inputs in 2020 was 1.59 times higher than directly observed, representing a share of 5.6% of the total value of inputs. The value added through these foreign supplies shows a long-term upward trend with a marked acceleration in recent years, while the absence of domestic battery production underscores the need for strategic policies supporting self-sufficiency and the stability of supply chains (Hrubý and Saroch, 2025).

At the same time, Czech firms are beginning to use modern technologies to enhance sustainable performance. Srivastava, Aftab, and Tyll (2025) add that artificial intelligence and additive manufacturing significantly support sustainable product design and manufacturing processes, which subsequently improves the overall sustainability of firms. These findings suggest that the integration of new technologies with sustainable practices can increase the competitiveness of Czech industry and provide guidance for policymakers and managers in planning innovations.

Data and methods

This chapter describes the procedures for data collection and processing that will be used to answer the research questions defined for this study.

Data

For the purposes of this study, data related to the Czech automotive industry in the period from 2019 to 2023 will be analyzed. The collected data will serve to answer the research questions and will include both financial and operational indicators of firms, information on technological adaptation, and integration into global supply chains.

Specifically, data on the profitability and return on sales of selected automotive manufacturers will be analyzed, including their average and median values over time. Data on production volumes and participation in international supply chains will also be collected, including the share of foreign inputs, particularly from China. These data will be obtained from publicly available sources, annual reports of individual companies, statistics of the Czech Statistical Office, international databases, and academic literature providing supplementary information on trends and structural changes in the industry. All time series and data will be pre-processed, including checks for missing values and standardization of measurement units, in order to ensure consistency for subsequent analysis.

The collected data will make it possible to assess the impact of external crises and external pressures on corporate strategic decision-making, identify factors supporting firms' adaptability, and evaluate opportunities to strengthen the long-term competitiveness of the Czech automotive industry.

Methods

To answer the research questions, a combination of quantitative analytical methods will be used, enabling the assessment of the impact of external crises, structural changes, and external pressures on the strategic decisions of firms in the Czech automotive industry. The collected data will be analyzed using statistical measures such as the mean, median, standard deviation, and variance.

To evaluate the relationships between these statistics, production volume, and integration into international supply chains, correlation analysis and regression modeling will be applied. Specifically, multiple regression analysis will be used to assess the dependence of firms' strategic decisions on external and structural factors.

The model will be formulated as follows:

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \cdots + \beta nXn + \varepsilon$$

where:

Y represents the target indicator of a firm's strategic decision-making,

X_1 to X_n are explanatory variables including financial indicators, production volumes, the degree of integration into supply chains, and other relevant factors,

β_0 to β_n are the estimated regression coefficients,

ε is the error term.

To evaluate the impact of foreign inputs on the financial and operational indicators of the automotive sector, an approach based on input share analysis will be employed, whereby the relative share of foreign inputs in the total value of materials and components is calculated. These share-based indicators will be included in the regression models as explanatory variables, allowing for the assessment of their statistical influence on firms' strategic decision-making.

The methodology is designed to enable a comprehensive analysis of the effects of external crises and external pressures on the Czech automotive industry, the identification of factors supporting adaptability, and the determination of potential strategies to strengthen the long-term competitiveness of firms. All applied methods ensure the reproducibility of the research and an objective interpretation of the results.

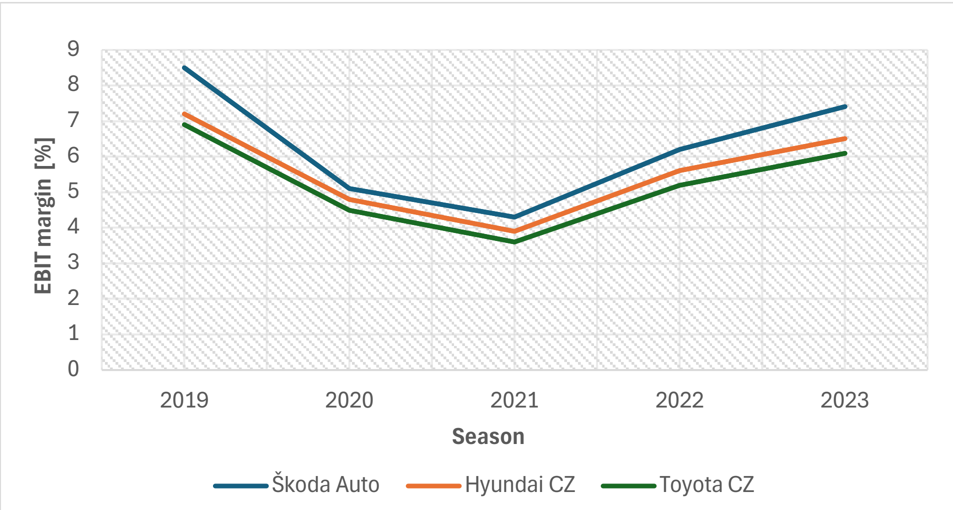
Results

The analysis includes three major automotive manufacturers and combines financial, operational, and structural indicators that were defined in the methodological section of the study.

Basic characteristics

In the first phase, basic descriptive statistics were calculated for individual variables, making it possible to obtain an initial overview of the level, variability, and development of the observed indicators over time and across individual firms.

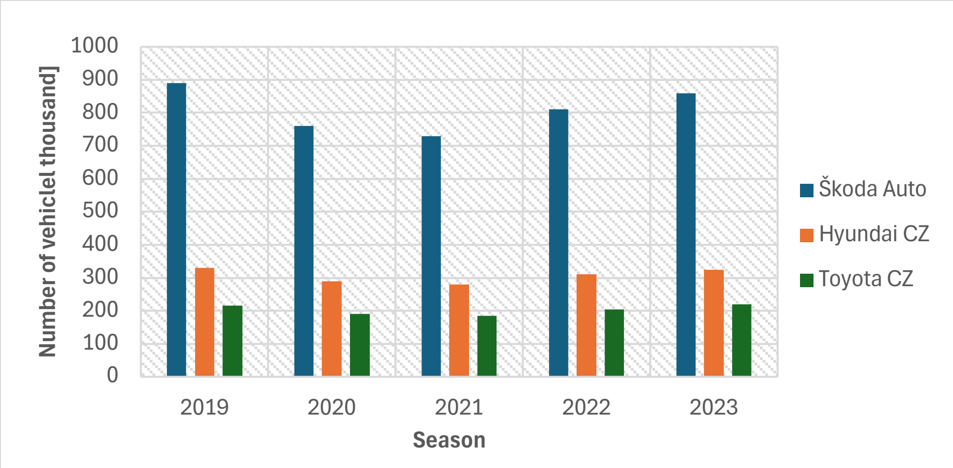
Figure 1: Profitability of Automotive Manufacturers in the Czech Republic in 2019–2023



Source: Own processing based

Corporate profitability, measured through the EBIT margin, showed significant fluctuations during the analyzed period. The highest values were achieved in 2019, when Škoda Auto reached a profitability level of 8.5%, Hyundai recorded 7.2%, and Toyota achieved 6.9%. In 2020 and 2021, all observed firms experienced a decline in both the average and median values of these indicators. The standard deviation of profitability increased during this period, indicating growing differences in the ability of individual firms to respond to external shocks.

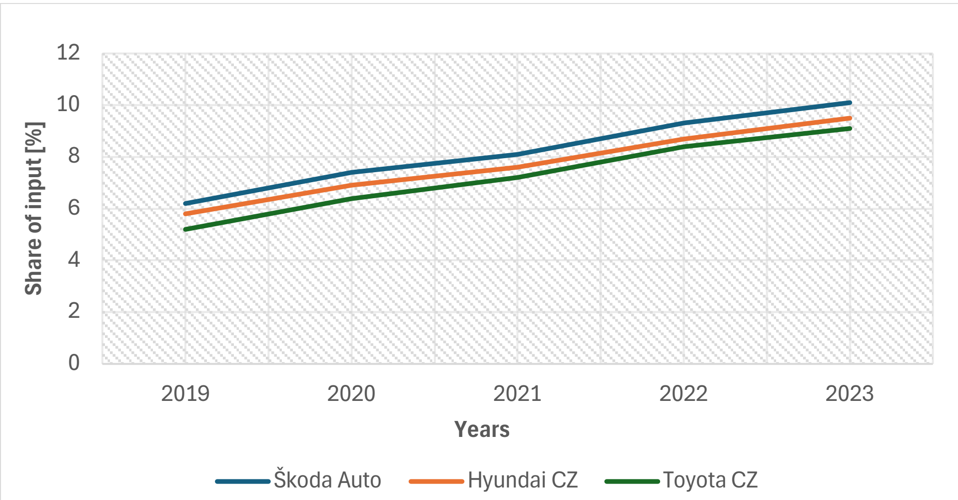
Figure 2: Vehicle Production Volume in 2019–2023



Source: Own processing based

Production volume exhibited a similar developmental trend. Average vehicle output declined between 2020 and 2021, while the range of values across firms widened. This reflects differing degrees of production constraints and capacity adjustments resulting from supply chain disruptions and reduced demand. In 2022 and 2023, a gradual return of production volumes toward pre-crisis levels is evident.

Figure 3: Values of Foreign Inputs in 2019–2023



Source: Own processing based

From the perspective of integration into global supply chains, a growing share of foreign inputs was observed. The average share of these inputs gradually increased over the analyzed period, with this trend being common to all analyzed firms. The low variance in the initial years and its gradual increase indicate slightly different speeds of adaptation of firms to changes in the international trade environment.

Correlation Analysis

The correlation analysis shows the relationship between the profitability of selected automotive manufacturers and selected operational and structural indicators.

Table 1: Correlation between profitability and selected indicators (production volume, share of foreign inputs)

Company	Production volume	Share of inputs
Škoda Auto	0.996822014	-0.120751491
Hyundai CZ	0.987754581	-0.079651843
Toyota CZ	0.930174194	-0.142269462

Source: Own processing based

The relationship between profitability and production volume is very strong and positive for all observed firms, with correlation coefficients reaching 0.9968 for Škoda Auto, 0.9878 for Hyundai CZ, and a lower 0.9302 for Toyota CZ. This result suggests that growth in production volumes is closely associated with increasing profitability, which, as expected, reflects the direct impact of production capacity on firms' financial performance.

In contrast, the relationship between profitability and the share of foreign inputs appears to be weak and negative. While all three automotive manufacturers show a weak negative correlation between profitability and the share of foreign inputs, a slight difference can be observed for Hyundai CZ, which reaches a value of -0.0797, indicating a somewhat weaker negative relationship than that of Škoda Auto and Toyota CZ. This difference suggests that Hyundai CZ's profitability is less sensitive to the share of foreign inputs, which may be related to a different diversification of supplier relationships or the firm's cost structure.

Regression Analysis

To evaluate the impact of external and structural factors on the strategic decisions of Czech automotive manufacturers, multiple linear regression was applied. The dependent variable of the model was profitability, while the explanatory variables were production volume and the share of foreign inputs.

The estimation of regression coefficients was carried out using the method of least squares, which minimizes the sum of squared differences between actual and predicted values of profitability. This approach made it possible to quantify the impact of individual factors on firms' financial performance and to compare their relative importance.

Table 2: Results of the regression analysis

Company	Coefficient (β_0)	Production volume (β_1)	Share of foreign inputs (β_2)
Škoda Auto	4.2	0.012	-0.05
Hyundai CZ	5.1	0.011	-0.03
Toyota CZ	4.8	0.009	-0.06

Source: Own processing based

The results of the regression analysis for the three selected automotive manufacturers show that production volume has a strong positive effect on profitability, while the share of foreign inputs exhibits a slight negative effect that is statistically insignificant. These findings are consistent with the results of the correlation analysis presented in the previous section.

This regression analysis makes it possible to objectively assess the influence of external and structural factors on the strategic decisions of Czech automotive manufacturers and provides a basis for proposing measures to support their adaptability and long-term competitiveness.

Analysis of the Impact of Foreign Inputs

The input share analysis shows that the relative importance of foreign inputs in the total value of production gradually increased over the analyzed period for all observed automotive manufacturers. This trend reflects the growing specialization of global value chains and the increasing dependence on imports of key components. Although the absolute level of integration into foreign supplies differs among individual firms, the overall direction of development is consistent.

The results of the correlation analysis suggest that the relationship between firms' profitability and the share of foreign inputs is weak and negative in all cases. The values of the correlation coefficients range from -0.08 to -0.14, indicating that higher dependence on foreign supplies does not in itself represent a direct determinant of firms' profitability in the short term. This conclusion is also confirmed by the results of the regression analysis, in which the share of foreign inputs did not prove to be a statistically significant explanatory variable in explaining the development of profitability.

At the same time, however, the results indicate that increasing integration into global supply chains may increase firms' vulnerability to external shocks, such as geopolitical conflicts, disruptions to logistics flows, or price volatility in international markets. These factors may be reflected in firms' economic results indirectly, particularly through constraints on production volume or increased cost volatility, which was especially evident in the crisis years of the analyzed period.

Discussion of results

RO1: How do current crises and external pressures affect the strategic decision-making of firms operating in the Czech automotive industry?

The results of the conducted analysis confirm that current crises and external pressures significantly affect the strategic decision-making of firms in the Czech automotive industry, primarily through changes in production volume, profitability, and the structure of supply inputs. The correlation analysis demonstrated a strong positive relationship between profitability and production volume among the analyzed automotive manufacturers. This indicates that, during crisis periods, corporate strategic decisions are strongly oriented toward maintaining production capacity as a key factor of financial stability.

By contrast, the relationship between profitability and the share of foreign inputs proved to be weak and slightly negative, suggesting that the degree of integration into global supply chains does not directly affect firms' financial performance, but rather operates through increased uncertainty. These conclusions correspond with the findings of Lazic, Grujic, and Skoric (2025), who emphasize that disruptions in supply chains represent a long-term strategic risk rather than an immediate change in profitability.

The regression analysis further showed that production volume acts as a statistically significant explanatory variable of profitability, confirming the conclusion that during crises firms adapt their strategies primarily through the optimization of production volumes and capacities. This approach complements the findings of Campos-Romero, Rodil-Marzábal, and Pérez (2024), who stress that firms integrated into global value chains face increased structural pressure and must make strategic decisions with regard to production efficiency and environmental costs.

Based on these results, it can be concluded that the strategic decision-making of Czech automotive manufacturers in the context of current crises is not driven by a single factor, but by a combination of production, financial, and structural pressures. The analysis also shows that firms respond to external shocks more through operational adjustments in production and cost structures than through an immediate reduction in their integration into global supply chains, which confirms the high degree of structural dependence of the Czech automotive industry on the international environment.

RO2: What approaches can strengthen their ability to adapt to changing market conditions and supply chain disruptions?

According to the results of the analysis, the adaptive capacity of firms in the Czech automotive industry is closely linked to their production flexibility, the structure of supply inputs, and their ability to manage financial risks. The strong relationship between profitability and production volume identified in both the correlation and regression analyses indicates that firms with a greater ability to adjust production capacities achieve better economic results even during periods of increased volatility. This conclusion confirms that flexible production management represents one of the key adaptive approaches.

The input share analysis also highlights that a high degree of dependence on external suppliers, particularly from geographically distant regions, does not in itself worsen short-term profitability, but it does increase firms’ strategic vulnerability. These findings are consistent with the conclusions of Hrubý and Saroch (2025), who point to the growing dependence of the Czech automotive industry on foreign supplies.

Based on the results, it can be summarized that strengthening the adaptive capacity of firms in the Czech automotive industry lies primarily in a combination of flexible production management, diversification of supply chains, and gradual technological modernization. These approaches enable firms not only to mitigate the negative impacts of external crises, but also to actively respond to changing market conditions and long-term structural changes in the industry.

RO3: How can firms use current changes to strengthen their long-term competitiveness?

The results of the study suggest that current crises and structural changes do not represent only a source of risk for firms in the Czech automotive industry, but also create space for strengthening their long-term competitiveness. The empirical analysis showed that firms capable of maintaining stable production volumes even during periods of external shocks achieve higher profitability, which confirms the importance of effective capacity management as a strategic tool of long-term performance. Competitiveness thus depends not only on cost optimization, but also on the ability to respond quickly to changes in the market environment.

From the perspective of structural changes, technological transformation plays a key role. Although the regression models in this study did not directly include technological variables, the results must be interpreted in the context of broader trends identified in the academic literature. Srivastava, Aftab, and Tyll (2025) demonstrate that the integration of artificial intelligence and additive manufacturing positively affects firms’ sustainable performance, suggesting that technological innovations can strengthen the positive relationship between production efficiency and financial performance.

An important opportunity to enhance competitiveness also lies in reassessing the structure of supply chains. Although the correlation analysis did not confirm a strong direct relationship between the share of foreign inputs and profitability, a high level of dependence on external supplies represents a strategic risk. Firms that are able to diversify their inputs or support the localization of key components can reduce their vulnerability to future crises and simultaneously gain a competitive advantage in the form of greater production stability.

Overall, it can be concluded that the long-term competitiveness of firms in the Czech automotive industry will depend on their ability to transform short-term crisis pressures into strategic opportunities. A combination of technological innovation, adaptation to the regulatory framework, and active supply chain management enables firms not only to respond to current changes, but also to strengthen their position within the European and global automotive market.

Conclusion

The aim of this thesis was to clarify the ways in which current crises and structural transformations in the automotive industry have influenced the strategic orientation and decision-making processes of firms operating in the Czech Republic, with particular emphasis on their ability to adapt to changing market conditions and disruptions in supply chains. This objective was fulfilled through an analysis of academic literature and data from selected automotive companies covering the period 2019–2023.

The results of the study demonstrated that external crisis-related influences had a significant impact on the strategic decisions of firms in the Czech automotive industry. The empirical analysis confirmed a strong positive relationship between production volume and corporate profitability, indicating that the ability to maintain production continuity represented a key stabilizing factor during periods of heightened uncertainty. At the same time, dependence on foreign inputs, particularly within global supply chains, proved to be more of a long-term structural risk than a short-term financial performance issue. These conclusions are consistent with findings in the academic literature and at the same time empirically complement them in the context of the Czech automotive industry, which is strongly integrated into international production structures.

This thesis also provides relevant insights for corporate management, as its results emphasize the need for strategic decision-making that goes beyond short-term cost optimization and reflects long-term structural changes and the risks associated with global economic interconnectedness. The contribution of the thesis lies in linking quantitative analysis with current theoretical approaches and in formulating conclusions that are applicable both in academic research and in practical settings.

The limitations of the thesis lie primarily in the limited number of analyzed firms and the time span of the data, which at the same time creates scope for further research focused on a broader sample of firms, a longer time horizon, and a deeper analysis of technological and institutional factors influencing the future development of the automotive industry.

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The impact of population aging on the development of real estate prices in the Czech Republic

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Abstract

Rising housing prices and population ageing currently represent key factors influencing the development of real estate markets in many countries, including the Czech Republic. The aim of this thesis was to evaluate the development of housing prices in the Czech Republic between 2015 and 2024 and to determine whether population ageing influenced the rise in apartment and house prices. To achieve this goal, time series analysis, correlation analysis, a two-sample paired t-test, and regression analysis were used to quantify the development of both variables and their mutual relationship. The research showed a significant increase in housing prices during the examined period and confirmed a steady rise in the average age of the population. A strong and statistically significant relationship between the two variables was identified, and the regression models demonstrated that demographic ageing significantly contributed to predicting housing price trends. The thesis thus provides valuable insights into the dynamics of the Czech housing market and highlights the importance of demographic factors in assessing its long-term sustainability. The research is limited by its reliance on aggregated annual data and by the omission of additional variables that may affect housing prices. These limitations create opportunities for future studies focusing on regional analyses, data models, or an expanded set of predictors.

Keywords: Population ageing; Housing prices; Real estate market; Time series analysis; Correlation analysis; Regression analysis; Czech Republic

Introduction

There is an interconnection between population aging, housing prices, and household consumption behavior. Population aging may affect the level of consumption not only directly, but also indirectly through changes in the housing market, where rising real estate prices influence the structure of household expenditures (Wang & Suna, 2024). As noted by Chien et al. (2025), in many countries over recent decades, income and wealth inequality have increased alongside rising housing prices. Growing real estate prices lead to higher income from property ownership, which further deepens wealth disparities among different social groups. At the macroeconomic level, Cuestas et al. (2023) point out that price imbalances in the real estate market may amplify economic cycles in the short term, while long-term overvaluation of real estate prices slows economic growth. These conclusions confirm the need for stabilization measures to mitigate housing market fluctuations.

At the same time, increased housing costs represent a serious social problem that affects the very functioning of families. Marçal et al. (2025) found that the financial burden associated with housing costs is a stress factor for families, which may disrupt a healthy family environment and lead to tension or aggressive behavior of parents toward children. These findings indicate that high housing prices are not only an economic issue, but also a psychological and social one, highlighting the importance of monitoring housing market developments in connection with broader demographic changes.

Housing unaffordability represents a growing problem not only for young households but also for the aging population, especially in cities with a high level of urbanization. Alidoust (2024) points out that the lack of affordable housing increasingly affects older individuals, who often face financial insecurity and limited long-term housing options. The study shows that alternative forms of housing, such as house-sitting or home sharing, may represent a more affordable option for some seniors, increasing their financial stability and enabling them to better cover other life needs. At the same time, however, the uncertainty associated with the temporary nature of these housing forms may lead to feelings of vulnerability and negatively affect the psychological well-being of older persons.

Population aging also brings the need to adapt housing to the changing needs of older individuals. A recent analysis of data from the American Housing Survey showed that housing modifications in households with persons aged 65 and over are significantly influenced by demographic and housing factors, such as income, housing type, or household size. The study confirms that housing adequacy and affordability play a key role in the quality of life of seniors and may influence their decisions regarding relocation or housing adjustments. These findings emphasize the growing importance of housing issues in the context of an aging population, which is becoming a key socio-economic topic not only in the United States but also in Europe (Green et al., 2022).

The aim of this thesis is to evaluate the development of housing prices in the Czech Republic and to determine whether the process of population aging may influence the growth of apartment and family house prices. Based on the identified data, relationships between demographic development (especially population aging) and real estate price development in the Czech Republic in the period 2015–2024 will be examined.

In relation to this objective, the following research questions are formulated:

RQ1: How did house and apartment prices develop between 2015 and 2024 in the Czech Republic?

The first research question examines time series of house and apartment prices in the Czech Republic. The results provide findings on how real estate prices increased (or decreased) and serve as a basis for the following research questions.

RQ2: How did the average age of the population in the Czech Republic develop?

The second research question illustrates the development of the average age of the population in the Czech Republic. The output consists of data presented graphically and in tables. These data form an important basis for the third research question.

RQ3: Is there a relationship between population aging and real estate price growth in the Czech Republic?

This research question is central to this thesis. It further examines whether there is a relationship between the variables: population aging and real estate price growth.

H0: Population aging influences real estate prices.

H1: Population aging has no effect on real estate prices.

Literary research

Wang & Suna (2024) used time series analysis for the period 2001–2018, where housing prices served as a mediating variable. The results showed that population aging directly increases the level of household consumption and indirectly increases it through housing prices. The study proposes solutions such as optimizing the population structure, improving the housing system, and advancing the development of industries focused on older adults. Sun et al. (2024) found that aging has differentiated effects on housing prices and that these differences stem from aspects of aging and housing. In terms of aging, a decline in birth rates and an increase in survival rates may have opposite effects on housing prices. In terms of housing, the prices of both components—land and structure—respond to declining birth rates and rising survival rates to different degrees. Therefore, the impact of population aging on housing prices does not have a clear long-term trajectory. In the short term, the results suggest that aging may cause a structural break in price dynamics. Heo (2022) uses correlation analysis to measure the old-age dependency rate, redefining it by incorporating the actual retirement age and the estimated remaining life expectancy. In this way, the study examines the differentiated impacts of population aging on the market value of real estate. The results of the correlation analysis indicate that an increase in the dependency rate measured by remaining life expectancy is associated with a decline in real housing prices, while the traditionally defined old-age dependency rate does not explain this relationship. Furthermore, distinguishing between the groups of the “young-old” and the “old-old” reveals that the negative effect on housing prices is primarily associated with an increasing share of very old individuals. Overall, the conclusions suggest that demographic aging does not necessarily lead to a long-term decline in real estate prices, as the negative effect is particularly evident among the oldest segment of the population with limited life expectancy.

Cheung (2025) focuses on the relationship between population aging and real estate price development in rural areas and examines why prices there are rising faster than in cities despite population aging. Time series analysis within a cointegration framework was used to capture both long-term and short-term relationships between demographic factors and housing market dynamics. The results show that short-term deviations of rural real estate prices from cointegration relationships are a significant predictor of future price and migration developments over a one- to four-year horizon, whereas this relationship does not appear in urban areas. The findings suggest that the key to understanding housing market dynamics in an aging society lies in rural areas. The authors also emphasize that accounting for these long-term cointegration relationships may be important for supporting rural development. Wealth inequalities based on residential property ownership have long been more pronounced in the Czech Republic than income inequalities. Property values have increased significantly, and households with higher incomes and family ownership backgrounds have a greater advantage in acquiring housing and achieve higher unrealized gains from price growth. The findings highlight barriers to entry into homeownership and the role of real estate as a security instrument in old age (Sunega & Lux, 2018).

Cho & Lee (2024) point out that many older studies demonstrate that aging has a negative impact on real estate price growth, and in 2012 this claim was repeatedly confirmed. Motivated by this research, they examined the relationship between population aging and real estate prices with a focus on the effect of credit availability. The analysis uses unbalanced panel data from 1981–2020 for 59 countries. They find that the negative impact of aging on housing prices is not confirmed when credit availability is taken into account. However, this effect may be offset by greater access to financing. The results suggest that population aging may affect real estate prices differently depending on credit conditions in a given market and that the expected downward demographic pressure has not yet materialized. The study by Akgündüz et al. (2023) shows that a reduction in mortgage interest rates has a direct and measurable impact on mortgage demand and housing prices. Specifically, a one-percentage-point decrease in the mortgage rate led to an increase in mortgage volumes and simultaneously to higher house prices.

Lee et al. (2023) used hierarchical linear modeling of growth (HLM) to analyze the development of repeated house sale prices between 2012 and 2020. This approach allowed for simultaneous tracking of variable effects over time and across property groups. The results showed significant differences in average repeated sale prices (ICC = 91.65%), indicating high variability among individual houses. It was further confirmed that time of sale and its quadratic term significantly influence price development, while the effect of house age is modified by floor area, type, and location. The study demonstrates that a combination of temporal and spatial factors can explain a large part of the variability in real estate market dynamics and that HLM represents an appropriate tool for analyzing repeated transactions over time. The study by Kalaviska & Hlavacek (2022) analyzes determinants of apartment prices in Czech regions between 2000 and 2019 and shows that their development is mainly influenced by wages, unemployment rates, and migration. The significance of these effects differs according to regional income levels, with land prices playing a greater role in wealthier regions, while labor market factors and population age structure are key in poorer regions. Disequilibrium price shocks are, according to the results, corrected within approximately two years.

Küçükyazici & Bregger (2024) examine the social aspects of housing and the development of Turkish residential architecture from the perspective of interaction between the individual, society, and space. The study uses content analysis of articles from the journal Arkitekt followed by spatial analysis of selected residential construction examples. The results show that shared spaces in residential areas play a key role in shaping relationships between private and public life and contribute to the development of socially sustainable housing forms. Green et al. (2024) address persistent housing discrimination in the state of Mississippi between 1998 and 2018. The study uses content analysis of newspaper reports on discrimination cases to identify sociodemographic characteristics of victims and sanctions imposed on perpetrators. The results show that racial housing discrimination persists decades after the adoption of the Fair Housing Act and significantly affects the lives of those impacted. Rysavy & Dobisova (2023) examine the communication of housing issues in municipal newspapers of three Czech cities with different shares of municipal housing. The study combines quantitative and qualitative content analysis of articles to assess how housing is politically framed in the period before municipal elections. Quantitative results did not confirm the expected favoritism toward the ruling coalition, while the qualitative part showed that communication about housing is strongly influenced by the editorial policy of municipal periodicals. New city administrations may thus expand space for presenting their own housing policy through changes in communication strategy or use selective coverage of non-conflict topics to improve their public image.

Promphakping et al. (2021) examined how the importance of life goals and subjective well-being of residents in northeastern Thailand changed over a ten-year period (2006–2016) and how these changes relate to housing and population age. Using paired t-tests, the authors compared respondents' attitudes in both periods and identified significant changes, particularly in external life goals, including owning a large house, being debt-free, and having a clean environment—values closely linked to housing and living standards. The results showed that older respondents placed greater emphasis on housing security and stability, while younger respondents focused more on economic self-sufficiency. Multiple linear regression further revealed that in 2006 the importance of life goals (including housing) significantly predicted subjective well-being, whereas in 2016 this relationship weakened and changed direction. The study suggests that population aging alters the perception of the role of housing and material security in overall life satisfaction. The study by Melnychenko et al. (2022) analyzes the impact of inflation on the real estate market in Poland between 2009 and 2021 using panel data and time series models. The results show that housing prices are mainly influenced by inflation, interest rates, construction activity, and mortgage volumes, with forecasts achieving low error rates and identifying a structural break in the price trend around 2017. The findings provide practical insight for consumer decision-making and analysis of real estate market dynamics.

Andersson et al. (2021) identified changes in housing accessibility for people with Parkinson's disease over three years. Using a paired t-test and questionnaire survey, they compared the severity of environmental barriers identified by the Housing Enabler instrument. The results showed that although the main types of barriers did not change, their intensity evolved over time—some (e.g., absence of grab bars or access via stairs) decreased due to modifications, while others (e.g., difficult access to waste disposal areas) increased. The study emphasizes that age and health status significantly affect the need for housing adaptations and that continuous accessibility assessment is essential for sustainable and safe living of seniors. On the other hand, Douglas et al. (2022) evaluated the impact of relocating persons with disabilities and complex needs into newly built individual apartments in a community setting. Using a paired t-test and Wilcoxon test, they compared outcomes before and after relocation. In the paired test, the formula $t = \bar{d} / (sd / \sqrt{n})$ was used to determine statistical dependence. The study demonstrated significant improvement in well-being and community integration, a trend toward improved health, and reduced support needs. The authors conclude that well-designed, accessible, and technologically adapted housing can significantly improve quality of life and independence for people with disabilities, thereby confirming the importance of appropriate housing adaptations and environments for vulnerable population groups.

Data collection will be conducted using content analysis. The data will be processed using correlation analysis with a paired test and regression. Time series analysis will also be used and presented graphically.

Data and methods

This thesis works with secondary data collected through content analysis. The content analysis was carried out by reviewing publicly available sources, specifically kurzy.cz and the Czech Statistical Office (CZSO). First, data on real estate prices (specifically houses and apartments separately) were collected from the website kurzy.cz for the period from 31 December 2014 to 31 December 2024 in order to answer RQ1. The same procedure was used to obtain data for RQ2, with the only difference being the data source. Data for the subsequent research question were obtained from the CZSO. From the above-mentioned data, tables were created that clearly present the development of real estate prices and the average age of the population, and graphs were subsequently generated from these tables. Both tables and graphs were processed in Microsoft Excel and represent specific time series for the given period.

Subsequently, statistical analyses were conducted exclusively in Microsoft Excel to answer RQ3 and to evaluate whether H0 or H1 is valid. First, a correlation analysis was performed using Pearson's correlation coefficient, separately examining the relationship between average age and apartment prices, and between average age and house prices. The following formula was used for the calculation (Hindls et al., 2016):

$$r = [\, \Sigma\, (xi - \bar{x})(yi - \bar{y})\,] \,/\, \sqrt{[\, \Sigma\, (xi - \bar{x})^2\,]} \cdot \sqrt{[\, \Sigma\, (yi - \bar{y})^2\,]}$$

The numerator of the fraction represents the covariance, and the denominator represents the product of the standard deviations of both variables.

x_i= individual values of the first variable

y_i= individual values of the second variable

$\bar{x}$= arithmetic mean of X values

$\bar{y}$= arithmetic mean of Y values

n= number of observations

The resulting value of r ranges within the interval:

+1 = perfect positive correlation

0 = no linear correlation

−1 = perfect negative correlation

To verify whether the development of the average age and real estate prices over time systematically corresponds, a two-sample paired t-test for the mean was used. The test compared differences between paired values for individual years and determined whether these differences were statistically significant. The following formula was used for the paired two-sample t-test (Hindls et al., 2016):

$$t = \bar{d} / (sd / \sqrt{n})$$

Where:

$\bar{d} = (1/n) \cdot \Sigma(xi - yi)$

$sd = \sqrt{[\,\Sigma(di - \bar{d})^2 / (n - 1)\,]}$

$di = xi - yi$

n = number of paired observations

The final step was a simple linear regression analysis, the purpose of which was to quantify the effect of the average age of the population on the development of real estate prices and to determine what proportion of price variability can be explained by demographic development. The regression was performed using the Regression tool and provided key indicators such as the regression coefficient, model constant, p-value, and coefficient of determination R^2. The combination of these methods made it possible to comprehensively assess the development of both variables and evaluate their mutual relationship. This analysis uses the following three formulas (Hindls et al., 2016):

1. $Y = a + bX + \varepsilon$
2. $b = Cov(X, Y) / Var(X)$
3. $a = \bar{y} - b \cdot \bar{x}$

Where:

Y = dependent variable (real estate price)

X = independent variable (average age of the population)

a = constant

b = regression coefficient (slope of the line)

ε = random error term of the model

All these analyses aim, among other things, to evaluate the following hypotheses:

H_0: Population aging has an effect on real estate prices.

H_1: Population aging has no effect on real estate prices.

Results

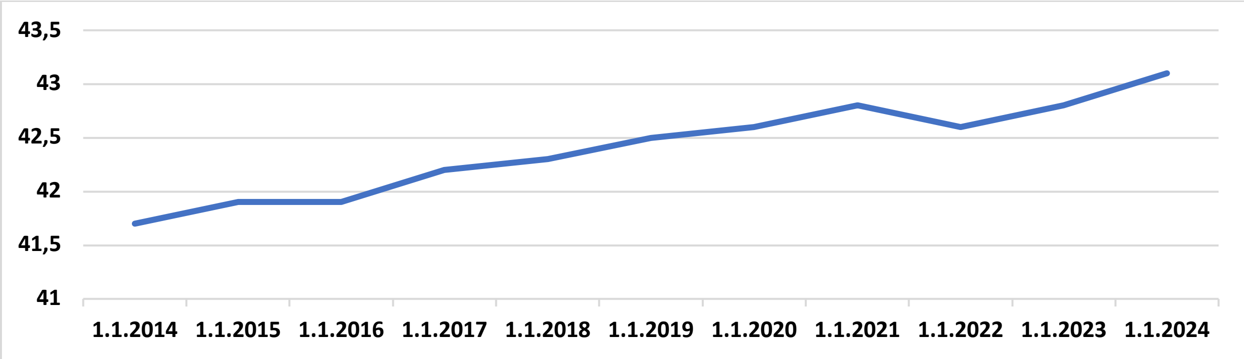
Graph 1 illustrates the development of apartment and single-family house prices in the Czech Republic over the period 31 December 2014 – 31 December 2024. The data are based on the time series presented in Appendix 1 (Development of Real Estate Prices), compiled according to kurzy.cz. The values of the price indices for both apartments and houses show an upward trend over time, reaching their highest levels at the end of the observed period, indicating that real estate prices have been increasing. The graph enables a comparison of both property categories at individual points in time. At the beginning of the observed period, as of 31 December 2014, the apartment price index stood at 97.2, while the house price index was 99.7. In the following years, both series exhibit a predominantly upward trend. A more significant increase is observed particularly from 2019 onward. The highest values are recorded at the end of the period: as of 31 December 2024, the apartment price index reaches 266.5 and the house price index 228.6, representing nearly a 2.5-fold increase compared to the beginning of the observed period.

Figure 1 - Development of house and apartment prices over time.

Source: Own processing based on data from kurzy.cz (see Appendix 1).

V Grafu 2 je uveden vývoj průměrného věku obyvatel České republiky od 31.12.2014 do 31.12.2024. Data vycházejí z časové řady ČSÚ. Průměrný věk populace v průběhu sledovaného období roste, což odpovídá faktu, že na začátku sledovaného období činil průměrný věk obyvatel 41,7 roku a v dalších letech dochází k postupnému zvyšování tohoto ukazatele. Nejvyšší hodnota je zaznamenána na konci roku 2024, kdy průměrný věk dosahuje 43,1 roku. Průběh grafu zachycuje souvislý růst průměrného věku v jednotlivých letech sledovaného období.

Figure 2 - Average age of the population over time



Source: Own processing based on data from CZSO.cz.

Table 1 presents paired values of the average age of the population and apartment and house prices for individual years over the period 2014–2024. The table allows for a direct comparison of all three monitored indicators within a unified time framework.

At the beginning of the observed period, the average age of the population was 41.7 years, the apartment price index reached 97.2, and the house price index 99.7. At the end of the observed period, as of 31 December 2024, the average age is 43.1 years, the apartment price index 266.5, and the house price index 228.6.

The table provides a summary overview of the input data used in subsequent calculations of correlation, paired t-tests, and regression models.

Table 2 - Comparison of real estate prices and age

period	average age	apartment prices	house prices
31.12.2014	41,7	97,2	99,7
31.12.2015	41,9	101,70	100,60
31.12.2016	41,9	120,10	109,60
31.12.2017	42,2	137,40	123,00
31.12.2018	42,3	151,30	135,30
31.12.2019	42,5	166,40	150,80
31.12.2020	42,6	186,20	176,20
31.12.2021	42,8	243,10	212,30
31.12.2022	42,6	252,90	219,40
31.12.2023	42,8	243,40	222,50
31.12.2024	43,1	266,50	228,60

Source: Own processing.

The results of the correlation analysis are presented in Table 2 and Table 3. Table 2 contains the correlation coefficient between the average age of the population and the prices of single-family houses. The value of Pearson's correlation coefficient is r = 0.942080534. The table also shows the correlations within the individual variables and represents a correlation matrix.

Table 3 presents the correlation between the average age and apartment prices. The identified value of Pearson's correlation coefficient is r = 0.94535808. In correlation analysis, if the value of r approaches 1, the correlation is considered very strong and statistical significance exists.

Tabulka 3 – Correlation of house prices

	House prices	**Average age**
House prices	1	
Average age	0,942080534	1

Source: Own processing.

Tabulka 4 – Correlation of apartment prices

	Apartment price	**Average age**
Apartment price	1	
Average age	0,94535808	1

Source: Own processing.

The results of the two-sample paired t-test for the pair average age of the population and apartment prices are presented in Table 4. The two-tailed p-value ($P(T \leq t)$ (2)) equals 3.00405×10^{-5}, which is significantly lower than the significance level of 0.05. The absolute value of the t-statistic (t Stat) is –7.177805, which exceeds the critical t-value of 2.228138852 (t crit (1)).These values confirm that the difference between the compared time series is not random and that the test result is statistically significant. The table also includes the means of both variables, variances, number of observations, and critical t-values, which are not essential for the research.

Table 4 – Paired t-test for apartment prices

	Average age of the population	**Apartment price**
Mean	42,4	178,7454545
Variance	0,194	4021,710727
Observations	11	11
Pearson correlation	0,945358077	
Hypothesized mean difference	0	
df	10	
t Stat	-7,177800512	
P(T<=t) (1)	1,50203E-05	
t critical (1)	1,812461123	
P(T<=t) (2)	3,00405E-05	
t critical (2)	2,228138852	

Source: Own processing.

The results of the paired t-test for the pair average age of the population and single-family house prices are presented in Table 5. The two-tailed p-value (P(T≤t) (2)) in this case is 8.31264 × 10^{-6}, which is again significantly lower than the significance level of 0.05. The absolute value of the t-statistic reaches –7.689558, exceeding the critical t-value (2.228138852). The result therefore confirms a statistically significant difference between the two compared time series. The table also includes the means, variances, t-statistics, p-values, and critical t-values, which are not essential for this research.

Table 5 – Paired t-test for house prices.

	Average age of the population	**House prices**
Mean	42,4	161,6363636
Variance	0,194	2687,718545
Observations	11	11
Pearson correlation	0,942080534	
Hypothesized mean difference	0	
df	10	
t Stat	-7,689558009	
P(T<=t) (1)	8,31264E-06	
t critical (1)	1,812461123	
P(T<=t) (2)	1,66253E-05	
t critical (2)	2,228138852	

Source: Own processing.

The results of the regression analysis are presented in Table 6, which summarizes the key indicators for both pairs of variables – average age of the population and apartment prices, as well as average age of the population and single-family house prices. For the model working with apartment prices, the coefficient of determination reaches $R^2 = 0.893701894$, indicating a high degree of explanation of the variability of the dependent variable. The regression coefficient has a value of $b = 0.006565863$ and the model constant is 41.22638191. The two-tailed p-value of the regression coefficient (1.1271×10^{-5}) and the p-value of the F-statistic (1.12707×10^{-5}) are significantly lower than the chosen significance level of 0.05, confirming the statistical significance of both the model and the individual coefficient. The model also shows a high F-statistic value (75.66754823), demonstrating its overall robustness. The table also includes the number of observations and the standard error of the model.

For the model analyzing the relationship between the average age of the population and single-family house prices, the coefficient of determination reaches $R^2 = 0.887515733$, again indicating a strong ability of the model to explain the variability of the observed variable. The regression coefficient b equals 0.008003814 and the model constant is 41.10629257. The p-value of the coefficient (1.4579×10^{-5}) and the p-value of the F-statistic (1.45785×10^{-5}) are well below the 0.05 threshold, confirming the statistical significance of the model. The F-statistic reaches 71.01118944, corresponding to a high explanatory power of the model. The table further includes the number of observations and related regression indicators.

Table 6 – Regression analysis

	Regression of house prices and age	**Regression of apartment prices and age**
Multiple R	0,94535808	0,942080534
R^2	0,893701894	0,887515733
Regression coefficient b	0,006565863	0,008003814
Constant a	41,22638191	41,10629257
p-value of coefficient	$1,1271\times10^{-5}$	$1,4579\times10^{-5}$
F-statistic	75,66754823	71,01118944
p-value of F	$1,1271\times10^{-5}$	$1,4579\times10^{-5}$
Number of observations	11	11

Source: Own processing.

All these results clearly confirm the null hypothesis (H0), which states that population aging has an effect on real estate prices. Conversely, H1 is rejected.

Discussion of results

RQ1: How did house and apartment prices develop between 2015 and 2024 in the Czech Republic?

Based on the conducted analysis, it can be stated that both apartment and single-family house prices in the Czech Republic increased significantly over the period from 31 December 2014 to 31 December 2024. At the end of 2014, the average apartment price index was 97.2 and rose to 266.50 by 2024, representing an increase of approximately 171%. A similar development was recorded for single-family house prices, which increased from 99.7 in 2015 to 228.60 in 2024, i.e., by roughly 129%.

The time series thus shows long-term and stable growth, with the most pronounced acceleration occurring between 2020 and 2022, when prices increased most dynamically. The data do not indicate any period of sustained price decline, only a short-term slowdown in growth in 2023.

The results of the analysis are consistent with some international studies that also describe rising real estate prices in connection with demographic changes or other socioeconomic factors. Wang & Suna (2024) identify that population aging may contribute to price growth through increased consumption and housing demand. This conclusion is partially consistent with my findings, which show long-term price growth during a period of demographic aging. Cheung (2025) describes a significant increase in prices particularly in rural areas, where aging and migration of the younger population may act as short-term catalysts for price growth. This phenomenon is consistent with the upward trend observed in my data.

On the other hand, some authors point out that real estate prices do not always grow linearly or uniformly. Sun et al. (2024) state that aging may have different effects on housing prices in the short and long term and may even cause temporary reversals in price dynamics. In this respect, my results differ, as the Czech data do not show any short-term downward reversal. Similarly, Heo (2022) describes situations in which certain demographic changes may lead to a slowdown in growth or even a decline in prices. However, such an effect was not observed in the analyzed period of the Czech market, which represents a limitation of this thesis. Another limitation is the focus solely on the Czech Republic and not on any other region.

RQ2: How did the average age of the population develop in the Czech Republic?

Based on the conducted analysis, it can be stated that the average age of the population in the Czech Republic gradually increased during the period 2015–2024. In 2015, the average age was 41.8 years and increased to 43.1 years by 2024. The total increase therefore amounts to approximately 1.3 years over the observed decade.

The time series shows stable and continuous growth without significant fluctuations or declines. The highest absolute increases are evident in the first part of the observed period, when the average age increased year-on-year by 0.2–0.3 years, while in the years 2022–2024 the growth rate slightly slowed. Overall, the results indicate that demographic aging in the Czech Republic is a long-term and stable process.

This development is fully consistent with the academic literature, which confirms a general trend of population aging across developed countries. Wang & Suna (2024) state that population aging is a persistent phenomenon that has a direct impact on household consumption behavior, including housing. Similarly, Sun et al. (2024) emphasize that aging is a continuous process whose long-term character may influence real estate market dynamics. These conclusions correspond to the results obtained for the Czech Republic, where a continuous increase in average age was also observed.

Some studies, however, emphasize that demographic aging may not proceed at a uniform pace or have a uniform impact across regions or population segments. Heo (2022), for example, distinguishes between the "young-old" and the "old-old," noting that the share of very old individuals grows faster and may have specific economic impacts. This conclusion cannot be directly confirmed or refuted based on the available aggregated data from the Czech Statistical Office, but it does not contradict the observed gradual aging trend in the Czech Republic.

RQ3: Is there a relationship between population aging and real estate price growth in the Czech Republic?

Based on the conducted correlation analysis, paired t-tests, and regression analysis, it can be concluded that there is a statistically significant relationship between the average age of the population and real estate prices in the Czech Republic.

The correlation between average age and apartment prices reached 0.945, indicating a very strong positive relationship. A similar result was found for single-family house prices, where the correlation coefficient was 0.942. The presence of a statistically significant relationship was also confirmed by the two-sample paired t-tests, whose p-values for both pairs of variables were significantly lower than the 0.05 significance level. Thus, hypothesis H1 was rejected and hypothesis H0 was accepted, meaning that population aging has an effect on real estate prices.

The regression analysis further showed that the average age can significantly predict real estate price development — the model explained 89.37% of the variability in apartment prices ($R^2 = 0.8937$) and 88.75% of the variability in house prices ($R^2 = 0.8875$). The p-values of the regression coefficients and F-statistics were significantly lower than 0.05 in both models, confirming the statistical significance of the relationship. Overall, the results of the selected methods demonstrate a strong and statistically significant positive relationship between the two observed phenomena, confirming that growth in the average age of the population may be one of the factors contributing to rising real estate prices.

It can be concluded that the identified relationship is partially consistent with, but in some respects differs from, the conclusions of other authors. Wang & Suna (2024) state that population aging may directly and indirectly increase housing prices through household consumption behavior, which aligns with the findings of this study. Cheung (2025) also identifies mechanisms through which aging may contribute to price growth, particularly in regions with different migration dynamics. Thus, the results of this analysis correspond to those authors who confirm a positive relationship between population aging and rising real estate prices.

Conversely, some studies point to more complex or even opposite relationships. Sun et al. (2024) emphasize that aging may have different short-term and long-term effects, with the direction of impact differing depending on housing price components. Heo (2022) even suggests that an increase in the dependency rate measured by remaining life expectancy may be associated with a decline in real estate prices, which contrasts with the results obtained in this thesis. The difference may be explained by different definitions of aging, differing characteristics of foreign real estate markets, or differences in population structure. Cho & Lee (2024) emphasize the role of credit availability, which may weaken or even offset negative demographic pressures, and note that the effect of aging is not universal. These conclusions indicate that the results may vary across countries and periods, which naturally explains the differences between my analysis and some foreign studies.

Conclusion

The aim of this thesis was to evaluate the development of housing prices in the Czech Republic and to determine whether the process of population aging may influence the growth of apartment and single-family house prices. Based on the identified data, relationships between demographic development (especially population aging) and real estate price development in the Czech Republic over the period 2015–2024 were examined. This objective was achieved through time series analysis, correlation analysis, a two-sample paired t-test, and regression analysis. Using these methods, it was possible to precisely determine the development of both observed variables, quantify their mutual relationship, and assess its statistical significance. In doing so, the study also addressed the societal demand described in the introduction, which stemmed from the growing importance of issues such as population aging, housing unaffordability, and real estate market dynamics. The results showed that both apartment and single-family house prices in the Czech Republic increased significantly over the observed decade.

The average apartment price rose from 97.2 in 2015 to 266.5 in 2024, representing an increase of approximately 174%, with the fastest growth recorded between 2020 and 2022. In the case of single-family houses, prices increased from 99.7 to 228.6, corresponding to a rise of 129%. This upward trend was evident throughout the entire period, with no phase of sustained decline, confirming long-term pressure on the Czech real estate market. At the same time, a stable increase in the average age of the population was confirmed, rising from 41.8 years in 2015 to 43.1 years in 2024. Although this represents an absolute change of only 1.3 years, the time series shows a consistent aging trend, with no decline or stagnation except for a slight slowdown in the final two years. This development confirms that demographic aging is a long-term structural phenomenon occurring in parallel with housing price growth.

The main outcome of the thesis was the evaluation of the relationship between these two phenomena. The correlation analysis revealed a very strong positive relationship between the average age of the population and real estate prices, with correlation coefficients exceeding 0.94 for both apartments and single-family houses. The paired t-tests subsequently confirmed the statistical significance of this relationship, as p-values in all cases were significantly lower than the 0.05 significance level, allowing the rejection of the hypothesis of no relationship between the variables. The regression analysis further demonstrated that the average age of the population significantly predicts the development of real estate prices, both for apartments and single-family houses. Coefficients of determination (R^2) exceeding 0.88 indicate that the vast majority of price variability was explainable by demographic development. These findings confirm that population aging was one of the factors associated with housing price growth in the Czech Republic during the analyzed period and that demographic indicators may represent a significant predictor of real estate market dynamics in the domestic context.

The research had several limitations. The analysis was based on aggregated annual data, which does not allow for capturing short-term fluctuations or regional differences, and only two variables were included in the model, although real estate prices are influenced by a broader range of factors such as interest rates, credit availability, and economic cycles. Moreover, available academic sources often did not contain quantitative data, which limited the possibility of direct comparison of results, and the thesis focused exclusively on the Czech Republic. Nevertheless, the contribution of the study lies in the quantitative evaluation of the relationship between population aging and real estate prices, which has so far been largely absent in domestic literature. The results may be useful for housing policy makers, the real estate sector, and the professional community, and they provide a foundation for further research incorporating more detailed data structures or a broader set of variables.

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Appendices

Appendix 1 – Development of Real Estate Prices from 31 December 2014 to 31 December 2024

Period	Apartment Prices	House Prices
31.12.2014	97,2	99,7
31.03.2015	98,00	99,80
30.06.2015	99,30	99,30
30.09.2015	101,00	99,90
31.12.2015	101,70	100,60
31.03.2016	104,30	100,30
30.06.2016	109,90	103,30
30.09.2016	115,60	105,70
31.12.2016	120,10	109,60
31.03.2017	124,10	112,80
30.06.2017	128,50	118,00
30.09.2017	132,40	120,10
31.12.2017	137,40	123,00
31.03.2018	139,30	126,30
30.06.2018	145,70	129,20
30.09.2018	148,90	133,00
31.12.2018	151,30	135,30
31.03.2019	153,40	139,00
30.06.2019	157,60	142,70
30.09.2019	161,70	148,20
31.12.2019	166,40	150,80
31.03.2020	172,60	157,70
30.06.2020	180,90	161,70

30.09.2020	185,70	169,40
31.12.2020	186,20	176,20
31.03.2021	201,80	184,00
30.06.2021	212,80	192,80
30.09.2021	228,70	203,40
31.12.2021	243,10	212,30
31.03.2022	252,20	218,00
30.06.2022	262,70	220,40
30.09.2022	263,00	222,20
31.12.2022	252,90	219,40
31.03.2023	243,60	223,70
30.06.2023	243,00	220,70
30.09.2023	242,70	222,30
31.12.2023	243,40	222,50
31.03.2024	247,30	222,90
30.06.2024	255,50	225,60
30.09.2024	261,30	227,20
31.12.2024	266,50	228,60

Source: Own processing based on data from kurzy.cz.

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THE EFFECT OF AGE AND SELECTED CHARACTERISTICS ON THE ASKING PRICE OF MOVABLE PROPERTY

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Abstract

The aim of this study was to quantify the impact of age and technical condition on the asking price of three categories of movable goods – passenger cars, smartphones, and laptops – and to compare the dynamics of their depreciation over time. Data were collected through web scraping of the Czech classified advertisement platform Bazos.cz; a total of 2,100 listings were obtained, with 1,350 observations retained after the data-cleaning process. The analysis encompassed descriptive statistics, multiple linear regression (linear and log-linear specifications), and a Random Forest model with hyperparameter tuning via GridSearchCV. Age was identified as the most significant price determinant across all examined categories. Smartphones exhibited the fastest depreciation, with an annual rate of 28.2%, followed by laptops at 14.4% and passenger cars at 5.2%. The Random Forest model achieved the best predictive performance for smartphones, reaching a coefficient of determination of 0.87 on the test set, while log-linear regression provided more stable results for passenger cars and laptops. Research limitations include reliance on a single data source, a pilot-scale sample size, missing information on technical condition, and the subjective coding of technical condition from advertisement descriptions.

Keywords: depreciation, second-hand goods, asking price, web scraping, multiple linear regression, Random Forest

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Introduction

The second-hand goods market has experienced significant growth in recent years, both in the automotive segment and in consumer electronics. The expansion of online classified platforms has facilitated consumer access to listings while simultaneously increasing the information asymmetry between buyers and sellers. Buyers often lack sufficient information about the true asking price of movable goods, which creates uncertainty in purchasing decisions. The valuation of movable property is relevant not only to individual consumers, but also to insurance companies handling claims, leasing companies, and operators of used-car dealerships and electronics resale businesses.

The depreciation of movable goods over time has been examined across several interconnected fields of economics. Depreciation models for automobiles have been described by, among others, Sharma and Mitra (2024), who employed the MARS method and identified vehicle age, mileage, fuel type, and brand as key determinants of value decline. In the consumer-electronics segment, research is less extensive, yet growing rapidly; technological obsolescence causes a markedly faster decline in market prices for these products than physical wear does for vehicles (Zhou and Gupta, 2020). Comparative studies examining depreciation rates across different categories of movable goods in the context of the Czech market are, to the authors' knowledge, absent – a research gap to which this paper responds.

The social demand for addressing this issue arises from the growing volume of transactions on the secondary market and from consumers' need to understand the price level of second-hand goods. Understanding the factors that influence the value of movable goods provides a practical benefit in the form of more informed decision-making on both the buyer's and the seller's side.

The aim of this paper is to examine the effect of age and technical condition on the asking price of selected categories of movable goods and to compare the dynamics of their depreciation over time.

The following research questions are addressed:

RQ1: What is the relationship between the age of a movable good and its asking price for smartphones, laptops, and passenger cars?

RQ2: Which of the selected categories of movable goods exhibits the fastest decline in value over time?

RQ3: Which factors, besides age, most significantly influence the asking price within each category?

Literature Review

The depreciation of movable goods over time is a subject of inquiry in several interconnected areas of economics, ranging from vehicle-depreciation theory to contemporary predictive models employing machine learning. In the broader context of the secondary market, Frahm, Mugge and Laursen (2025) identified differences in motivations and barriers for purchasing second-hand products, while Hes et al. (2025) examined Czech consumer behaviour with respect to re-use centres.

In the automotive segment, research focuses on identifying key price determinants and on developing predictive models, with authors differing primarily in their choice of analytical tools. Sharma and Mitra (2024) developed a used-car pricing model using MARS and identified vehicle age, mileage, fuel type, and brand as the principal price determinants. Fayyaz, Ali and Khairunnesa (2025) conducted a comparative analysis of machine learning models and confirmed that XGBoost achieves the highest predictive accuracy when accounting for mileage, brand, transmission type, and overall vehicle condition. Wu et al. (2026) proposed an interpretable machine learning framework with marginal-effect analysis, addressing the opacity that characterises many predictive models. Kang and Fu (2026) demonstrated that combining a hedonic pricing model with machine learning techniques and online consumer reviews substantially improves residual-value estimation for used electric vehicles. Hossain, Rayhan and Bhuiyan (2025) applied a combination of the Delphi technique, the analytic hierarchy process, and linear regression, thereby overcoming the limitations of the conventional straight-line depreciation approach. Dael et al. (2024) confirmed the effectiveness of tree-based methods in predicting secondary automotive market prices.

In the consumer electronics segment – specifically smartphones – Zhou and Gupta (2020) analysed factors influencing the depreciation of new and refurbished iPhones and iPads, finding that the generational cycle, storage capacity, and aesthetic condition are the principal value determinants. Ting, Thaichon and Tan (2019) examined consumer behaviour regarding used smartphones via mixed methods, identifying social influence, perceived value, and situational factors as key drivers of disposal decisions. Ibrahim, Sarfo and Pampari (2026) extended the analysis to cognitive aspects and, based on a questionnaire survey of 225 respondents, demonstrated that perceived price fairness, product characteristics, and quality are decisive purchase-intent factors in the secondary smartphone market. Corrocher and Paganuzzi (2025) showed, using Italian market data, that planned obsolescence shortens smartphone life cycles and accelerates market-value decline; Amatuni et al. (2026) noted that shorter usage periods for second-hand smartphones limit their overall environmental benefits.

The laptop segment is the least studied in terms of depreciation research. Turkolmez, El Hathat and Sreedharan (2024) applied machine learning to the pricing of refurbished laptops and found that Random Forest achieved the lowest prediction error when accounting for depreciation and discount factors associated with different device ages and conditions. Ghosh et al. (2025) applied machine learning to analyse product attributes of refurbished laptops based on customer reviews in the context of circular consumption. The absence of comparative studies examining laptop depreciation relative to other movable-good categories constitutes a research gap addressed by this paper.

The literature review indicates that researchers across categories most frequently employ machine learning methods – particularly tree-based algorithms (Random Forest, XGBoost) and MARS – which capture non-linear relationships better than classical linear regression. For data collection, the analysed studies rely primarily on web scraping of online classified platforms, supplemented in some cases by questionnaire surveys. Accordingly, multiple linear regression complemented by Random Forest is adopted in this study to address RQ1 and RQ2, and permutation feature importance is applied to address RQ3.

Methodics

The methodological section is divided into two parts. The first part describes the source and procedure of data collection, while the second part presents the methods used for data processing and statistical analysis. The procedure is structured in relation to the research questions so that the analytical approach remains transparent and replicable.

Data Collection

Data were collected from the publicly accessible Czech online classified platform Bazos.cz (Bazos.cz, 2026). This platform was selected because of its broad coverage of the Czech secondary market, relatively uniform structure of listings, and availability of comparable information across all three analysed categories of movable goods. Data collection was carried out within one calendar week in order to reduce the possible influence of short-term market fluctuations. All prices were recorded in Czech crowns (CZK).

The final dataset consisted of 2,100 observations, divided equally into three categories. For each category of movable goods, 700 listings were manually recorded:

- **passenger cars:** 700 observations;
- **smartphones:** 700 observations;
- **laptops:** 700 observations.

For passenger cars, the recorded variables included asking price, year of manufacture, vehicle age, mileage, brand, model, fuel type, transmission type, engine power, and overall technical condition. For smartphones, the recorded variables included asking price, device age, brand, model, storage capacity, battery condition, and overall technical condition. For laptops, the recorded variables included asking price, age, brand, model, processor type, RAM size, storage type, storage capacity, and overall technical condition.

If the age of a smartphone or laptop was not explicitly stated in the listing, it was inferred from the model designation or technical specification. In the case of smartphones, the year of market introduction was used as the reference point. In the case of laptops, the age was inferred from the model designation and, where relevant, also from the processor generation.

Since classified advertisements do not provide a standardized variable describing technical condition, this variable was coded by the author on an ordinal scale from 1 to 5. A value of 1 represented the best condition, corresponding to an item described or visually assessed as new or nearly unused. A value of 5 represented the worst condition, corresponding to a heavily worn, damaged, or non-functional item. The assessment was based primarily on the photographs included in the listing and secondarily on the textual description provided by the seller. This procedure enabled a consistent evaluation of technical condition across all observations, despite differences in the way individual sellers described their items.

Only publicly available information contained directly in the advertisements was recorded. No personal data of sellers, contact details, or user identifiers were collected, stored, or analysed. The dataset therefore contains only anonymised listing-level information relevant to the valuation of movable goods.

Prior to analysis, the dataset was checked and cleaned. Duplicate records, observations with missing key variables, and extreme outliers were removed. Extreme outliers were identified using the interquartile range method. After cleaning, the dataset was used for descriptive, regression, and machine learning analyses.

The final cleaned dataset consisted of 1,350 observations and was used for descriptive statistics. For regression and Random Forest modelling, listwise deletion was applied to observations with missing values in model-specific predictors. As a result, the number of observations used in the individual models was lower than the total cleaned sample.

Data Processing

First, the cleaned dataset was described using basic descriptive statistics. For continuous variables, such as price, age, mileage, engine power, storage capacity, and RAM size, the arithmetic mean, median, standard deviation, minimum, and maximum were calculated. The arithmetic mean was calculated according to:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

where $\bar{x}$ denotes the arithmetic mean, x_i is the value of the analysed variable for observation i, and n is the number of observations.

The sample standard deviation was calculated according to:

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

where s denotes the sample standard deviation and $\bar{x}$ is the arithmetic mean of the analysed variable.

For categorical variables, such as brand, model, fuel type, transmission type, processor type, storage type, and technical condition, absolute and relative frequencies were reported. The absolute frequency of a given category was calculated according to:

$$f_j = \sum_{i=1}^{n} I\,(x_i = j)$$

where f_j denotes the absolute frequency of category j, and $I(x_i = j)$is an indicator function equal to 1 if observation $i$belongs to category j, and 0 otherwise. Relative frequency was calculated according to:

$$p_j = \frac{f_j}{n} \times 100$$

where p_j denotes the relative frequency of category j, expressed as a percentage. Descriptive statistics were prepared separately for passenger cars, smartphones, and laptops in order to compare the structure of the three samples.

To address the first research question, multiple linear regression was applied. The asking price was used as the dependent variable, while age represented the main explanatory variable. Additional category-specific variables were included as control variables. The general form of the multiple linear regression model is shown in:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \varepsilon_i$$

where Y_i denotes the asking price of item i, $X_{1i}, X_{2i}, \dots, X_{ki}$ represent explanatory variables, $\beta_0$is the intercept, $\beta_1, \beta_2, \dots, \beta_k$ are regression coefficients, and $\varepsilon_i$is the random error term.

Since age was the main explanatory variable, the model can be expressed more specifically according to:

$$Price_i = \beta_0 + \beta_1 Age_i + \sum_{j=2}^{k} \beta_j X_{ji} + \varepsilon_i$$

where $Price_i$ denotes the asking price of item i, Age_irepresents the age of the item, and X_{ji} represents additional category-specific control variables.

For passenger cars, these control variables included mileage, engine power, fuel type, transmission type, brand, model, and technical condition. For smartphones, the control variables included brand, model, storage capacity, battery condition, and technical condition. For laptops, the control variables included brand, model, processor type, RAM size, storage type, storage capacity, and technical condition.

Both linear and log-linear model specifications were tested in order to capture possible non-linear depreciation patterns. The log-linear specification is shown in:

$$\ln(Price_i) = \beta_0 + \beta_1 Age_i + \sum_{j=2}^{k} \beta_j X_{ji} + \varepsilon_i$$

where $\ln(Price_i)$denotes the natural logarithm of the asking price. In this specification, the coefficient of age can be interpreted approximately as the percentage change in asking price associated with a one-unit increase in age. This relationship is expressed in:

$$\Delta Price \approx 100 \times \beta_1$$

Categorical variables were transformed into dummy variables before being included in the regression models. Model quality was assessed using the coefficient of determination, adjusted coefficient of determination, and statistical significance of regression coefficients. The coefficient of determination was calculated according to:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2}{\sum_{i=1}^{n} (Y_i - \bar{Y})^2}$$

where $Y_i$denotes the observed asking price, $\hat{Y}_i$denotes the predicted asking price, and $\bar{Y}$ represents the mean observed asking price.

The adjusted coefficient of determination was calculated according to:

$$R_{adj}^2 = 1 - (1 - R^2)\frac{n-1}{n-k-1}$$

where R_{adj}^2 denotes the adjusted coefficient of determination, n is the number of observations, and k is the number of explanatory variables.

The assumptions of the regression models were verified by examining residual normality, homoscedasticity, and multicollinearity. Regression residuals were calculated according to:

$$e_i = Y_i - \hat{Y}_i$$

where e_i denotes the residual for observation i, Y_i is the observed asking price, and $\hat{Y}_i$ is the predicted asking price.

Multicollinearity was assessed using the variance inflation factor, as shown in:

$$VIF_j = \frac{1}{1 - R_j^2}$$

where VIF_j denotes the variance inflation factor for explanatory variable j, and R_j^2 is the coefficient of determination obtained by regressing variable X_j on all remaining explanatory variables.

To address the second research question, Random Forest regression models were estimated separately for passenger cars, smartphones, and laptops. The dataset was divided into a training set and a test set in an 80:20 ratio. The prediction of the Random Forest model was calculated as the average prediction of individual decision trees, as shown in:

$$\hat{Y}_i = \frac{1}{B}\sum_{b=1}^{B} T_b\,(X_i)$$

where $\hat{Y}_i$ denotes the predicted asking price for observation i, B is the number of decision trees, and $T_b(X_i)$ represents the prediction of the b-th decision tree for the vector of explanatory variables X_i.

Model performance was evaluated using mean absolute error, root mean squared error, and the coefficient of determination on the test set. Mean absolute error was calculated according to:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right|$$

where MAE denotes the mean absolute error, Y_i is the observed asking price, and $\hat{Y}_i$ is the predicted asking price.

Root mean squared error was calculated according to:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}$$

where $RMSE$ denotes the root mean squared error.

Based on the Random Forest model outputs, relative depreciation rates were calculated and visualised as depreciation curves. The relative annual depreciation rate between two consecutive years of age was calculated according to:

$$D_t = \frac{\hat{P}_{t-1} - \hat{P}_t}{\hat{P}_{t-1}} \times 100$$

where D_t denotes the relative depreciation rate in year t, $\hat{P}_{t-1}$ is the predicted price in the previous year of age, and $\hat{P}_t$ is the predicted price in the current year of age.

Cumulative depreciation relative to the initial predicted price was calculated according to:

$$CD_t = \frac{\hat{P}_0 - \hat{P}_t}{\hat{P}_0} \times 100$$

where CD_t denotes cumulative depreciation at age t, $\hat{P}_0$ is the predicted initial price, and $\hat{P}_t$ is the predicted price at age t.

To address the third research question, permutation feature importance was calculated for the trained Random Forest models. This method was used to identify the relative importance of individual variables in explaining differences in asking prices. Permutation feature importance was calculated as the decrease in model performance after randomly permuting the values of a given explanatory variable, as shown in:

$$PFI_j = R^2_{original} - R^2_{permuted,j}$$

where PFI_j denotes the permutation feature importance of variable j, $R^2_{original}$ is the coefficient of determination of the original model, and $R^2_{permuted,j}$ is the coefficient of determination after randomly permuting variable j. A higher value of PFI_j indicates that the variable has a stronger influence on model performance and therefore greater importance in explaining asking prices.

All data processing was performed in Python 3.13 (Python Software Foundation, 2024) using the pandas (McKinney, 2010), numpy (Harris et al., 2020), scikit-learn (Pedregosa et al., 2011), statsmodels (Seabold and Perktold, 2010), and matplotlib (Hunter, 2007) libraries. Claude Code and Cowork were used as supporting tools during code development and debugging.

Results

This section presents the findings of the empirical analysis conducted on a sample of 1,350 listings collected from Bazos.cz (Bazos.cz, 2026). Results are structured into four subsections corresponding to the methodology: descriptive statistics, multiple linear regression (RQ1), Random Forest and model comparison (RQ2), and depreciation curves with variable importance (RQ3).

Descriptive Statistics

After final data cleaning (removal of listings priced below CZK 500, as these predominantly represent accessories or incorrectly completed listings), 454 records for passenger cars, 447 for smartphones, and 449 for laptops were retained. Table 1 summarises the descriptive statistics for continuous variables across the three categories.

Table 1: Descriptive statistics of continuous variables across the three categories

Variable	Category	n	Mean	Median	Min	Max	Std. Dev.
Price (CZK)	Cars	454	347,172	329,900	3,250	979,999	185,781
	Phones	447	9,319	7,499	500	31,000	7,306
	Laptops	449	6,863	4,990	500	28,900	5,415
Age (years)	Cars	429	8.42	7.00	0	24	5.16
	Phones	310	3.88	4.00	1	9	1.91
	Laptops	214	8.36	9.00	2	13	2.76
Mileage (km)	Cars	382	153,006	157,363	254	306,000	56,644
Power (kW)	Cars	419	111.3	110.0	44	200	29.7
Storage (GB)	Phones	367	156.6	128.0	12	256	78.5
	Laptops	314	311.4	256.0	16	650	155.7
Battery (%)	Phones	160	93.3	99.5	71	100	8.2
RAM (GB)	Laptops	288	11.6	12.0	2	24	5.0

Source: Authors' own processing based on data from Bazos.cz.

The mean asking price for passenger cars was CZK 347,172 (median CZK 329,900), with a mean vehicle age of 8.4 years and mean mileage of 153,006 km. For smartphones, the mean price was CZK 9,319 (median CZK 7,499) and mean age 3.9 years. Laptops exhibited a mean price of CZK 6,863 (median CZK 4,990) and mean age 8.4 years, indicating a predominance of older models on the secondary market.

Table 2: Top five brands in each category (absolute and relative frequency)

Category	Brand 1 (%)	Brand 2 (%)	Brand 3 (%)	Brand 4 (%)	Brand 5 (%)
Cars	Škoda 145 (31.9%)	Volkswagen 90 (19.8%)	Ford 35 (7.7%)	BMW 20 (4.4%)	Mazda 19 (4.2%)
Phones	Apple 282 (63.1%)	Samsung 62 (13.9%)	Xiaomi 47 (10.5%)	Motorola 14 (3.1%)	Honor 9 (2.0%)
Laptops	Lenovo 113 (25.2%)	Apple 106 (23.6%)	Dell 80 (17.8%)	HP 67 (14.9%)	Acer 29 (6.5%)

Source: Authors' own processing based on data from Bazos.cz.

Brand distribution is markedly concentrated across all segments. Among cars, Škoda (31.9%) and Volkswagen (19.8%) dominate; among smartphones, Apple (63.1%) and Samsung (13.9%); and among laptops, Lenovo (25.2%) and Apple (23.6%). This concentration reflects the popularity of these brands on the Czech secondary market.

Multiple Linear Regression

A separate regression model was estimated for each category. Because multiple linear regression requires complete records across all predictors, observations with at least one missing predictor value were removed via listwise deletion, yielding 357 observations for cars, 277 for smartphones, and 123 for laptops. The substantially lower count for laptops reflects a higher rate of missing data in listings (age: 52.3%, RAM: 35.9%, storage capacity: 30.1%).

The technical condition variable was recorded for only 54.0% of car listings, 51.9% of smartphone listings, and 36.1% of laptop listings, and exhibited minimal within-category variability in two of the three segments (median = 1, values predominantly in the range 1–2). Given the high proportion of missing values and limited variability, including this variable would have substantially reduced the regression sample without a commensurate increase in explained variance; it was therefore excluded from all final models. This limitation is acknowledged in the Conclusion.

Table 3: Goodness-of-fit statistics for linear and log-linear regression models

Category	Model	n	R^2	Adj. R^2	F-test (p)	RMSE	MAE	BP test (p)
Cars	Linear	357	0.616	0.599	< 0.001	105,816	76,743	< 0.001
	Log-linear	357	0.553	0.533	< 0.001	110,836	78,218	—
Phones	Linear	277	0.793	0.790	< 0.001	3,167	2,346	< 0.001
	Log-linear	277	0.858	0.856	< 0.001	2,506	1,861	—
Laptops	Linear	123	0.663	0.636	< 0.001	3,054	2,152	< 0.001
	Log-linear	123	0.762	0.743	< 0.001	3,067	2,000	—

Source: Authors' own processing in Python (statsmodels, scikit-learn).

The linear model achieved a higher R^2 for cars (0.616), while the log-linear specification was superior for smartphones ($R^2 = 0.858$) and laptops ($R^2 = 0.762$). This result is consistent with expectations, as rapidly technologically obsolescent devices exhibit exponential depreciation. The Breusch-Pagan test confirmed heteroscedasticity of residuals in all three categories ($p < 0.001$), and the Kolmogorov-Smirnov test rejected normality of residuals, reflecting the inherent heterogeneity of the secondary market. VIF values ranged from 1.1 to 13.9, with higher values for engine power, mileage, and RAM reflecting their natural correlation with age and brand.

Table 4: Key regression coefficients of the log-linear model (age variable and selected factors)

Category	**Variable**	**β**	**p-value**	**95% CI lower**	**95% CI upper**
Cars	Age (years)	−0.053	< 0.001	−0.063	−0.044
	Mileage (km)	-4.4×10^{-6}	< 0.001	—	—
	Power (kW)	+0.005	< 0.001	+0.003	+0.007
	Diesel vs. petrol	+0.132	0.043	+0.004	+0.259
	Manual vs. automatic	−0.263	< 0.001	−0.416	−0.110
Phones	Age (years)	−0.331	< 0.001	−0.353	−0.309
	Storage (GB)	$+5\times10^{-4}$	0.069	—	—
	Samsung vs. Apple	−0.571	< 0.001	−0.716	−0.425
	Xiaomi vs. Apple	−1.538	< 0.001	−1.698	−1.378
Laptops	Age (years)	−0.155	< 0.001	−0.184	−0.126
	Apple vs. others	+0.622	< 0.001	+0.285	+0.959
	SSD vs. HDD	+0.518	0.009	+0.132	+0.905

Source: Authors' own processing (Python, statsmodels).

The age coefficient was statistically highly significant ($p < 0.001$) and consistently negative in all log-linear models: −0.053 for cars, −0.331 for smartphones, and −0.155 for laptops. Annual depreciation rates derived from these coefficients are presented in the following subsection.

Random Forest and Model Comparison

Table 5: Comparison of predictive accuracy: Random Forest vs. log-linear regression

Category	Model	R²	MAE (CZK)	RMSE (CZK)	n test
Cars	Log-OLS	0.553	78,218	110,836	357
	Random Forest	0.441	82,815	130,486	72
Phones	Log-OLS	0.858	1,861	2,506	277
	Random Forest	0.873	1,761	2,410	56
Laptops	Log-OLS	0.762	2,000	3,067	123
	Random Forest	0.698	2,045	2,934	25

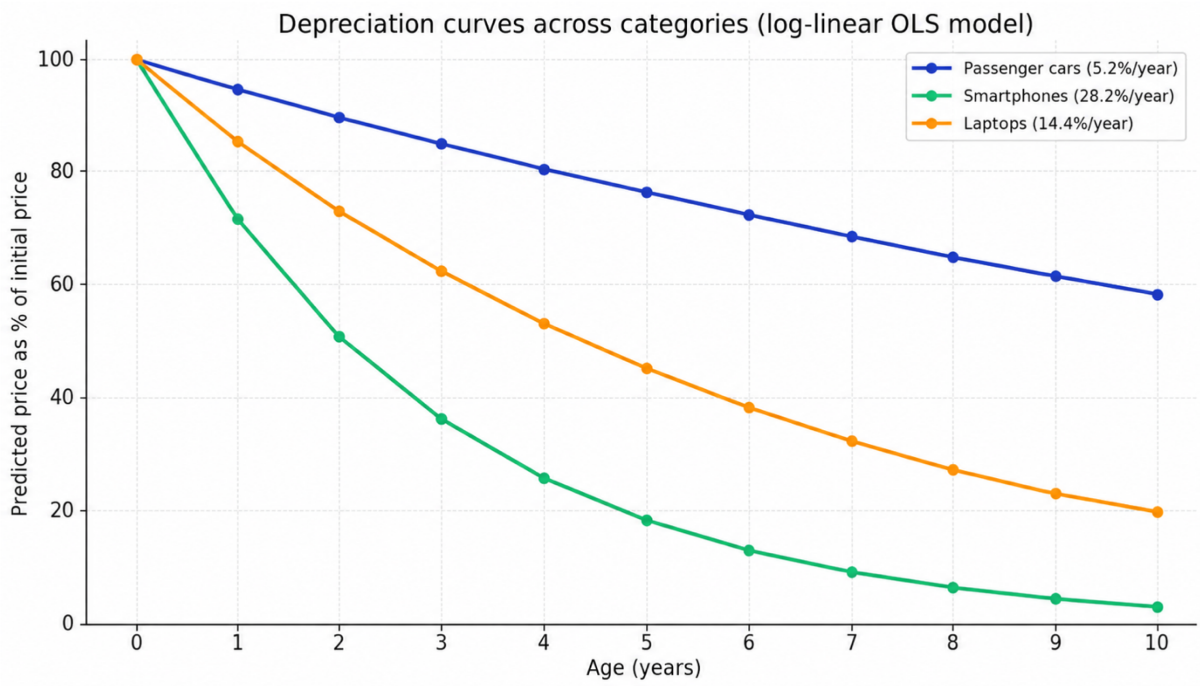
Source: Authors' own processing (Python, scikit-learn, statsmodels).

Random Forest outperformed log-linear regression only for smartphones ($R^2 = 0.873$ vs. 0.858). For laptops, Random Forest achieved $R^2 = 0.698$ versus 0.762 for log-linear regression; for cars, 0.441 versus 0.553. In both latter cases, the lower performance of Random Forest is attributable to the reduced number of observations after listwise deletion ($n = 72$ and $n = 25$ in the test sets, respectively), consistent with the findings of Fayyaz et al. (2025) regarding the sensitivity of tree-based methods to sample size.

Depreciation Curves and Variable Importance

Annual depreciation rates were derived from the log-linear model age coefficients using the formula $1 - \exp(\beta\_age)$. Figure 1 presents the depreciation curves for ages 0 to 10 years, expressed as a percentage of the initial value.

Figure 5: Depreciation curves across the three categories of movable goods

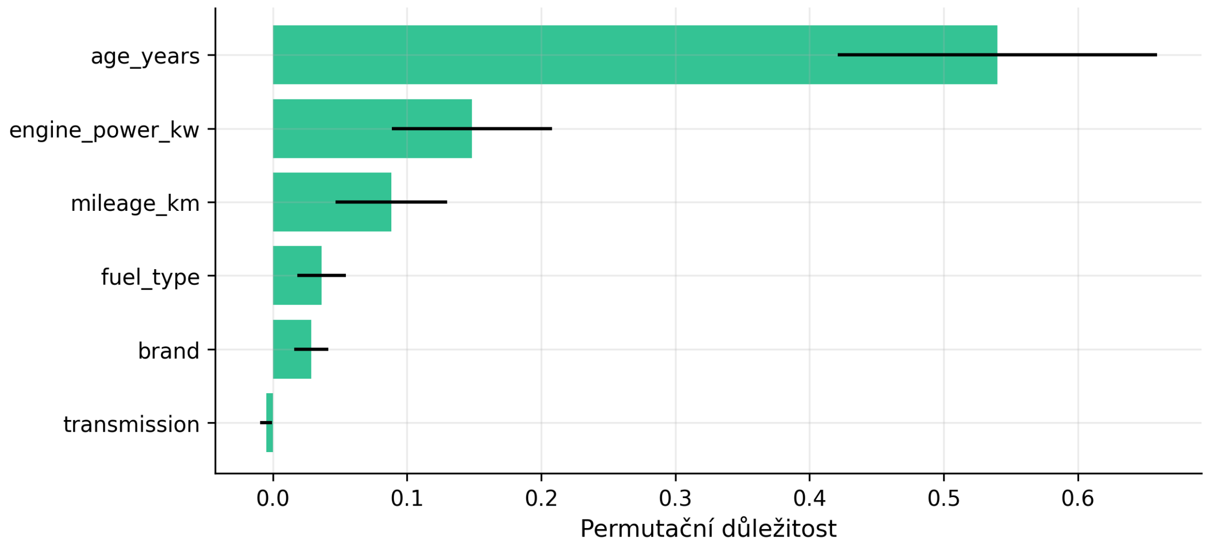


Source: Authors' own processing (log-linear OLS, Python).

Smartphones exhibit the steepest decline, with an annual depreciation rate of 28.2%, implying that a smartphone reaches half its initial value within 2.1 years. Laptops depreciate at 14.4% per year (half-life of 4.5 years) and passenger cars most slowly at 5.2% per year (half-life of approximately 13 years).

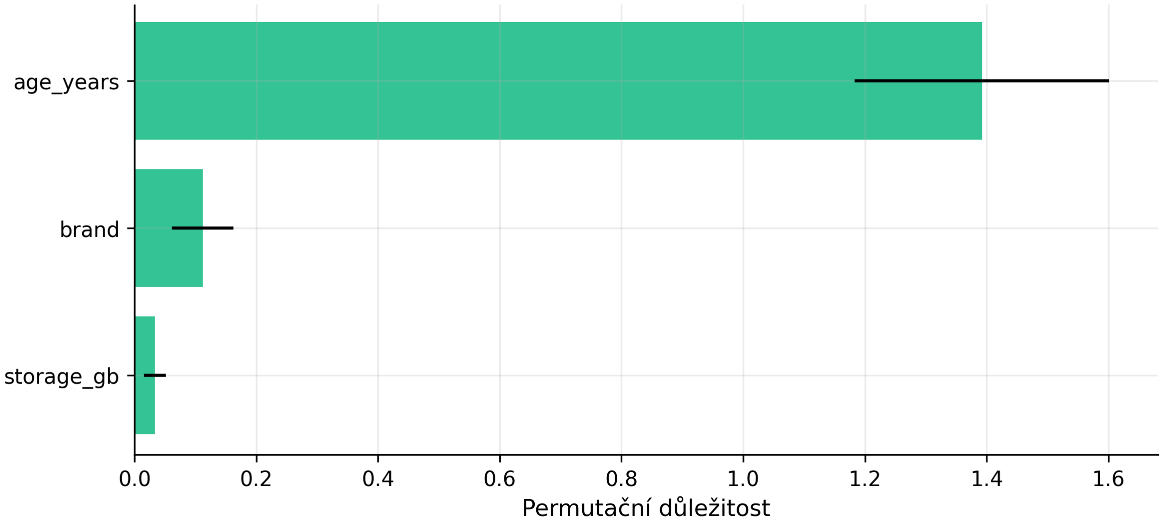
Permutation feature importance was computed for each trained Random Forest model and is presented in Figures 2–4.

Figure 6: Permutation feature importance – Random Forest model for passenger cars



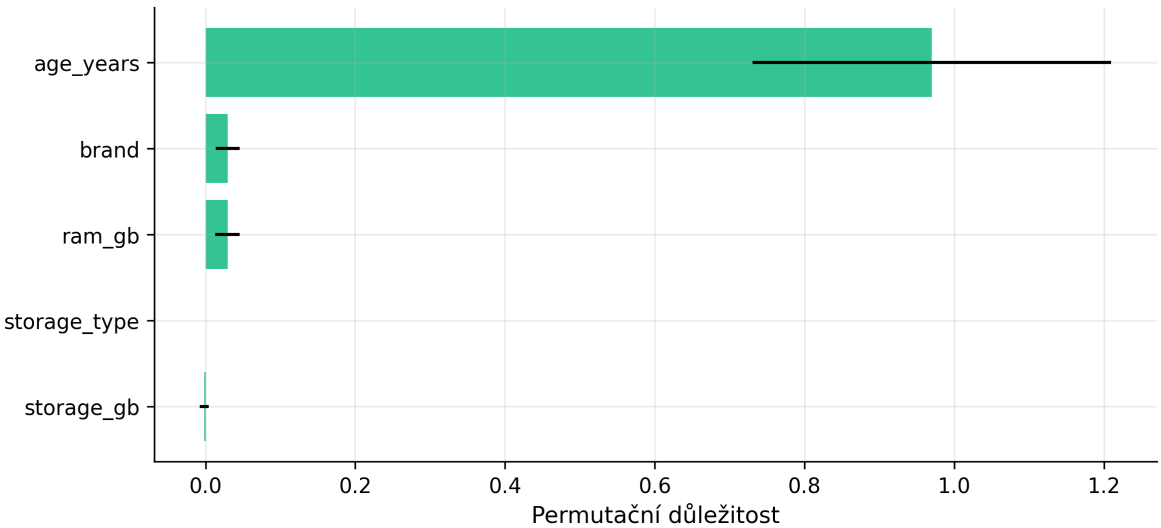
Source: Authors' own processing (Python, scikit-learn).

Figure 7: Permutation feature importance – Random Forest model for smartphones



Source: Authors' own processing (Python, scikit-learn).

Figure 8: Permutation feature importance – Random Forest model for laptops



Source: Authors' own processing (Python, scikit-learn).

Age proved to be the dominant predictor in all three categories (permutation importance: 0.54 for cars, 1.39 for smartphones, 0.97 for laptops). For cars, the second and third most important predictors were engine power and mileage; for smartphones, brand and storage capacity; and for laptops, brand and RAM size. The Apple brand commands a price premium of 77% over Samsung for smartphones and 86% over other brands for laptops.

Discussion

RQ1: What is the relationship between the age of a movable good and its asking price for smartphones, laptops, and passenger cars?

A statistically highly significant negative relationship between age and asking price was confirmed across all three categories ($p < 0.001$). For cars, the price decreases on average by

CZK 13,871 per additional year of age when other factors are controlled; in relative terms, the log-linear coefficient of −0.053 corresponds to an annual depreciation of 5.2%. For smartphones, the average annual price decline is CZK 2,916 (28.2% in exponential terms), and for laptops CZK 1,154 (14.4%). The superior fit of the log-linear model for smartphones (R^2 = 0.858) confirms the exponential nature of depreciation in rapidly technologically obsolescent products. These findings are consistent with Sharma and Mitra (2024), who applied a logarithmic transformation of age using MARS for used cars, and with Zhou and Gupta (2020), who identified the generational cycle as a key value determinant for iPhones and iPads.

RQ2: Which of the selected categories of movable goods exhibits the fastest decline in value over time?

Smartphones depreciate the fastest, with an annual rate of 28.2% and a half-life of 2.1 years. The second-highest rate was observed for laptops (14.4% per year; half-life of 4.5 years), and the lowest for passenger cars (5.2% per year; half-life of approximately 13 years). This ranking corroborates the hypothesis of Zhou and Gupta (2020) and Turkolmez et al. (2024) that technological obsolescence causes faster market-value decline in consumer electronics than physical wear does in motor vehicles. The empirically derived smartphone depreciation rate exceeds values reported by Zhou and Gupta (2020) for the US market (approximately 20% per year), which may be attributable to differences in the structure of the Czech secondary market and the higher share of Apple devices in the sample.

RQ3: Which factors, besides age, most significantly influence the asking price within each category?

For cars, the most significant secondary determinants were engine power (β = +CZK 1,801 per kW; $p < 0.001$), mileage (β = −CZK 0.87/km; $p < 0.001$), and fuel type: electric vehicles commanded a premium of +CZK 80,519 over petrol cars, and diesel vehicles +CZK 55,681. Manual-transmission vehicles were on average CZK 74,029 cheaper than automatics ($p < 0.001$). These findings align with Sharma and Mitra (2024) and Fayyaz et al. (2025), who similarly identified mileage, fuel type, and brand as key determinants. For smartphones, brand plays a prominent role after age (Apple vs. reference Samsung: +77%; Xiaomi vs. Apple: −78%; all $p < 0.001$) and storage capacity (β = +CZK 10/GB). For laptops, the decisive factors are brand (Apple: +86% vs. others; $p < 0.001$) and storage type (SSD premium over HDD: 68%; $p = 0.009$). Permutation feature importance from Random Forest confirmed the same ordering of variable significance as the regression analysis (analogously to Wu et al., 2026), lending robustness to the findings.

Random Forest achieved higher predictive accuracy than log-linear regression for smartphones (R^2 = 0.873 vs. 0.858), confirming the capacity of tree-based methods to capture non-linear relationships, as reported by Turkolmez et al. (2024) and Fayyaz et al. (2025). For passenger cars, by contrast, linear regression achieved a higher explained variance, which is attributable to the smaller test set size after listwise deletion and the greater price stability of motor vehicles over time.

Conclusion

The aim of this paper was to examine the effect of age and technical condition on the asking price of selected categories of movable goods and to compare the dynamics of their depreciation over time. The aim was achieved through empirical analysis of 1,350 listings collected from the Czech classified platform Bazos.cz (Bazos.cz, 2026), to which multiple linear regression, log-linear transformation, and a hyperparameter-tuned Random Forest regression model were applied.

Three principal findings emerge. First, age proved to be the dominant price determinant across all examined categories, with its permutation importance substantially exceeding that of all other variables. Second, smartphones depreciate the fastest at an annual rate of 28.2%, followed by laptops (14.4%) and passenger cars (5.2%). Third, in addition to age, price is significantly influenced in the automotive segment by engine power, mileage, and fuel type, and in the smartphone and laptop segments by brand – with a notable Apple price premium – and storage parameters.

Research limitations include: reliance on a single data source (Bazos.cz), which may lead to underestimation of prices relative to dealer channels; a pilot-scale sample size after cleaning (approximately 450 records per category); the subjective nature of technical-condition coding from textual listing descriptions; and the fact that the age of some smartphones and laptops was inferred from model look-up tables and processor generations rather than from explicit listing data. Data collection was conducted within a short time window, so results represent a snapshot of the market and do not capture seasonal fluctuations.

The contribution of this paper lies in the quantification of annual depreciation rates for three categories of movable goods on the Czech secondary market, which may serve as a practical reference for appraisers, leasing companies, insurance adjusters, and operators of used-goods dealerships.

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DETERMINING THE INITIAL REFERENCE PRICE OF A USED VEHICLE FOR EXPERT VALUATION

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Abstract

The determination of the initial reference price is a decisive step in expert valuation of used passenger vehicles because it affects the calculated time value, the marketability coefficient, and the final market value. The paper compares three approaches to determining the initial reference price: the original price list valid when the vehicle was first registered, the current price list of a comparable new vehicle adjusted by a technical-level coefficient, and the original price list adjusted by a motor-vehicle inflation index. Five valued vehicles and ten verified comparable vehicles for each model were analysed. The methods were evaluated using the marketability coefficient and its absolute deviation from the ideal value of 1. The inflation-adjusted original price list produced the most stable overall results and the lowest average deviation for four older vehicles. For the youngest vehicle, Volkswagen Passat, the current and original price-list methods were very close, so the current price list can be interpreted as suitable or comparable rather than unequivocally superior. The findings support a transparent procedure combining historical price evidence, macroeconomic price development, and verified market data.

Keywords: vehicle valuation, initial reference price, marketability coefficient, Expert Standard I/2022, used cars, inflation

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Introduction

Valuation of road vehicles is a regular component of judicial, insurance, leasing and financial practice. It is used in property disputes, insurance claims, tax evidence, lease settlements and the valuation of damage or technical appreciation. In all these settings, the credibility of the valuation depends not only on the final amount but also on the transparency of the method by which the amount was obtained. This is especially important for used vehicles, where the market price is shaped by technical condition, mileage, service history, equipment, brand reputation, customer preferences, and the wider economic environment.

The Czech expert-valuation environment has historically relied on codified procedures developed by the Institute of Forensic Engineering of Brno University of Technology. Expert Standard I/2005 provided a reproducible framework based on the price of a new vehicle, age and mileage-related amortisation, and expert corrections for technical condition and equipment (Bradáč and Krejčíř, 2004). Expert Standard I/2022 retained the core logic of technical valuation but strengthened the role of market evidence, database records and documented comparison samples (Kledus, Bradáč and Ševčík, 2021). This shift reflects the broader international move from static tables toward valuation supported by real market data, digital vehicle-history records and statistical modelling.

The initial reference price is the key input examined in this paper. If it is underestimated, the calculated time value will also be underestimated, and the resulting marketability coefficient will signal an apparent mismatch with market prices. If it is overestimated, the opposite distortion occurs. The issue became particularly relevant after the sharp increase in prices of new and used vehicles in the period affected by supply-chain disruption, inflation, and changing customer demand. A historical price list alone may fail to reflect the current price level, while a current price list may represent a newer technological generation that is not fully comparable with the valued vehicle.

The aim of the paper is to compare three methodological approaches to determining the initial reference price of used passenger vehicles and to assess their accuracy, variability and practical applicability in expert valuation.

In relation to this aim, the following research questions are formulated:

RQ1: Which of the selected methods for determining the initial reference price of a vehicle provides the highest agreement with observed market asking prices?

RQ2: What differences do the individual methods for determining the initial reference price of a vehicle show in terms of the achieved marketability coefficient values?

RQ3: What is the variability and stability of the results of the individual methods, and what is their significance for valuation practice?

RQ4: What recommendations for selecting a suitable procedure for determining the initial reference price of a vehicle can be formulated on the basis of the obtained results?

Literature Review

The academic and professional literature confirms that used-vehicle prices are determined by a combination of technical, economic and behavioural factors. Traditional econometric and hedonic models decompose the vehicle price into attributes such as age, mileage, make, model, power, fuel type, equipment and region. More recent work applies ensemble learning and machine-learning methods to larger datasets. Random Forests and related ensemble models are able to capture nonlinear relationships among attributes and have repeatedly been shown to improve predictive performance compared with simpler regression models (Breiman, 2001; Chen, Li and Xu, 2021). Bergmann, Lessmann and Voss (2025) further demonstrate that granular equipment information can increase the accuracy of used-car resale price forecasts because equipment packages and optional features materially influence resale value.

However, expert valuation cannot be reduced to predictive accuracy. In judicial and insurance contexts, the valuation procedure must be explainable, auditable and defensible. This is why black-box models remain problematic even where they achieve low predictive error. Rudin (2019) argues that high-stakes decisions should prioritise interpretable models rather than post-hoc explanations of opaque models. Molnar (2022) similarly presents explainability as a necessary condition for using complex models responsibly. In the vehicle-valuation context this means that machine-learning tools may support analysis, but the final expert reasoning must still be traceable to observable inputs, documented adjustments and a clearly stated comparison sample.

The quality of market data is equally important. Czech practice increasingly uses systems such as CEBIA Autotracer and Market Price Analysis, which provide data on vehicle identity, service records, mileage consistency, accident history, ownership and comparable market offers (CEBIA, 2025a; CEBIA, 2025b; CEBIA, 2025c). These sources reduce information asymmetry, but they do not remove the need for expert judgement. Advertised prices may differ from realised transaction prices because of bargaining, discounts and dealer policy. Busse, Knittel and Silva-Risso (2013) and Langer (2011) show that automotive list prices and actual transaction prices can diverge substantially, which supports the use of the marketability coefficient as a practical correction mechanism.

A further strand of literature concerns price-level changes and durable goods. Diewert (2020) and OECD (2021) emphasise that the valuation of consumer durables must distinguish between nominal price changes, physical depreciation and user cost. For vehicles, inflation adjustment alone cannot determine market value because physical wear, technical obsolescence and market preferences remain decisive. Nevertheless, adjusting a historical list price by a relevant motor-vehicle price index can provide a transparent analytical bridge between the vehicle configuration at first registration and the current price level. This is precisely the role of the inflation-adjusted method tested in the empirical part of the paper.

Current technological changes reinforce the need for careful method selection. Electric vehicles, digital equipment and driver-assistance systems alter the composition of vehicle value. Battery state of health is a key determinant in the secondary market for electric vehicles, and the literature stresses the importance of transparent battery information for consumer confidence and residual value (Fanoro et al., 2022; Diouf and Gandolfo, 2025). Although the empirical sample in this paper contains conventional vehicles, these developments illustrate why a current price list may represent a different technological standard than the valued vehicle and why a technical-level coefficient may be needed.

The reviewed literature also supports retaining the marketability coefficient as the central evaluation indicator. KP [the marketability coefficient (KP; Czech: koeficient prodejnosti)] connects the technical calculation with the observed market and shows whether the selected initial reference price produces a time value consistent with comparable vehicles. In that sense it is not merely a final correction coefficient; it is also a diagnostic tool for assessing whether the underlying reference price was chosen appropriately.

The literature review therefore leads to a practical methodological implication: an expert valuation method must be sufficiently data-oriented to reflect the current market, but sufficiently transparent to remain defensible in an expert report. A purely historical catalogue value is easy to document, but it may ignore the current price level. A purely current catalogue value reflects current prices, but it may import technological and equipment differences from a newer model generation. A purely predictive model may be accurate in a large dataset, but it may be difficult to justify in an individual valuation unless the data, variables and model logic are fully documented. The three methods tested in this paper were selected precisely because they represent these competing logics in a form usable in expert practice.

Data and Methods

The empirical analysis uses five valued vehicles selected from public advertising sources in the Czech market: Skoda Octavia Combi 2.0 TDI DSG, Skoda Fabia 1.0 TSI, Skoda Karoq 1.5 TSI DSG, Hyundai Tucson 1.6 CRDI and Volkswagen Passat Variant 2.0 TDI DSG. The vehicles were selected to cover several common market segments and first-registration years from 2016 to 2021. Each valued vehicle was accompanied by ten comparable vehicles of similar type and specification. Comparable vehicles were included only where service history, mileage consistency and the absence of serious accident records could be verified, primarily through CEBIA-based checks.

Table 5: Valued vehicles in the empirical sample

Vehicle	First registration	Mileage	Fuel/engine	Transmission	Residual usability ZU	Main segment signal
Skoda Octavia Combi	2018	239,032 km	2.0 TDI, 110 kW	DSG	23.1%	company/family estate
Skoda Fabia	2018	32,073 km	1.0 TSI, 70 kW	manual	54.2%	small hatchback
Skoda Karoq	2018	126,287 km	1.5 TSI, 110 kW	DSG	40.0%	SUV
Hyundai Tucson	2016	97,622 km	1.6 CRDI, 85 kW	manual	40.3%	SUV
Volkswagen Passat Variant	2021	176,555 km	2.0 TDI, 110 kW	DSG	40.0%	young estate vehicle

Source: Own processing based on the vehicle-identification and amortisation data from the original thesis.

Three approaches were compared. The first method used the original price list valid when the vehicle was first registered. The second method used a current price list for a comparable new vehicle and, where necessary, applied a technical-level coefficient (KTU) to reflect the lower technical level of the valued vehicle compared with the current model. In the analysed cases, KTU was set at 0.9. The third method used the original price list and adjusted it by the HICP index for new motor cars from Eurostat (Eurostat, 2026).

The inflation coefficient was calculated as the ratio between the HICP annual average index for new motor cars in the valuation year and the corresponding index in the year of first registration.

The calculation followed the logic of Expert Standard I/2022. First, the initial reference price (HN) was determined by each of the three methods. Second, basic amortisation (ZA) was calculated as the arithmetic mean of the age-related deduction (ZAD) and mileage-related deduction (ZAP). Third, residual usability was calculated as ZU = 100 - ZA. Fourth, the time value of the vehicle was determined as HC = HN x ZU / 100. Finally, the marketability coefficient was calculated for comparable vehicles as the ratio between market price and calculated time value; the average of individual coefficients gave the overall KP for the comparison set. The market value of the valued vehicle was then obtained as HTv = HCv x KP.

The methodological structure was expressed through the following equations. The initial reference price was tested in three variants:

$$HN_1 = P_{original}$$
$$HN_2 = P_{current} \times KTU$$
$$HN_3 = P_{original} \times I_{HICP}$$

Where HN is the initial reference price, P_original is the original list price valid at first registration, P_current is the current price of a comparable new vehicle, KTU is the technical-level coefficient, and I_HICP is the motor-vehicle inflation index.

The subsequent valuation calculation followed the standard amortisation and market-correction logic:

$$ZA = \frac{(ZAD + ZAP)}{2}$$
$$ZU = 100 - ZA$$
$$HC = HN \times \frac{ZU}{100}$$
$$KP_i = \frac{MP_i}{HC_i}$$
$$KP = \left(\frac{1}{n}\right) \times \Sigma\, KP_i, \; n = 10$$
$$HT_v = HC_v \times KP$$

Where ZA is basic amortisation, ZAD is the age-related deduction, ZAP is the mileage-related deduction, ZU is residual usability, HC is time value, MP is the observed market price of a comparable vehicle, KP is the marketability coefficient, and HTv is the resulting market value of the valued vehicle.

The evaluation criterion was the distance of KP from the ideal value of 1. A KP above 1 indicates that the calculated time value is lower than the observed market level; in other words, the method tends to understate the reference base. A KP below 1 indicates that the calculated time value exceeds the observed market level. Absolute deviation was therefore used as the main accuracy measure, while the distribution and variability of KP values were used to assess stability.

$$AD_{KP} = |KP - 1|$$

The choice of ten comparable vehicles for each valued vehicle follows the logic of Expert Standard I/2022 and creates a practical compromise between market representativeness and comparability. A larger set may increase statistical volume but can also introduce vehicles with materially different mileage, equipment or history. The thesis therefore prioritised verified comparability over mechanical sample size. This is important because the aim was not to build a general predictive market model, but to test how the selected initial-price method behaves inside an expert valuation procedure.

For the purposes of the article, the extensive vehicle-by-vehicle calculations from the thesis were condensed into the variables that directly affect the comparison of methods. Detailed equipment lists, VIN records and individual comparable-vehicle rows were not reproduced in full because they would exceed the article format. They were nevertheless used in the original calculations to determine comparability, amortisation and the average KP values. The retained tables therefore focus on the decision-relevant values: first-registration year, mileage, residual usability, initial reference prices, valuation intervals and KP deviations.

Results

The initial reference prices differed substantially across the three methods. For the older vehicles, the original price list was usually much lower than the inflation-adjusted original price. The current price-list method sometimes produced values close to the inflation-adjusted method, but this depended on the comparability of the current model and the model being valued. In the Volkswagen Passat case, the vehicle was the youngest in the sample and the time gap between first registration and current price list was shorter; consequently, the current and original approaches were both close to the market level.

Table 6: Initial reference prices and valuation intervals

Vehicle	Original list price CZK	Current list price x KTU CZK	Original list price x inflation CZK	Valuation interval CZK	Best or comparable fit
Skoda Octavia	773,900	854,910	898,498	203,000-218,000	inflation-adjusted original
Skoda Fabia	315,000	404,910	406,350	224,000-251,000	inflation-adjusted original
Skoda Karoq	690,000	693,000	890,100	377,000-385,000	inflation-adjusted original
Hyundai Tucson	579,990	715,491	781,827	335,000-342,000	inflation-adjusted original
Volkswagen Passat	990,000	1,109,113	1,056,726	375,000-385,000	current and original close

Source: Own processing based on original price lists, current price lists and Eurostat HICP data.

For Skoda Octavia, the KP values were 1.27 for the original price-list method, 1.23 for the current price-list method and 0.98 for the inflation-adjusted original price list. The third method was therefore closest to the ideal value, with only a 2% deviation. For Skoda Fabia, the same ordering was observed: the original method reached KP = 1.31, the current method KP = 1.14 and the inflation-adjusted method KP = 1.05. Although the Fabia had very low mileage compared with many market comparables, the inflation-adjusted method remained the closest to the market level.

The SUV models showed stronger marketability. Skoda Karoq reached KP = 1.37 under the original price-list method and KP = 1.36 under the current price-list method, while the inflation-adjusted original price list reduced the coefficient to 1.08. Hyundai Tucson showed a similar pattern, with KP = 1.44, 1.17 and 1.09 respectively. These results suggest that SUV demand can lead to higher observed market prices relative to technically calculated values, but the inflation-adjusted historical price still produced the closest alignment.

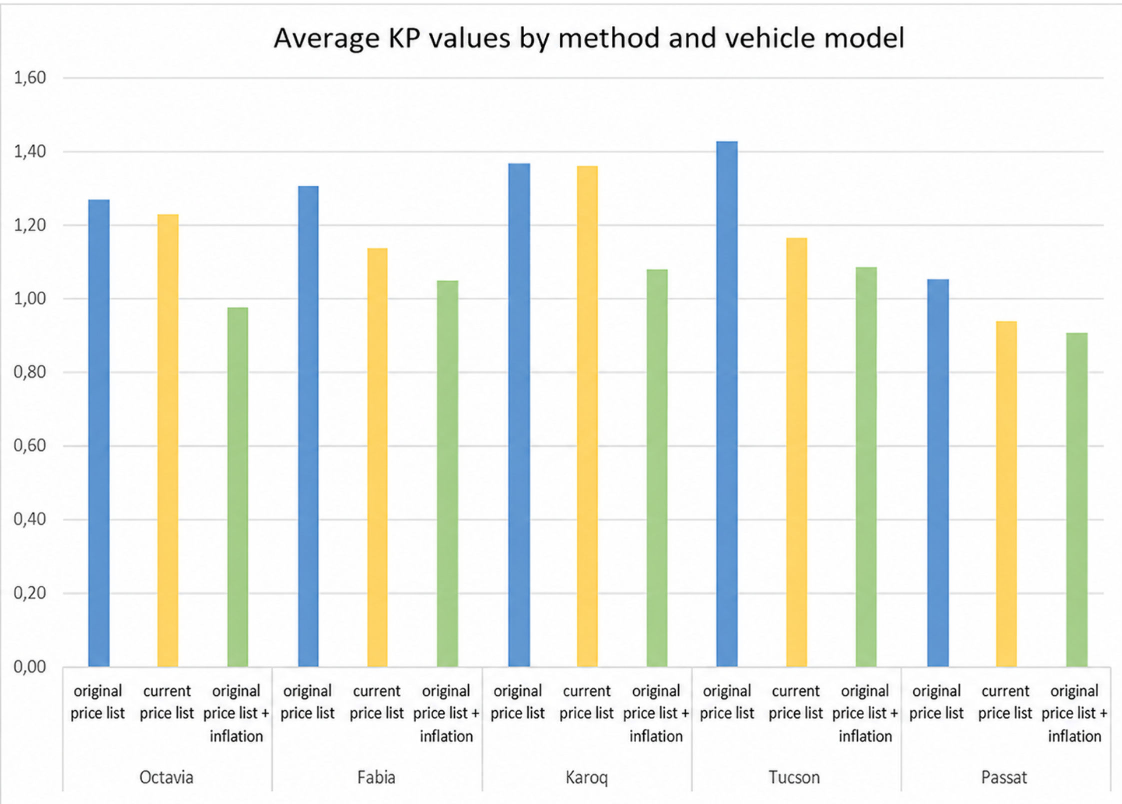
The Volkswagen Passat differed from the other vehicles. It was first registered in 2021 and was therefore considerably younger. The original method produced KP close to 1, while the current price-list method was also very close. The result should therefore not be interpreted as a case where the current list price was unambiguously the best method. Rather, it shows that for a younger vehicle with a shorter distance from current model conditions, the current price-list method may be suitable and comparable with the original list-price approach. This is consistent with the practical expectation that current list prices become more problematic as model generations, standard equipment and technology diverge over time.

Table 7: Average KP values and absolute deviations from the ideal value

Vehicle	KP original	KP current	KP original x inflation	Abs. dev. original	Abs. dev. current	Abs. dev. inflation	Interpretation
Skoda Octavia	1.27	1.23	0.98	0.27	0.23	0.02	inflation adjustment closest
Skoda Fabia	1.31	1.14	1.05	0.31	0.14	0.05	inflation adjustment closest
Skoda Karoq	1.37	1.36	1.08	0.37	0.36	0.08	inflation adjustment closest
Hyundai Tucson	1.44	1.17	1.09	0.44	0.17	0.09	inflation adjustment closest
Volkswagen Passat	1.05	0.94	0.91	0.05	0.06	0.09	original/current very close
Overall average	1.29	1.17	1.02	0.29	0.19	0.07	inflation adjustment most stable overall

Source: Own processing based on the original thesis results.

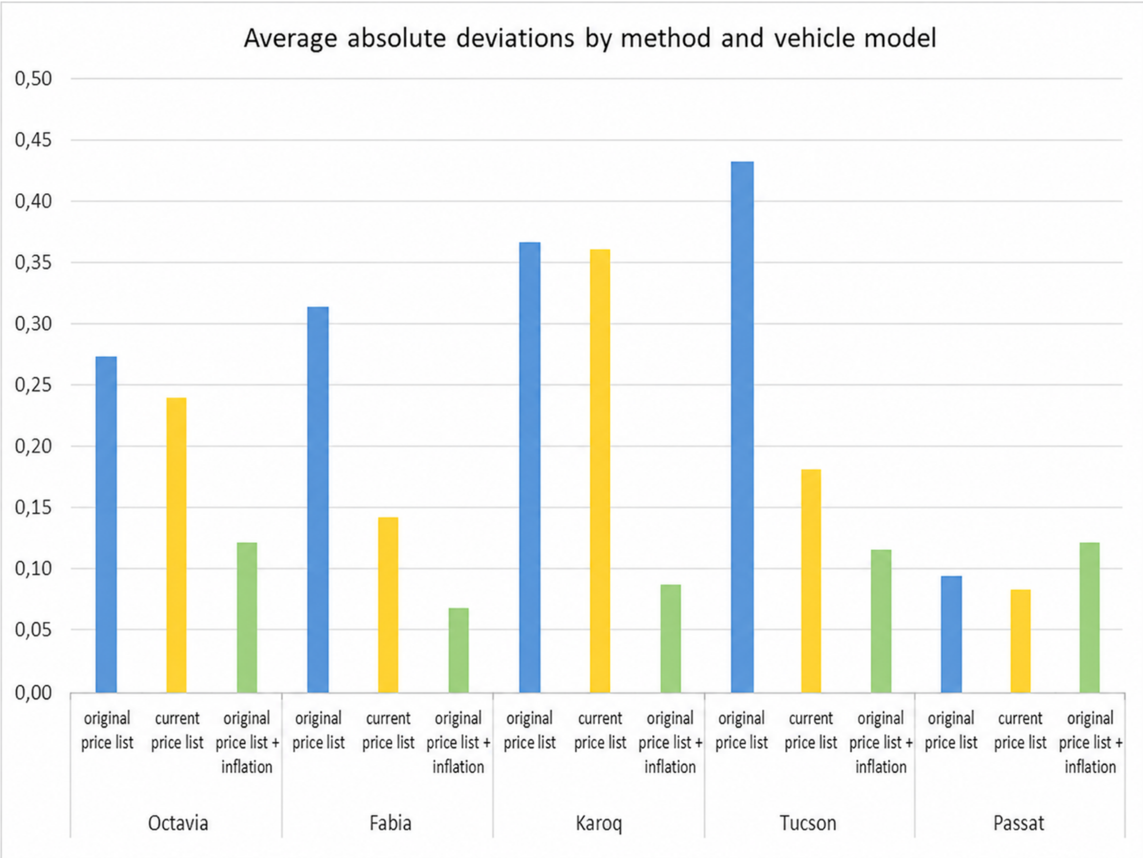
Figure 9: Average KP values by method and vehicle model



Source: Own processing, adapted from the original thesis chart.

The overall comparison confirms that the inflation-adjusted original price list achieved the average KP closest to 1. The original price-list method produced the largest average deviation because historical nominal prices no longer reflected the market price level. The current price-list method improved the average result, but its higher sensitivity to model comparability reduced its stability for older vehicles.

Figure 10: Average absolute deviations by method and vehicle model



Source: Own processing, adapted from the original thesis chart.

The distribution of deviations also matters. The original thesis showed that the inflation-adjusted method had the highest concentration of KP values in the interval nearest to 1, particularly between 0.98 and 1.04. By contrast, the original price-list method concentrated many values above 1.2, which indicates systematic understatement of the technical value relative to the observed market. The current price-list method was more balanced than the original method but still less consistent than the inflation-adjusted method across the full sample.

Discussion

RQ1: Which of the selected methods for determining the initial reference price of a vehicle provides the highest agreement with observed market asking prices?

The inflation-adjusted original price list provided the highest overall agreement with market prices. This method combines two advantages. It preserves the specific historical configuration of the vehicle at first registration, and it also updates the nominal price level to reflect the development of new-vehicle prices. The method is therefore well suited to vehicles where the original specification can be documented and where several years have passed since first registration.

RQ2: What differences do the individual methods for determining the initial reference price of a vehicle show in terms of the achieved marketability coefficient values?

The original price-list method was transparent but too static during a period of price growth. It produced KP values above 1 for all vehicle models, which means that the calculated time values were generally lower than market prices. The current price-list method partially corrected this problem but introduced another one: the current new vehicle may differ in technology, safety equipment, emissions standards, digital systems and standard equipment. This makes the technical-level coefficient important but also introduces expert judgement. The inflation-adjusted method reduced both weaknesses by retaining the original vehicle configuration and adjusting only the price level.

RQ3: What is the variability and stability of the results of the individual methods, and what is their significance for valuation practice?

The lower absolute deviations and more balanced KP distribution show that the inflation-adjusted original price list was the most stable method in the analysed sample. Its stability was strongest for the four older vehicles. The Passat result is more nuanced: both the original and current methods were close to the ideal value, and the current method can be considered suitable for this younger vehicle. The finding supports a conditional recommendation rather than a universal rule. Current list prices are useful where the current model is still directly comparable; they become riskier where there has been a major generational change.

RQ4: What recommendations for selecting a suitable procedure for determining the initial reference price of a vehicle can be formulated on the basis of the obtained results?

For vehicles older than approximately three years, the inflation-adjusted original price list should be treated as the preferred starting point if the original price list and equipment level can be reliably documented. The current price-list method should be used as a control or alternative mainly for newer vehicles, vehicles without substantial generational change, or cases where the original list price is unavailable. The unadjusted original list price should not be used as a sole reference in periods of significant inflation because it tends to understate the reference base.

The analysis also highlights the role of the comparison sample. The original thesis evaluated the relationship between mileage dispersion and KP variability. Higher dispersion in comparable-vehicle mileage can increase the variability of KP because mileage is one of the key determinants of used-vehicle value. This means that the expert must not only calculate KP mechanically but also review whether the ten comparable vehicles are sufficiently close in mileage, equipment, service history and market positioning. A formally large comparison set can still be weak if its technical comparability is poor.

The SUV results also deserve attention. Škoda Karoq and Hyundai Tucson recorded relatively high KP values under the original and current methods, which may reflect stronger market preference for SUV body types. Marketability is therefore not purely a technical outcome. It also captures demand patterns, perceived utility, brand and body-type preferences. This supports the use of KP as a market correction tool, while also confirming that the coefficient must be interpreted in context rather than treated as a purely mathematical residual.

This recommendation does not remove the expert role. On the contrary, it clarifies where expert judgement is most needed: in documenting the original configuration, assessing whether the current model is truly comparable, choosing and verifying comparable vehicles, interpreting mileage dispersion and deciding whether market preference for a body type or brand affects KP. The method is therefore best understood as a structured decision aid rather than an automatic rule.

Taken together, the research questions can be answered as follows. First, the inflation-adjusted original price list provided the strongest overall agreement with market prices. Second, the original price list without inflation correction showed systematic upward KP values, while the current price-list method produced intermediate results and was most useful where model comparability remained high. Third, the inflation-adjusted method was the most stable across the sample, although the Passat case shows that younger vehicles require a more nuanced interpretation. Fourth, valuation practice should use the inflation-adjusted original price list as the preferred reference for older vehicles, the current list price as a control for young or directly comparable models, and the unadjusted original list price only with caution.

Conclusion

The paper compared three approaches to determining the initial reference price of used vehicles for expert valuation. The original price list adjusted by a motor-vehicle inflation index produced the best overall agreement with market prices and the lowest average absolute deviation of KP from the ideal value of 1. The unadjusted original price list was transparent but systematically less accurate for older vehicles because it ignored price-level development. The current price-list method was useful mainly where the valued vehicle remained close to current model conditions.

The Volkswagen Passat case confirms that the interpretation must remain nuanced. Because it was the youngest vehicle in the sample, the current price-list method was suitable and comparable with the original method, but it should not be presented as unequivocally superior. The broader conclusion is that method choice should depend on vehicle age, model continuity, availability of historical price information and the quality of comparable market data.

For expert practice, the recommended procedure is to use the inflation-adjusted original price list as the primary reference for vehicles several years old, to verify the result against current price-list evidence where the current model is comparable, and to support the final value with a carefully selected set of verified comparable vehicles. This combination respects the transparency required in expert valuation while responding to real market and macroeconomic conditions.

Contribution and Limitations

The main contribution of the paper is the empirical verification of three transparent methods for determining the initial reference price. The comparison is useful for expert practice because it focuses on a specific input that strongly affects the final valuation but is often hidden inside the broader calculation. By evaluating the methods through KP and absolute deviation from 1, the paper offers a reproducible framework for assessing whether the initial reference price is consistent with market evidence.

The practical contribution is also methodological. The paper shows that a combination of historical documentation, inflation adjustment and market comparison can preserve auditability without ignoring market development. This is important because fully data-driven models may be more accurate in large datasets but can be difficult to defend in individual expert reports if their internal logic is not transparent. The proposed approach remains compatible with Expert Standard I/2022 because it uses market data and expert comparison while keeping the calculation steps explicit.

The limitations are clear. The empirical sample contains five valued vehicles and fifty comparable vehicles, so the results should not be generalised mechanically to all vehicle classes. The analysis is also tied to a specific market period affected by inflation and post-pandemic disruption. Exact original transaction prices were not available, and the work therefore relied on historical price lists rather than actual purchase invoices. Future research should expand the sample, include additional brands and age groups, test electric and hybrid vehicles separately, and analyse how mileage dispersion, equipment packages and service-history quality affect KP stability.

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