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}^2denotes 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 across the three categories

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	R^2	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

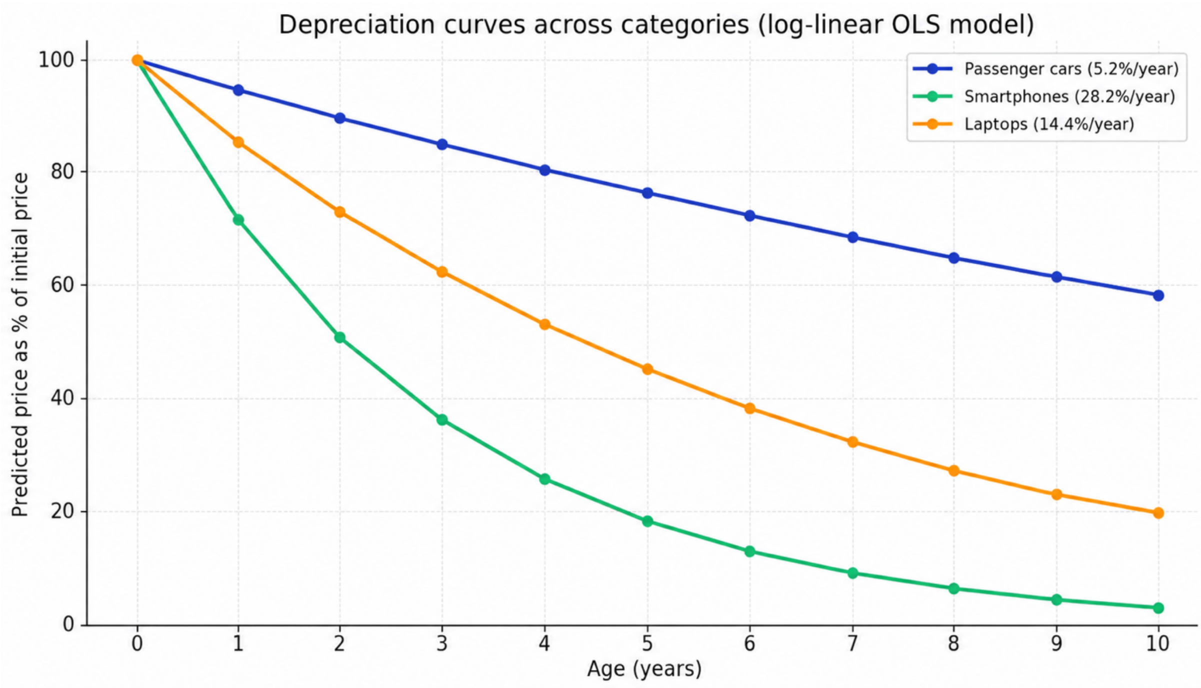
Source: Authors' own processing (Python, scikit-learn, statsmodels).

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 (RQ3)

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 1: Depreciation curves across the three categories of movable goods

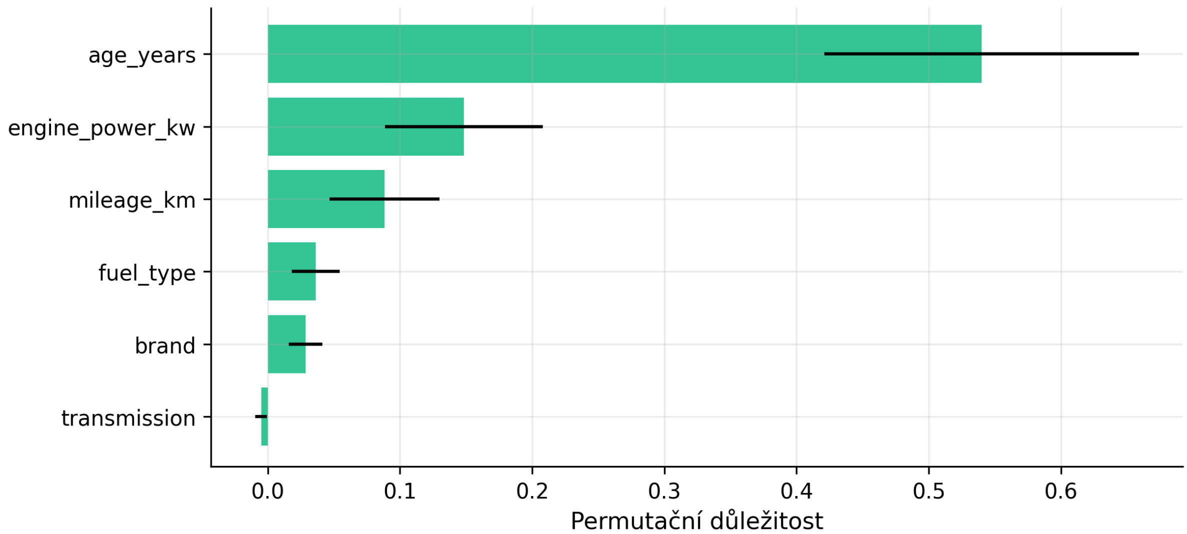


Source: Authors' own processing (log-linear OLS, Python).

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).

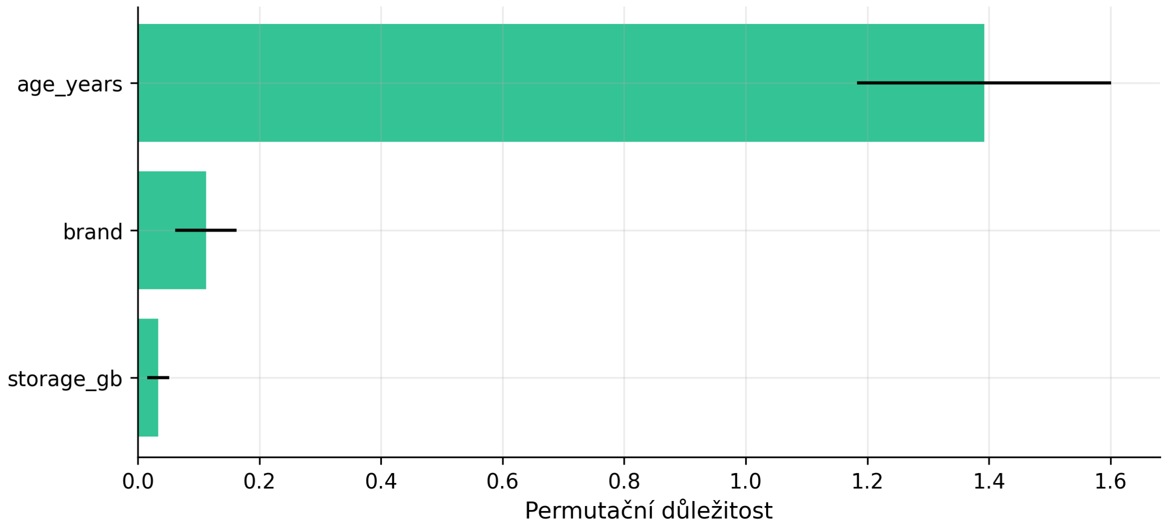
Permutation feature importance was computed for each trained Random Forest model and is presented in Figures 2–4.

Figure 2: Permutation feature importance – Random Forest model for passenger cars



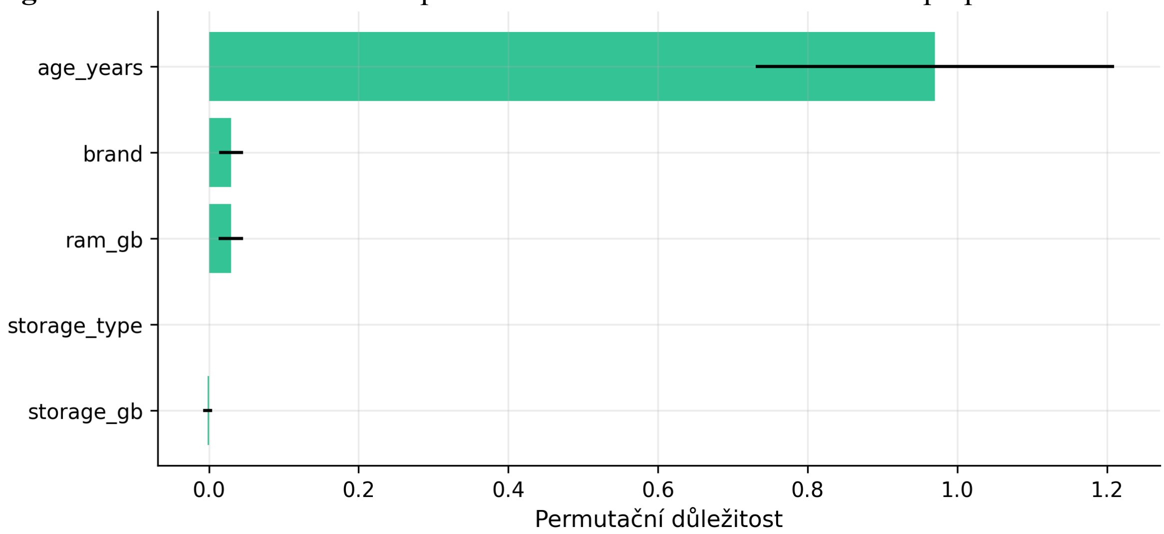
Source: Authors' own processing (Python, scikit-learn).

Figure 3: Permutation feature importance – Random Forest model for smartphones



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

Figure 4: 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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