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USING GOOGLE TRENDS TO ANALYZE INTEREST IN TRAVEL INSURANCE

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Purpose: The aim of the article is to use Google Trends data to examine the seasonal pattern in interest in travel insurance.
Design/methodology/approach: This article examines the use of Google Trends to study the frequency of queries related to „ubezpieczenie turystyczne” [travel insurance] and „EKUZ” [European Health Insurance Card] in Poland. We applied the Holt-Winters method with multiplicative seasonality for our analysis. The statistical analysis was conducted using Statistica software.
Findings: In the context of studying queries related to „ubezpieczenie turystyczne” and „EKUZ”, Google Trends offers insights into seasonal variations and emerging trends.
Research limitations/implications: This research has several limitations, notably the reliance on search queries to measure interest levels, which may not accurately represent actual tourist behavior. Furthermore, the relationships and patterns identified were tested solely within a single country, thereby constraining the generalizability of the findings to other regions and cultural contexts.
Practical implications: The data indicate seasonality, reflecting the public's heightened interest during peak travel periods. This seasonal pattern is crucial for policymakers and businesses in the travel and insurance sectors, enabling them to tailor their services and marketing strategies accordingly.
Social implications: The extensive volume of searches conducted via Google generates trend data, which can be analyzed using Google Trends, a publicly accessible tool that compares the volume of internet search queries across different regions and time periods. Consequently, Google Trends can offer indirect estimates and has the potential to detect specific patterns earlier than traditional systems.
Originality/value: This study contributes original insights by utilizing Google Trends data to analyze and understand seasonal patterns and interest level for travel insurance.
Keywords: Google Trends, time series, seasonal pattern, Holt-Winters model.
Category of the paper: Research paper.

1. Introduction

Travelers are adopting various strategies to mitigate travel-related risks, with travel insurance being a prominent option (Chien et al., 2017; Ulbinaite et al., 2014; Luna-Cortés, Brady, 2024). Despite its importance in modern travel contexts, where potential or actual risks are a significant concern, there remains a gap in understanding travel insurance purchase behavior. This gap is particularly notable given the increasing emphasis on safety and risk management among travelers.

The rise of the Internet has revolutionized how we access and analyze data, particularly regarding opinions, beliefs, and interests. The analysis of online search queries has gained prominence in big data analytics and academic research. As internet penetration continues to grow, researchers increasingly use search traffic data, social media data, and other web-based sources to gain insights into user behavior. The vast volume of data generated daily allows for comprehensive analyses that reveal patterns and shifts in behavior over time. Among the various tools available, Google Trends stands out as a valuable resource for understanding public interest and behavior. For instance, spikes in search queries can indicate emerging public concerns or interests. The passive collection approach of Google Trends ensures that the data reflect genuine user behavior, enhancing the reliability of findings. Advanced analytical techniques applied to these large datasets enable the identification of subtle trends and correlations that might not be apparent through traditional research methods. Furthermore, integrating various web-based data sources provides a more holistic view of online behavior. Consequently, insights from search traffic and social media data are invaluable across various fields, including economics (Nagao et al., 2019; Aaronson et al., 2022; Costa et al., 2024; Liu et al., 2021; Simionescu et al., 2020; Limnios, You, 2021), tourism (Menzel et al., 2023; Çekim, Koyuncu, 2022; Scott, 2021; Havranek, Zeynalov, 2021), and management (Prabakaran et al., 2024; Alves de Castro et al., 2020; Ruiz-Viñals et al., 2024; Glogovețan et al., 2023).

Google Trends provides a powerful platform for accessing and analyzing large datasets reflecting public interest over time (Mavragani et al., 2018; Arora et al., 2019). Its ability to offer real-time data and historical trends is crucial for studying various phenomena. By examining search frequencies, researchers can infer levels of public interest and identify patterns that may not be immediately apparent through traditional survey methods. Google Trends reports the popularity of internet searches primarily through the Relative Search Volume (RSV) (Cebrián, Domenech, 2024). The tool allows users to analyze data based on search terms, timeframes, and geographic regions, presenting data as a percentage relative to peak popularity. An RSV value of 100 represents the highest search ratio for a term. Although the RSV series can exhibit inconsistencies due to its sampling method - where the same query might yield different results when repeated (Franzén, 2023) - it remains a valuable tool for identifying general trends and patterns over extended periods.

The aim of this article is to use Google Trends data to examine seasonal patterns in interest in travel insurance. This article delves into the use of Google Trends to study the frequency of queries related to "ubezpieczenie turystyczne" [travel insurance] and "EKUZ" [European Health Insurance Card] in Poland. In analyzing these queries, we aim to highlight the seasonal patterns and trends that emerge from this data. Such an analysis not only sheds light on interest in travel-related financial coverage but also underscores the practical utility of using Google Trends for statistical inference in various research domains.

Seasonality involves systematic intra-year movements influenced by weather, calendar events, and economic decisions. A useful way of examining seasonal patterns is to estimate the average monthly seasonal indices. Most definitions and concepts of seasonality describe the phenomenon only in general terms or relate to its causes. Pattern and amplitude are the two main facets of seasonality (De Cantis, Ferrante, 2011; Ferrante et al., 2018). Quantitative measurements are essential for comparing the degree of seasonality of the phenomenon over different time periods. An example of a quantifiable definition of the appearance of tourist seasons is given by Lim and McAleer (2008). Therefore, we hypothesize: Analysis of Google Trends data reveals that the search interest for "ubezpieczenie turystyczne" and "EKUZ" significantly increases during the weeks leading up to the vacation season, indicating a strong seasonal pattern correlated with peak travel periods (Hypothesis 1).

In recent years, there has been growing interest in utilizing search query data from sources like Google Trends to model temporal processes (Bokelmann, Lessmann, 2019; Havranek, Zeynalov, 2021; Önder, Gunter, 2016; Höpken et al., 2019). Studies have demonstrated that time series data on the frequency of tourism-related search terms from Google Trends serves as a valuable predictor for short-term tourism demand forecasting across various regions worldwide. This approach enhances the accuracy of forecasting models by incorporating real-time data reflecting consumer interest and intent. Therefore, we hypothesize: Changes in the search volume for "ubezpieczenie turystyczne" and "EKUZ" on Google Trends can be used as a predictive indicator of actual travel behavior and insurance purchase trends, reflecting broader socio-economic factors influencing travel decisions (Hypothesis 2).

2. Travel insurance as an important element of financial coverage

Numerous studies have explored tourists' intentions and behaviors regarding travel insurance (Chien et al., 2017; Ulbinaite et al., 2014). These studies indicate that the decision to purchase travel insurance is primarily influenced by perceived risks. Perceived risk theory identifies this construct as multidimensional, encompassing physical, psychological, social, financial, performance, and timing dimensions (Kerr, Kelly, 2019). The impact on the intention to purchase insurance is contingent upon how tourists perceive these risk dimensions when traveling (Kerr, Kelly, 2019). Furthermore, some research in the field of tourism has concentrated on the theory of expected utility (Kerr, Kelly, 2019). According to this theory, consumers make decisions by weighing an uncertain loss (such as an injury while traveling) against a certain loss (such as the cost of insurance) (Schneider, 2004). The intention to purchase travel insurance increases with the perceived likelihood and value of the uncertain loss (Kerr, Kelly, 2019). Thus, the more significant and probable the perceived risks, the stronger the motivation for tourists to invest in travel insurance as a precautionary measure.

Personality traits play a pivotal role in the purchase of products closely tied to the psychological aspects of decision-making. This is particularly relevant in the context of travel insurance, where individual differences can influence the perception and response to risk. Understanding the psychological factors that drive insurance purchases can provide deeper insights into consumer behavior, helping to tailor insurance offerings more effectively to meet travelers' needs.

Empirical evidence suggests that specific personality traits, such as conscientiousness and neuroticism, significantly impact travel insurance purchase behavior (Sarman et al., 2020). Conscientious individuals, who are typically more organized and cautious, are more likely to seek the security provided by travel insurance. Similarly, individuals exhibiting higher levels of neuroticism, characterized by anxiety and worry, may also be more inclined to purchase travel insurance as a precautionary measure. These findings highlight the importance of considering psychological dimensions in the marketing and development of travel insurance products.

Research indicates that in addition to perceived risk, other variables significantly influence travelers intention to purchase travel insurance. Digital technology is profoundly transforming the distribution of insurance, enabling companies to reach customers through multiple channels. Alt et al. (2021) conducted a cross-sectional survey study to examine this phenomenon, collecting 422 questionnaires from a convenience sample of the Romanian population. The data was segmented based on consumer information touchpoints (online vs. offline), purchase channel preferences (offline through a professional vs. online through a standardized platform), and personal characteristics (age, marital status, and children). The analysis revealed that information channel preferences were the most significant clustering variables, followed by purchase channel preferences, marital status, having children, and age. Four distinct consumer segments were identified: young fully offliners (23.7%), mature fully offliners (31.5%), committed online searchers (23.2%), and cross-channel onliners (21.6%). Notably, many travelers exhibit a preference for face-to-face interactions with service providers when making their decision, and they tend to favor purchasing from familiar providers. Dall'Olmo-Riley, Scarpi, and Manaresi (2009) examined the factors influencing the purchase of services online across two countries, the UK and Italy. Their findings indicated that despite differences in the relative uptake of internet shopping between the two countries, the general trends remained consistent. Specifically, there was a prevalent need for face-to-face contact with the service provider before making an online purchase and a preference for buying services from a familiar provider. Additionally, they found that prior general experience with online shopping significantly increases the likelihood of consumers purchasing services online (Dall'Olmo-Riley et al., 2009). Building on these insights, Yu and Chen (2018) emphasized that trust is a crucial factor in the acquisition of travel insurance. The presence of trust in the service provider can significantly enhance the likelihood of purchasing travel insurance, underscoring the importance of establishing and maintaining strong, reliable relationships with customers.

Several scholars, including Gössling et al. (2020), Kock et al. (2020), Sigala (2020), and Tan and Caponecchia (2021) have highlighted the profound and unprecedented impacts of the COVID-19 pandemic on the tourism industry and the insurance market. The magnitude of the pandemic has precipitated a comprehensive transformation within these sectors, leading to substantial alterations in tourist behaviors during and after the outbreak. These changes encompass shifts in travel preferences, heightened health and safety concerns, and an increased reliance on technology for travel planning and experiences. As a result, the pandemic has necessitated adaptive strategies within the industry to address evolving consumer expectations and ensure sustainable operations in the new normal (Tan, Caponecchia, 2021; Gössling et al., 2020; Kock et al., 2020; Sigala, 2020). Tan, Caponecchia (2021) investigated the impact of COVID-19 on public perception of travel insurance. During the crisis, many travelers faced denial of insurance claims due to the exclusion of non-diversifiable catastrophic risks. Consequently, the perceived lack of protection further discourages insurance purchases and destabilizes the market.

The European Health Insurance Card should not be considered a substitute for travel insurance as it does not cover private healthcare or costs such as repatriation or lost/stolen property (Groza, 2023; Weremczuk, Józefecka, 2020). Additionally, it does not cover expenses incurred when traveling specifically for medical treatment, nor does it guarantee free healthcare services. The rising trend in international travel underscores the growing relevance of travel insurance. Travel insurance serves as a crucial financial safeguard for international tourists, covering unexpected events such as medical emergencies, trip cancellations, and lost luggage (Olszewski-Strzyżowski, Dróżdż, 2015; Forlicz et al., 2018; Forlicz et al., 2017). In an increasingly interconnected world, the importance of such coverage cannot be overstated, offering peace of mind to travelers venturing beyond their home countries.

3. Methods

Önder and Gunter (2016) confirm that including Google Trends data in forecasting tourism demand for a major European city enhances forecast accuracy across various source markets and forecast horizons, particularly with native language searches. Data collection spanned from

January 2004 to June 2024 and focused on search terms in Polish. A dataset of interest was acquired from the Google Trends. We collected data on relative search volumes (RSVs), which Google reports as percentages relative to the peak search volume during the specified time period, scaled by the total search volume for each specific search term. These data are normalized and presented on a scale from 0 to 100.

According to previous studies (De Cantis, Ferrante, 2011; Ferrante et al., 2018), analyzing seasonality can focus on several key aspects. These include the pattern of seasonal swing, which is the distribution of seasonal factors within the months of a given year, and the amplitude of seasonal swing, which measures the extent of variation throughout the year.

The Holt-Winters method models three aspects of a time series: a typical value (average), a slope (trend) over time, and a cyclical repeating pattern (seasonality) (Woo et al., 2022; Hendri, Fadhlia, 2024). The Holt-Winters method has two variations based on the nature of the seasonal component: additive and multiplicative. The additive decomposition is the most appropriate if the magnitude of the seasonal fluctuations does not vary with the level of the time series (Figure 1). When the variation in the seasonal pattern appears to be proportional to the level of the time series, then a multiplicative decomposition is more appropriate (Figure 2).

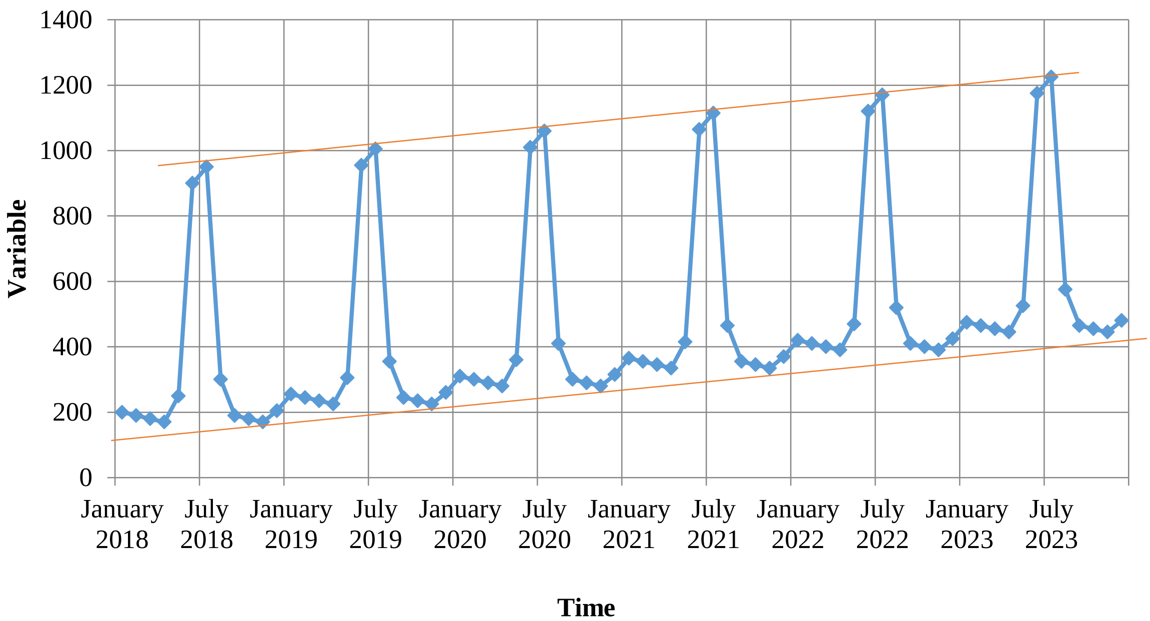

Figure 1. Additive seasonality (magnitude of seasonal fluctuations remain approximately stable).

Source: own elaboration.

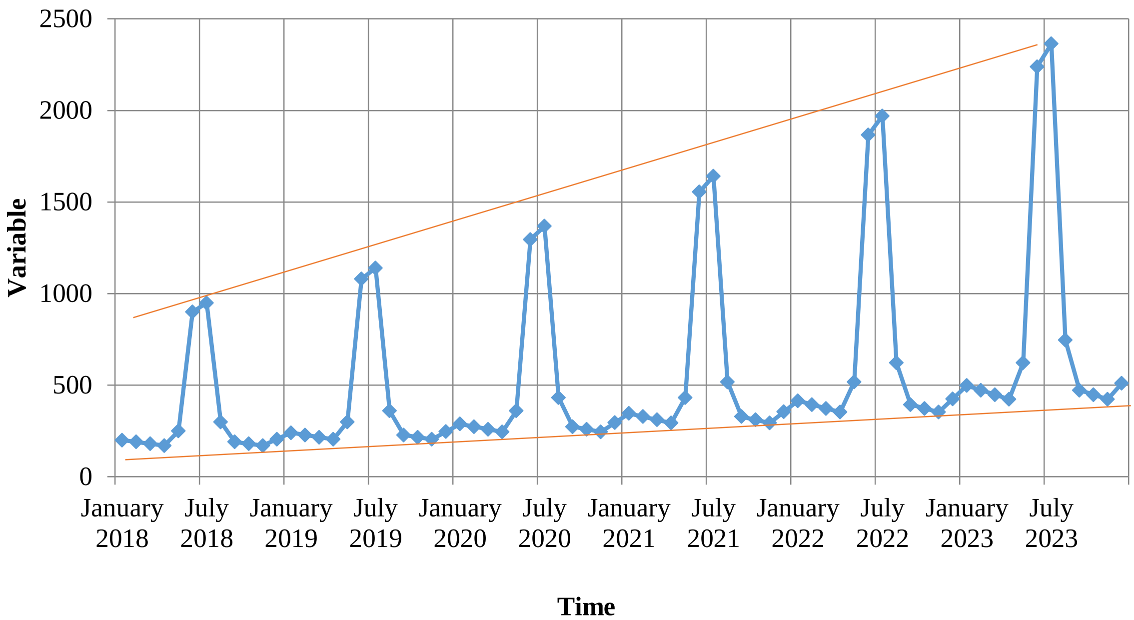

Figure 2. Multiplicative seasonality (magnitude of seasonal fluctuations vary).

Source: own elaboration.

The Holt-Winters model includes a forecast equation and smoothing equations for the level, trend, and seasonality of the time series (L_t for level, T_t for trend, and S_t for seasonality, with corresponding smoothing parameters α, β, and γ). These components work together to provide a comprehensive framework for modeling and forecasting time series data with seasonal patterns. F_{t+m} is the m-steps ahead forecast. The Holt-Winters method employs p seasonal indices to model the seasonal pattern of length p.

The additive method (Formulas 1-4) is suitable when seasonal variations remain approximately constant throughout the series. In this method, the seasonal component is expressed in absolute terms.

$$Level: L_t = \alpha\left(Y_t - S_{t-p}\right) + (1-\alpha)(L_{t-1} + T_{t-1}) \tag{1}$$

$$Trend: T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \tag{2}$$

$$Seasonality: S_t = \gamma(Y_t - T_t) + (1-\gamma)S_{t-p} \tag{3}$$

To forecast, we should add the appropriate seasonal index for the time period we are forecasting to the preliminary forecast (Formula 4):

$$Forecast: F_{t+m} = L_t + mT_t + S_{t-p+m} \tag{4}$$

The multiplicative method (Formulas 5-8) is ideal when seasonal variations change proportionally to the series level. In this method, the seasonal component is expressed in relative terms (percentages).

$$Level: L_t = \alpha\left(\frac{Y_t}{S_{t-p}}\right) + (1-\alpha)(L_{t-1} + T_{t-1}) \tag{5}$$

$$Trend: T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \tag{6}$$

$$Seasonality: S_t = \gamma\left(\frac{Y_t}{L_t}\right) + (1-\gamma)S_{t-p} \tag{7}$$

To forecast, we should multiply the preliminary forecast by the appropriate seasonal index for the time period we are forecasting (8):

$$Forecast: F_{t+m} = (L_t + mT_t)S_{t-p+m} \tag{8}$$

Consider the following examples. Suppose we recorded the monthly passenger load on international flights (in thousands) over a period of 6 years for Country 1 (Figure 3) and Country 2 (Figure 4). There appears to be a linear upward trend in passenger loads over the years, and a recurring pattern or seasonality within each year (most travel occurs during the summer months). Seasonal components can be additive in nature (Figure 3) or multiplicative (Figure 4).

Let us start with Figure 3. In this case, the seasonality is additive. Seasonal index is expressed in absolute terms. Suppose the seasonal index for July is 625 and the seasonal index for January is -108. Thus, we should add an absolute amount of 625 (thousands) to the respective preliminary forecast to account for this seasonal fluctuation in July (Formula 4). Similarly, we should add -108 (thousands) to the respective preliminary forecast to account for this seasonal fluctuation in January.

Alternatively, for Country 2 (Figure 4), the seasonality is multiplicative. Thus, we should multiply the preliminary forecast by the appropriate seasonal index for the time period we are forecasting (Formula 8). The seasonal index is expressed in percentages. Suppose the seasonal index for July is 254% and the seasonal index for January is 74%. To forecast the monthly passenger load for July, we should multiply the preliminary forecast by the seasonal index of 254%. To forecast the monthly passenger load for January, we should multiply the preliminary forecast by the seasonal index of 74%.

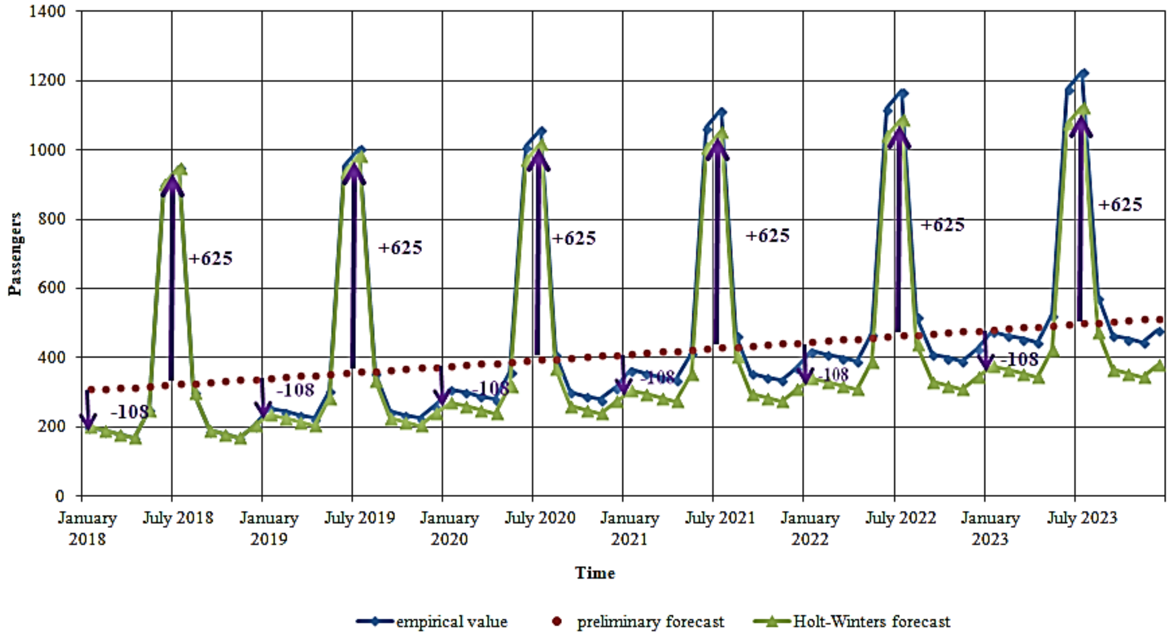

Figure 3. Seasonal patterns: additive seasonality

Source: own elaboration.

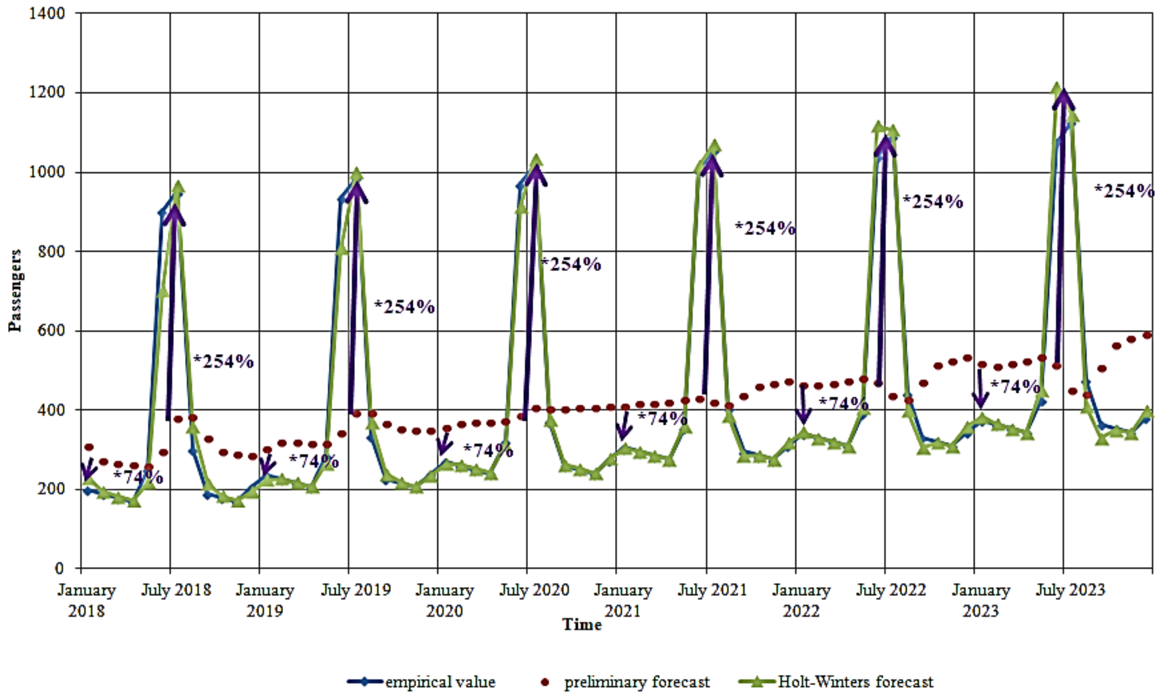

Figure 4. Seasonal patterns: multiplicative seasonality

Source: own elaboration.

4. Results

We conducted a seasonality test on all Google Trends data in our sample, examining monthly seasonal effects. This approach allowed us to identify and analyze patterns in search behavior over an extended period. The Holt-Winters method is appropriate for modeling this data, as it can account for the proportional seasonal variations observed. Statistical analysis was conducted using Statistica software.

Figure 1 and Figure 2 present the interest over time of „EKUZ" [European Health Insurance Card] and "ubezpieczenie turystyczne" [travel insurance]. With reference to Figure 1 and Figure 2, seasonality can be clearly observed. The maximum load peaks are within the summer period (June) each year.

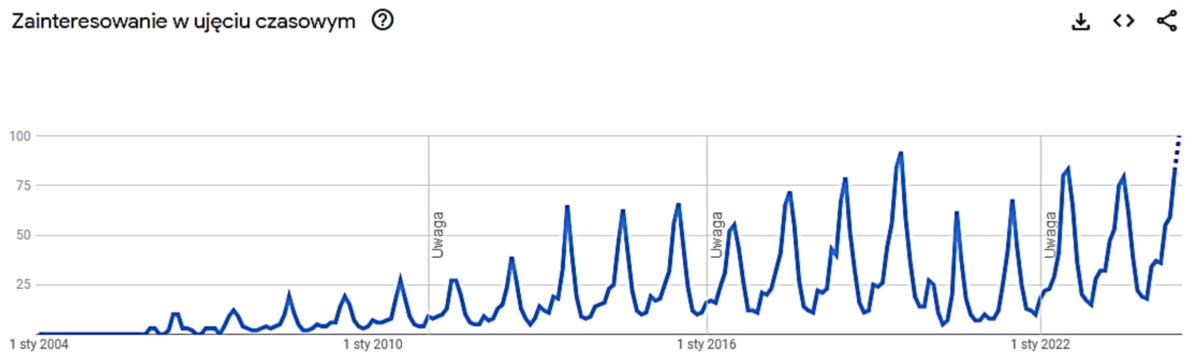

Figure 5. Interest over time ("EKUZ").
Source: Google Trends.

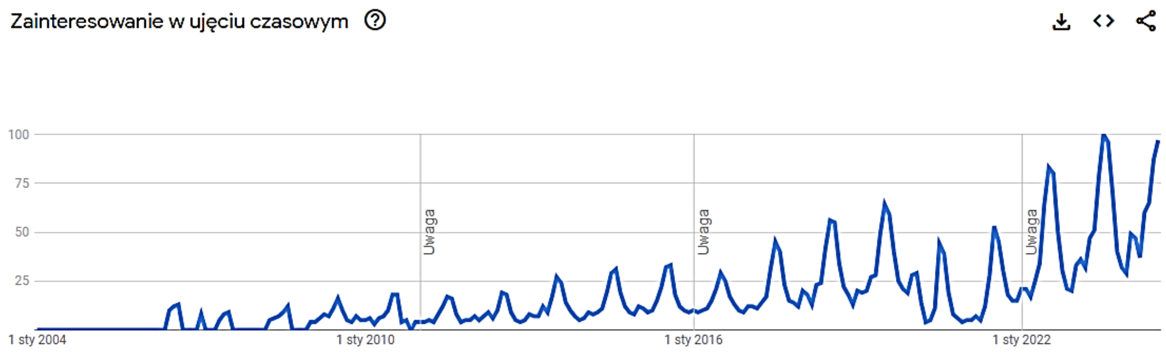

Figure 6. Interest over time ("ubezpieczenie turystyczne").
Source: Google Trends.

Time series plots show a slight upward trend throughout the years for RSV of „EKUZ" [European Health Insurance Card] and "ubezpieczenie turystyczne" [travel insurance]. Given the clear seasonality observed in the interest over time as depicted in Figure 5 and Figure 6, a suitable method for forecasting in this scenario would be the multiplicative Holt-Winters model. This model is ideal for handling data with seasonal patterns where the amplitude of the seasonality varies proportionally with the trend. By decomposing the time series into level, trend, and seasonal components, the multiplicative Holt-Winters method can accurately model the recurring peaks observed in June.

To utilize seasonal indices, each observation must be assigned to one of the p calendar units that constitute the complete period, such as January, February, etc., for monthly observations. The seasonal index quantifies how a particular month compares on average relative to others. This index allows for the identification of seasonal variations by providing a standardized measure of monthly differences. By analyzing these indices, we can better understand and adjust for seasonal effects in the data. In the case of the multiplicative model, where the original series is the product of the trend, seasonal, and irregular components, Lim and McAleer (2008) define high seasons as months for which the corresponding seasonal indices exceed 100%.

Table 1.
The seasonal indices expressed as percentages

Month	"EKUZ"	"ubezpieczenie turystyczne"
January	65.1%	67.2%
February	60.7%	58.2%
March	85.9%	71.6%
April	105.6%	84.2%
May	190.3%	142.0%
June	243.8%	213.5%
July	169.0%	199.8%
August	88.5%	114.8%
September	45.4%	71.2%
October	36.9%	56.0%
November	39.8%	51.2%
December	68.8%	70.4%

Source: own calculations.

The Holt-Winters method was used to identify the significance of and isolate the periodic component (seasonality) of each time series. Due to the presence of a value of 0 in the initial period of the analysis, data from June 2007 onwards (for "EKUZ") were included in the calculations for the Holt-Winters model. The data (relative search volumes of „EKUZ") shows that interest peaks in the summer months, with the highest value in June (243.8%), followed by a significant decline in the autumn and winter months, reaching its lowest in October (36.9%) (Table 1, Figure 7). This pattern suggests that the demand for travel-related services increases substantially during the summer, likely due to higher travel activity during this period.

Due to the presence of a value of 0 in the initial period of the analysis, data from June 2009 onwards (for "ubezpieczenie turystyczne") were included in the calculations for the Holt-Winters model. The relative search volumes for "ubezpieczenie turystyczne" demonstrate a pronounced seasonal pattern, with interest peaking in the summer months (Table 1, Figure 8). The highest value is recorded in June, at 213.5%, indicating a surge in interest likely associated with increased travel activities. This is followed by a significant decline in the autumn and winter months, with the lowest value observed in November at 51.2%. This trend suggests a strong seasonal influence on the search behavior for travel insurance, correlating with the typical travel season and diminishing during the off-peak periods.

Understanding seasonal trends is crucial for stakeholders in the travel and insurance industries to optimize their marketing and resource allocation strategies. Lim and McAleer (2008) define high seasons as periods during which the seasonal indices surpass a threshold of 100%. When the seasonal index exceeds this threshold, it indicates that the demand or activity level during these months is significantly higher than the average, denoting peak periods in the seasonal cycle. This approach allows for a quantifiable assessment of seasonal fluctuations and helps in identifying periods of elevated demand. By setting the threshold at 100%, Lim and McAleer provide a clear benchmark for distinguishing between high and low seasons, facilitating more accurate planning and resource allocation. Such a metric is crucial for businesses and policymakers aiming to optimize their strategies in response to predictable variations in demand throughout the year.

The concept of seasonality, lays a critical role in forecasting phenomena that exhibit periodic fluctuations (Figure 7, Figure 8). By identifying high seasons as months with seasonal indices exceeding 100%, researchers and practitioners can effectively recognize periods of heightened activity or demand within a given time series. This quantifiable benchmark facilitates precise forecasting by allowing for adjustments based on expected peaks and troughs.

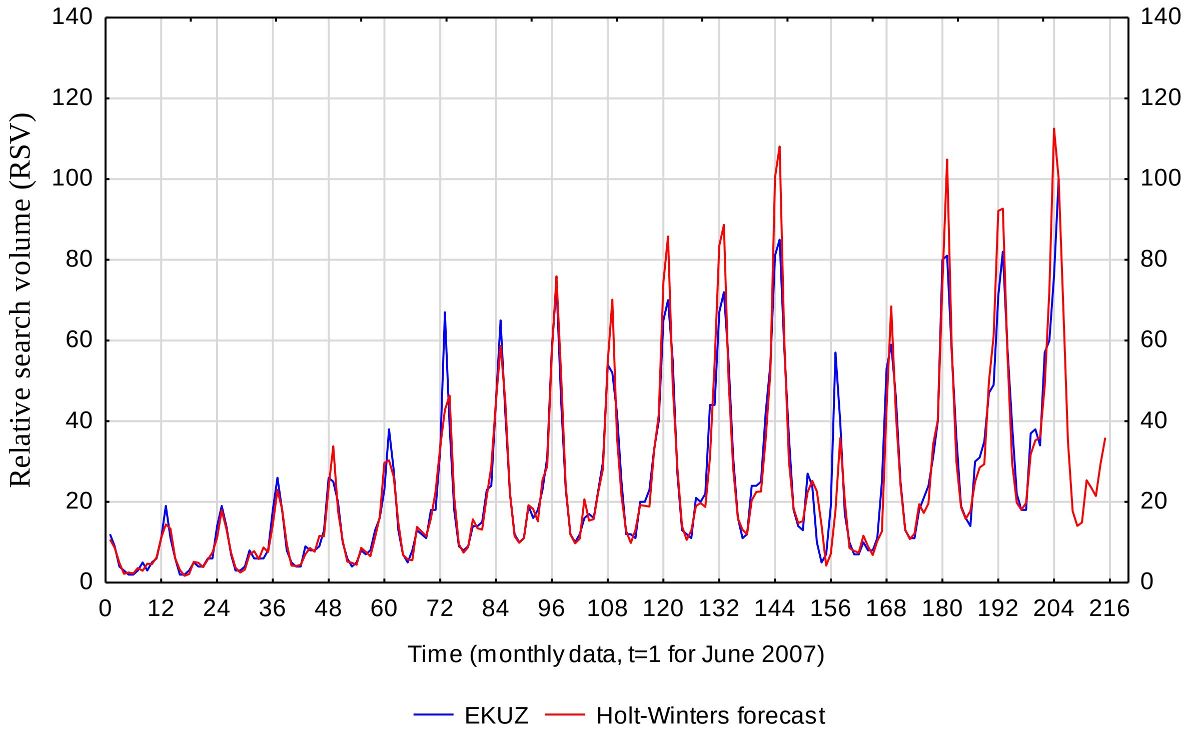

Figure 7. Interest over time ("EKUZ", t = 1 for June 2007) and Holt-Winters forecast results.

Source: own calculations.

Utilizing seasonal indices in forecasting models helps to improve the accuracy of predictions by incorporating anticipated variations into planning and resource allocation strategies. For instance, policymakers can better allocate resources and design interventions to address seasonal demands. Thus, the integration of seasonal indices into forecasting practices enhances the ability to anticipate and respond to cyclical changes, ultimately leading to more informed and effective decision-making.

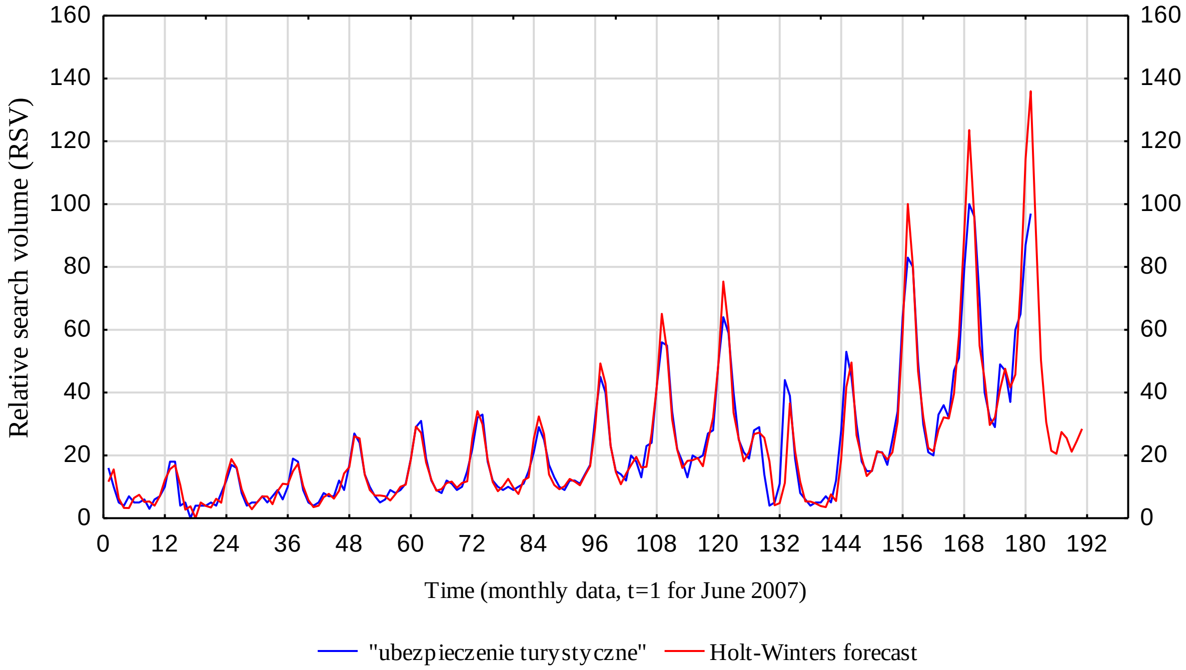

Figure 8. Interest over time ("ubezpieczenie turystyczne", t = 1 for June 2009) and Holt-Winters forecast results.

Source: own calculations.

5. Discussion

Seasonality is a critical phenomenon affecting various economic sectors, particularly tourism, which experiences significant fluctuations due to temporal imbalances in visitor numbers, expenditures, and transportation usage. The comprehensive yet underexplored nature of tourism seasonality necessitates a thorough analysis to assist managers in optimizing resource use. Key areas of research include defining seasonality, measurement, causes and impacts. A review of methodological and applied academic works on tourism seasonality by De Cantis and Ferrante (2011) reveals a variety of approaches and statistical tools used to study this phenomenon. Despite the diversity of methods, there is a notable similarity in the aims of these studies. Commonly used tools and techniques in the study of seasonality include seasonality indexes, which play a crucial role in predicting future values based on time series data. Seasonality indexes adjust initial predicted values derived from smoothed trend lines, modifying these values according to the specific season being forecasted. By applying the seasonal index, researchers can correct predictions upwards or downwards, thereby accounting for seasonal fluctuations. This method enhances the accuracy of forecasts by integrating the systematic intra-year movements characteristic of seasonal patterns. Consequently, seasonality indexes are essential for making precise predictions and informed decisions in various fields impacted by seasonal variations.

In Poland, the awareness and purchase of travel insurance have steadily increased, particularly among frequent travelers and those embarking on long-haul journeys. This trend is mirrored in the increasing frequency of Google searches for “EKUZ” and “ubezpieczenie turystyczne”, indicating heightened public interest and awareness. Factors contributing to this rise include greater exposure to global travel risks and a proactive approach to financial planning for unforeseen circumstances. Furthermore, the ongoing global events, such as pandemic COVID-19, have amplified the need for comprehensive travel insurance.

Travelers are more informed, seeking policies that offer adequate coverage. This shift in consumer behavior is evident in the seasonal spikes in Google searches for travel insurance, correlating with peak travel seasons and periods of heightened travel advisories. Data on relative search volumes for “EKUZ” and “ubezpieczenie turystyczne” indicates a distinct seasonal pattern, with interest peaking during the summer months. The highest value is observed in June, followed by a significant decline in the autumn and winter months. This trend suggests that public interest in “EKUZ” and “ubezpieczenie turystyczne” is significantly higher during the summer, likely due to increased travel activity, and diminishes considerably during the off-peak travel seasons.

The research hypotheses were confirmed through the analysis. Hypothesis 1, which posited that the search interest for "ubezpieczenie turystyczne" and "EKUZ" significantly increases during the weeks leading up to the vacation season, indicating a strong seasonal pattern correlated with peak travel periods, was supported. This confirms the utility of Google Trends data in forecasting travel-related behaviors and trends. Hypothesis 2, which proposed that changes in the search volume for "ubezpieczenie turystyczne" and "EKUZ" on Google Trends can serve as predictive indicators of actual travel behavior and insurance purchase trends, was also supported.

This research presents several limitations. A notable limitation is that it measures interest levels through search queries, which may not accurately reflect actual tourist behavior. Additionally, the relationships and patterns identified were tested only within a single country, which limits the generalizability of the findings to other regions and cultural contexts. Consequently, the applicability of the results to different geographic and cultural settings remains uncertain. Further studies involving multiple countries and diverse cultural backgrounds are needed to validate and extend these findings.

6. Conclusion

Seasonality significantly impacts tourism. This sector experiences heightened demand during specific, predictable periods of the year, such as the summer vacation months and holiday seasons, when people are more likely to travel. Consequently, travel insurance providers must anticipate these peaks and adjust their operations and marketing strategies accordingly. The predictable nature of these fluctuations allows for strategic planning to optimize resource allocation and customer service. Understanding the seasonality of travel insurance sales is crucial for maximizing profitability in the insurance industry and ensuring adequate coverage for travelers during high-demand periods.

The Holt-Winters method is a widely used approach in forecasting that effectively accounts for both trend and seasonality in time series data. This method extends exponential smoothing techniques to incorporate seasonal variations, making it particularly useful for predicting phenomena with regular cyclical patterns. By applying the Holt-Winters model, practitioners can decompose a time series into its trend, seasonal, and irregular components, which enhances the accuracy of forecasts. The method offers two primary variations: the additive model, which is suited for data with constant seasonal effects, and the multiplicative model, which is appropriate for data where seasonal effects vary proportionally to the level of the series. The flexibility of the Holt-Winters method allows it to adapt to various types of seasonal behavior, improving predictions across diverse applications. Consequently, its use in forecasting helps organizations and researchers make more informed decisions by providing reliable estimates of future trends based on historical data.

The analysis of queries related to „travel insurance" and „EKUZ" in Poland reveals not only the seasonal patterns in public interest but also the broader implications for the travel and insurance industries. The findings underscore the high functionality and potential of Google Trends as a research tool, offering valuable insights that can inform policy and business decisions.

Seasonality may be caused by various factors, such as weather, vacations, and holidays, and consists of periodic, repetitive, and generally regular and predictable patterns in the levels of a time series. It is essential for organizations to identify and measure seasonal variations within their market to effectively plan for the future and prepare for temporary increases or decreases in labor requirements as demand for their services fluctuates over certain periods. This may necessitate periodic expenditure on advertising and other activities that can be organized in advance. Additionally, organizations need to determine if the variation they have experienced exceeds the expected amount, beyond what usual seasonal variations account for. Understanding these patterns helps in optimizing resource allocation and strategic planning.

The extensive volume of searches conducted via Google generates trend data, which can be analyzed using Google Trends, a publicly accessible tool that compares the volume of internet search queries across different regions and time periods. Consequently, Google Trends can offer indirect estimates and has the potential to detect specific patterns earlier than traditional systems. In conclusion, the integration of Internet-derived data, particularly through tools like Google Trends, represents a significant advancement in social science research.

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