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Importance-Performance Analysis Based on Text Mining

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Abstract:

Purpose: *Importance-performance analysis (IPA) has gained significant recognition in research of service quality. This study enhances the existing body of knowledge in three significant ways. Firstly, the primary aim of this article is to demonstrate how to conduct IPA using text mining techniques to analyze opinions scraped from the internet, eliminating the need for extensive questionnaires (novel approach). Secondly, we propose a simple statistical data adjustment technique based on the Cronbach alpha coefficient. Thirdly, we provide a literature survey of the evolution of IPA in time.*
Design/Methodology/Approach: *The narrative review of literature subject was used as well as three case studies applying novel approach to IPA in examples of three different hotels in Poland.*
Findings: *We assessed the effectiveness of the novel approach through case studies of three hotels of varying quality. In our opinion, all hotels were accurately diagnosed in the IPA conducted.*
Practical implications: *We believe our approach is flexible enough to accommodate further enhancements, including both the techniques for extracting information from text and refining the IPA itself.*
Orginality/Value: *IPA based on text mining is an interesting alternative to the traditional approach which typically involves researching hundreds or even thousands of respondents through personal questioning.*

Keywords: *Tourism, hotel services, quality, text mining, importance-performance analysis.*

JEL Codes: *C18, C80, D22.*

Paper type: *Conceptual and research article.*

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1. Introduction

Importance-performance analysis (IPA), despite its limitations, has gained significant recognition in research of service quality, throughout nearly fifty years of its development. The primary aim of this article is to demonstrate how to conduct IPA using text mining techniques to analyze opinions scraped from the internet, eliminating the need for extensive questionnaires.

We propose methods for extracting both the importance and performance of attributes from customer opinions. Conducted analysis refers to service of quality in hotel sector in Poland. We present case studies of three hotels of varying quality. Research on service quality is critically important from both customer satisfaction and profitability perspectives for service establishments.

2. Literature Review: The Evolution of IPA Model

As noted by Wojciechowska (2021), despite numerous studies, this issue remains underexplored and inadequately presented in Polish literature, particularly concerning tourist services. Insufficient attention is given to analyses of service quality, service improvement, customer evaluations, and investments aimed at enhancing services, even though these factors significantly influence customers' perceptions of service quality research and their satisfaction, ultimately impacting service providers' profits (Rudawska, 2000).

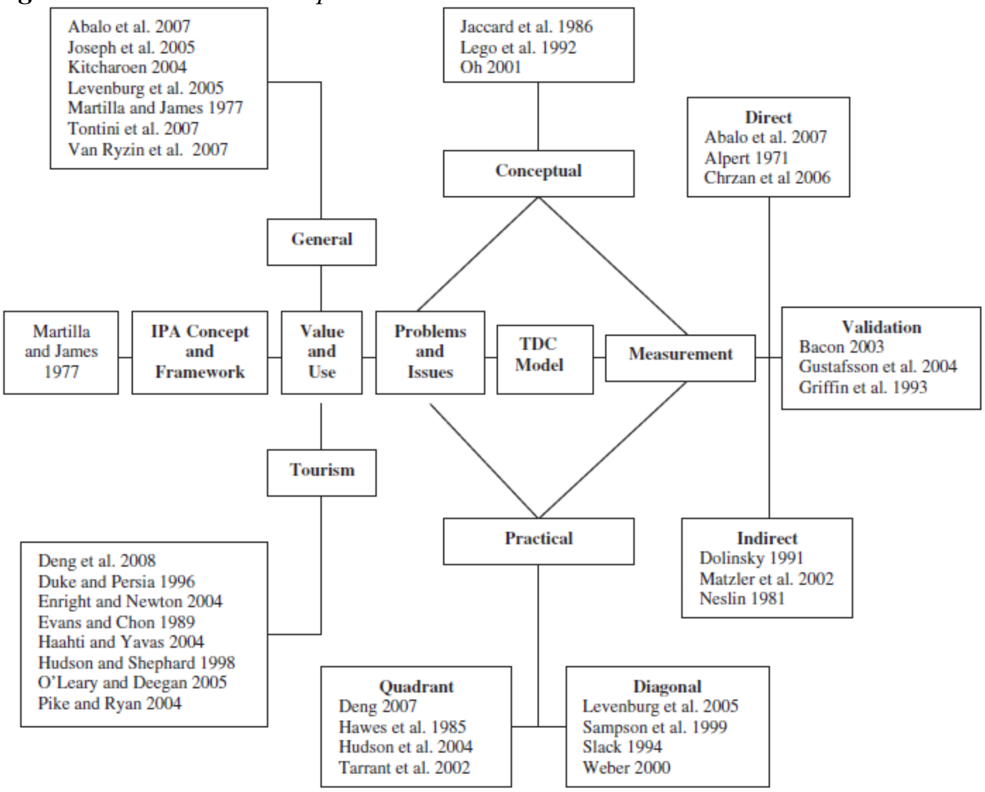
The study of service quality has a much longer tradition in Western literature, resulting in a greater volume of research and publications on the subject. The pioneers of quality research include W.E. Deming, J.M. Juran, P.B. Crosby, and K. Ishikawa. Deming defined quality as "the expected degree of uniformity and reliability at the lowest possible cost and adjustment to market requirements" (1982).

A straightforward method for measuring service quality is the Importance-Performance (IPA) method, proposed by Martilla and James (1977). IPA is treated as a valuable technique in creating business strategies, particularly in tourism. It has been widely utilized to understand customer satisfaction and prioritize service provision strategies based on the premise that satisfaction results from the perceived importance of a service and a corresponding judgment of its performance (Hua and Chen, 2019).

According to Slack (1994), the utility of the IPA method lies in its ability to simultaneously assess both the importance of individual attributes for buyers and the satisfaction with the delivery of the service package. While management may choose to focus on either importance or performance metrics alone, combining both provides significantly better insights into customer satisfaction assessments and necessary changes in service delivery strategies.

The IPA literature emphasizes the need to enhance IPA research with measures of reliability and validity (Azzopardi and Nash, 2013), prompting many researchers to explore this area (Figure 1).

Figure 1. *IPA literature map*



Source: *Azzopardi and Nash 2013.*

Researchers have aimed to fully grasp the IPA method's applicability across various domains regarding service quality enhancement efforts aimed at increasing customer satisfaction levels. The IPA technique serves as a fundamental diagnostic decision-making tool (Matzler, Sauerwein, and Heischmidt, 2003; Johns, 2001) and is often described as a "valuable screening tool" (Rial, Varela, and Real, 2008) facilitating the identification of priority areas for improvement (Sampson and Showalter, 1999) while directing limited resources where they are most needed (Levenburg and Magal 2005).

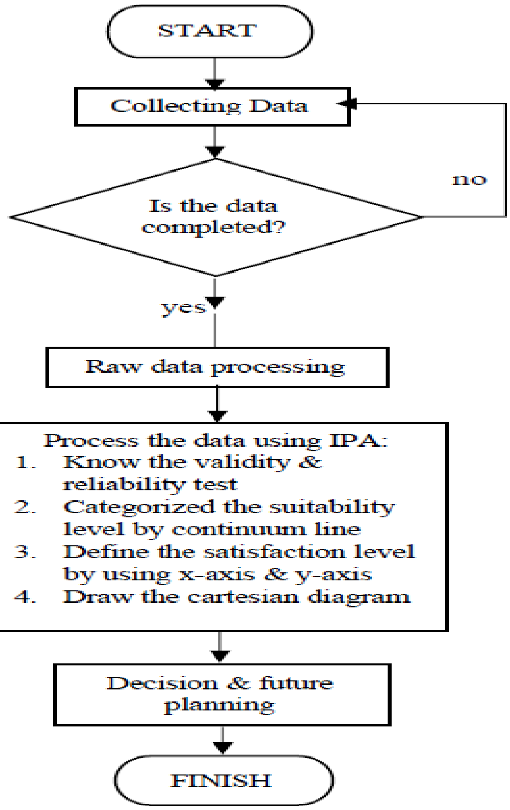
Due to its simplicity, low cost, ease of interpretation, and universal applicability, IPA analysis is frequently employed to assess customer satisfaction and the quality of products offered by companies across various sectors of the economy, e.g., in tourism, education, healthcare, banking, public administration, food services, information technology, and more (Sever, 2015).

Importance-performance analysis is considered an unconventional yet effective alternative for assessing perceived service quality (Yildiz, 2011). The logic of the analysis involves comparing the performance and importance of each relevant attribute (Abalo, Varela, and Manzano, 2007). In the context of service quality evaluation, performance reflects customer perceptions of current service delivery, while importance indicates the relative customers' value assigned to each relevant attribute within a particular context of service evaluation.

This model suggests that when perceived performance exceeds expectations, it leads to positive disconfirmation (i.e., satisfaction), whereas when expectations exceed perceived performance, it results in negative disconfirmation (i.e., dissatisfaction) (Sever, 2015). The comparison between performance and the importance of service attributes can provide management with valuable information and assist in making decisions regarding service management priorities that should enhance and sustain customer satisfaction.

IPA is based on measuring the importance of features (importance) and their implementation in the product (performance) using a specific procedure (Figure 2).

Figure 2. *IPA research procedure*



Source: *Yuhefizar, Utami, and Sudiman 2022.*

The process typically identifies key features through group interviews or management insights (though it may also utilize online reviews). Decision-makers would benefit significantly from understanding customer sentiments while formulating improvement strategies amid varied competition over different timeframes (Bi, Liu, Fan, and Zhang, 2019).

Respondents are then prompted to express their views concerning feature importance (reliability, responsiveness, and tangibility) along with their perceptions related specifically towards provided services.

Ultimately calculations yield an importance-realization matrix plotting various dimensions along X-axis versus Y-axis coordinates indicating respective performance versus significance assessments across four quadrants (Stobiecka, 2007):

Quadrant 1: High performance, high importance—maintain current efforts (area I),
Quadrant 2: Low performance, high importance—focus efforts here (area II),
Quadrant 3: Low performance, low importance—minimal attention required (area III),
Quadrant 4: High performance, low importance—potential resource reduction (area IV).

This model assists organizations in pinpointing strengths alongside areas needing enhancement, e.g., if rated high on importance but low on performance signifies immediate attention should be devoted thereon.

Customers responding to the two types of scaled questions assess the same dimensions of service quality twice (which serve as assessment criteria from the buyers' perspective)-once regarding their significance during the service provision process and again concerning the level of implementation of these dimensions.

The first group of questions pertains to the significance of individual features of offers in the decision-making process for customers, while the second group refers to the same features but already with one specific offer of a specific service provider. The results obtained are compared in the matrix format presented above.

This process yields an assessment of the desired quality of the two aforementioned parameters. The closer the given attribute is to the diagonal of the matrix, the more its implementation aligns with the needs of customers (more on this topic in: Keyt, Yavas, and Riecken (1994), Binks, Ennew, and Reed (1993), Matzler, Sauerwein, and Heischmidt (2003).

Area I outlines features that are equally important and significant for service buyers, about which they have no particular comments and assesses the level of their implementation as very good. Consequently, the service provider does not need to take any special actions regarding these parameters, only those necessary to maintain the current level of service provision. This area is sometimes referred to as the zone of proper services. Features included in area II are parameters of the offer that are important to customers, but they evaluate their implementation by the service provider at a rather low level.

Therefore, this area contains features that require immediate improvement and special attention from the service provider. This area is sometimes called the zone of urgent needs or service quality deficiency. The factors identified in this quadrant represent significant weaknesses and threats to competitiveness. In areas III and IV, one can find features of offers that have a smaller impact on customers' decision-making; they are less important to them.

Consequently, the analysis of both areas is somewhat less binding for the service provider, and even features found in area IV should be a source of potential savings by reducing costs associated with the current level of performance of these activities (limiting what the customer did not expect and does not expect). Area III is often referred to as the zone of improving service properties, while zone IV is known as the zone of excess quality.

This method allows for a graphical presentation of the importance of individual criteria for assessing the service from the customer. It is based on the philosophy that to improve overall quality from the customer's viewpoint, it is not necessary to enhance all features of a given service; rather, one should focus primarily on those that are important and significant for service customers.

Despite clear advantages inherent within IPA approaches, notable limitations exist that could compromise results accuracy including reliance upon two main assumptions (Matzler, Bailom, Hinterhuber, Renzl, and Pichler, 2004):

- Performance metrics depend on predetermined variables,
- Relationships between measured performances display linear symmetrical nature throughout analyses periods surveyed.

Many critics challenge these notions arguing fluctuations surrounding attribute performances correlate directly against shifts occurring surrounding deemed important factors thus undermining traditional applications thereof (Matzler, Sauerwein, and Heischmidt, 2003).

Utilizing flawed methods when calculating scores tied toward either aspect might lead managerial decisions astray (Zhao, Xu, Cai, Hu, and Hong 2022). Overall, the technique remains surrounded by conceptual, methodological, and measurement ambiguities (e.g., the ambiguous understanding of the concept of "importance," which is not identical to the concept of „expectation") to distinguish between these two concepts, some authors define importance as a desired outcome and expectations as a tolerated outcome (Oh, 2001).

IPA has faced substantial criticism regarding its arbitrary measurement validity, along with concerns about its poor discriminant and predictive validity. Issues surrounding reliability and validity remain largely unaddressed, even in the latest studies on service quality (Oh, 2001). This situation may arise from respondents lacking the necessary awareness or knowledge to accurately evaluate the significance of various product or service attributes.

Additionally, biases such as survey fatigue can lead to distorted evaluations of attribute importance, particularly since direct measures require a series of repetitive questions within the same questionnaire (Carman, 1990). While using indirect measurement methods can positively impact respondents' motivation and engagement (Azzopardi and Nash, 2013).

Neslin (1981) highlights that the aggregate nature of statistical analyses tends to overlook individual variations in importance weights. This oversight can increase experimental error and diminish the precision of estimations. Consequently, these factors may contribute to a perceived disinterest and detachment among respondents. Such biases could help explain the tendency for customers to uniformly rate all attribute importances as high (Gustafsson and Johnson, 2004; Garver, 2003).

The inflation of ratings for attribute importance may be attributed to the research procedures employed in many studies using IPA. Wade and Eagle (2003) contend that since the questionnaire that solicits attribute importance is derived from a list of attributes deemed significant by prior qualitative studies or literature reviews, there is an inherent tendency to rate these attributes as highly important.

Furthermore, consumers often regard service factors as more or less significant based on their satisfaction levels; as a result, service attributes generally cluster in the first or third quadrant. Additionally, it remains ambiguous whether consumers view a service factor as significant due to its presence or absence. More ambiguities can be found in Tuan *et al.* (2022).

In practice, the performance of a quality factor is frequently derived from customer satisfaction ratings, which is less contentious (as the usual measurement procedure involves taking the mean of the performance ratings obtained from an appropriate group of people using a metric or Likert scale).

However, when analyzing importance attributes, the results can be obtained in two ways. One is from ratings provided by respondents (stated or explicit importance). Bottomley, Doyle, and Green (2000) argue that direct ratings outperform other methods due to their provision of more consistent importance weights and a general preference among respondents.

Alternatively, implicit importance can be derived through various calculation methods (such as statistical techniques). For example, Deng (2007) suggested merging partial correlation analysis with natural logarithm transformation to assess attribute importance. Partial ranking techniques can address some challenges related to derived importance measures and those based on rating scales.

This approach entails asking respondents to rank attributes according to their significance, resulting in a distribution of ranking scores that allows for effective differentiation among the attributes. Since participants must evaluate their preferences in relation to the other attributes, the resulting importance weights reflect a competitive assessment of the stated importance across all attributes.

By focusing only on their top preferences, this method may alleviate rater fatigue and foster increased engagement, however research conducted by Sampson and Showalter (1999) as well as Mersha and Adlakha (1992) did not bring the expected results in the form of adequate value distribution within the IPA space).

This concept was also previously mentioned by Bacon (2003), who argued that direct measures tend to capture the importance of attributes more effectively than indirect measures, although this did not eliminate the shortcomings of the former. Bacon further asserts that direct assessments of importance can often be misleading due to uniformly high ratings. The root of this issue lies within Martilla and James' methodology, where the initial step is to identify the most salient attributes of a product or service through qualitative studies (focus groups and/or unstructured interviews) or by reviewing existing research.

This methodology naturally tends to produce high importance ratings on a metric or Likert scale for all assessed attributes, leading to their clustering at the upper section of the IPA grid or concentration in the positive quadrants of the IPA, indicating strong correlations between attribute importances and performances, which has serious implications for the validity of the findings.

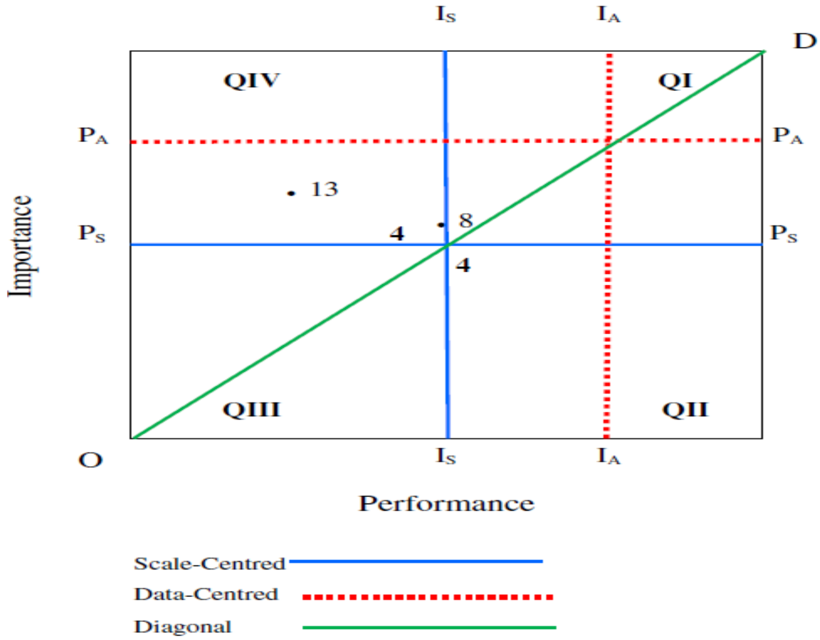
However, alternative methods for determining crosshair points could result in attributes being placed in different quadrants. Moreover, nearly 40% of attributes within the IPA framework either lie on one of the axes or are positioned too close to either axis, complicating the interpretation of these outcomes for decision-makers (borderline attributes may not be understood in the same way as distinctly categorized attributes) (Enright and Newton, 2004). Tarrant and Smith (2002) conclude that this issue is amplified with smaller sample sizes (fewer than 400 participants).

A minor change in the positioning of an attribute can lead to a substantial shift in the inferred priority (Bacon, 2003). This undermines the purpose of the analysis, as the IPA diagram aims not just to document absolute importance and performance values but to differentiate between attributes as targets for improvement (Abalo, Varela, and Manzano, 2007).

Another conceptual challenge associated with the IPA method is the risk of incorrectly distributing product features on the matrix (misinterpretation of points near the discrimination thresholds) and misreading results. A further complication lies in accurately establishing the set of attributes used to measure their importance and performance, which is crucial for making informed investment decisions based on information derived from the selected attributes (Oh, 2001).

The aforementioned challenges connect to the proper placement of the horizontal and vertical axes, which determines the positioning of individual attributes (e.g., 4, where 4,8,13 are sample attributes in Figure 3) within the four quadrants. Axis scaling frequently reveals significant inconsistencies among studies that have utilized the IPA grid to identify areas for action to gain competitive advantage or for informed decision-making (Figure 3).

Figure 3. *Quadrant (actual-data-centered vs. scale means) and diagonal partitions*



Source: *Azzopardi and Nash 2013.*

As illustrated, different scaling can lead to significantly different categorizations of attributes and interpretation of results. Traditionally, the placement of the axes is considered “a matter of judgment” because the goal is to measure the relative, not absolute, importance and performance levels of attributes.

A method for estimating the optimal threshold for distinguishing performance scores on an IPA plot and finding the point in the performance scores that best distinguishes truly satisfactory from unsatisfactory attributes, and the assessment of the IPA validity and the reliability of its thresholds, using ROC approach, can be found in Sever (2015). Many studies adopt a data-centric approach in which the average values of observed importance and performance ratings define the intersection of the IPA matrix (Levenburg and Magal, 2005; Weber, 2000; Eskidsen and Kristensen, 2006).

However, some studies adopt a scale-centered methodology, where the average values from established scales (for instance, a score of 4 on a 7-point Likert scale) define the intersection points of the vertical and horizontal axes (Chen and Lee, 2006; Evans and Chon, 1989, Go and Zhang, 1997; Hawes and Rao, 1985; Tarrant and Smith, 2002; Tonge and Moore, 2007; Tontini and Silveira, 2007).

Oh (2001) posits that the scale-centered method is preferable as it enhances clarity when elucidating research findings. Conversely, the data-centered approach also maintains a level of transparency and validity, provided that the results are analyzed in accordance with its underlying assumptions. Most researchers use the mean values of actual importance and performance ratings when specifying thresholds (Dwyer, Cvelbar, Edwards, and Mihalic 2012; Liu, Liu, Huang, and Wen 2010). Nonetheless, some authors opt for median values when a true interval scale cannot be assumed (Shieh and Wu, 2011).

As depicted, there is also a diagonal line in Figure 3 illustrating alternative possibilities for categorizing attributes and making specific management decisions based on this categorization (Hawes and Rao, 1985; Ziegler *et al.,* 2012). This diagonal, tilted at a 45-degree angle, separates areas with different priorities, serving as a distinguishing threshold between satisfaction and dissatisfaction, in contrast to the original vertical and horizontal lines.

Bacon (2003) defines this line as an iso-priority diagonal, where all points along it share equal improvement priorities ($I = P$). Points above the line indicate a high priority for improvement and opportunity ($I > P$), while the points below suggest low priorities ($I < P$). In his research, he demonstrated that the performance of the diagonal line model is relatively superior to other models. The adjusted R^2 of the diagonal line was found to be higher than that of the scale-centered method and greater than the adjusted R^2 of the data-centered quadrant model.

As far as possible approaches to IPA based on text mining are concerned, we should mention the work of Nam et al. (2019). It is an interesting technique which allows for calculating the importance of attributes in real-time by means of a probability distribution. However, the performance of attributes must be user assessed on a numerical scale.

The above description of the evolution of the IPA model is not exhaustive. Only specific threads concerning the limitations, imperfections, or even defects of the IPA model and attempts to modify it by various researchers have been highlighted. As mentioned, most limitations are related to conceptual issues, attribute selection, model validation, the ambiguity of the concept of "importance", the method of determining the intersection point, scale selection, and respondents' knowledge, among others. Nevertheless, IPA and alternative methods for measuring service quality, their importance, and satisfaction are used in many areas and are considered essential tools for making decisions regarding service quality improvement and broader customer care.

3. New Methodology Description

Given the various approaches to IPA and our goal of applying information retrieved from business reviews through text mining we decided to adopt the approach to IPA proposed by Abalo *et al.* (2007). We chose this method because it effectively addresses the dilemma between the data-centered and scale-means IPA versions.

Additionally, Abalo's approach utilizes an iso-line that divides the whole quadrant into five easily interpretable areas. However, a significant trait is its requirement for respondents to rank the importance of all attributes. In our view, this condition poses a serious drawback as most individuals would struggle to rank all attributes, for example, in hotel reviews.

For many, a few attributes may be equally important, and it is unclear how to compare "bathroom quality" and "breakfast quality." If the bathroom is in very poor condition, one might assert that it ranks higher than breakfast quality. Conversely, if there is merely a smudge on the bathroom mirror, one might prioritize breakfast quality instead.

We propose a technique that allows us to overcome this limitation by obtaining a ranking of the attributes through text mining, thereby bypassing the drawback of Abalo's approach. Another interesting characteristic of our proposal is that we do not have to carry out any interview or even research focused especially on the assessment of hotel services. All that is required is to scrape opinions or assessments from Internet websites that have been available for a reasonable time.

As far as text mining is concerned, one has an enormous number of algorithms to choose from, depending on the task at hand. In this work, we are concerned with 1) detecting all instances of any attribute from a predefined set of attributes and 2) determining whether the attribute was assessed positively, negatively, or neutrally (which is equivalent to a neutral assessment). For the first task, we will not employ any algorithm and will conduct it manually. For the second task, there are two groups of algorithms—supervised and unsupervised. Supervised algorithms require a training set of annotated documents.

However, since we aim to avoid sending questionnaires to respondents, as traditional IPA requires, obtaining such a training set is not feasible. The only viable option is to use unsupervised algorithms capable of categorizing any statement about any attribute as positive, negative, or neutral. However, this work is a novel approach to IPA, and we are basically concerned with investigating the capabilities of our proposal rather than the potential applications of text mining algorithms to this proposal. Therefore, the second task will also be performed manually.

This does not mean that the results we publish are crippled due to the lack of the presence of any text mining algorithm. No, rather on the contrary because manually performed text mining is always supposed to be flawless as long as we assume satisfactory level of the English language fluency.

Abalo's modification of IPA involves the following proposal. Suppose n raters select their top k attributes from among s attributes and rank them using natural numbers from 1 (most preferred) to k (least preferred), with no ties allowed. These rankings are then utilized to assign each attribute i an importance value p_i lying in the interval [0,1]. Denoting by g_{ij} the rank assigned to the i-th attribute by the j-th rater, we recode the g_{ij} as ranking scores h_{ij} that lie within the desired interval, increasing with the degree of preference rather than decreasing, and assign the value 0 to all attributes not mentioned by rater j:

$$h_{ij} = \begin{cases} \dfrac{k - g_{ij} + 1}{k} & if\ g_{ij}\ not\ void \\ 0 & otherwise \end{cases} \tag{1}$$

The scores (1) are further employed in the final measure p_i of the importance of the i-th attribute:

$$p_i = \left(n^{-1} \sum_j h_{ij} \right)^{k/s} \tag{2}$$

We aim to achieve similar effects of all importance values of all attributes to lie within the interval [0,1] and do not overcrowd any area of the final IPA quadrant, by counting the frequency with which each attribute is mentioned in customer business reviews.

We applied the Cronbach alpha coefficient to incorporate overall or general opinions about the business to a reasonable extent. The coefficient is given by the formula:

$$\alpha = \frac{s}{s-1}\left(1 - \sum_i s_i^2 / s_c^2\right) \tag{3}$$

where s_i^2, s_c^2 denote the variance of a single attribute and the variance of the total scale, respectively. The rationale for using the Cronbach alpha coefficient is as follows: If we assign an importance rating of 0 to any attribute not mentioned in a review and a rating of 1 to each attribute that was mentioned, we must determine how much weight to assign to each attribute in the case of a generally positive opinion (e.g., *the company is doing well*).

Conversely, how much importance weight should we assign in the case of a generally negative opinion (e.g., *the company's a complete failure*)? We propose to assign to any attribute the smallest number from the interval [0,1] that yields a Cronbach alpha value greater than 0.7. The value of 0.7 is a generally accepted threshold, indicating that the collected data can be considered reliable. This idea will be applied separately to importance and performance.

Thus, the final shape of our proposal is as follows. Let n denote the number of reviews (not raters, as we do not need raters) of the business being assessed. Let k represent the number of predefined attributes considered.

- For each specific type of review, assign an importance value of 1 to any attribute mentioned and a value of 0 to each of the remaining attributes.
- For each general type of review, assign the importance value of x to all attributes.
- For x, substitute the smallest number from the interval [0,1] that yields a Cronbach alpha value greater than 0.7.

Regarding performance, we propose using the same technique with the condition of assigning negative values, i.e., −1 or negative x whenever the assessment is negative. Once we have established the values with which each attribute was assessed in all reviews, we have to decide on the final rating for each attribute. In our opinion, this is much simpler in the case of performance, as all we need to do is relate the value of positive opinions to the number of opinions.

Therefore, we propose the following rule for determining the attributes' performance:

For each attribute, divide the sum of all positive assessments from all reviews by the number of reviews (both specific and general) in which the attribute was assessed.

A similar technique for importance is inadequate, as most reviews tend to mention only a couple of the most popular attributes. Therefore, if we related the number of times an attribute was mentioned to the number of reviews, it would marginalize the importance of the most less popular attributes.

To achieve an importance rating within the interval [0,1], we propose to relate the number of times an attribute was mentioned to the number of times the most popular attribute was mentioned. Thus, our tentative proposal is:

For each attribute, divide the sum of points (both fractional from general reviews and full "ones" from specific reviews) by the sum of points that the most popular attribute received.

This proposal, however, favors sets of reviews with a high percentage of general reviews. Conversely, if we limited ourselves to full "ones," such an approach would completely disregard general reviews.

Therefore, our final proposal is to adopt the aforementioned tentative proposal in both variants and take the arithmetic mean of both numbers as the final rating of attributes' importance. This proposal implies that one of the attributes (the most popular one) must have its importance equal to 1, i.e., the maximum possible value. In our opinion, this is not a significant issue.

4. Results and Interpretation

We present three case studies applying our approach to IPA in examples of three different hotels in Poland. The reviews were scraped from the Internet in the years 2020-2021. The hotels were selected to represent a broad range of quality. This selection was performed on the basis of the hotels' assessments given on the website in the form of the arithmetic mean of the Likert five-star scale for the overall hotel assessment.

Thus, we chose a high-quality hotel (above 4.5 stars given by clients), a medium-quality hotel (roughly 3.5 stars given by clients), and a low-quality hotel (roughly 1.8 stars given by clients). For each hotel, we analyzed 50 reviews, typically short. In our opinion this number does not influence the primary purpose of our research, i.e., to find out about the possibility of a reasonable IPA application without the need of questionnaires.

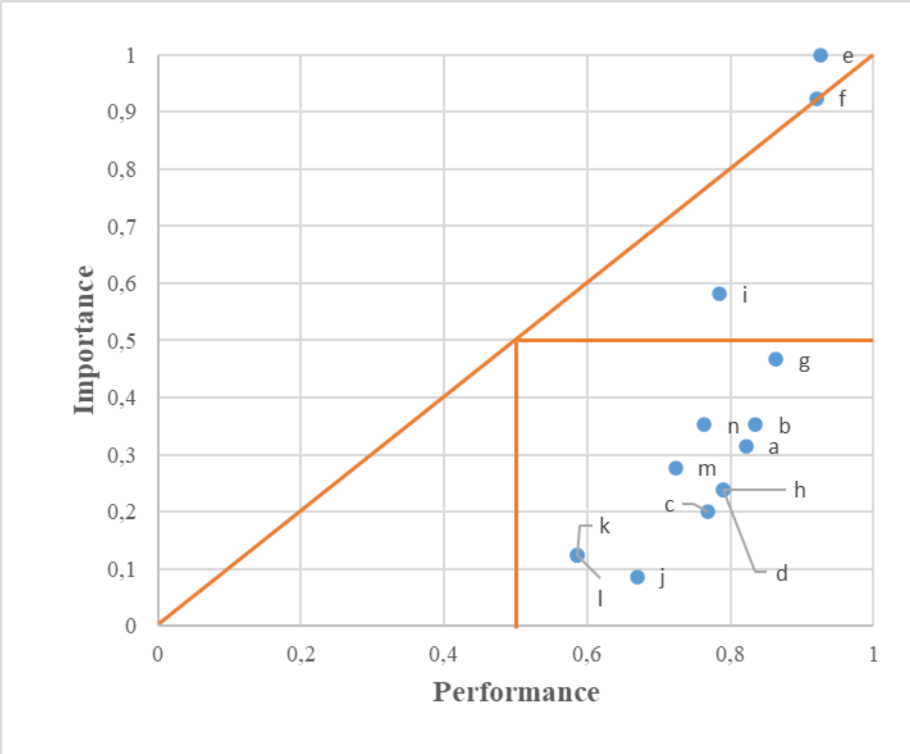
This is a relatively small data set and does not require substantial financial resources. We considered a set of 14 popular attributes established based on a larger number of hotels situated in Poland. The attributes are denoted as follows: *a*—hotel's building and premises, *b*—hotel's location, *c*—prices, *d*—quietness, *e*—breakfast quality, *f*—cleanliness, *g*—staff culture, *h*—bathroom condition, *i*—room condition, *j*—heating, *k*—air conditioning, *l*—internet availability, *m*—free parking, *n*—staff efficiency.

The number of 14 attributes does not cover all possible aspects of the hotel business assessment, some specialists might argue for more, however it does not make any sense to introduce other an attribute which appeared in a broader set of opinions but does not appear in the 50 opinions under study or appears only once.

In the case of the high-quality hotel, all attributes' performance was well above the medium level, which is a correct finding and the most valuable conclusion.

Only one attribute (breakfast quality) was rated with slightly higher importance than performance; however, its performance was rated above 0.9, indicating that management should not be concerned about this result. Slightly disappointing are the results regarding the importance of the attributes, as too many of them fall into the lower right quadrant (Figure 4).

Figure 4. *Modified IPA for a high-quality hotel*



Source: *Own research.*

In the case of the medium-quality hotel (Figure 5), almost all attributes lie above the diagonal, suggesting poorer performance than importance. However, such an inference would be overly harsh, as six attributes (*a*, *b*, *c*, *d*, *h*, *m*) are very close to the diagonal, which may be interpreted as a relatively good result consistent with the overall medium quality of the hotel.

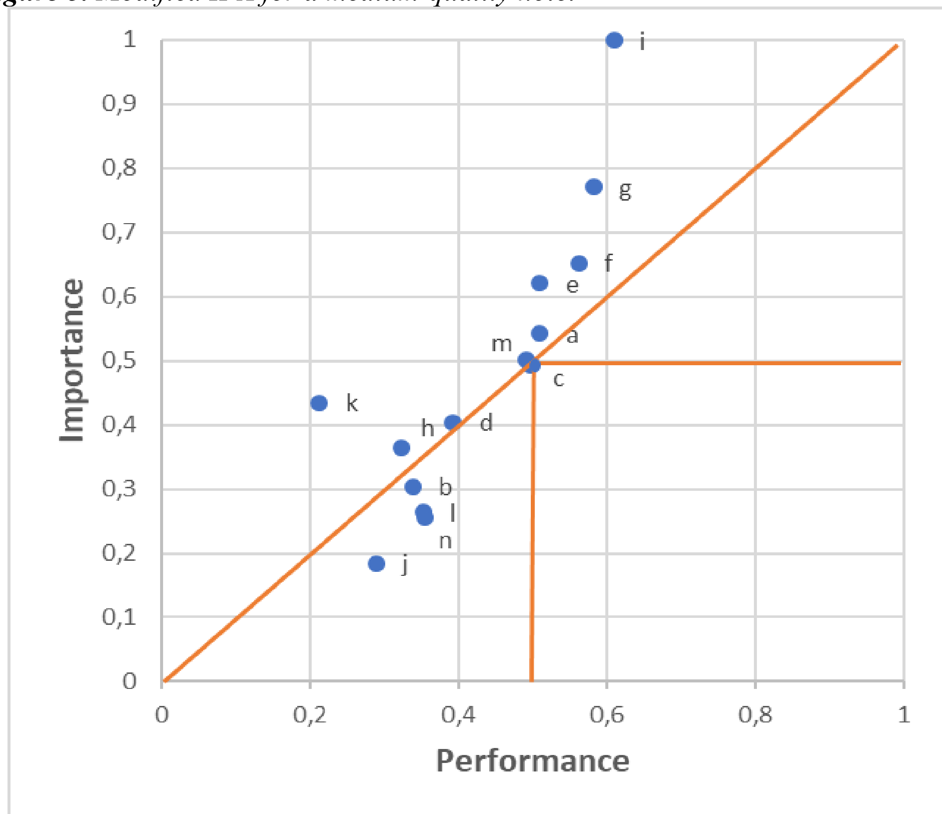
If the traditional approach were applied concerning the performance, we would observe that approximately half of the attributes were rated with good importance (i.e., above 50%), which again aligns with the medium quality of the hotel. Thus, the business owner knows that he should focus on improving attributes: *a*, *b*, *c*, *d*, *h*, *m*, and has a reasonable chance of enhancing their level.

In the case of the low-quality hotel, research finding aligns with the overall poor quality of the hotel (Figure 6). Only attribute *n* (staff efficiency) is relatively well assessed, and the business owner will not need to put much effort into enhancing it.

However, attributes *a*, *c*, *e*, *f*, *g*, *h*, *i*, *j* require significant attention and improvement. Notably, if the traditional approach were applied, the results would differ significantly and inaccurately.

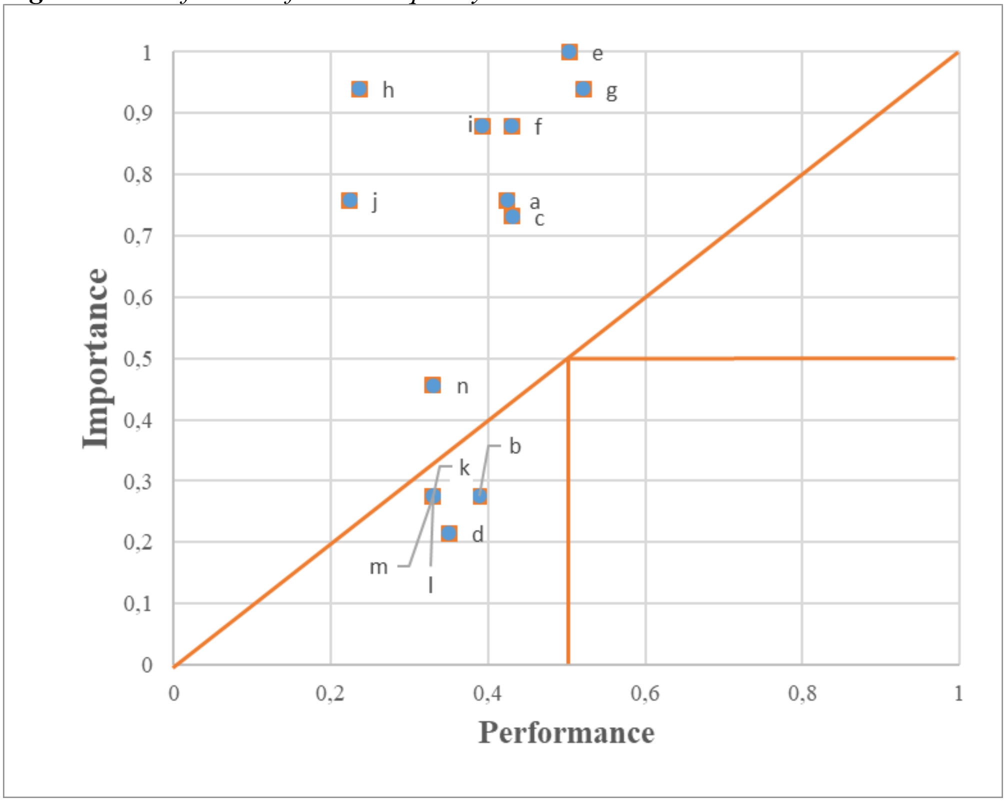
For instance, regarding performance, we would find that two attributes, *e* and *g* (breakfast quality and staff culture), would be rated with relatively good performance (i.e., close to 50%), which again is consistent with the poor quality of the hotel.

Figure 5. *Modified IPA for a medium-quality hotel*



Source: *Own research.*

Figure 6. *Modified IPA for a low-quality hotel*



Source: *Own research.*

5. Conclusions

IPA is a widely used tool for microeconomic and managerial analysis, likely due to its simplicity. However, it is not without weaknesses, such as ambiguities in possible interpretations or measurement scale choices. In this article, we proposed a novel approach to IPA based on text mining.

Text is composed of client-written opinions and can be easily and readily obtained by scraping it from internet websites. The text analysis is straightforward and involves counting the occurrences of any attribute from a predefined set of attributes describing the assessed business, as well as considering the sentiment of these occurrences. We believe that importance-performance analysis based on text mining is an interesting alternative to the traditional approach, which typically involves researching hundreds or even thousands of respondents through personal questioning.

The literature review follows that our approach is cheaper, faster, and equally reliable as most IPA modifications, as well as its original version. This article is meant as a conceptual proposal and thus we limit our presentation to an exemplary set of three business units, however, the proposal involves the necessary data processing enabling the transformation of counting of instances into measuring importance and performance.

Through the proposed data processing techniques, we receive [0, 1] scales in the quadrant, which are easy to interpret and yield favorable results. Our findings are based on the analysis of three hotel businesses of varying quality (poor, medium, and good), which we believe were accurately diagnosed in the IPA conducted. We propose a solution to the dilemma of choosing between the data-centered and scale-means versions of IPA.

Our proposed approach is flexible enough to accommodate further improvements, including improved techniques for extracting information from text and those concerning the very IPA.

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