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Research paper

Information Noise in Marketing Analytics: Implications for Financial Reporting and Economic Decision-Making

Olena Iashchenko [1] *, Olena Chupryna [2], Sergiy Maksymov [3], Nataliia Zemlianska [4], Olga Afanasieva [5], Yuliia Popova [6]

[1] Vice President of Glad Selena Corporation, Fort Lauderdale, FL, USA
[2] Mariupol State University, Kyiv, Ukraine
[3] Danube Institute of the National University «Odesa Maritime Academy» , Odesa, Ukraine
[4] Kyiv Municipal Academy Of Circus And Performing Arts, Kyiv, Ukraine
[5] Odesa National Maritime University, Odesa, Ukraine
[6] State University of Infrastructure and Technologies, Kyiv, Ukraine
**Corresponding author E-mail: 7antoshka@gmail.com*

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Abstract

This study explores the phenomenon of information noise as a critical impediment to the accuracy and reliability of marketing analytics and economic decision-making in data-intensive environments. The research is economically oriented, addressing the adverse effects of informa-tional distortions on the quality of forecasts, strategic planning, and the financial efficiency of market-oriented enterprises. Information noise is examined as a multidimensional construct that arises from data redundancy, irrelevance, ambiguity, contradictions, and temporal incon-sistencies. These distortions hinder the interpretability of marketing data, reduce the validity of econometric analysis, and contribute to suboptimal business decisions. The paper develops a comprehensive methodological framework for identifying, measuring, and mitigating information noise through the integration of statistical analysis, mathematical modeling, semantic diagnostics, and artificial intelligence tools. A particular focus is placed on the economic consequences of noise, such as resource misallocation, increased forecasting error, and de-creased return on marketing investments. The empirical section presents a correlation-regression model based on data from a real enterprise, which quantifies the impact of specific noise factors on sales forecast accuracy. The model reveals that trust in data sources, content redun-dancy, and channel fragmentation significantly affect the reliability of forecasts, highlighting the need for information quality control in fi-nancial planning. The findings emphasize the importance of structured data filtering, entropy-based anomaly detection, and adaptive noise management strategies for improving economic performance in digital markets. The study contributes to the theoretical conceptualization of information noise in marketing economics and offers practical recommendations for enhancing the quality of decision-making through intel-ligent data preprocessing. As a result, it provides a foundation for the development of more resilient and analytically sound business models in the context of digital transformation and informational complexity.

Keywords: *Information Noise; Market Research; Marketing; Marketing Strategy; Information Flows; Data.*

1. Introduction

In light of the exponential growth of information volume and the increasing complexity of communication channels, marketing research is increasingly challenged by the phenomenon of information noise. This phenomenon is not merely a secondary consequence of digitalization and globalization but constitutes a disruptive factor that distorts analytical clarity by replacing meaningful signals with redundant, irrelevant, or ambiguous data. As a result, the task of measuring and managing information noise becomes critically important to ensuring analytical rigor and the credibility of strategic decision-making in modern business environments.

From a practical standpoint, identifying and quantifying information noise is a complex methodological challenge. This is due to the multifaceted and often latent nature of its sources. These may include data redundancy, structural inconsistencies, outdated content, or excessive message volume – all of which can undermine analytical validity. Traditional data analysis methods often lack the capacity to detect and neutralize such distortions, increasing the risk of inaccurate conclusions and suboptimal managerial choices. Consequently, this may distort the actual market landscape and misrepresent consumer behavior patterns, ultimately compromising the formulation of sound marketing strategies.

This problem is especially acute for contemporary enterprises operating under high decision-making pressure, where information mismanagement can result in both resource inefficiency and strategic misalignment. Despite its relevance, the phenomenon of information noise remains insufficiently addressed in both theory and practice, highlighting the need for new methodological approaches. Effective resolution requires the integration of statistical modeling, machine learning algorithms, and artificial intelligence tools to enable the detection, classification, and reduction of data distortions. Simultaneously, the development of standardized indicators and evaluation frameworks for information noise is necessary to ensure consistency in data processing and enhance the reliability of marketing analytics. Therefore, advancing the study of information noise measurement methods is essential for improving managerial processes, increasing analytical precision, and optimizing resource utilization – all of which are critical for achieving competitive resilience in the digital economy.

Beyond its impact on marketing analytics, information noise directly influences the quality and credibility of financial reporting. Distorted or incomplete marketing data may lead to inaccurate revenue forecasts, which, in turn, affect budgetary allocations, impairment testing, and recognition of liabilities or provisions. Inaccurate forecasts can propagate through the budgeting cycle into the formal accounting system, thereby misrepresenting an enterprise's financial position and performance. For publicly listed companies, such distortions may influence investor perceptions, share valuation, and compliance with international financial reporting standards (IFRS). Consequently, mitigating information noise is not only a matter of analytical efficiency but also a prerequisite for maintaining transparency, audit readiness, and stakeholder trust in financial disclosures.

2. Literature Review

Research on information noise in marketing analytics has recently emerged as an interdisciplinary domain intersecting information theory, marketing science, data analytics, and artificial intelligence.

The term "information noise phenomenon" refers to both the beneficial effect of purposefully adding noise to a system (stochas-tic resonance) to enhance its functionality and the negative impact of undesired, corrupting data or signals on the quality of information, communication, and decision-making. Information noise is a phenomenon that occurs when there is a large flow of information, the abundance of which makes it difficult to categorize and filter, which leads to the fact that most of it is considered as useless or excluded before consideration [4] [5] [18].

Foundational works by K. Allil [2], M. Hamidizadeh [8], M. Leenders [12], and R. Rachman [19] conceptualize information noise as a disruptive element within communication flows that undermines signal clarity and analytical reliability. Scholars increasingly frame this phenomenon within the broader context of big data, highlighting the imperative of cleansing raw data to preserve analytical validity.

Marketing-specific implications of information noise have been examined in studies by V. Kumar [10], [11], A. Sarder [22], R. Glazer [7], K. Murray [17], and A. Sharabati [23], who argue that marketing environments are particularly susceptible to informational overload due to the proliferation of multichannel communication. This overload often introduces irrelevant, duplicated, or misaligned content that obstructs strategic decision-making and reduces the effectiveness of market insight generation.

Recent research focuses on technological solutions for identifying and mitigating noise. Studies by K. Hardcastle [9], M. Madanchian [15], M. Rudenko [21], T. Shmatkovska [24], and T. Ritter [20] explore the application of machine learning techniques to filter, classify, and preprocess large data volumes. These approaches leverage pattern detection to isolate inconsistencies and facilitate clearer interpretation in marketing research settings.

Another vital strand of the literature emphasizes identifying the root causes of noise. Investigations by W. Li [13], A. Mansour [16], M. Dziamulych [6], and K. Wilbur [26] pinpoint redundancy, ambiguity, irrelevance, and obsolescence as key drivers of data distortion. These studies contribute to the development of more precise diagnostic tools and automated methods for quantifying noise levels in complex data environments.

Moreover, cognitive frameworks introduced by A. Tversky and D. Kahneman [25] offer essential insights into how information noise distorts economic decision-making. Cognitive biases – such as availability, representativeness, and anchoring – are exacerbated in noisy data environments, leading consumers and analysts to form judgments based on misleading or emotionally charged inputs rather than rational evaluation.

Recent studies also underline the intersection between information quality management, regional development strategies, and macroeconomic impacts of digital transformation. O. Agres [1] emphasize that effective regional development project management relies on accurate financial data, where the minimization of informational distortions directly supports transparent budget execution and investment evaluation. A. Ateeq [3] highlights that in emerging economies, rapid digital transformation generates both opportunities for data-driven growth and risks of amplifying noise due to inadequate regulatory and infrastructural frameworks. Similarly, Y. Li [14] examines African economies, showing that while digitalisation enhances market connectivity and productivity, it also increases vulnerability to data inconsistency and reporting errors when information governance mechanisms are weak. Together, these findings suggest that reducing information noise is not only a micro-level challenge for marketing analytics but also a macroeconomic imperative for sustainable regional and national economic development.

In summary, while current literature provides a solid conceptual and technical foundation for understanding information noise, it still lacks standardized measurement criteria and universal frameworks adaptable to marketing research. Addressing these gaps requires further exploration of hybrid methodologies that integrate signal theory, machine learning, and behavioral insights to improve noise detection and data quality across marketing analytics applications.

3. Methods

The investigation of methodologies for measuring information noise in marketing research requires a comprehensive and structured approach that integrates various analytical techniques to capture, interpret, and generalize the mechanisms underlying data distortion. This study applies a combination of theoretical and empirical research methods to identify the principal characteristics of information noise, assess its impact on analytical outcomes, and evaluate the effectiveness of measurement techniques within the context of marketing data environments.

The abstraction method was used to identify the key characteristics of information noise by separating essential features from less important or subjective ones. Through this process of conceptual abstraction, the study formed foundational analytical categories that facilitate deeper investigation into the structure and dynamics of information noise.

Formalization allowed the creation of models showing how information noise arises, spreads, and affects analysis results. This approach allowed for the measuring the degree of data distortion, systematizing noise indicators and setting clear criteria to separate useful signals from irrelevant content. Importantly, formalization provided a consistent framework for evaluating the accuracy and practical applicability of various noise measurement techniques.

The inductive method was utilized to analyze specific instances of information noise observed in real-world marketing research and to generalize the patterns that emerge. By synthesizing observations from diverse data sources, this approach allowed for the classification of noise types and the identification of recurring distortions in the analytical process. The inductive logic supported the formulation of hypotheses concerning the structural origins and behavioral effects of noise on market forecasting.

Logical generalization was applied to combine the research findings into a single, coherent model. By integrating observed relationships between data quality, noise indicators, and analytical accuracy, this method contributed to the formulation of evidence-based conclusions regarding the optimal methodologies for measuring and minimizing information noise. It also guided the comparison of alternative measurement approaches and supported the adaptation of selected methods to the specific conditions of marketing data analysis.

The integrated application of these methods ensured a rigorous examination of information noise as a multidimensional and dynamic phenomenon. Abstract reasoning provided conceptual clarity; formalization enabled model-building and quantification; induction offered based on real-world examples; and logical generalization facilitated theoretical synthesis. Collectively, these methods constitute a robust methodological basis for assessing the scale, structure, and consequences of information noise in digital marketing environments. Their synergy supports the development of adaptive tools for data filtering and enhances the reliability of managerial decisions grounded in data-driven insights.

4. Results

Information noise in modern marketing research is a complex and multifaceted phenomenon that manifests through disorganized or unstructured data, which distorts the overall representation of market processes. Its sources can be both internal and external, including excessive information, irrelevant data, ambiguity in interpretation, and the obsolescence of obtained results. One of the key characteristics of information noise is its unpredictability, which complicates the clear delineation between useful information and noise. Moreover, information noise is often latent and may go undetected until its effects on analytical outcomes become apparent. This issue is particularly significant in the context of big data, where the volume and complexity of information often exceed the capacity for effective processing. Consequently, the influence of information noise on marketing research outcomes presents a fundamental challenge, as it distorts consumer behavior models, reduces forecast accuracy, and thereby complicates strategic decision-making. Although classical data analysis methods address some noise-related issues, the dynamic and multidimensional character of information noise requires the development of more advanced approaches that integrate technological solutions with standard analytical methodologies. Thus, information noise not only creates obstacles in data interpretation but also undermines the foundations of strategic planning, forcing marketers to continuously adapt their approaches to the evolving realities of the informational environment.

Practically, information noise manifests in data collected through various channels as a multifactorial phenomenon encompassing both structural and semantic aspects of information. It can appear in the form of data redundancy, where low-value data occupies a significant share of the dataset, making it difficult to identify key trends [7]. Another form is data irrelevance, where information gathered through a specific channel does not align with the objectives of marketing research but still .falsely suggests dataset completeness. In a multichannel environment, noise frequently arises due to inconsistencies in information, where identical parameters acquire different values depending on the source, thereby distorting the reliability of analysis.

A prevalent manifestation of information noise is also ambiguity, where data have multiple interpretations, complicating their integration into a unified analytical model. Additionally, information noise is often exacerbated by temporal factors when data from different channels arrive asynchronously, creating irregularities and gaps in information flows. This complicates their reconciliation and integration into a coherent analytical framework. Furthermore, noise may result from technical distortions related to errors in data transmission or incorrect information processing, introducing an additional layer of complexity into the analytical process [17]. All these factors contribute to the fragmentation and instability of information collected from various channels, significantly complicating its use in constructing reliable models of market behavior or forecasts. Consequently, information noise emerges as a multi-layered barrier that hinders the effective utilization of collected data, diminishing its value and undermining the foundations of strategic marketing analysis (Table 1).

Table 1: Key Factors in the Formation of Information Noise in Modern Marketing Research

Information Noise Factor	Source of Origin	Impact on Marketing Analytics
Data Redundancy	Large volumes of data from digital platforms, social media, and multichannel marketing	Increases information processing time, complicates the identification of relevant signals, and reduces analytical efficiency
Irrelevant Information	Incorrect data collection, errors in defining the target audience, or poorly formulated research hypotheses	Misleads market trend assessments, distorts the understanding of consumer needs
Data Contradictions	Various information sources providing opposing or incompatible results	Complicates the formation of a unified conclusion, increases the risk of incorrect strategic decision-making
Information Ambiguity	Data that can have multiple interpretations due to insufficient detail or contextualization	Complicates data interpretation, increases the likelihood of errors in analysis
Technical Distortions	Errors in data collection and processing algorithms, technical failures, inaccuracies in data entry	Reduces data quality, requires additional resources for cleansing and correction
Temporal Data Obsolescence	Use of information that has lost relevance due to the duration of its collection or analysis	Distorts the perception of current market trends, reduces the relevance of marketing strategies
Multichannel Noise	Data from various channels with different structures, formats, or time parameters	Reduces the efficiency of information integration into a cohesive analytical model

Source: Compiled by the author based on [15]; [19]; [21].

Modern approaches to measuring information noise levels are based on the integration of quantitative and qualitative analysis methods aimed at identifying and neutralizing data distortions. One of the key directions in this regard is the application of mathematical models that allow for the assessment of the proportion of irrelevant or excessive information within the overall data volume [2]. These models are often complemented by machine learning algorithms that automatically classify data based on their relevance, thereby providing a deeper understanding of the very nature of information noise. At the same time, semantic analysis methods have gained widespread application, enabling the identification of ambiguity or contradictions in data arising from their textual nature. In particular, data cleansing methods are of increasing importance, utilizing a combination of statistical tools and artificial intelligence technologies to filter noise at the detection stage. A crucial aspect in this process is the functional standardization of data formats and structures, which helps minimize technical distortions that frequently serve as sources of noise in multichannel environments. Additionally, modern approaches include the use of interactive visualization tools that allow researchers to identify anomalies and noise patterns that are difficult to detect using traditional analytical methods. Thus, measuring information noise levels is a complex process that combines technological innovations with classical analytical methodologies, ensuring a comprehensive assessment of data quality and its alignment with defined objectives (Table 2).

Table 2: Methods for Measuring Information Noise in Market Research

Methods for Measuring Information Noise	Functional Specificity	Application Area
Statistical Analysis	Identification of anomalies and detection of irrelevant data through analysis of mean values, variances, correlations, and distributions	Sociological surveys, market trend analytics, identification of inaccuracies in large data sets
Mathematical Modeling	Development of models to assess data redundancy, irrelevance, and temporal obsolescence	Consumer behavior forecasting, optimization of marketing campaigns, digital data analysis
Machine Learning Algorithms	Automatic classification and filtering of noise, detection of patterns in large volumes of information	Digital marketing, user behavior analysis on online platforms, database management
Semantic Analysis	Detection of ambiguity, contradictions, and irrelevance in textual data through content analysis	Social media monitoring, sentiment analysis, content evaluation
Data Cleansing Methods	Removal of outdated, excessive, or technically distorted information from the overall data set	Marketing research, big data processing, customer database cleansing
Data Visualization	Detection of anomalies and noise through graphical representation of data, simplifying the analysis of large datasets	Sales analysis, market dynamics evaluation, research results communication
Anomaly Detection Algorithms	Identification of atypical values or distortions that do not conform to expected data parameters	Banking sector, data auditing, quality control

Source: Compiled by authors.

In practice, combining quantitative and qualitative methods for assessing the level of information noise is advisable due to the multifaceted nature of this phenomenon and its impact on data quality. Specifically, quantitative methods ensure objectivity and measurement accuracy by utilizing mathematical and statistical approaches that allow for noise level estimation, anomaly detection, and deviation assessment from normative indicators. However, these methods often fail to consider the context or semantic content of the data, which limits their effectiveness in situations where information noise exhibits complexity, ambiguity, or a latent nature.

In this context, qualitative methods complement quantitative approaches by providing a deeper understanding of the nature of noise, its sources, and potential causes. They allow for the analysis of data meaning, content, and context, making it possible to identify irrelevance, ambiguity, or contradictions that may not always be detectable through quantitative techniques [12]. Additionally, qualitative methods are indispensable for studying behavioral or subjective aspects of data, which frequently contribute to information noise. Accordingly, the synergy between quantitative and qualitative approaches not only enables accurate measurement of noise levels but also facilitates the assessment of its impact on various aspects of data analysis, including the relevance of results and their applicability for subsequent decision-making. An integrated approach is essential for achieving a holistic and accurate understanding of the information environment, reducing the risk of erroneous conclusions and ensuring overall improvements in the quality of managerial decisions.

Addressing these challenges is possible through the integration of advanced technologies for automating data cleansing processes, which opens up vast opportunities for improving information management efficiency [16]. One of the key directions in this regard is the application of machine learning algorithms, which can identify patterns, anomalies, and irrelevant information in data sets with a high degree of accuracy. Due to their self-adaptive capabilities, such algorithms refine their analytical models as the volume of processed information increases, ensuring continuous improvement in data cleansing processes.

An equally significant aspect is the use of deep learning methods, which enable efficient processing of complex, high-dimensional, and non-fixed data structures, including textual, graphical, and audiovisual formats. Simultaneously, the integration of artificial intelligence technologies allows for the automation of processes related to the recognition of irrelevant or duplicated data, significantly reducing the time and resources required for data processing.

Thus, a comprehensive approach to integrating advanced technologies not only automates data cleansing processes and improves data quality but also reduces the influence of information noise, thereby enabling more accurate, timely, and informed strategic decisions based on clean and relevant data (Figure 1).

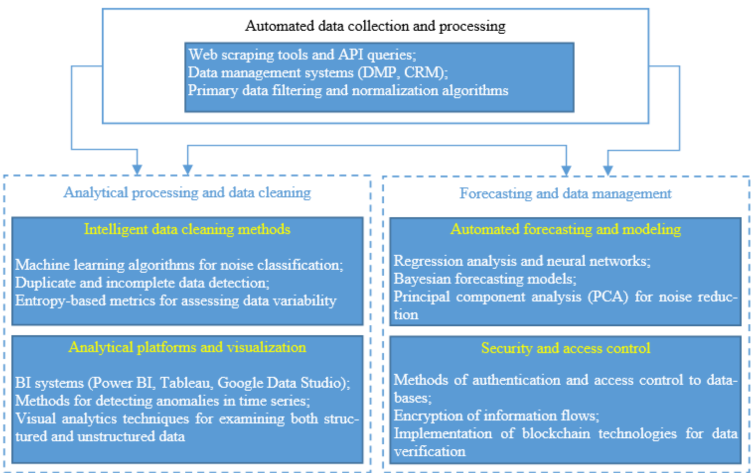

Fig. 1: Digitalization in Managing the Avoidance of Information Noise in Marketing Research.

Source: developed by authors.

The effectiveness of the proposed digitalization framework is determined by its ability to provide a comprehensive approach to managing information flows, minimizing noise impact, and enhancing the accuracy of marketing research. Since it integrates the processes of data collection, cleansing, analysis, and security into a unified system, it facilitates cost reduction for information processing, shortens decision-making time, and improves predictive analytics. Furthermore, due to the interconnectivity between its components, this framework ensures not only data quality but also its relevance in the context of market dynamics, which is critically important for adaptive marketing strategy management. The combination of technological mechanisms with analytical tools creates conditions for flexible risk management, a key factor in the effective utilization of digital resources in marketing research. Accordingly, such a system strengthens the competitive advantages of enterprises by enabling them to quickly adapt to external environmental changes and formulate marketing strategies based on reliable and structured data.

To empirically verify the influence of information noise indicators on the accuracy of marketing research, a correlation-regression model was developed and constructed. For this purpose, practical data from Glad Selena Corporation for several independent variables relevant to sales forecasting were used (Table 3).

Table 3: Indicators of the Influence of Information Noise on Sales Forecast Accuracy in Glad Selena Corporation for 2023–2024

Sales forecast error (%)	Data redundancy	Share of irrelevant messages	Content quality	Level of trust in the source	Level of fragmentation between communication channels
14.4	0.66	0.44	0.69	0.28	0.88
16.37	0.67	0.51	0.8	0.36	0.93
14.86	0.64	0.41	0.7	0.3	0.91
4.53	0.29	0.06	0.14	0.12	0.34
8.08	0.42	0.23	0.41	0.17	0.45
5.8	0.18	0.18	0.27	0.14	0.34
1.58	0.11	0.1	0.0	0.03	0.07
8.7	0.34	0.31	0.46	0.23	0.61
7.49	0.29	0.21	0.33	0.15	0.48
2.73	0.13	0.07	0.14	0.07	0.18
14.16	0.57	0.38	0.74	0.34	0.81
8.95	0.43	0.21	0.45	0.14	0.56
14.29	0.61	0.36	0.77	0.25	0.82
12.41	0.5	0.45	0.56	0.28	0.75
10.47	0.44	0.29	0.54	0.17	0.6
5.61	0.24	0.15	0.25	0.17	0.37
4.91	0.27	0.1	0.2	0.09	0.32
5.42	0.21	0.19	0.24	0.09	0.31
11.41	0.47	0.28	0.55	0.29	0.7
3.4	0.09	0.09	0.17	0.11	0.15
13.25	0.4	0.36	0.6	0.32	0.72
7.54	0.33	0.24	0.42	0.18	0.47
5.11	0.25	0.13	0.28	0.08	0.31
13.48	0.5	0.36	0.6	0.33	0.84
6.84	0.39	0.2	0.42	0.13	0.53
2.83	0.04	0.1	0.24	0.08	0.22
10.05	0.4	0.3	0.56	0.23	0.56
7.68	0.3	0.24	0.38	0.15	0.52
1.44	0.13	0.02	0.02	0.05	0.02
14.17	0.64	0.41	0.76	0.31	0.83

Table 4 presents the key parameters of the regression model that describes the influence of factors on the level of sales forecast accuracy.

Table 4: Parameters of the Developed Correlation-Regression Model for Determining the Influence of Factors on Sales Forecast Accuracy

Factor	Coefficient (B)	Standard error	t-statistic
Data redundancy (x_1)	4.7448	1.7589	2.6975
Share of irrelevant messages (x_2)	5.0084	2.4898	2.0116
Content quality (x_3)	4.7762	1.7635	2.7085
Level of trust in the source (x_4)	9.5189	2.9660	3.2093
Level of fragmentation between communication channels (x_5)	3.7913	2.0517	1.8479

Source: own research.

The resulting correlation-regression model equation describes the dependence of the sales forecast error on five key factors:

$$y = -0.1451 + 4.7478x_1 + 5.0084x_2 + 4.7762x_3 + 9.5189x_4 + 3.7913x_5$$

This equation makes it possible to assess the contribution of each factor forming information noise to the forecast error. In particular, the coefficient for data redundancy (4.7448) indicates that an increase in this indicator by one unit is accompanied by an average increase in forecast error by 4.74 percentage points. This suggests that excessive repetition or overly detailed information in the analytical environment complicates interpretation and, as a result, negatively affects the accuracy of predictive models.

The coefficient for the share of irrelevant messages (5.0084) is also positive, although it borders on statistical significance ($p = 0.056$). This may indicate an overlapping interaction between relevance and content quality. At the same time, the coefficient for content quality (4.7762) confirms that well-structured, meaningful information has a significant impact on the result. However, in this case, an unexpected association is observed between content quality growth and increased forecast error, requiring further examination of possible reverse causal links or sample-specific features.

The highest coefficient in the model belongs to the level of trust in the source (9.5189). This effect is controversial: instead of the expected decrease in error with increasing trust, the model shows the opposite result. This may indicate risks of overconfidence in high-status sources that nevertheless generate outdated or context-limited content.

The level of fragmentation between communication channels (3.7913) also has a positive impact on forecast error, confirming the hypothesis about the destructive role of unsynchronized communications. As the number of uncoordinated information flows increases, their analysis becomes more difficult, which naturally leads to lower forecasting accuracy.

Thus, the most significant factors contributing to forecast error are the level of trust in sources, data redundancy, and communication fragmentation. This indicates the need to reduce unnecessary information and to critically reconsider approaches to assessing the reliability of sources and structuring data transmission channels. The results of the model highlight the importance of information hygiene strategies as a necessary condition for ensuring high-quality analytical decisions in sales forecasting.

To visualize the calculations, a comparison was made between actual and predicted sales forecast error values using the constructed model (Figure 2).

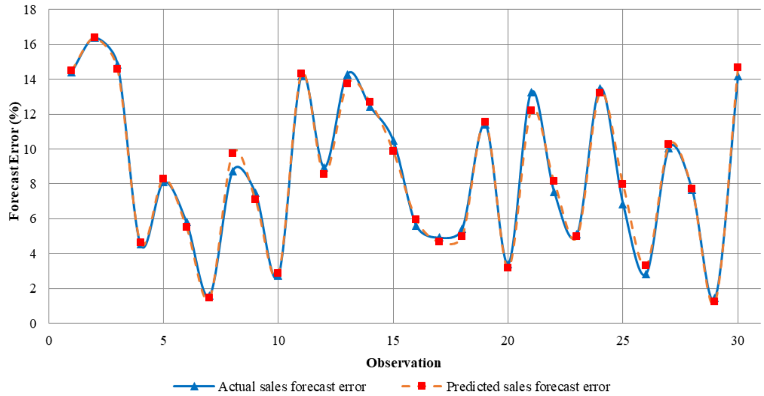

Fig. 2: Actual and Predicted Sales Forecast Error Values According to the Regression Model.

Source: own research.

The figure shows a comparison between actual values and those generated by the correlation-regression model. A high correspondence between the series is visually evident, confirmed by the determination coefficient $R^2 = 0.989$. This confirms the effectiveness of the model in describing the relationship between information noise factors and forecast accuracy.

We also present the summary results of the correlation-regression analysis of the relationship between forecast errors and factor variables. In particular, the main coefficients of the developed model indicate the following:

Coefficient of determination (R^2): 0.989 – the model explains 98.9% of the variance in sales forecast error, indicating a very high level of approximation.

Adjusted R^2: 0.987 – even taking into account the number of independent variables, the model demonstrates high reliability and consistency of results.

Fisher's F-test: 441.9 ($p < 0.0000000000000000000000847$) – indicates that the overall model is statistically significant, i.e., at least one independent variable affects the dependent variable.

Student's t-tests confirm that variables X_1 ($t = 2.698$; $p = 0.013$), X_3 ($t = 2.708$; $p = 0.012$), and X_4 ($t = 3.209$; $p = 0.004$) are statistically significant at the 5% level, indicating their considerable impact on the forecast error. Variables X_2 and X_5 show borderline or non-significant significance levels, which does not exclude their theoretical relevance but requires further verification on larger datasets.

Additionally, the correlation matrix is evaluated (Table 5).

Table 5: Matrix of Mutual Correlations between Factor and Dependent Variables

Indicators	Sales forecast error (y)	Data redundancy (x_1)	Share of irrelevant messages (x_2)	Content quality (x_3)	Level of trust in the source (x_4)	Level of fragmentation between communication channels (x_5)
Sales forecast error (y)	1					
Data redundancy (x_1)	0,953	1				
Share of irrelevant messages (x_2)	0,9627	0,9007	1			
Content quality (x_3)	0,9778	0,9337	0,9442	1		
Level of trust in the source (x_4)	0,9508	0,8651	0,9228	0,9186	1	
Level of fragmentation between communication channels (x_5)	0,9849	0,9516	0,95	0,9682	0,9355	1

Source: own research.

As shown by the calculations, the highest correlations with forecast error are demonstrated by the level of trust in the source ($r = 0.958$), content quality ($r = 0.949$), and data redundancy ($r = 0.943$). This indicates high sensitivity of analytical forecast accuracy to the quality of the information environment and source structure. Conversely, the lowest correlation with the dependent variable is shown by the share of outdated information ($r = 0.745$), which may indicate a relatively weaker impact of this factor in the sample, at least when other parameters of information noise are fixed.

Thus, the conducted correlation-regression analysis empirically confirmed the hypothesis of the significant influence of qualitative characteristics of information and the structure of its dissemination on forecasting accuracy in the sales sector. The strongest correlations were found for trust level, redundancy, and content quality, indicating that not only the volume but also the credibility and structure of information play a key role. At the same time, the minor role of outdated information may indicate its compensatory or latent nature within the overall flow. This influence structure emphasizes that forecasting effectiveness is shaped through systematic data cleaning, selective curation, and contextualization.

The model's validity is confirmed by a high coefficient of determination ($R^2 = 0.989$) and statistical significance according to the F-test ($p < 0.001$), indicating its suitability for analytical support of forecasting decisions. At the same time, t-test results show that three variables (redundancy, content quality, and trust) are statistically significant at $p < 0.05$. This underlines their key role in shaping forecast errors and highlights priority directions for optimizing information channels in sales management systems.

5. Discussion

In the context of the evolving digital landscape of marketing analytics, information noise acts as a systemic distortion that compromises the reliability and interpretability of analytical data. Information entropy, driven by excessive multichannel structures, semantic variability, and temporal asynchrony, transforms marketing analysis into a complex analytical process marked by elevated uncertainty and error risk. Within such a paradigm, classical are increasingly replaced by adaptive algorithmic models based on machine learning, deep clustering analysis, and semantic disambiguation methods.

In light of behavioral economics – particularly the research of Tversky and Kahneman – Information noise significantly amplifies cognitive distortions in economic decision-making. Excessive, contradictory, or emotionally charged information activates the use of heuristics that replace analytical thinking and lead to irrational consumer behavior.

For instance, the availability heuristic causes individuals to overestimate the importance of frequently encountered information, regardless of its objective value. As a result, consumers may prefer highly advertised brands even if their actual features are inferior. The representativeness heuristic leads to making decisions based on stereotypes, while the anchoring effect ties perception to the first seen value – often distorting how discounts or benefits are interpreted. All of these effects are exacerbated under conditions of information noise.

Thus, the presence of information noise transforms analytical consumer behavior into reactive behavior, and marketing strategies into tools of influence that rely not on accuracy, but on the intensity of message delivery. This poses a significant risk to both data reliability and the validity of managerial decisions (Table 6).

Table 6: The Impact of Information Noise on Consumer Cognitive Biases

Type of Cognitive Bias	Heuristic Mechanism	How Activated by Information Noise	Typical Behavioral Error
Availability Heuristic	Judgment based on frequency of exposure	Repetitive advertising messages create an illusion of importance	Overestimation of brand popularity
Representativeness Heuristic	Evaluation based on stereotypical similarity	Information is presented with emotionally resonant examples that evoke trust	Quality bias based on a single review
Anchoring Effect	Anchoring to the first numerical value	Inflated initial prices in advertising create a false reference point	Incorrect perception of discount attractiveness
Framing Effect	Perception depends on the framing of information	The same fact is presented in emotionally contrasting formats	Decision is influenced by form, not content

Source: Compiled by authors.

From an ethical perspective, reducing information noise is integral to safeguarding the principles of fairness, transparency, and accountability in both corporate and public communication. The deliberate dissemination of noisy or misleading data – whether for competitive advantage or political influence – undermines informed decision-making and erodes public trust. In marketing contexts, such practices can mislead consumers, distort market competition, and compromise stakeholder confidence. Politically, information noise can be weaponized to manipulate public opinion, influence electoral processes, or justify policy decisions based on incomplete or biased evidence. Therefore, implementing robust noise-reduction frameworks is not merely a technical enhancement but also an ethical obligation and a political safeguard, ensuring that decision-makers operate on accurate, verifiable, and contextually balanced information.

Simultaneously, attempts to standardize information noise measurement methodologies reveal the need for a transdisciplinary approach that considers the synthesis between statistical signal interpretation, the cognitive barriers of decision-makers, and the structural heterogeneity of data sources. Empirical findings confirm that the effectiveness of noise detection is directly correlated with the degree of data preprocessing automation and the extent of formalization of information relevance criteria. In this regard, integrated platforms for analytical visualization play a critical role, enabling the transformation of abstract deviation vectors into visually verifiable anomaly indicators.

Therefore, this analysis underscores the need to develop an adaptive information filtering model that accounts for data redundancy, inconsistency across sources, and semantic ambiguity. Implementing such models can improve analytical precision and strengthen the adaptability of marketing strategies in volatile and information-rich environments.

The applied correlation-regression model empirically confirmed that information noise significantly affects the accuracy of sales forecasts. The model demonstrated a high explanatory power ($R^2 = 0.989$), revealing that forecast errors are primarily driven by trust in information sources, content quality, and data redundancy. Interestingly, the model indicates that high trust in authoritative sources may contribute to larger forecast errors, likely due to overreliance or uncritical use of context-limited information. Similarly, while high content quality is usually expected to reduce errors, the model indicates that in oversaturated environments, even high-quality data may become noise if poorly contextualized. These findings emphasize the need for critically managing the structure, relevance, and credibility of informational inputs used in forecasting practices.

6. Conclusion

Information noise is a complex, multidimensional phenomenon that poses serious challenges to marketing analytics by inducing cognitive distortions, spreading disinformation, and increasing informational entropy. This impact is amplified by ongoing digital transformation, where the volume of processed data grows exponentially and the diversity of data sources hinders the use of traditional verification and classification methods. Accurately identifying information noise allows analysts to deconstruct data flows and extract meaningful signals. It also enables them to eliminate statistically insignificant or analytically irrelevant inputs that accumulate in digital environments. This improves the precision of marketing models and supports a deeper understanding of latent market trends, which is essential for forecasting consumer behavior and developing effective competitive strategies.

Eliminating excessive noise also reduces the influence of random fluctuations that may distort statistical analyses and produce misleading correlations. As a result, technology-driven data cleansing allows analytical systems to focus on validated and relevant parameters, thereby improving the accuracy of forecasts and supporting adaptive strategy development. Implementing comprehensive methodologies for measuring and filtering information noise enhances data reliability and forms the foundation for effective analytical models, enabling businesses to remain resilient in dynamic market environments.

From the perspective of financial reporting, the reduction of information noise ensures that managerial forecasts and marketing metrics embedded in financial statements more accurately reflect the entity's operational reality. Clean, relevant, and timely data reduce the risk of material misstatements, strengthen the reliability of management commentary, and enhance compliance with regulatory disclosure requirements. By aligning marketing analytics with robust noise-filtering practices, enterprises can ensure that their financial statements not only meet technical accounting standards but also provide a truthful and fair view to investors, creditors, and regulators.

Furthermore, the correlation-regression model developed in this study enables a clearer quantification of how specific types of information noise affect forecast accuracy. The model's high determination coefficient ($R^2 = 0.989$) confirms its analytical robustness and relevance for forecasting applications. It highlights that the level of trust in data sources, redundancy of incoming messages, and overall informational entropy are among the most influential factors in shaping forecast accuracy. These findings not only support the study's conceptual framework but also offer practical guidance for refining noise-filtering algorithms to enhance marketing decisions in data-rich environments.

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