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Intelligent Data Management for Small Business Enhancement

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Abstract.
In the industry 4.0 era, there exists a pressing need for intelligent data management solutions to enhance the operations of small businesses. This study introduces a pioneering methodology that harnesses the power of AI-driven analysis of internal voice communications, an often-overlooked source of valuable insights within the small business environment. The research centers on an advanced platform that utilizes the Regularized Bayesian Approach, meticulously tailored for the processing of unstructured and semi-structured data, with a specific focus on internal voice messages. This methodology enables the generation of in-depth insights into employees' emotional, psychological, and motivational states. Furthermore, the integration of data with a psychometric system enables the production of comprehensive personality evaluations, providing digital portraits for every employee. These portraits offer valuable insights into employee well-being and motivations, particularly beneficial for small businesses with limited HR resources. The potential benefits for small businesses are multifaceted and research-driven, including enhanced employee safety, improved efficiency, advanced risk management, and streamlined HR processes. Additionally, this research underscores the growing relevance and potential of this approach in the Emotion AI market. Through the analysis of voice messages, entities, intent, and relationships between utterances can be discerned, offering a comprehensive view of employee sentiment, loyalty, and satisfaction. This study serves as the foundation for fostering a positive work environment, enhancing productivity, and providing a roadmap for mental health improvement and reduced attrition in small businesses. It contributes to the evolving field of intelligent data management and its applications in enhancing small business operations.

Keywords: voice recognition, small business enhancement, emotion AI, artificial intelligence, Bayesian approach

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1. Introduction

Small businesses play a vital role in the global economy, yet they often face unique challenges in managing their operations and fostering a positive work environment. In the digital age, the effective utilization of unstructured voice data has emerged as a transformative opportunity for small enterprises. This research aims to outline the objectives and significance of the study, shedding light on why this topic is of paramount importance and what it contributes to the existing body of knowledge in the field of small business management.

At its core, this research addresses the pressing challenges faced by small businesses, such as resource constraints, operational efficiency, employee well-being, and competitiveness. By harnessing the power of unstructured voice data analysis and integration, the study seeks to provide innovative solutions that can redefine the way small businesses operate and make informed decisions.

The scope of the research encompasses the analysis of internal voice interactions within companies, with a focus on Speech Emotion Recognition (SER) and the Regularized Bayesian Approach (RBA) for emotion detection and well-being assessment. This approach allows for the extraction of valuable insights from unstructured voice data, offering profound insights into employee sentiments, motivations, and overall well-being.

The importance of this research lies in its potential to:

Enhance Employee Well-being: By proactively addressing mental health indicators from voice interactions, small business owners can reduce turnover and promote employee well-being.

Improve Operational Efficiency: Data-driven strategies enable personalized communications, expediting decision-making processes and fostering interactions.

Advance Risk Management: Real-time monitoring of voice interactions enables the early identification of potential risks, ensuring a safe and secure workplace.

Streamline Human Resources: Automated analysis reduces the workload for small business HR professionals, providing actionable recommendations and insights.

The methodological approach involves a comprehensive examination of unstructured voice data through advanced analysis techniques, including SER and RBA, with the aim of uncovering hidden patterns, sentiments, and motivations within these data. This contributes to the development of innovative decision support systems tailored for small businesses.

As the research progresses, this paper will provide insights into the methodologies, challenges, and achievements that shape the research journey. It will establish the research problem, supported by a set of questions, and highlight the methodological approach used to examine this problem. Furthermore, it will outline the potential outcomes the study can reveal, shedding light on the transformative potential of unstructured voice data analysis for small businesses.

In summary, this introduction establishes the context and significance of the research, emphasizing its potential contributions to the field of small business management. It outlines the scope and objectives of the study, setting the stage for a comprehensive exploration of the transformative power of unstructured voice data analysis and integration for small businesses.

The research team looks forward to presenting the research findings and engaging in discussions with fellow scholars and experts at THE 1ST INTERNATIONAL CONFERENCE ON CREATIVE DESIGN BUSINESS AND SOCIETY, collectively advancing the understanding of how to harness the power of data for the betterment of small businesses and society as a whole.

2. Literature Review

The quest for intelligent measurement and data analytics has been a recurring theme in the field of science and technology. Dr. Leonard Finkelstein and Dr. Daniel Hofmann laid the foundation for intelligent measurement, emphasizing its importance in providing objective information [1]. Dr. Hofmann and Dr. Karaya furthered this concept by introducing intelligent measurements as a means to obtain precise data [2]. The theoretical underpinning of accuracy in measurement systems was explored by Dr. Vladimir Rosenberg, while Dr. Vladimir Knorring contributed to the understanding of measurement techniques [3]. Dr. Joel Michell critically examined the history of measurement in psychology [4].

In the context of intelligent measurements, Dr. Svetlana Prokopchina developed methods and tools based on Bayesian approaches to enhance measurement processes in complex tasks [5]. Dr. Prokopchina, Dr. Dmitry Nedosekin, and Dr. Evgeny Chernyavsky explored information technologies for intellectualizing measurement processes [6]. Dr. Stanley Stevens and Dr. Louis Thurstone delved into scaling techniques, offering valuable insights [7,8]. Dr. Friedrich Von Hayek emphasized the importance of knowledge in measurement processes [9]. Dr. Louis Guttman introduced scaling for qualitative data [10], while Dr. Georg Rasch and Dr. David Andrich presented probabilistic models for intelligence and attainment tests [11,12].

Dr. Andre Maul, Dr. Laura Mari, and Dr. Mark Wilson discussed property evaluation types and structural models for direct measurement [13]. Dr. Aldo Giordani and Dr. Laura Mari discussed property evaluation types and structural models for direct measurement

[14]. Dr. Leonard Finkelstein addressed the definition of measurement, distinguishing between widely, strongly, and weakly defined measurements [15]. Dr. Mark Wilson constructed measures using item response modeling approaches [16], while Dr. Paul Holland focused on sampling theory foundations for item response theory models [17].

The International Vocabulary of Metrology (VIM) introduced by JCGM outlined fundamental concepts for measurement [18]. Dr. Giovanni Rossi proposed a probabilistic theory of measurement and explored measurability [19,20]. Dr. Laura Mari and Dr. Vincenzo Lazarotti discussed property evaluation types and structural models for direct measurement [13]. Dr. Aldo Giordani and Dr. Laura Mari discussed property evaluation types and structural models for direct measurement [14]. Dr. Leonard Finkelstein addressed the definition of measurement, distinguishing between widely, strongly, and weakly defined measurements [15]. Dr. Mark Wilson constructed measures using item response modeling approaches [16], while Dr. Paul Holland focused on sampling theory foundations for item response theory models [17].

The contributions of Dr. Veronika Zaslavskaya and her colleagues introduced modern perspectives on data analytics, including the utilization of unstructured and semi-structured data in business intelligence systems [21]. Their work emphasized the significance of big data in the context of business analytics, data analysis methodologies, and the application of intelligent data analysis techniques in economic systems.

In summary, the literature provides a comprehensive understanding of intelligent measurement, scaling techniques, and the role of Bayesian approaches in measurement processes. Additionally, recent research highlights the importance of data analytics, particularly the utilization of unstructured data in business intelligence systems, and the application of intelligent data analysis techniques in modern organizational management.

2.1. Hypotheses

Hypothesis 1: The implementation of intelligent data management solutions can enhance efficiency and support more informed decision-making in small businesses.

Hypothesis 2: The lack of accessible and user-friendly data management solutions restricts small businesses' ability to leverage data for strategic decision-making.

Hypothesis 3: The utilization of intelligent solutions for analyzing unstructured data can assist small businesses in effectively managing information complexity and accounting for both internal and external factors.

3. Methodology Research

The research commenced by elucidating the chosen research methodology and the rationale for its selection. It further detailed the methodology that was deemed most suitable for investigating workplace well-being enhancement, considering various influencing factors. By combining numerical and linguistic information and incorporating the degree of certainty, Scale with Dynamic Constraints (SDC) offered a holistic view of measurement results, capturing variability and uncertainty in measurement data and facilitating decision-making.

The data collection process for this research involved gathering information from various sources to comprehensively assess workplace well-being. The primary source of data was voice recordings of internal discussions conducted in communal channels within the organization. These voice interactions served as a rich reservoir of information for understanding employee sentiments, emotions, and well-being indicators.

Additionally, the research incorporated results from psychometric tests designed for a comprehensive assessment of individual personalities. These tests provided valuable insights into the psychological aspects of employees, contributing to a more holistic understanding of their well-being. Furthermore, managerial accounting data spanning over 11 years from the fitness club's management system were leveraged to gain insights into long-term trends and their potential impact on employee well-being. This historical data provided valuable context for assessing the evolution of workplace dynamics. The research also made use of data from the Customer Relationship Management (CRM) system of the fitness club where the study was conducted. This data included customer interactions, feedback, and engagement metrics, which could offer insights into the club's customer-centric practices and their effects on employee well-being.

To evaluate the influence of external factors, supplementary datasets from publicly available statistics were integrated into the analysis. These datasets encompassed a wide array of external environmental factors, including economic indicators, regional demographics, and social trends. They were selected based on their potential relevance to employee well-being and their capacity to provide a comprehensive view of external forces. Throughout the data collection process, stringent measures were implemented to ensure data privacy and confidentiality. All datasets, including the supplementary ones, underwent a rigorous de-identification process to safeguard individual and organizational identities.

The integration of these diverse datasets aimed to offer a holistic assessment of workplace well-being. By combining internal voice interactions, psychometric assessments, managerial accounting data, CRM system information, and external environmental factors, the research sought to uncover complex relationships and dependencies that contribute to a nuanced understanding of employee well-being. These data-driven insights allowed for a more comprehensive evaluation of workplace well-being in the context of modern organizations.Data Processing for SER, Natural Language Processing (NLP), and RBA.

In the research aimed at enhancing workplace well-being, data processing played a pivotal role in preparing the inputs for SER, NLP, and the RBA. These advanced techniques required careful data preparation to extract valuable insights from voice interactions and textual data. For SER and NLP, voice recordings were collected from internal voice interactions, textual data from various sources, including CRM systems and fitness club management data. Data preprocessing for SER involved cleaning audio recordings, removing noise, and segmenting voice interactions. In the case of NLP, textual data underwent preprocessing steps such as text cleaning, tokenization, and lemmatization to standardize and enhance the quality of the text.

Feature extraction was a critical step for both SER and NLP. In SER, acoustic features were extracted from voice recordings, including pitch, intensity, and spectral features. These features were essential for training machine learning models to recognize emotional states in the voice. For NLP, techniques like TF-IDF (Term Frequency-Inverse Document Frequency) and word embeddings (e.g., Word2Vec or GloVe) were employed to convert text data into numerical vectors, preserving semantic relationships and context.

RBA required a distinct data processing approach to construct the Dynamic Compact Solution Space (DCSS) and Models with Dynamic Constraints (MDC). Data integration was crucial, as RBA integrated data from SER and NLP with other sources, including psychometric test results and fitness club management data. To construct DCSS within RBA, data processing techniques were adapted to accommodate uncertainty and adaptability. The DCSS was designed to be dynamic, adjusting its boundaries and properties based on changing information and measurement requirements. Data integration and transformation ensured that information from various sources could be integrated seamlessly into the DCSS.

MDC within RBA were central to adapting to changing information. Data processing for MDC involved autonomous adaptation of structures and parameters based on incoming data. Knowledge integration from various sources was facilitated through data preprocessing and transformation, enriching the measurement model's basis for future analysis.

Data analysis is explored, focusing on the handling of loosely organized and unattributed data, specifically within the internal voice exchanges of the corporate group voice communication channels. According to statistical data, an average of 100 MB of audio data is generated by an individual user in one calendar month. Consequently, for an organization with 10,000 staff members, the annual volume of data resulting solely from voice interactions accumulates to 12 TB of loosely structured data. The organized data section, archived in the database during message recording, comprises details regarding the sender, recipient (or the designated channel for the message), date and time of transmission, message duration in milliseconds, and its format (e.g., audio recordings of discussions).

Data analysis is delved into, with a focus on processing weakly structured and unstructured data, specifically internal voice interactions within the company's group voice communication channels. According to statistics, the average volume of audio data generated by a single user in one calendar month is approximately 100 MB. Therefore, for a company with 10,000 employees, the volume of data derived solely from voice interactions amounts to 12 TB of weakly structured data per year.

Having knowledge of data distribution patterns specific to the project, a system has been developed that allows for efficient data analysis adaptation for companies of varying sizes. For instance, for large enterprises with tens of thousands of employees, the volume of data may reach tens of terabytes per year, as indicated in the statistics. However, for small and medium-sized businesses, the data volume may be significantly lower, and this can be tailored to accommodate each company's specific requirements.

As for the structured data, which is stored in the database at the time of message recording, it includes information about the sender, recipient (or the channel to which the message was sent), date and time of sending, message length in milliseconds, and its type (e.g., audio file of conversations). However, the actual content within the message, available for subsequent analysis and interpretation, significantly surpasses the initial structured part. Various approaches and methods are employed for analyzing individual voice messages:

Semantic meaning of the message: Speech recognition (speech-to-text) is employed to extract the semantic meaning of the message, resulting in unstructured text data.

Emotional tone of the message: SER is used to analyze the emotional tone of the message, providing a list of time stamps from the start and presumed emotions.

Frequency of specific word mentions: Comparison with a predefined dictionary (e.g., company name) is used to determine the frequency of specific word mentions, resulting in a list of words and their counts.

Speech characteristics (volume, speech rate, pauses): Analysis based on spectral-temporal features, cepstral features, amplitude-frequency features, or nonlinear dynamics features is conducted to assess speech characteristics. This results in a list of features and their corresponding indices.

Presence of background noise: Analysis based on spectral-temporal features, cepstral features, amplitude-frequency features, or nonlinear dynamics features is utilized to detect the presence of background noise, yielding a list of time stamps from the start and noise indices.

The methodology, results, and application of voice message analysis in the context of negotiations are as follows:

Presence and speed of response to requests: Machine learning and neural networks based on spectral-temporal features are used to determine the presence and speed of response to requests, resulting in a responsiveness index. This index assesses individual employee performance.

Employee satisfaction: Machine learning and neural networks are employed to analyze employee satisfaction, providing an interaction index (communications). This index evaluates communication levels among employees and identifies potential bottlenecks.

Repetitions of requests and clarifications: Machine learning and neural networks based on spectral-temporal features are used to identify repetitions of requests and clarifications, resulting in a completeness index. This index assesses employee qualification.

Context of mentioning the company name: Machine learning and neural networks, along with named entity recognition methods, are utilized to determine the context of mentioning the company name. This yields an employer satisfaction index, assessing employee satisfaction with the employer.

Team dynamics: Machine learning and neural networks are applied to analyze team dynamics, resulting in an organization's team satisfaction index. This index evaluates team satisfaction and the compatibility of employees.

To obtain even more substantiated results, the next step involves merging the dataset of processed (structured) internal negotiations with other company datasets containing information about the same user from ERP, CRM, and other systems. In general, combined datasets enable more accurate employee classification, the identification of behavioral patterns, and various other insights.

NLP techniques are employed to transcribe and process the spoken content of internal voice interactions. Through advanced algorithms, intents, entities, and relationships are extracted from the transcribed text, enabling a deeper layer of understanding. This allows for the deciphering of specific intentions or objectives expressed in voice conversations, providing insights into the goals, concerns, or needs of participants. NLP also aids in identifying entities within the text, such as names, dates, or keywords relevant to the conversation, helping to pinpoint key topics or individuals of interest. Additionally, sentiment analysis, a subset of NLP, assesses the emotional tone of the transcribed content, complementing the emotional insights obtained through SER by focusing on linguistic cues.

The integration of NLP with SER insights leads to a synergistic analysis of audio data. By combining SER-detected emotions with NLP-extracted intents, it becomes possible to discern whether specific emotional states are associated with particular intentions. For instance, instances where happiness correlates with positive work-related intentions can be identified. NLP also aids in recognizing conversational patterns indicative of conflicts or disagreements. When coupled with SER's emotional insights, this enables the identification of emotional triggers of conflicts and the proposal of strategies for resolution. Furthermore, NLP reveals the topics or subjects discussed in conversations. When aligned with SER data, it allows for an understanding of how emotional states relate to specific topics. For example, it can be determined if stress is frequently linked to discussions about workload.

The chosen approach is executed on the InfoAnalyst platform, which leverages the RBA for robust analysis. RBA provides a structured framework for incorporating both

SER and NLP insights, ensuring that the fusion of data is seamless and yields actionable results.

By combining SER and NLP on the InfoAnalyst platform, organizations gain the ability to make informed decisions that enhance workplace well-being. Early identification of conflicts and emotional triggers allows for proactive conflict resolution, contributing to a healthier work environment. Understanding intents and sentiments aids in refining communication strategies, fostering better employee engagement. The fusion of SER and NLP assists in identifying potential risks, such as attrition, compliance breaches, or safety concerns, enabling timely interventions.

The combined power of SER and RBA extends beyond well-being analysis to offer organizations a holistic approach to assessing brand loyalty, preventing fraud, and enhancing efficiency. By harnessing the emotional insights extracted from voice interactions, organizations can make data-driven decisions that positively impact their bottom line and overall performance.

4. Results and Discussion

This section focuses on translating insights gained from SER and the RBA analysis into practical steps for creating a positive work environment and enhancing workplace well-being.

Emotional insights derived from SER and RBA offer a blueprint for fostering a positive work environment. Stressors, sources of dissatisfaction, and potential conflicts within the workplace can be identified using these insights. Armed with this knowledge, proactive measures can be taken. For instance, if the analysis reveals high stress levels among employees, stress-reduction programs, flexible work hours, or counseling services can be implemented. Regular feedback loops ensure that these measures are effective and adjusted as needed.

Workplace well-being is closely linked to employee satisfaction and productivity. SER and RBA help in understanding the emotional states of employees, enabling tailoring of well-being programs to individual needs. For instance, if the analysis indicates that a significant portion of employees experiences anxiety, mindfulness sessions, mental health resources, or workshops to alleviate anxiety symptoms can be introduced. Personalized well-being plans can be created based on the emotional insights, ensuring that employees receive the support they require to thrive.

Emotional insights can uncover potential conflicts or team dynamics issues before they escalate. RBA's regularization techniques aid in quantifying the severity of conflicts and identifying their root causes. Organizations can use this information to implement conflict resolution strategies, team-building exercises, or targeted training programs. By addressing conflicts proactively, a harmonious work environment where employees collaborate effectively and feel valued can be created.

Implementing practical solutions is an iterative process. Organizations must establish monitoring mechanisms and feedback loops to assess the impact of interventions continually. SER and RBA can be used to track changes in emotional states and well-being indicators over time. Regular surveys, sentiment analysis of voice interactions, and one-on-one feedback sessions can provide valuable data for evaluating the effectiveness of implemented solutions. Adjustments can be made based on real-time insights to ensure ongoing improvement in workplace well-being.

In essence, the practical implementation of SER and RBA insights empowers organizations to create a work environment that prioritizes employee well-being, fosters positivity, and resolves conflicts constructively. A data-driven approach to these initiatives can not only enhance the satisfaction and mental health of the workforce but also boost productivity, employee retention, and overall organizational success.

Under the realm of analyzing employee well-being through internal voice interactions, one cannot overlook the critical aspect of sensitivity to the nuanced and complex emotions expressed in these interactions. This sensitivity is of paramount importance, as it significantly influences the accurate interpretation of emotional states and, by extension, the effectiveness of interventions and improvements in workplace well-being.

Emotions are intricate, multifaceted constructs that encompass a broad spectrum of human experiences. They range from simple and straightforward expressions like happiness or sadness to more complex and layered emotions that are often challenging to discern solely through voice interactions. In the context of workplace well-being, employees may experience a wide array of emotions, influenced by factors such as work-related stress, interpersonal dynamics, and personal circumstances.

One of the primary challenges in analyzing employee well-being through internal voice interactions is the recognition and understanding of nuanced emotions. Employees may not always express their emotions explicitly, and these emotions may be masked by other conversational elements, making them less apparent. For instance, an employee might convey contentment on the surface while harboring underlying feelings of frustration or anxiety.

The ability to detect and decipher nuanced emotions is crucial for gaining a comprehensive understanding of employee well-being. Neglecting these subtleties can lead to incomplete or inaccurate assessments. Sensitivity to complex emotions enables researchers and organizations to delve deeper into the factors contributing to employee well-being, identify potential stressors or sources of dissatisfaction, and tailor interventions more effectively.

To address the challenge of complex emotions, the analysis of internal voice interactions should integrate contextual cues. These cues include not only the words spoken but also the tone of voice, pace of speech, pauses, and non-verbal elements like sighs or laughter. Contextual analysis provides valuable insights into the emotional undercurrents of conversations, allowing for a more holistic assessment.

Advanced machine learning algorithms and pattern recognition techniques play a pivotal role in the identification of complex emotions. These technologies can analyze speech patterns and linguistic nuances to infer emotional states accurately. Additionally, machine learning models can be trained to recognize patterns associated with specific emotions, contributing to a more refined analysis.

While the analysis of nuanced emotions is essential, it must be conducted with the utmost sensitivity and ethical considerations. Employee consent, as discussed in the previous section, plays a crucial role in ensuring that their emotional expressions are analyzed responsibly and with respect for privacy. Furthermore, the insights gained should be used constructively to support employee well-being rather than for punitive measures.

In conclusion, addressing complex emotions with sensitivity is integral to the accurate assessment of employee well-being through internal voice interactions. Recognizing and understanding the nuanced emotional states of employees contribute to a more comprehensive analysis, enabling organizations to implement targeted interventions and improvements that foster a positive work environment and enhance workplace well-being.

The discussion of the results begins by considering the existing literature on intelligent measurement and data analytics. Dr. Leonard Finkelstein and Dr. Daniel Hofmann's work laid the foundation for intelligent measurement, emphasizing its importance in providing objective information [1]. The findings align with their perspective, as it was observed that the implementation of intelligent data management solutions indeed enhances efficiency and supports more informed decision-making in small businesses, thus validating Hypothesis 1.

However, the research also revealed challenges related to the accessibility and user-friendliness of these solutions. This aligns with the work of Dr. Aldo Giordani and Dr. Laura Mari, who discussed property evaluation types and structural models for direct measurement [14]. The results suggest that the lack of accessible solutions restricts small businesses' ability to leverage data effectively, supporting Hypothesis 2.

Furthermore, the analysis considered the role of Bayesian approaches in measurement processes, as proposed by Dr. Svetlana Prokopchina [5]. It was found that the utilization of intelligent solutions for analyzing unstructured data can assist small businesses in effectively managing information complexity, as implied by Hypothesis 3.

In summary, the study's findings are consistent with the literature, highlighting the positive impact of intelligent data management solutions on efficiency and the challenges related to accessibility. Additionally, the results support the idea that these solutions can effectively handle unstructured data, aligning with the literature's emphasis on data analysis methodologies. The integration of these findings with existing knowledge contributes to a better understanding of the role of intelligent data management in small businesses.

5. Conclusion

In conclusion, this research has explored the multifaceted realm of intelligent data management solutions and their application within small businesses. The study has primarily focused on their impact on enhancing operational efficiency, accessibility, and the management of unstructured data, including the analysis of internal voice interactions, the recognition of emotions through SER, and the promotion of employee well-being within the corporate landscape. The findings presented in this study align with the existing literature on intelligent measurement and data analytics, reaffirming the pivotal role of these solutions in elevating operational efficiency and facilitating more informed decision-making processes within the small business sector.

However, it is crucial to emphasize the challenges surrounding the accessibility and user-friendliness of these solutions, as their successful integration relies on overcoming these barriers. Addressing these challenges and tailoring intelligent data management solutions to the specific needs of small enterprises are essential for the broader adoption of data-driven strategies. Furthermore, the research has shed light on the critical role of these solutions in effectively managing and extracting valuable insights from unstructured data sources, particularly through the prism of internal voice interactions. The integration of RBA and SER technologies has allowed for a more profound understanding of employee sentiments, contributing to the enhancement of workplace well-being.

As the path forward is navigated, it is essential for researchers to explore strategies aimed at making intelligent data management solutions more accessible and user-friendly for small businesses. Future research endeavors should delve deeper into the unique challenges faced by small enterprises in adopting and implementing these solutions, focusing on developing effective strategies to overcome these hurdles. Furthermore, the potential of artificial intelligence and machine learning in optimizing data management processes, particularly in the context of internal voice interactions and emotion recognition, warrants further examination. This opens up an exciting avenue for future research, where exploration can occur regarding how these cutting-edge technologies can empower small businesses to fully leverage their data resources while fostering a workplace environment that prioritizes employee well-being.

In summary, this study contributes significantly to the expanding body of knowledge concerning intelligent data management solutions within the context of small businesses. It highlights their advantages while recognizing the challenges that require careful attention. By simultaneously addressing operational efficiency, data accessibility, emotion recognition, and employee well-being, a foundation can be laid for a more inclusive, efficient, and emotionally intelligent era of data-informed decision-making in the small business landscape.

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References

[1] Finkelstein L, Hofmann D. Intelligent measurement: a view of the state of art and current trends. Measurement. 1987;5(4):151–3.

[2] Hofmann D, Karaya K. Intelligent measurements for obtaining objective information in science and technology. In: X International Congress of IMECO; 1985; Prague. International Measurement Confederation (IMEKO).

[3] Rosenberg VY. Introduction to the theory of accuracy of measuring systems. Moscow: Sov. Radio; 1975.

[4] Michell J. Measurement in psychology: critical history of a methodological concept. Cambridge: Cambridge University Press; 1999. DOI: 10.1017/CBO9780511490040.

[5] Prokopchina SV. Development of methods and tools for Bayesian measurement intellectualization in complex object monitoring tasks. St. Petersburg; 1995.

[6] Prokopchina SV, Nedosekin DD, Chernyavsky EA. Information technologies of intellectualization of measuring processes. St. Petersburg: Energoatomizdat; 1995.

[7] Stevens SS. On the theory of the scales of measurement. Science. 1946;103(2684):677–80.

[8] Thurstone LL. A method of scaling psychological and educational tests. J Educ Psychol. 1925;16(7):16.

[9] von Hayek FA. The pretense of knowledge. Nobel Prize Lecture, December 11. Stockholm School of Economics.

[10] Guttman L. A basis for scaling qualitative data. Am Sociol Rev. 1944;9(2):139–50. DOI: 10.2307/2086306.

[11] Rasch G. Probabilistic model for some intelligence and attainment tests. Copenhagen: Danish Institute Educational Research; 1960.

[12] Andrich D. Rasch models for measurement. Thousand Oaks: Sage Publications; 1988.

[13] Mari L, Wilson M, Maul A. Measurement across the sciences: developing a shared concept system for measurement. New York: Springer; 2021.

[14] Giordani A, Mari L. A structural model of direct measurement. Measurement. 2019;145:535–50. DOI: 10.1016/j.measurement.2019.05.060.

[15] Finkelstein L. Widely, strongly and weakly defined measurement. Measurement. 2007;34(1):39–48.

[16] Wilson M. Constructing measures: an item response modeling approach. New York: Routledge; 2005.

[17] Holland P, Erlbaum. On sampling theory foundations of item response theory models. Psychometrika. 1990;55(4):577–601.

[18] International vocabulary of metrology – basic and general concepts and associated terms (VIM). Joint Committee for Guides in Metrology; 2012.

[19] Rossi GB. A probabilistic theory of measurement. Measurement. 2006;39:39–50.

[20] Rossi GB. Measurability. Measurement. 2007;40:545–62.

[21] Zaslavskaya VL, et al. Problems of using semistructured and unstructured data in business intelligence systems. S-Lib. 2022.