Data and Metadata. 2024; 3:.564
doi: 10.56294/dm2024.564

ORIGINAL

Decision supporting approach based on suitable chatbot system for big data analytics

Enfoque de apoyo a la toma de decisiones basado en un sistema de chatbot adecuado para el análisis de grandes datos

Evan Asfoura[1], Gamal Kassem[2]

[1]Faculty of business studies, Arab Open University. Riyadh, Saudi Arabia.
[2]Business Informatic, German University in Cairo. Cairo, Egypt.

Cite as: Asfoura E, Kassem G. Decision supporting approach based on suitable chatbot system for big data analytics. Data and Metadata. 2024; 3:.564. https://doi.org/10.56294/dm2024.564

Submitted: 04-05-2024 **Revised:** 04-09-2024 **Accepted:** 23-12-2024 **Published:** 24-12-2024

Editor: Dr. Adrián Alejandro Vitón Castillo

Corresponding Author: Evan Asfoura

ABSTRACT

Introduction: the increasing reliance of organizational decision-makers on advanced information systems and analytical tools highlights the transformative potential of big data analytics in modern business environments. As organizations accumulate vast amounts of data, the ability to harness this information effectively has become critical for informed decision-making and strategic planning. However, the complexity of big data analytics and the evolving demands of business environments pose challenges, particularly for managers navigating data-driven cultures. Effective utilization of these tools requires comprehensive training and support, especially for newly appointed managers
Objective: this paper presents a chatbot-based system designed to bridge the gap between decision-makers and big data analytics. By leveraging natural language processing (NLP) and machine learning, the proposed chatbot facilitates interactive learning and real-time engagement with analytical insights. This system empowers decision-makers to navigate analytical outputs efficiently, fostering improved decision-making processes.
Method: the research adopts a design science methodology to develop and evaluate this innovative approach. Initial findings suggest that the chatbot enhances accessibility and usability of analytics tools, reduces the technical burden on managers, and promotes a more effective data-driven decision-making culture
Results: chatbot-based decision support solution demonstrated its potential to transform decision-making processes in data-driven organizations. By addressing the feedback gathered during this evaluation phase, future iterations of the system can further enhance its utility and effectiveness.
Conclusions: this study contributes to the growing discourse on integrating artificial intelligence tools in organizational decision-making and highlights their potential to transform managerial practices in a data-intensive era.

Keywords: Big Data Analytics; Chatbot; Decision-Making; Natural Language Processing; Design Science Methodology.

RESUMEN

Introducción: la creciente dependencia de los responsables de la toma de decisiones organizacionales en sistemas avanzados de información y herramientas analíticas destaca el potencial transformador del análisis de grandes datos en los entornos empresariales modernos. A medida que las organizaciones acumulan vastas cantidades de datos, la capacidad de aprovechar esta información de manera efectiva se ha vuelto crucial para la toma de decisiones informada y la planificación estratégica. Sin embargo, la complejidad del análisis de grandes datos y las demandas cambiantes de los entornos empresariales plantean desafíos, especialmente

para los gerentes que navegan en culturas basadas en datos. La utilización efectiva de estas herramientas requiere capacitación y apoyo exhaustivos, especialmente para los gerentes recién designados.
Objetive: este artículo presenta un sistema basado en chatbot diseñado para cerrar la brecha entre los responsablesde la toma de decisiones y el análisis de grandes datos. Aprovechando el procesamiento de lenguaje natural (PLN) y el aprendizaje automático, el chatbot propuesto facilita el aprendizaje interactivo y la interacción en tiempo real con conocimientos analíticos. Este sistema capacita a los responsables de la toma de decisiones para navegar eficientemente por los resultados analíticos, fomentando procesos de decisión mejorados.
Método: la investigación adopta una metodología de ciencia de diseño para desarrollar y evaluar este enfoque innovador. Los hallazgos iniciales sugieren que el chatbot mejora la accesibilidad y la usabilidad de las herramientas analíticas, reduce la carga técnica para los gerentes y promueve una cultura de toma de decisiones más efectiva basada en datos.
Resultados: la solución de soporte a la toma de decisiones basada en chatbot demostró su potencial para transformar los procesos de toma de decisiones en organizaciones impulsadas por datos. Al abordar los comentarios recopilados durante esta fase de evaluación, las iteraciones futuras del sistema pueden aumentar aún más su utilidad y efectividad.
Conclusiones: este estudio contribuye al creciente debate sobre la integración de herramientas de inteligencia artificial en la toma de decisiones organizacional y destaca su potencial para transformar las prácticas gerenciales en una era intensiva en datos.

Palabras clave: Grandes Datos; Chatbot; Toma de Decisiones; Procesamiento de Lenguaje Natural; Metodología de Ciencia de Diseño.

INTRODUCTION

In today's digital landscape, data is often referred to as the "digital oil" that powers the operational and strategic functions of organizations.[1] This metaphor underscores the pivotal role data plays in driving business success. Research has consistently demonstrated that data-driven organizations tend to achieve higher levels of productivity and efficiency.[2] A culture rooted in data-driven practices promotes fact-based decision-making, empowering organizations to innovate and deliver new products and services with greater precision. Consequently,[3] leveraging data analytics has become a cornerstone of modern decision-making processes, enabling companies to enhance the speed and quality of their decisions.[4] Despite its advantages, adopting a data-driven approach presents significant challenges. One of the key hurdles lies in effectively translating the insights from big data analytics into actionable decisions that address specific business problems.[5] Research has highlighted that decision-makers often struggle to bridge the gap between the outcomes of analytics and their practical application in organizational contexts. Moreover, the role of decision-makers throughout the data lifecycle, including their interactions and contributions at various stages, remains insufficiently defined. This lack of clarity can hinder the seamless integration of analytics into decision-making workflows.[1] The growing interest in the value of big data and business analytics has sparked extensive discourse on their potential to drive organizational success. While big data has undoubtedly enabled companies to harness data-driven insights for improved decision-making, there remains a notable gap in academic research regarding the development of frameworks or empirical models that facilitate the effective application of analytics.[6] Current literature does not adequately address the interplay between decision-makers and analytics resources, nor does it provide comprehensive strategies for fostering a data-centric culture within organizations.[7]

Today, organizations utilize data by combining natural language processing (NLP) and machine learning techniques to deliver various types of information to users through AI-powered chatbots. These systems are trained using natural-language data from historical user interactions, which an intelligent system processes to learn how to automatically suggest responses in text format. Advancements in data mining and machine learning have the potential to enhance decision-making capabilities. As a result, chatbots have become increasingly practical for everyday applications such as help desk tools, information retrieval systems, automated phone answering, and advertising tools, supporting sectors like education, business, and e-commerce. The development of artificial intelligence and deep learning has further improved chatbot performance, allowing them to simulate human conversations and continuously learn from experience.[10] A chatbot is an artificial entity designed to engage in anonymous conversations via message exchanges, resembling human-to-human interaction, with one participant being the chatbot. This type of system is referred to as a "conversational chatbot".[11,12] As previously mentioned, advancements in machine learning and deep learning have significantly impacted chatbot performance, making them reliable and capable of providing automatic, adaptive, human-like conversations. Chatbots are now used in various fields, such as customer service and data collection, overcoming the limitations of traditional human-machine interaction.[11] The term "chatbot" combines "chat" and "robot," and it simulates human conversation through a text-based dialogue system.[13] AI-powered chatbots derive their knowledge from machine learning and deep learning algorithms running in the background, while the front end uses natural language processing to interpret human language, feeding it into the backend for knowledge extraction. Chatbots can be applied across different business sectors, helping to reduce time and labor costs while increasing efficiency, ultimately enhancing business value.[14]

Classify chatbots into two categories: those based on rules and those driven by Artificial Intelligence (AI).[15] Rule-based chatbots are more limited because they function strictly according to predefined programming, whereas AI-based chatbots can understand natural language beyond simple commands and continuously improve through interaction due to their ability to handle multiple states. The core of chatbot development involves defining rules for generating responses. These rules can range from simple pattern matching to more complex grammatical analysis to understand the context of conversations. Natural language processing (NLP) is a classical approach used in building these conversational agents.[16] The most critical component of a chatbot is the chatbot engine, often referred to as the Natural Language Understanding (NLU) engine. This engine is responsible for converting natural language input into machine-understandable actions. To achieve an acceptable level of accuracy, chatbot engines use NLP models and machine learning techniques, focusing on identifying user intents and relevant entities.[15]

Entities, the second important component, represent the parameters needed to fulfill an intent—such as location, time, or type of cuisine. These help in identifying the necessary details for a specific action. Chatbot engines are trained by grouping entities that lead to the same action. Common entities can be predefined and reused in various contexts. Deep learning methods are applied to identify intents and extract entities, treating entity extraction as a sequence classification task, often using Conditional Random Fields.[12]

Describe chatbot architecture as consisting of three key components:[29] the knowledge base, the interpreter program (including the analyzer and generator), and the user interface. The knowledge base holds the system's intelligence, consisting of keywords, phrases, and corresponding responses. It can be implemented using data files, text files, databases, or XML files. The interpreter program interacts with the user interface, where the analyzer reads the user's input and examines its syntax and semantics using techniques like pattern matching, substitution, and sentence splitting. The chat engine then matches the analyzer's output with the knowledge base to determine the appropriate response. Finally, the generator formulates a grammatically correct response to display through the user interface. In recent years, education has emerged as one of the most promising application areas for chatbot technology, especially in vocational guidance.[17] Additionally, there is increasing demand to integrate chatbot technology into e-learning platforms. The use of chatbots in e-learning mimics interactive educational experiences, as chatbots can track students' behavior and provide personalized support. can assess and modify the content to enhance the skills of individual students or groups based on their knowledge level.[17,18,19]

Thee main objective of this work is to develop a robust framework that enhances the interaction between decision-makers and analytics tools. By doing so, this study seeks to provide practical insights and contribute to the growing body of knowledge on data-driven decision-making, equipping organizations to harness the full potential of their data resources

State of the art

This section explores the challenges organizations face when attempting to implement data-driven decision-making. One major obstacle is the insufficient knowledge and skills among business managers, which hampers the development of a data-driven culture.[1,9,20,21] Additionally, visualization models are still not providing managers and business users with the support needed to generate meaningful insights and make effective decisions.[9,24,25] For a successful data-driven culture, organizations must be able to extract valuable information and knowledge, meaning decision-makers must be able to correctly interpret data and derive actionable insights.[9] Interestingly, the challenges preventing organizations from becoming data-driven are less about data or technology and more about managerial and cultural issues. The main barrier is a lack of understanding about how to use analytics to enhance business operations[20] According to findings from the Delphi method,[5] noted that a key challenge is the difficulty decision-makers face in linking big data analytics outcomes with business decision-making to solve specific problems. Furthermore, the outlined steps to create a data-driven decision-making environment often fail to clearly define the role of managers and decision-makers throughout the data lifecycle and their interactions in these stages.[1] The biggest barrier to becoming data-driven remains the lack of understanding about how analytics can improve business performance.[20]

As previously mentioned, data-driven decision-making is a dynamic process involving both managers and data scientists, where analytics is treated as a strategic asset for the organization.[3,6] Emphasize the importance of linking the strategic aspects of a company with the data collected.[9] For instance, Key Performance Indicators (KPIs) should be connected to the data analytics process, as these measures directly influence organizational strategy. It is critical to continuously monitor and reassess the relevance and impact of KPIs to avoid making poor decisions based on flawed data or misinterpretations. Another significant challenge is ensuring that decision-makers and frontline employees can effectively adopt and use big data analytics tools, which is often hindered by a lack of technical expertise. A Harvard study stresses that senior managers must remove obstacles that hinder progress and affect frontline performance. Organizations need to invest in training and equipping frontline employees to better serve the company's needs.[21] Moreover, managerial challenges often outweigh technical ones, as senior executives may be reluctant to trust data when it conflicts with their experience and intuition. To become truly data-driven, organizations must undergo a management revolution. where leaders and executives embrace the use of business analytics in the decision-making process.[22] As previously mentioned, visualization serves as a bridge between decision-makers and analytics. Its goal is to provide decision-makers with meaningful insights to make critical decisions. Consequently, humans play a crucial role in generating knowledge from visual analytics. In visual analytics, visualizations display the output of analytical models, such as clustering models, as well as visual representations of the models themselves.[23,24] However, both the visual analytics and machine learning communities have identified gaps between analytical tools and human interaction in data analytics systems, which limits their effectiveness in solving real-world problems. Various models have been proposed to conceptualize the integration of machine learning and interactive visualizations. Yet, these models still tend to have either a strong focus on human/visualization aspects or a strong focus on algorithms.[24] Additionally, in some instances, poorly designed dashboards hinder the communication of vital information. As a result, visualizations may fail to convey critical insights as effectively as managers expect. In other cases, individuals responsible for interpreting the dashboards may lack the training needed to correctly understand the data.[9]

A review of the literature reveals that decision-makers often struggle to link the results of big data analytics with business decision-making to address specific business problems, which remains a key challenge for organizations trying to become data-driven. Furthermore, managers and stakeholders involved in the data-driven decision-making process frequently lack the technical skills needed to act on the insights generated. The visualization models proposed so far continue to either lean heavily toward human/visualization elements or toward algorithmic components. In other words, the visual analytics literature lacks sufficient guidance and know-how to help decision-makers effectively interpret analytical outputs. As a result, a gap exists between decision-makers, who may lack technical expertise, and the effective use of data analytics tools in a data-driven culture. Decision-makers often struggle to connect analytical outputs to specific business problems. Additionally, the blending of analytics tools with decision-makers' knowledge is not well supported, as varying levels of business analytics expertise among decision-makers are not adequately addressed. There is a lack of specific guidelines for decision-makers to manage big data analytics outputs, as noted in the literature review. Therefore, there is a need for a solution that supports interaction between decision-makers and big data analytics tools within the decision-making process. The goal of this research is to bridge the interaction gap between decision-makers and the big data analytics pool. The research question this study seeks to answer is: "How can the interaction between the big data analytics pool and decision-makers be supported to gain key insights in a data-driven culture?"

METHOD

This research adopts a design science research (DSR) methodology to address the challenges of integrating decision-makers with big data analytics. The DSR approach is ideal for developing practical and innovative IT solutions, as it combines theory-driven insights with actionable artifacts to solve real-world problems. The methodology consists of several iterative stages, including problem identification, conceptual design, artifact development, demonstration, and evaluation.

Problem Identification

The initial phase involved identifying the challenges decision-makers face when utilizing big data analytics in a data-driven organizational culture. Semi-structured interviews were conducted with stakeholders, including decision-makers and technical experts, to gather insights into the pain points, such as difficulty interpreting analytical outputs and aligning them with business objectives. Key findings highlighted the need for a tool to bridge the interaction gap between decision-makers and analytics

Conceptual Design

Based on the problem definition, a conceptual framework for a chatbot-based decision support system was developed. The design incorporates three key components (figure 1):

Knowledge Base: A repository of performance measures and KPIs aligned with organizational objectives, serving as the foundation for chatbot responses.

Analytical Models: Techniques such as decision trees, clustering, and regression to provide actionable insights.

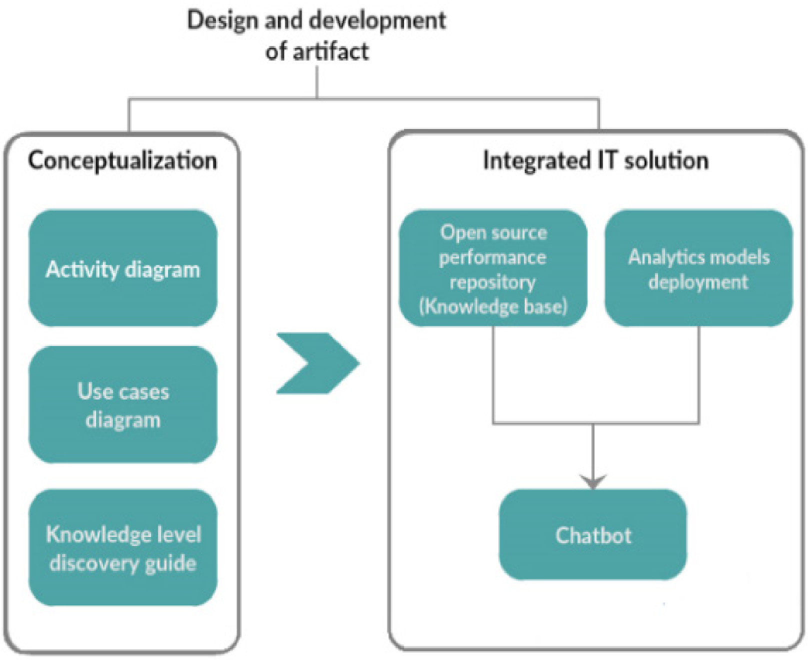

Figure 1. Desyncing phase

Chatbot Interface: An AI-powered conversational agent employing natural language processing (NLP) to facilitate interactions between decision-makers and the analytics pool.

Activity diagrams, use-case diagrams, and a knowledge-level recognition guide were created to refine the system's architecture and functionalities.

Artifact Development

The chatbot system as use case was developed iteratively, integrating the following components:

- Knowledge Base Construction: A repository of KPIs was designed based on Parmenter's methodology, incorporating attributes like measure name, frequency, Balanced Scorecard perspectives, and strategic objectives.
- Analytical Model Deployment: Using the CRISP-DM methodology, models were built and aligned with strategic objectives such as profitability, sales growth, and customer retention.
- Chatbot Implementation: The chatbot was programmed to interact with the knowledge base and analytical models using NLP and rule-based logic. It was developed using tools such as IBM Watson Assistant, ensuring scalability and adaptability across business functions.

Evaluation

The evaluation phase employed both qualitative and quantitative methods to assess the artifact's effectiveness. Two evaluation approaches were used:

- Black Box Evaluation: Open-ended interviews were conducted among 4 decision makers and 1 expert in the field for understanding user perspectives on the chatbot's usability, reliability, and alignment with business needs.
- Glass Box Evaluation: A rating scale was applied to evaluate aspects such as sentence accuracy, relevance of responses, and user-friendliness.

Feedback from the evaluation phase informed iterative refinements to the chatbot system, including suggestions for integrating visualizations, multilingual support, and additional KPIs.

Use case implementation

For the first component, the performance measures repository will serve as an open-source resource. It will act as the knowledge base and will The proposed IT solution addresses key challenges identified during interviews, particularly the difficulty decision makers face in connecting the organization's Key Performance Indicators (KPIs) with the big data analytics pool to extract valuable insights. To tackle this, the solution will utilize a performance measure database based on Parmenter (2015). This database, serving as an open-source repository, will be developed as a use case and comprises performance measures gathered by KPI teams in collaboration with senior management, monthly report reviews, and external research. The database includes six key attributes: the measure's name, its frequency, the relevant Balanced Scorecard (BSC) perspective, the applicable BSC teams, the sectors that can utilize the measure, and the strategic objective it supports. For this project, the researchers will concentrate on performance measures relevant to the sales and marketing functions, focusing on the customer and financial perspectives of the Balanced Scorecard. This selection aligns with interview insights and the widespread use of big data analytics in marketing and customer satisfaction. According to[26] marketing has been a key area for experimenting with big data approaches, as these solutions help extract insights more quickly than traditional human analysis. Research also shows that the use of big data in marketing has significantly grown each year, as highlighted by.[27]

The second part of the solution involves deploying analytics models. This research will focus on three techniques: decision trees, clustering, and regression. These techniques were selected based on interview feedback and their applicability across different types of data analytics. The deployment process will follow the CRISP methodology, a widely-used data mining framework that consists of six phases: business understanding, data understanding, data preparation, modeling, evaluation, and deployment.[28] The performance measure database identifies four strategic objectives: increasing profitability, optimizing operations, boosting sales, and building long-term relationships with profitable customers. Each of these objectives will be addressed using the selected analytical techniques.

The third and most critical component of the artifact is the "chatbot." The chatbot will be designed using the chat script approach, which operates by defining topics, concepts (such as entities and intents), and logical rules. It matches user queries with predefined topics and executes the appropriate rule. Concepts are defined using sets of words, nouns, adverbs, or parts of speech.[16]

The key design components required for the chatbot are:

1. Concepts (elements, objectives).
2. Subjects, reasoning rules, and conversation structure.

The demonstration phase aims to evaluate the usability of the proposed IT solution. Interviews were conducted where decision makers and field experts were asked to begin using the solution, following a defined process:

- The decision maker or expert selects the desired strategic objective to achieve.
- They then choose the relevant KPI measures.
- The decision maker/expert engages in a conversation with the chatbot to make data-driven decisions based on the chosen strategic objective.
- Finally, they assess the level of support provided by the solution and evaluate the overall chatbot interaction experience.

The design and development phase consists of two main stages: first, conceptualizing the integrated IT solution, and then proceeding with its design and development (figure 2). Figure 2 illustrates the architecture of the proposed IT artifact, highlighting the involved entities and their relationships. It presents a high-level view of the system's structure to demonstrate how the solution aligns with user requirements.

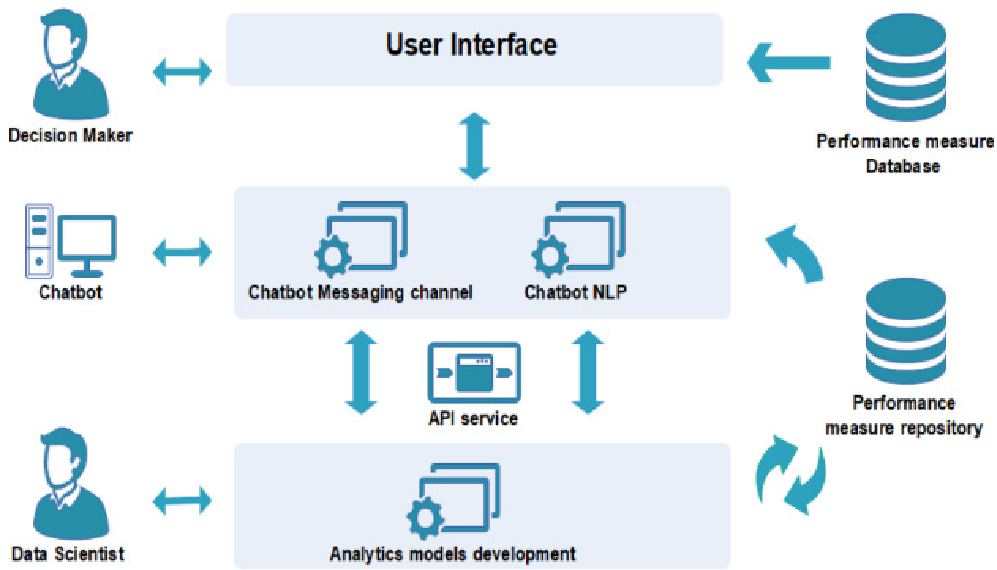

Figure 2. concept of interactive processes for supporting decision making

In the architecture of the interactive decision support solution (figure 2), the key users (actors) are the decision maker, the chatbot, and the data scientist. The decision maker interacts with the system through a user interface to initiate a conversation with the chatbot. They also have access to the performance measure database, which stores the organization's KPI measures. The chatbot includes a messaging platform and natural language processing (NLP) capabilities to enable intelligent interactions. It connects to the open-source performance measure repository, which acts as the chatbot's knowledge base. This ensures that both the chatbot and the data scientist are working with the same data. The data scientist develops analytical models using data from the performance measure repository to help achieve the organization's KPI objectives. Communication between the chatbot and the data scientist occurs through an API service.

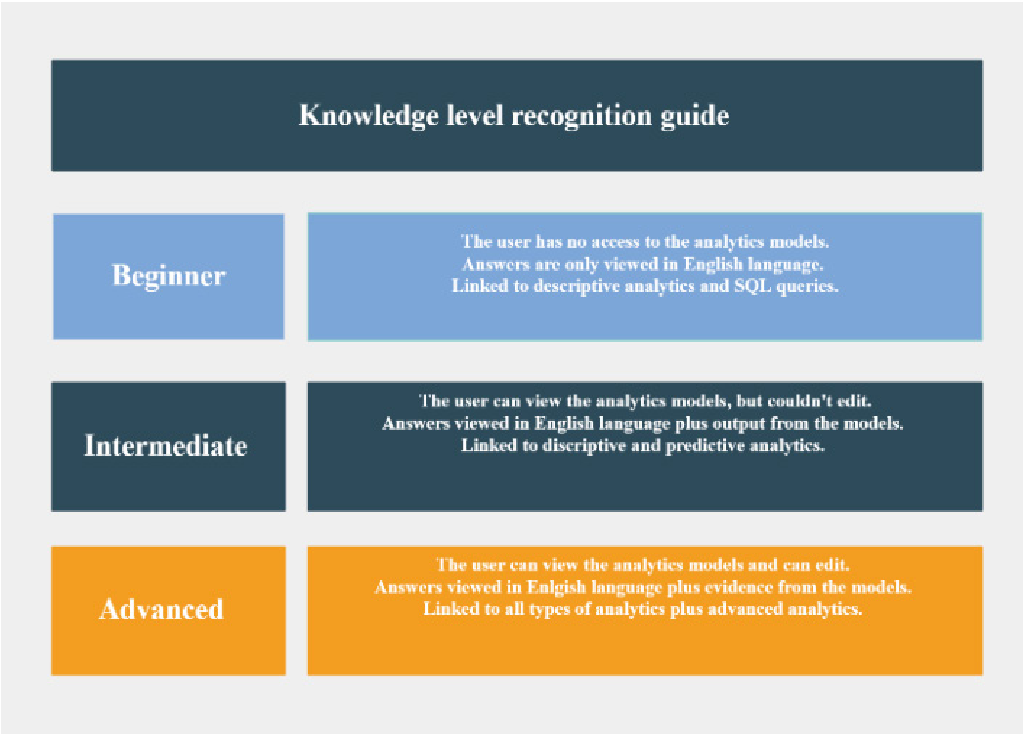

Figure 3. Recognition guide of kn0wledge level

Since bots can assess and adjust content based on the user's knowledge level[17,19] this research introduces a knowledge level recognition guide, which categorizes users into three levels: beginner, intermediate, and advanced. Drawing from the "three stages of analytics adoption model" created by[4] organizations in the "aspirational stage" are considered to have basic knowledge, placing them at the beginner level. Those in the "experienced stage" fall into the intermediate level, while organizations in the "transformed stage" are classified as advanced. Figure 3 illustrates each knowledge level along with its corresponding features.

Evaluation and Results

The evaluation of the chatbot-based decision support solution yielded both qualitative and quantitative insights, demonstrating its effectiveness in bridging the gap between decision-makers and big data analytics tools. The results are summarized below:

Black Box Evaluation

Figure 4 illustrates the initial interaction with the chatbot using IBM Watson Assistant, where the chatbot begins by explaining how it can assist the user. It prompts the user to select which analytics model to start with. If the user types "decision tree," for example, the bot asks the user to choose a specific model based on the strategic objective. For instance, if the user selects the profit model, the bot provides a brief description of the dataset and the model's purpose. From there, the user can ask the chatbot questions related to KPI measures, receiving answers based on the chosen model. The proposed IT solution was evaluated by four decision makers and one expert. These individuals were asked questions regarding each criterion defined earlier, with two of them already having been involved during the problem definition phase, making this a follow-up to assess how well the solution addressed their challenges in a data-driven environment. The evaluation was divided into two parts: Glass box evaluation and Black box evaluation. For the Black box evaluation, open-ended questions were asked for each criterion, while the Glass box evaluation used a rating scale from 1 to 5, where 1 indicated very poor and 5 represented excellent.

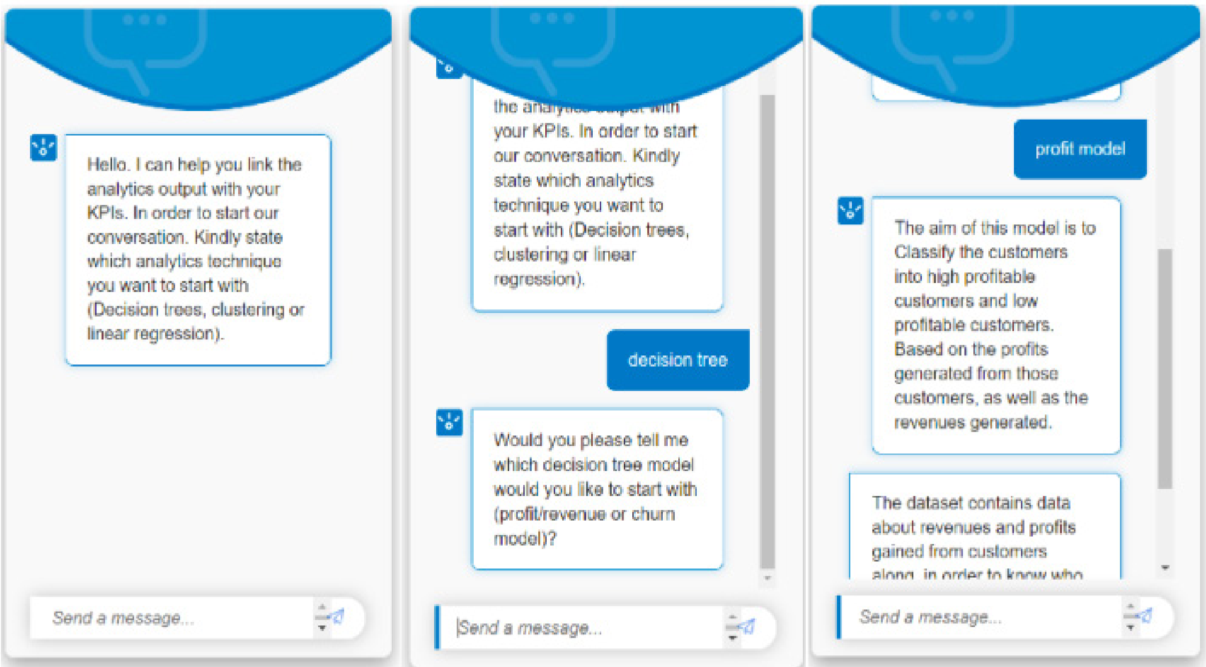

Figure 4. Starting interface

In the Black Box Evaluation, participants were asked open-ended questions about the solution's usability, validity, reliability, and alignment with business needs. The findings are summarized below in table 1.

Table 1. Black Box Evaluation

Criterias	Evaluation results
Usefulness	Participants found the solution highly beneficial, citing its ability to facilitate natural language interactions with analytical models and deliver instant results. They appreciated the 24/7 availability of the chatbot, which significantly reduced dependency on technical teams. Suggestions for improvement included incorporating additional strategic objectives and expanding the library of KPIs.
Validity	The solution was deemed valid as it effectively bridged the gap between technical analytics outputs and business perspectives. The chatbot provided clear, actionable insights, although the accuracy of responses depended on the quality of the underlying analytical models.
Reliability	The artifact demonstrated a high degree of reliability. Participants noted that the system's integration with analytical models ensured consistency in results. Additionally, users could assess the accuracy, precision, and recall of the models before making decisions.
Accuracy	The overall accuracy of the chatbot's responses was rated at approximately 80 %. Participants recommended adding tips or predefined keywords to guide users in framing their queries for improved results.
Ease of Use	The chatbot was praised for its intuitive design, allowing users to interact in natural language without requiring technical expertise. Suggestions for further enhancements included integrating visualizations, charts, and personalized features, such as the ability to recognize user names and provide tailored guidance.
Alignment with Business Needs	The solution aligned well with organizational objectives, provided that KPIs were clearly defined at the outset. Participants emphasized the importance of ensuring that the chatbot's responses are directly tied to strategic goals.
Scalability	Participants found the solution scalable across multiple business domains, such as healthcare, banking, and retail. Recommendations for improving scalability included adding multilingual support (e.g., Arabic) and incorporating AI-driven visualizations to create a more dynamic and interactive environment.

Additional feedback included requests for features such as exporting reports in various formats (e.g., Excel, PDF), providing navigation tips, and linking analytical insights to data sources.

Glass Box Evaluation

The Glass Box Evaluation involved a quantitative assessment using a rating scale from 1 to 5, where 1 represented "very poor" and 5 represented "excellent." The results are as follows in table 2.

Table 2. Glass Box Evaluation

Criterias	Evaluation results
Thoroughness:	Scores ranged from 3 to 4, with participants noting that the solution adequately addressed key decision-making needs but could benefit from greater flexibility.
Sentence Accuracy	Rated 4 by two evaluators and 5 by the remaining two, indicating a high level of precision in the chatbot's responses.
Word Accuracy	Four participants rated it 4, and one gave it a 5, reflecting consistent accuracy in recognizing user inputs.
Understandability	Ratings varied, with two participants assigning a score of 3, one giving a 4, and another a 2. This indicates room for improvement in ensuring clarity and comprehensibility of responses.
Humanness	Evaluators rated the chatbot's conversational tone as 4 (two evaluators), 3 (one evaluator), and 2 (one evaluator), suggesting that while the chatbot mimicked human interaction effectively, further enhancements in natural language processing could improve its performance.

Summary of Findings

The evaluation revealed that the proposed solution met its objectives and successfully bridged the gap between business users and technical analytics tools. However, participants identified opportunities for improvement to enhance user experience and system performance. Key recommendations included:

- Adding dynamic visualizations and charts to present data insights more effectively.
- Expanding the repository of KPIs and strategic objectives.
- Enabling multilingual capabilities and enhancing chatbot personalization.
- Providing export options for reports in multiple formats and linking data sources for transparency.

Overall, the proposed chatbot-based decision support solution demonstrated its potential to transform decision-making processes in data-driven organizations. By addressing the feedback gathered during this evaluation phase, future iterations of the system can further enhance its utility and effectiveness.

DISCUSSION

The evaluation of the chatbot-based decision support solution yielded both qualitative and quantitative insights, demonstrating its effectiveness in bridging the gap between decision-makers and big data analytics tools. The results are summarized below:

Implications for Practice

The proposed system represents a significant step toward democratizing access to big data analytics by reducing the technical barriers for managers and business leaders. The chatbot enables intuitive interactions, allowing users to query analytical models and access key performance indicators (KPIs) without requiring advanced technical expertise. This capability aligns with the growing demand for tools that support non-technical users in navigating data-intensive environments.

By effectively linking analytical outputs with business objectives, the chatbot promotes strategic alignment and ensures that data insights are actionable and relevant. Participants emphasized that such systems have the potential to enhance decision-making efficiency, reduce dependency on technical teams, and foster a more agile response to business challenges.

Challenges and Areas for Improvement

Despite its strengths, the evaluation highlighted areas requiring further refinement. One recurring issue was the chatbot's limited ability to provide detailed explanations or guidance for complex queries. Enhancing the system's NLP capabilities to better understand nuanced questions and deliver more comprehensive responses will be crucial.

The chatbot's conversational tone and humanness, though adequate, could be further improved to create a more engaging user experience. Incorporating advanced natural language generation techniques could enhance the chatbot's ability to simulate human interaction effectively.

Participants also identified gaps in visualizing data insights. While the system provided robust textual outputs, the absence of dynamic visualizations limited its ability to present complex data intuitively. Adding visual elements, such as charts and dashboards, could significantly improve the comprehensibility and impact of the chatbot's responses.

Contribution to Theory and Research

This research contributes to the literature on artificial intelligence (AI) applications in organizational decision-making by offering a practical framework for integrating chatbots into data-driven processes. Unlike previous studies that focus primarily on technical advancements, this study emphasizes the user experience and managerial implications of AI-powered decision support tools.

The study highlights the importance of aligning big data analytics outputs with organizational KPIs and underscores the role of tailored user interfaces in bridging the gap between technical tools and managerial needs. This perspective enriches the ongoing discourse on human-AI collaboration in data analytics, offering insights into how organizations can better support non-technical users.

Limitations and Future Research Directions

While the evaluation provided valuable insights, the study has certain limitations. The sample size for the evaluation was relatively small, limiting the generalizability of the findings. Future research should involve a larger and more diverse group of participants across different industries to validate the system's scalability and adaptability.

Additionally, the chatbot was tested primarily in English, which may restrict its applicability in non-English-speaking contexts. Future iterations should incorporate multilingual capabilities to address this limitation and expand the system's usability in global contexts.

Finally, while this research focused on integrating NLP and machine learning for textual interactions, future studies could explore the integration of voice-based interfaces to further enhance user accessibility and engagement.

Broader Implications

The adoption of AI-powered decision support tools such as the proposed chatbot has broader implications for organizations aiming to become data-driven. By reducing reliance on technical expertise, these tools empower decision-makers to independently derive insights, fostering a culture of innovation and agility. However, successful implementation requires careful consideration of organizational readiness, including training programs and change management strategies to ensure user acceptance and effective use of the technology.

CONCLUSIONS

The paper presents a chatbot-based decision support solution tailored to address challenges faced by decision-makers in leveraging big data analytics.. The proposed system integrates natural language processing, a robust knowledge base of KPIs, and advanced analytics models, facilitating intuitive interactions and improving data-driven decision-making processes. The evaluation highlighted the chatbot's usability, reliability, and alignment with business needs while identifying areas for improvement, such as dynamic visualizations, multilingual capabilities, and expanded KPI libraries. The solution demonstrated scalability across various industries, confirming its potential to transform managerial practices.

ACKNOLEDGEMENT

The authors extend their appreciation to the Arab Open University for Funding this work through AOU research fund No. (AOUKSA-524008)

BIBLIOGRAPHIC REFERENCES

1. Carillo, K. D. A. (2017). Let's stop trying to be "sexy"-preparing managers for the (big) data- driven business era. Business Process Management Journal, 23(3), 598-622.

2. rovost, F., & Fawcett, T. (2013). Data science and its relationship to big data and data-driven decision making. Big data, 1(1), 51-59.

3. Arunachalam, D., Kumar, N., & Kawalek, J. P. (2018). Understanding big data analytics capabilities in supply chain management: Unravelling the issues, challenges and implications for practice. Transportation Research Part E: Logistics and Transportation Review, 114, 416-436.

4. Long, Q. (2018). Data-driven decision making for supply chain networks with agent-based computational experiment. Knowledge-Based Systems, 141, 55-66.

5. Vidgen, R., Shaw, S., & Grant, D. B. (2017). Management challenges in creating value from business analytics. European Journal of Operational Research, 261(2), 626-639.

6. Sharma, R., Mithas, S., & Kankanhalli, A. (2014). Transforming decision-making processes: a research agenda for understanding the impact of business analytics on organisations. European Journal of Information Systems, 23(4), 433-441.

7. Cao, G., & Duan, Y. (2017). How do top-and bottom-performing companies differ in using business analytics? Journal of Enterprise Information Management, 30(6), 874-892.

8. Riikkinen, M., Saarij rvi, H., Sarlin, P., & L hteenm ki, I. (2018). sing artificial intelligence to create value in insurance. International Journal of Bank Marketing, 36(6), 1145-1168.

9. Bumblauskas, D., Nold, H., Bumblauskas, P., & Igou, A. (2017). Big data analytics: transf orming data to action. Business Process Management Journal, 23(3), 703-720.

10. Io, H. N., & Lee, C. B. (2017). Chatbots and conversational agents: A bibliometric analysis. Proceedings of IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Singapore, pp. 215-219.

11. Amato, F., Marrone, S., Moscato, V., Piantadosi, G., Picariello, A., & Sansone, C. (2017). Chatbots Meet eHealth: Automatizing Healthcare. Proceedingsof Workshop on Artificial Intelligence with Application in Health pp. 1-10.

12. McTear, M. (2018). Conversational Modelling for Chatbots: Current Approaches and Future Directions. In Proceedings of the 29th Conference on Electronic Speech Signal.

13. Zumstein, D., & Hundertmark, S. (2017). Chatbots-an interactive technology for personalized communication, transactions and services. IADIS International Journal on WWW/Internet, 15(1), 96-109.

14. Ravi, V., & Kamaruddin, S. (2017). Big Data Analytics Enabled Smart Financial Services: Opportunities and Challenges. Proceedings of International Conference on Big Data Analytics, pp 15-39.

15. Kar, R., & Haldar, R. (2016). Applying chatbots to the internet of things: Opportunities and architectural elements. International Journal of Advanced Computer Science and Applications 7(11), 2016.

16. Ramesh, K., Ravishankaran, S., Joshi, A., & Chandrasekaran, K. (2017). A survey of design techniques for conversational agents. Proceedings of International Conference on Information, Communication and Computing Technology, pp 336-350.

17. Hussain, S., & Athula, G. E. (2018). A conventional chatbot knowledge base to external knowledge source and introducing user based sessions for diabetes education. Proceedings of 32nd International Conference on Advanced Information Networking and Applications Workshops (WAINA), pp 698-703.

18. D'Aniello, G., Gaeta, A., Gaeta, M., & Tomasiello, S. (2016). Self-regulated learning with approximate reasoning and situation awareness. Journal of Ambient Intelligence and Humanized Computing, 9, 1-14.

19. Su, M. H., Wu, C. H., Huang, K. Y., Hong, Q. B., & Wang H. M. (2017). Chatbot using LSTM based multi-layer embedding for elderly care. Proceedings of the 2017 International Conference on Orange Technologies, ICOT, pp 70-74.

20. LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. MIT sloan management review, 52(2), 21.

21. Motamarri,S.,Akter,S.,&zanamandram,V.(2017).Doesbigdataanalyticsinfluence frontline employees in services marketing?. Business Process Management Journal, 23(3), 623-644.

22. McAfee, A., Brynjolfsson, E., Davenport, T. H., Patil, D. J., & Barton, D. (2012). Big data: the management revolution. Harvard business review, 90(10), 60-68.

23. Miller, H. G., & Mork, P. (2013). From data to decisions: a value chain for big data. It Professional, 15(1), 57-59.

24. Sacha, D., Stoffel, A., Stoffel, F., Kwon, B. C., Ellis, G., & Keim, D. A. (2014). Knowledge generation model for visual analytics. IEEE transactions on visualization and computer graphics, 20(12), 1604-1613.

25. Sacha, D., Sedlmair, M., Zhang, L., Lee, J. A., Peltonen, J., Weiskopf, D., & Keim, D. A. (2017). What you see is what you can change: Human-centered machine learning by interactive visualization. Neurocomputing, 268, 164-175.

26. Bendle, N. T., & Wang, X. S. (2016). Uncovering the message from the mess of big data. Business Horizons, 59(1), 115-124

27. Amado, A., Cortez, P., Rita, P., & Moro, S. (2018). Research trends on Big Data in Marketing: A text mining and topic modeling based literature analysis. European Research on Management and Business Economics, 24(1), 1-7. .

28. Nadali, A., Kakhky, E. N., & Nosratabadi, H. E. (2011). Evaluating the success level of data mining projects based on CRISP-DM methodology by a Fuzzy expert system. Proceedings of 2011 3rd International Conference on Electronics Computer Technology, pp. 161-165.

29. Reshmi, S., & Balakrishnan, K. (2016). Implementation of an inquisitive chatbot for database supported knowledge bases. sādhanā, 41, 1173-1178.

FINANCING

State the source of financing; otherwise state “Arab Open University.

CONFLICT OF INTEREST

Authors declare that there is no conflict of interest.

AUTHORSHIP CONTRIBUTION

Conceptualization: Evan Asfoura.
Data curation: Gamal Kassem.
Formal analysis: Gamal Kassem.
Research: Evan Asfoura.
Methodology: Evan Asfoura.
Project management: Gamal Kassem.
Resources: Gamal Kassem Software: Gamal Kassem.
Supervision: Gamal Kassem.
Validation: Evan Asfoura.
Display: Evan Asfoura.
Drafting - original draft: Evan Asfoura.
Writing - proofreading and editing: Evan Asfoura.