AI Adoption Phases in Business Intelligence: From Outsourcing to Human-Centered Systems

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***Abstract*—The integration of Artificial Intelligence (AI) into Business Intelligence (BI) is vital as it enables businesses to process vast amounts of information quickly and uncover patterns and trends that might otherwise go unnoticed. In this short paper, we propose a five-phase AI adoption in the context of BI drawing from our experience with numerous SMEs in Singapore and internationally. This progression begins with AI for BI 1.0, where businesses rely on outsourced AI services, offering accessible but limited AI capabilities. As organizations seek greater control, AI for BI 2.0 emerges, emphasizing in-house AI development with a focus on interpretability, making AI models more understandable to users. AI for BI 3.0 advances this by adding explainability, clarifying the decision-making processes of AI systems. The transition to AI for BI 4.0 introduces trust as a crucial factor, ensuring AI models are not only useful and robust but also faithful to the data they analyze. Finally, AI for BI 5.0, integrates human-centered design, enhancing decision-making through continuous feedback and adaptation. This phased evolution reflects the growing demands for transparency, trust, and collaboration in AI-driven BI, ultimately transforming AI from a tool into a trusted partner in business strategy.**

***Index Terms*—AI Adoption, Business Intelligence**

I. Introduction

By incorporating predictive analytics, Artificial Intelligence (AI) empowers Business Intelligence (BI) to forecast future trends and behaviors, helping organizations make proactive, data-driven decisions [1], [17], [21]. AI also facilitates real-time insights, which are critical for industries where timely decisions can have a substantial impact [2], [3], [20]. Automation of routine tasks like data cleansing and reporting is another advantage, reducing human error and allowing employees to focus on strategic objectives. With natural language processing (NLP), AI makes BI more accessible by enabling users to interact with data through conversational interfaces. This democratizes data-driven decision-making and ensures that insights are available to non-technical users [5], [19], [23].

AI enhances BI dashboards by providing personalized recommendations tailored to individual roles and objectives, optimizing decision-making and fostering evidence-based strategies [4], [10], [12], [15]. Businesses leveraging AI-powered BI gain a competitive edge by responding more effectively to market trends, achieving cost efficiencies through resource optimization, and scaling operations to meet evolving demands. Ultimately, AI transforms BI into a more powerful, adaptable, and strategic tool for modern organizations [6], [13], [16], [22].

Since 2016, SenticNet[1] has been offering Business-to-Business (B2B) sentiment analysis services, catering to companies engaged in market research. These services leverage advanced AI and NLP techniques to help organizations gain deeper insights into customer opinions, preferences, and market trends. By analyzing large volumes of textual data from diverse sources, SenticNet enables businesses to make data-driven decisions, enhance customer engagement, and refine their marketing strategies for better outcomes.

Through our interactions with various SMEs seeking to adopt AI, we developed a comprehensive five-phase AI adoption framework. This framework is designed to serve as a practical guide not only for small and medium-sized enterprises but also for research teams outside the field of computer science. It aims to help these organizations navigate the complexities of AI adoption, offering clear steps and strategies to overcome common challenges. By simplifying the process and making AI adoption more accessible, the framework empowers diverse teams to leverage AI effectively, enhancing their decision-making, efficiency, and innovation potential.

Each phase of AI adoption in BI–ranging from initial outsourcing to the development of sophisticated, interactive, in-house systems–represents a progressive integration of AI capabilities within an organization. This journey reflects a shift toward greater autonomy and control over AI tools, as well as an emphasis on building systems that are more transparent, trustworthy, and user-centric. This evolution is not merely a technological advancement but also a response to the changing expectations and demands of businesses. As organizations increasingly aim to maximize the value of AI, they seek solutions that can seamlessly align with their strategic objectives, foster collaboration, and build confidence among stakeholders.

Understanding these phases offers crucial insights into how businesses can effectively navigate their AI journey, balancing technical innovation with practical implementation. By refining their AI adoption, companies can unlock the full potential of their data, enhance decision-making processes, and gain a significant competitive advantage in a rapidly evolving marketplace. This phased approach ensures a structured pathway to leveraging AI as a transformative tool for BI.

[1]https://business.sentic.net

II. AI for BI 1.0 (AIS)

The first phase of Artificial Intelligence adoption in Business Intelligence, known as AI for BI 1.0, is characterized by reliance on outsourced AI services. During this period, many organizations start their AI journey by utilizing third-party platforms that offer AI capabilities as a service (AIS or AIaaS). These platforms provide businesses with pre-built AI models that integrate easily into their existing BI systems. The appeal of AIaaS lies in its accessibility: companies without in-house AI expertise can leverage AI's powerful data processing and analytical capabilities without needing to invest in building and maintaining their own AI infrastructure.

These AIaaS solutions are typically no-code or low-code, allowing users to deploy AI models without writing any code or with minimal coding requirements. This democratization of AI enables a wide range of organizations, from small businesses to large enterprises, to access AI-driven insights. However, the trade-off for this convenience is a lack of customization and flexibility. Since the AI models are pre-built by external vendors, businesses have limited ability to modify them to fit their specific needs. Additionally, reliance on outsourced AI means that organizations depend on these vendors for updates, maintenance, and support, which can limit their agility and responsiveness.

Despite these limitations, AI for BI 1.0 plays a crucial role in introducing AI to the business world. It allows organizations to experiment with AI and understand its potential without significant upfront investment or risk. As businesses become more familiar with AI and its capabilities, they seek greater control over their AI systems, leading to the next phase of AI adoption [11].

III. AI for BI 2.0 (IAI)

The second phase, AI for BI 2.0, marks a significant shift from reliance on outsourced AI services to developing in-house AI capabilities. This transition is driven by the desire for greater control, customization, and flexibility in applying AI within BI systems. By bringing AI development in-house, organizations can tailor AI models to better suit their specific business needs and objectives. This phase also introduces a critical focus on interpretability, which becomes increasingly important as businesses use AI for more complex and high-stakes decision-making processes [26].

Interpretability refers to how well the workings of an AI model can be understood by humans, particularly those without technical expertise [18]. In the context of BI, interpretability is crucial because it allows business leaders to trust and rely on AI-generated insights. Without interpretability, AI models often function as "black boxes" that produce results without clear explanations, leading to skepticism and reluctance to fully embrace AI-driven decisions [7]. In AI for BI 2.0, significant efforts are made to design AI models that are more transparent, enabling users to understand the factors influencing the AI's outputs. This phase also sees an increase in the internal expertise required to manage AI systems.

Organizations invest in building teams of data scientists, AI engineers, and other technical professionals capable of developing, maintaining, and refining AI models. This internal expertise allows businesses to create more sophisticated AI solutions that are closely aligned with their strategic objectives. Furthermore, having in-house AI capabilities enables organizations to respond more quickly to changes in the market or business environment, as they are no longer dependent on external vendors for updates or modifications. AI for BI 2.0 represents a significant step forward in the evolution of AI adoption in BI. By developing in-house AI capabilities and emphasizing interpretability, businesses gain greater control over their AI systems, leading to more customized and trusted AI-driven insights.

IV. AI for BI 3.0 (XAI)

As organizations continue to develop their in-house AI capabilities, the next logical progression is the addition of explainability, marking the transition to AI for BI 3.0. While interpretability in the previous phase focuses on making AI models more understandable, explainability goes a step further by clarifying why an AI model makes specific decisions [9]. This phase is driven by the increasing need for transparency, accountability, and trust in AI systems, especially as these systems begin to play a central role in critical business processes [27]. Explainability is essential because it allows business users not only to understand the outputs of an AI model but also to gain insights into the underlying decision-making process [14]. For instance, if an AI model predicts a drop in sales, explainability involves the model identifying the key factors that lead to this prediction, such as changes in consumer behavior, market trends, or internal company data. This level of insight is invaluable for decision-makers, as it provides a clear rationale for the AI's recommendations and enables them to make more informed choices.

The push for explainability in AI for BI 3.0 is also driven by regulatory requirements and ethical considerations. As AI systems become more prevalent in sectors like finance, healthcare, and human resources, regulators demand greater transparency regarding how these systems operate, particularly when they are used to make decisions with significant impacts on people's lives. Explainable AI (XAI) thus becomes a crucial component of compliance efforts, helping organizations demonstrate that their AI models are not only effective but also fair and unbiased [8]. In addition to regulatory compliance, explainability enhances user trust and confidence in AI-driven insights. When business leaders understand why an AI model makes certain predictions, they are more likely to trust and act on those insights. This trust is critical for the successful adoption of AI in BI, ensuring that AI is seen as a valuable tool rather than a mysterious system. AI for BI 3.0 represents a maturation of AI adoption, shifting the focus from merely understanding AI models to fully explaining their decisions. This phase lays the groundwork for more sophisticated AI systems that can be integrated more deeply into business processes, setting the stage for the next phase of AI evolution.

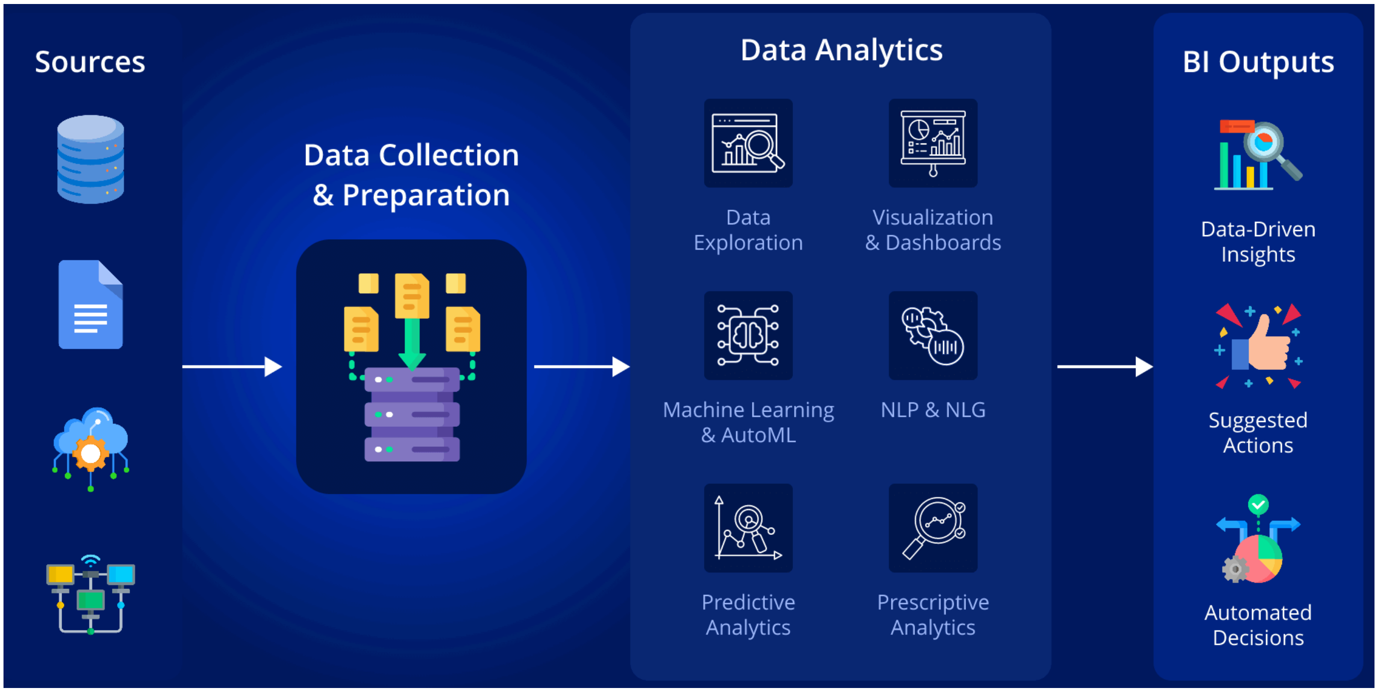

Fig. 1. An example of AI for BI pipeline by LeewayHertz, an AI Development Company (https://leewayhertz.com/ai-for-business-intelligence).

V. AI FOR BI 4.0 (TAI)

The fourth phase of AI adoption in BI, known as AI for BI 4.0, focuses on building trust in AI systems. As AI becomes more integral to business decision-making, it is no longer sufficient for AI models to be merely interpretable and explainable; they also need to earn user trust. Trust in AI is anchored on three core pillars: utility, robustness, and faithfulness [25]. These elements combine to develop AI systems that are not only effective in delivering actionable insights but also reliable in performance, ensuring consistent results.

Utility, the first pillar of trust in AI, refers to the practical value of the explanations provided by the AI model. In the context of BI, this means that the AI system should offer clear, relevant, and actionable explanations for its decisions and predictions. These explanations must be directly aligned with the business needs, allowing users to understand not only the outcome but also the rationale behind it. For example, in forecasting market trends, the AI should explain which factors influenced its predictions and how they relate to BI goals.

Robustness, the second pillar, focuses on the reliability of the explanations provided by an AI model across different scenarios or multiple iterations (e.g., asking the system why a specific decision was taken multiple times). A robust explanation should remain clear, accurate, and consistent, even when faced with fluctuations in data quality or unexpected changes in business conditions. For example, in BI, a robust explanation should not only account for typical trends but also adapt to anomalies or new data patterns without becoming misleading or ambiguous.

Faithfulness, the third pillar, refers to how well an AI model aligns with the data it is trained on and the real-world phenomena it represents. A faithful AI model accurately reflects the underlying data and is free from significant biases or errors. In BI, this means the AI model's predictions and recommendations should be closely aligned with the actual business environment and not distorted by irrelevant or misleading factors. Faithfulness is crucial for trust because it ensures that the AI system's outputs are grounded in reality and can be relied upon for informed decision-making.

In AI for BI 4.0, the emphasis on trust is critical as organizations increasingly depend on AI for high-stakes decisions. By focusing on utility, robustness, and faithfulness, businesses ensure their AI systems are not only effective and understandable but also trusted partners in the decision-making process. This phase marks a deeper integration of AI into business operations, where AI is seen as a reliable and essential tool for achieving strategic goals.

VI. AI FOR BI 5.0 (HAI)

The final phase of AI adoption in BI, AI for BI 5.0, introduces the concept of human-centered AI, which emphasizes the importance of interactivity between AI systems and their human users [24]. This phase represents the pinnacle of AI integration in BI, where AI is not only trusted and explainable but also interactive and responsive to human input. The focus of AI for BI 5.0 is on creating systems that work collaboratively with humans, enhancing decision-making processes through continuous feedback, adaptation, and engagement. Human-centered AI is designed with the user in mind, prioritizing usability, intuitiveness, and interactivity.

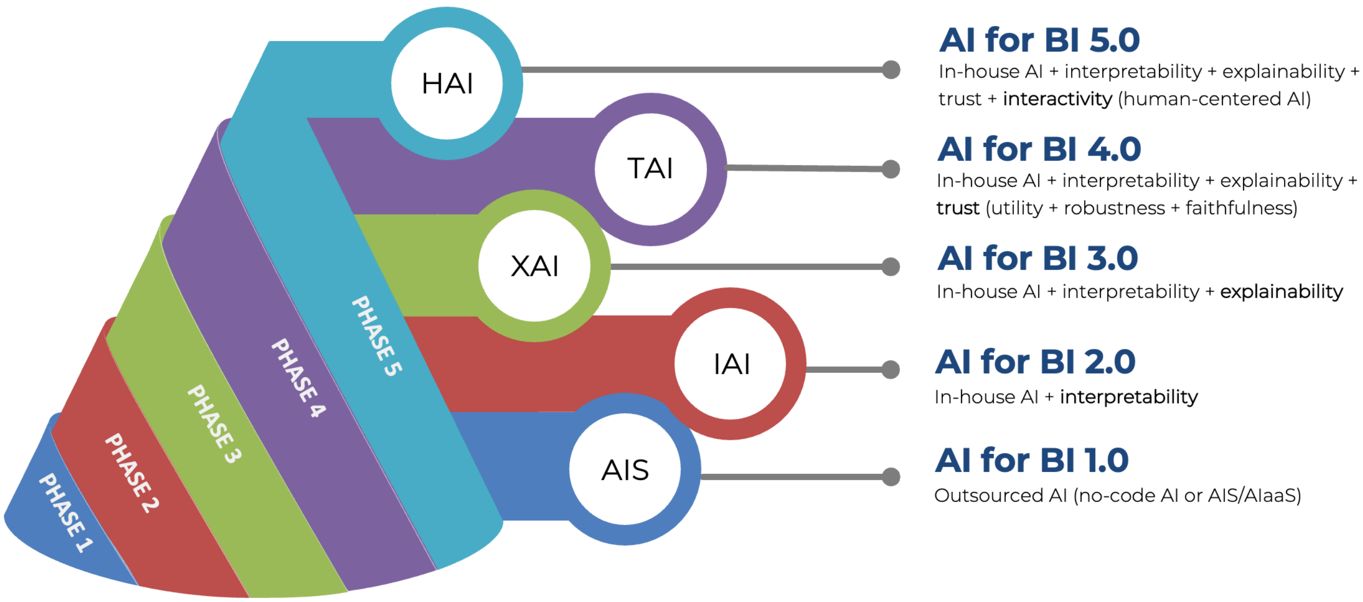

Fig. 2. Overview of the proposed five-phase AI adoption framework for Business Intelligence.

In the context of BI, this means that AI systems are not just tools that produce static outputs but are dynamic partners that interact with users in real-time. For example, an AI model in a human-centered BI system might present a range of potential outcomes based on different scenarios and allow the user to explore these scenarios interactively. The system could then refine its recommendations based on the user's feedback, creating a more personalized and relevant decision-making process.

Interactivity in AI for BI 5.0 goes beyond simple user interfaces; it involves creating AI systems that are adaptable and capable of learning from human input. This continuous learning process allows AI models to evolve with the business, responding to changes in strategy, market conditions, and user preferences. As a result, AI becomes more aligned with the needs of the organization, providing insights that are not only accurate but also contextually relevant.

The shift towards human-centered AI reflects a broader trend in technology towards more user-centric design. As AI systems become more complex and powerful, there is a growing recognition that their success depends not just on their technical capabilities but also on how well they integrate with human workflows and decision-making processes. AI for BI 5.0 embodies this approach, creating AI systems that are not only trusted and explainable but also collaborative and responsive to the unique needs of each user.

This final phase of AI adoption in BI represents the ultimate goal of AI integration: a seamless partnership between humans and AI that enhances decision-making, drives innovation, and supports the strategic objectives of the organization. By focusing on interactivity and human-centered design, AI for BI 5.0 ensures that AI is not just a tool but a true partner in the business intelligence process.

VII. Conclusion

In the age of the "AI or Die" mindset, businesses face the complex challenge of adopting AI, which goes beyond technical and financial concerns. A significant hurdle is the need for organizational change, e.g., retraining and upskilling staff. As AI transforms workflows, employees must adapt to new technologies and roles, requiring investment in training and development. Businesses must also address resistance to change and ensure that employees are equipped to work alongside AI tools. To this end, we proposed a five-phase framework designed to serve as a practical guide for small and medium-sized enterprises. From the initial phase of outsourced AI services to the development of sophisticated, human-centered AI systems, each stage of AI adoption brings new capabilities and opportunities for businesses. As AI matures, so too do the expectations and demands placed on these systems. Businesses must transition from relying on external vendors for basic AI functionality to developing in-house systems that are not only interpretable and explainable but also trustable and interactive.

As organizations increasingly adopt and refine AI for BI, the focus is shifting towards developing systems that do more than just deliver valuable insights. Rather than merely serving as tools for analysis, future AI systems are expected to work in tandem with human users, offering not only insights but also intuitive interactions that enhance the decision-making process. By understanding and embracing the various phases of AI adoption, businesses can unlock the full potential of AI, driving innovation, improving operational efficiency, and achieving a significant competitive advantage. As the business landscape continues to evolve, organizations that successfully integrate AI into their BI strategies will be better positioned to navigate challenges, capitalize on new opportunities, and stay ahead in an increasingly data-centric world.

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