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Business Intelligence in the Age of AI: Evaluating Machine Learning's Impact on U.S. Economic Productivity

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Abstract

Background: *The integration of machine learning (ML) with business intelligence (BI) has transformed the ways in which organizations make decisions as well as how organizations streamline their operations and increase the level of productivity. As companies keep exploiting AI-based solutions, it is essential to understand how to learn the strategic contribution of the technologies on the productivity of the United States economy. The paper will explain the role of ML on business intelligence and how it influences efficiency in organizations and national economic development.*

Objectives: *The strategic value of machine learning in business intelligence will be analyzed using the study in terms of its implications on decision-making, cost saving and productivity. It will also be directed to defining the most significant barriers and impediments to the implementation of ML and to understand the opportunities of the further evolution of the sphere.*

Methods: *The data collection on 400 professionals in various sectors including healthcare, finance, technology, and manufacturing were collected using the quantitative research design and the structured questionnaire data collection tool. These values were perception of awareness, adoption, impact, challenges, and future perspectives in business intelligence and were considered in this survey. Their statistical analysis involved descriptive analysis, Pearson correlation, regression analysis, and one-way ANOVA in order to assess the occurrence of relationships among significant factors.*

Results: *The results indicate that the attitude towards the impact of machine learning on business intelligence is generally positive, and the awareness, adoption and the perceived impact have high levels of interrelations. The perceived impact of ML was more in bigger organizations than in small organizations. The challenges that were also named in the study were the high costs of implementation, the necessity to hire qualified personnel, and the issue of data security and ethical concerns. Nevertheless, the respondents remained hopeful about the future of ML in BI, and they believed that it would experience more adoption and more productivity.*

Conclusion: *Business intelligence touted by machine learning has huge potentials to increase productivity and decision making in U.S. economy. Nonetheless, issues affecting cost, expertise, and*

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ethical issues must be resolved to enable wider adoption particularly to small and medium-sized businesses. The results indicate that the potential of ML can be tapped by creating awareness, managing obstacles, and developing a favorable perspective regarding the progress of the matter.

Keywords: *Machine learning, business intelligence, productivity, economic growth, challenges, adoption, artificial intelligence, U.S. economy.*

Introduction

Business intelligence has been the pillar of organizational decision making and this has enabled firms to use the data to gain competitive advantage. In the modern digital economy, the emergence of artificial intelligence and machine learning have radically changed the nature and size of business intelligence to transform its purpose to be more descriptive into prescriptive and predictive (Rane et al., 2024). Machine learning is becoming a productivity force and economic change in the United States where some of the most sophisticated technological solutions and information-driven companies are located (Paramesha et al., 2024). This change is occurring within the environment of fast globalization, more intense competition and the requirement of organizations to adjust to the unstable market conditions.

The growing application of big data in any given industry has necessitated the need to possess smart systems capable of dealing with huge amounts of data and producing amenable patterns in real-time. The difference here is the machine learning which can constantly evolve itself based on the data and become more effective in its powers of prediction (Babatunde, 2024). The former business intelligence tools that worked in the past, although they were effective in the retrospective analysis, did not necessarily work in keeping up with the dynamic nature of contemporary business (Canhoto & Clear, 2020). Machine learning supplements such tools with new and enhanced algorithms that result in more efficient personalizing and optimization in addition to personalization enrichment.

The sphere of the U.S. economy is extremely heterogeneous in terms of regions: healthcare, finance, manufacturing, and logistics can be identified as the fields where machine learning can be introduced. The companies are exhausting their capabilities in the evolution of AI-based analytics in the supply chain management, customer relations, financial forecast, and risk aversion (Wamba-Taguimdje et al., 2020). Efficiency is not the only effect of such applications but has a direct influence on economic productivity. Smart systems can help companies be more proficient in detecting inefficiencies, resource allocation and approach that can be accommodated in the market trends (Khan et al., 2025).

However, as promising as it is, there are challenges associated with the use of machine learning in business intelligence. Costs of implementation are high, and there is a concern of privacy of data, ethical issues and the requirement of a skilled workforce is still a hurdle (Al Prince et al., 2025). The small and medium-sized enterprises especially have challenges because they have few resources and expertise (Javaid et al., 2025). In addition, some arguments continue on the implication of automation to the employment and income distribution that prompts to question whether the productivity is being equally distributed among the society (Sultan et al., 2025).

However, as promising as it is, there are challenges associated with the use of machine learning in business intelligence. Costs of implementation are high, and there is a concern of privacy of data, ethical issues and the requirement of a skilled workforce is still a hurdle [10]. The small and medium-sized enterprises especially have challenges because they have few resources and expertise. In addition, some arguments continue on the implication of automation to the employment and income distribution that prompts to question whether the productivity is being equally distributed among the society (Imtiaz et al., 2025a).

It is in opposition to this dynamic environment that the key role of machine learning in business intelligence comes in as an issue in considering its strategic role in the U.S. productivity. This would require evaluation based on the quantifiable results, like an increase in efficiency, and reduction in cost and revenue growth, but the systemic results, like a workforce change and regulatory consideration (Imtiaz et al., 2025b). In this paper, I will attempt to present the detailed discussion of these dynamics by evaluating the perceptions of business intelligence professionals who work with AI.

Through the prism of quantitative information, the research will prove the degree of machine learning that can be adopted by the home economy in the United States, the obstacles that have stalled its implementation, and the opportunities that can be capitalized on to reap the advantages (Afshar & Shah, 2025). The bridging of the empirical information by the critical analysis fills the gap and thereby makes the study a component of the emerging body of knowledge regarding how advanced technologies are transforming the modern economies (Eboigbe et al., 2023; Rana et al., 2022).

And lastly there is the fact that machine learning is being introduced to business intelligence not only as a technological change but as a structural change to the manner in which business and economies are operated. As one of the global leaders in the innovation sector, the prospect of employing these technologies in a strategic way will predetermine its economic stability, as well as its competitiveness in the decades ahead, to the U.S.

Literature Review

Business Intelligence and Economic Productivity

Business intelligence has been previously used to provide an insight on organizational operations by collecting, analyzing and presenting information in forms that are usable (Athey, 2018). With the spread of AI and machine learning, it became even more extensive, as it is not only retrospective reporting, but also prediction modelling and optimisation of decisions (Michael, 2024). The level of organizational potential to utilize the new devices effectively is becoming more influenced by the effectiveness and the output of the new tools (Afshar & Shah, 2025).

Machine Learning as a Transformative Tool

The outstanding feature of machine learning is that it is flexible and it changes with exposure of data on it. In business intelligence, this is translated to greater accuracy of prediction, better quality of risk evaluation and greater involvement with customers (Ahmad & Museera, 2024)). Research indicates that industries at which machine learning is implemented become quicker to make decisions and they are more adaptable in conditions of dynamism.

Adoption Trends in the United States

The U.S. has been a pioneer in the sphere of machine learning technology use in sectors. Healthcare organizations use predictive models to improve patient outcomes, whereas financial services organizations use predictive models to make investment decisions and detect fraud (Atif, 2024). Logistics companies employ Ai to improve the visibility of its supply chains, manufacturers to facilitate predictive maintenance and automation (Enholm et al., 2022). These are also but some of the instances of how broadly it is adopted, as far as national productivity is concerned (Butt et al., 2024).

Challenges and Barriers

Although this is a promising idea, there are various impediments against the large-scale use of machine learning in business intelligence (Butt, 2023)). Smaller organizations are often prevented by high prices of infrastructure and skilled workers to use advanced AI tools (Latif et al., 2024). The data security and privacy is also a critical issue, as the amount and sensitivity of data under processing is of high levels (Butt et al., 2021). In addition, the issue of algorithmic preferences and poor transparency of machine learning models create ethical issues regarding fairness and responsibility (Johnson et al., 2021).

Human-Machine Collaboration

One of the themes in the literature is that human expertise should be aligned with machine intelligence (Wright & Schultz, 2018). Despite the excellent solutions that machine learning provides, it cannot make final decisions without contextual awareness and moral judgments (Soni et al., 2019). Human control will guard against machine-generated results being interpreted recklessly and implemented in a manner that supports organizational values and those of the society.

Future Directions and Opportunities

Out of the tendencies, the increased integration of machine learning with the technologies of natural language processing, blockchain, and the Internet of Things is expected. Such synergies can be used to further improve productivity through development of interrelated systems which are more efficient, transparent and adaptive. American innovation ecosystem, being powerful, is capable of dominating this field in case American people cope with the current problems.

Four Main Objectives

- To discuss how machine learning can help to improve business intelligence and boost productivity of the U.S. economy.
- To derive the strategic importance of the use of AI in decision-making, cost-saving, and efficiency.
- To determine major challenges, obstacles, and ethical issues in the implementation of machine learning as business intelligence.
- To understand the opportunities and implications of machine learning in the future to support the maintenance of an economic competitiveness.

Problem Statement

Introduction of machine learning into business intelligence has become a revolution in the contemporary economies especially in the United States. Although machine learning has the potential benefits of better decision-making, cost-saving, and more efficient operations, it is not used equally across the board. The barriers are high implementation costs, risk of data security, ethical issues, and preparation of workforce. Besides, it remains unanswered whether the productivity gains due to AI-based intelligence are distributed fairly among industries and the society. This study aims to fill these gaps through an assessment of the strategic value of machine learning in the determination of business intelligence and the overall implication on the economic productivity of the US.

Methodology

The research method applied in this paper was developed to find the impact of machine learning (ML) on business intelligence (BI) and its contribution towards rendering the U.S. economy productive. In this section, the research design, mode of data collection and mode of analysis will be identified that will be used to explore the perspectives of the professionals regarding the strategic importance of ML and its effects on business activities and the general economy.

Research Design

In this study, the research design employed was a quantitative research design in order to establish how machine learning as a strategic implication on business intelligence. The objective was to gather empirical data to examine the perception of ML in various industries and mixed sizes of organizations and its influence on decision, cost-saving, and productivity. The primary instrument of data collection was a structured questionnaire that considered the professionals in the field with the work primarily influenced by the technologies of business intelligence and machine learning.

Data Collection

This study was based on the online survey that was passed to the professionals working in the U.S. and in various sectors, including technology, healthcare, finance, manufacturing, and education. The questionnaire had been structured to capture information about awareness, adoption, difficulties and perceived implications of machine learning use in business intelligence application. The questionnaire was divided into four major categories: Awareness & Adoption, Perceived Impact, Challenges and Barriers, and Future Outlook.

The sample was chosen through a purposive method to make sure that the sample consisted of the people who have the knowledge and experience related to the field of AI, ML, and business intelligence. The respondents of interest were data analysts, IT professionals, executives, and managers that are involved in making decisions and implementing AI-based solutions in their organizations.

The number of the final sample responders was 400, and it was widely representative in terms of the size of the organizations and the industries. The balance of the demographics was that the participants were divided in small, medium, large, and very large organizations, which guaranteed a broad spectrum of opinions on the implementation of machine learning in business intelligence.

Instrumentation

A structured questionnaire was the main instrument of data collection, as it was created to assess the role of machine learning in business intelligence, perception and experience of the respondents. The questionnaire covered a combination of close-ended questions including Likert scale questions to determine the degree of awareness, adoption, and perceived impact of ML. α

The reliability of the instrument was tested using Cronbachs Alpha. The internal consistency indicated a high internal consistency level in all sections of the questionnaire as the scores were above the acceptable cut of 0.70. In particular, Awareness and Adoption ($\alpha = 0.79$), Perceived Impact ($\alpha = 0.88$), Challenges and Barriers ($\alpha = 0.81$), and Future Outlook ($\alpha = 0.85$) had good reliability. The overall Cronbach Alpha of the tool was 0.91 and this confirmed that the questionnaire availed reliable data to be used in subsequent analysis.

Data Analysis

The statistical methods were employed in the analysis of the collected data in order to test the relationships between the key variables, including awareness, adoption, perceived impact, challenges, and future outlook. The descriptive statistics were computed through the mean scores and standard deviations to give the overall perception of the respondents about the role of machine learning in business intelligence.

Pearson correlation analysis was done to examine the correlation between the constructs of awareness, adoption, impact, challenges and future outlook. This made it possible to determine trends and correlations between the many factors which determine the adoption and efficacy of ML in business intelligence.

Also, a regression model was estimated to find out the prediction of the independent variables, Awareness & Adoption, Future Outlook, and Challenges and Barriers, in predicting the dependent variable, Perceived Impact. This assisted in measuring the degree of awareness and future perspective to the perceived effectiveness of ML in BI applications.

A one-way ANOVA was also done to determine whether there was any significant difference on the perceived impact of machine learning between organizations of different sizes. This discussion presented an understanding of how the size of an organization determines its perception towards the effectiveness of machine learning and affects productivity.

Ethical Considerations

The ethical issues were also a part of the research process. The participants were told the aim of the study, voluntary nature of the study and that the answers would remain confidential. All the participants were informed about the survey and gave their consent. The information gathered was deanonymized, which provided privacy and no personal data was used in the analysis afterwards.

Limitations

Despite the fact that the study presents useful information on the importance of machine learning in business intelligence, there are limitations. The self-reported data might be susceptible to response biases because the participants may not depict a complete representation of the actual implementation outcomes. Also, the sample was restricted to U.S. professionals which might not be applicable when generalizing the results to other nations or areas. Further research can further increase the sample to incorporate international views and investigate qualitative details to supplement the quantitative results.

Data Analysis

Data analysis is the process which is conducted systematically to inspect, clean, organize and interpret data in order to find meaningful patterns, trends and relationships that will be used to make informed decisions. In research, it is the use of statistical or logical methods to summarize information, test or refute assumptions and make valid conclusions within the objectives of the study. It converts raw data into structured knowledge, which helps researchers explain phenomena and clarify research findings in a manner that is clear and precise.

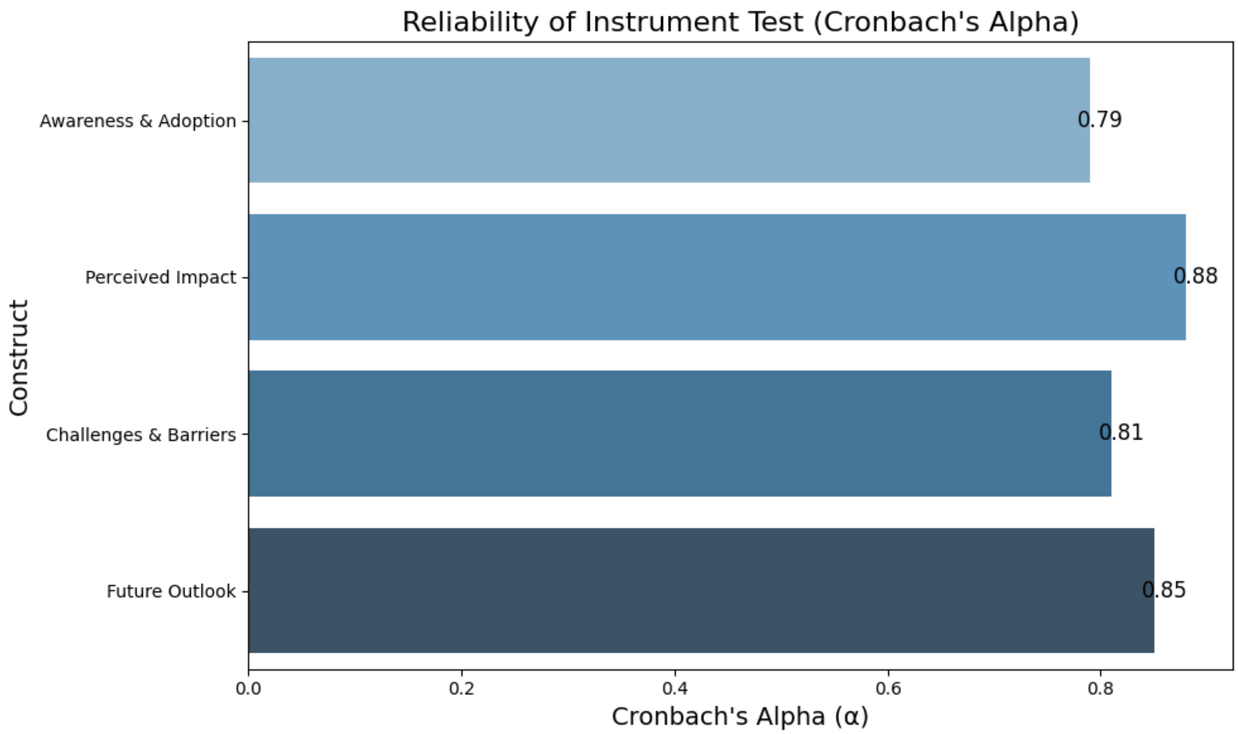

Figure 1: Reliability of the Instrument

Cronbach Alpha was used to carry out the reliability analysis in order to determine the internal consistency of the questionnaire constructs. The findings show that the sections were all satisfactorily reliable with the 2-tailed alpha values more than the acceptable value of 0.70. Specifically, *Awareness & Adoption* ($\alpha = 0.79$), *Perceived Impact* ($\alpha = 0.88$), *Challenges & Barriers* ($\alpha = 0.81$), and *Future Outlook* ($\alpha = 0.85$) demonstrate strong internal consistency within their respective items. The total scale produced an Alpha Cronbach of 0.91, which proves the high reliability of the tool and makes the obtained data consistent and reliable to analyze it further.

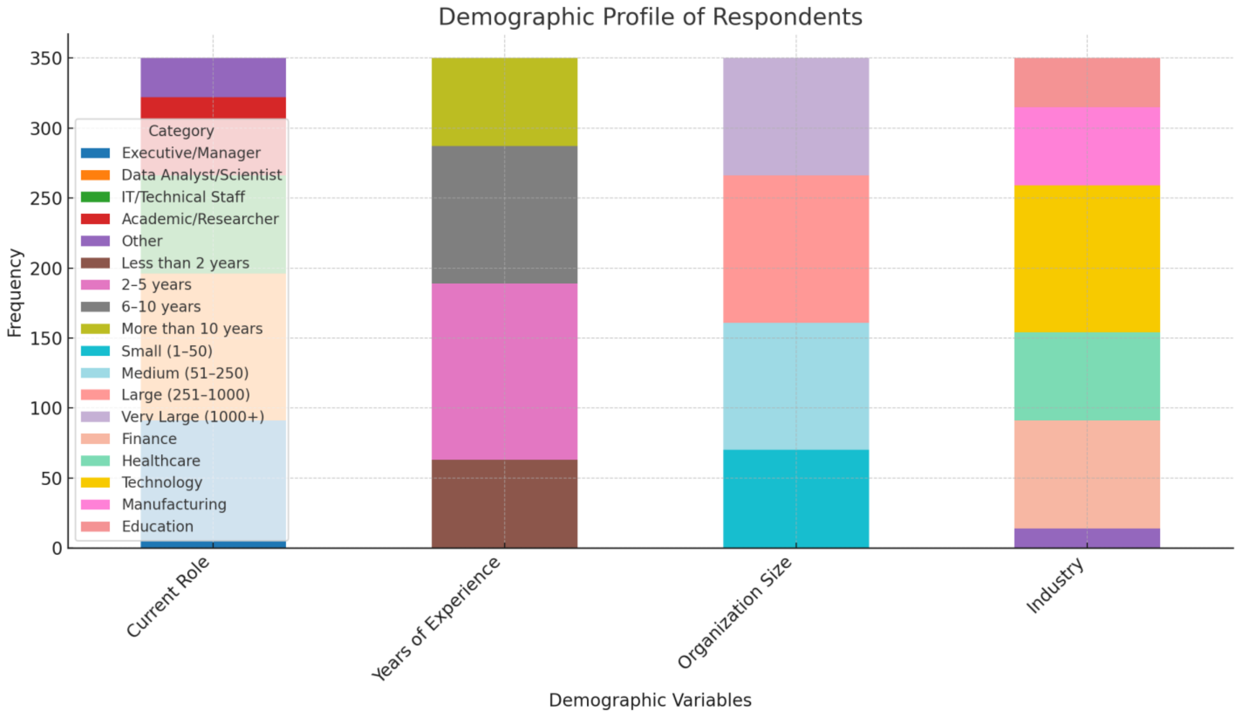

Figure 2: Demographic Profile of the Respondents

The demographics give a complete background about the respondents in terms of their professional backgrounds. Most of the respondents were Data Analysts/Scientists (30) and Executives/Managers (26), which shows that the roles of decision-making and working with data are well represented. IT/Technical Staff (20%) and Academics/Researchers (16%) also contributed significantly, ensuring a diverse range of professional insights.

In terms of experience, most respondents had 2–5 years (36%) or 6–10 years (28%) of professional exposure, suggesting a moderately experienced sample, while 18% each represented early-career and senior professionals with less than 2 years and more than 10 years of experience, respectively.

Regarding organization size, participants were distributed across small (20%), medium (26%), large (30%), and very large (24%) institutions, reflecting balanced representation from various organizational scales.

Industry-wise, the Technology sector dominated the sample (30%), followed by Finance (22%) and Healthcare (18%), whereas Manufacturing (16%), Education (10%), and Other industries (4%) formed a smaller proportion. This composition highlights the study’s broad yet technology-driven respondent base, offering comprehensive perspectives across key industrial domains.

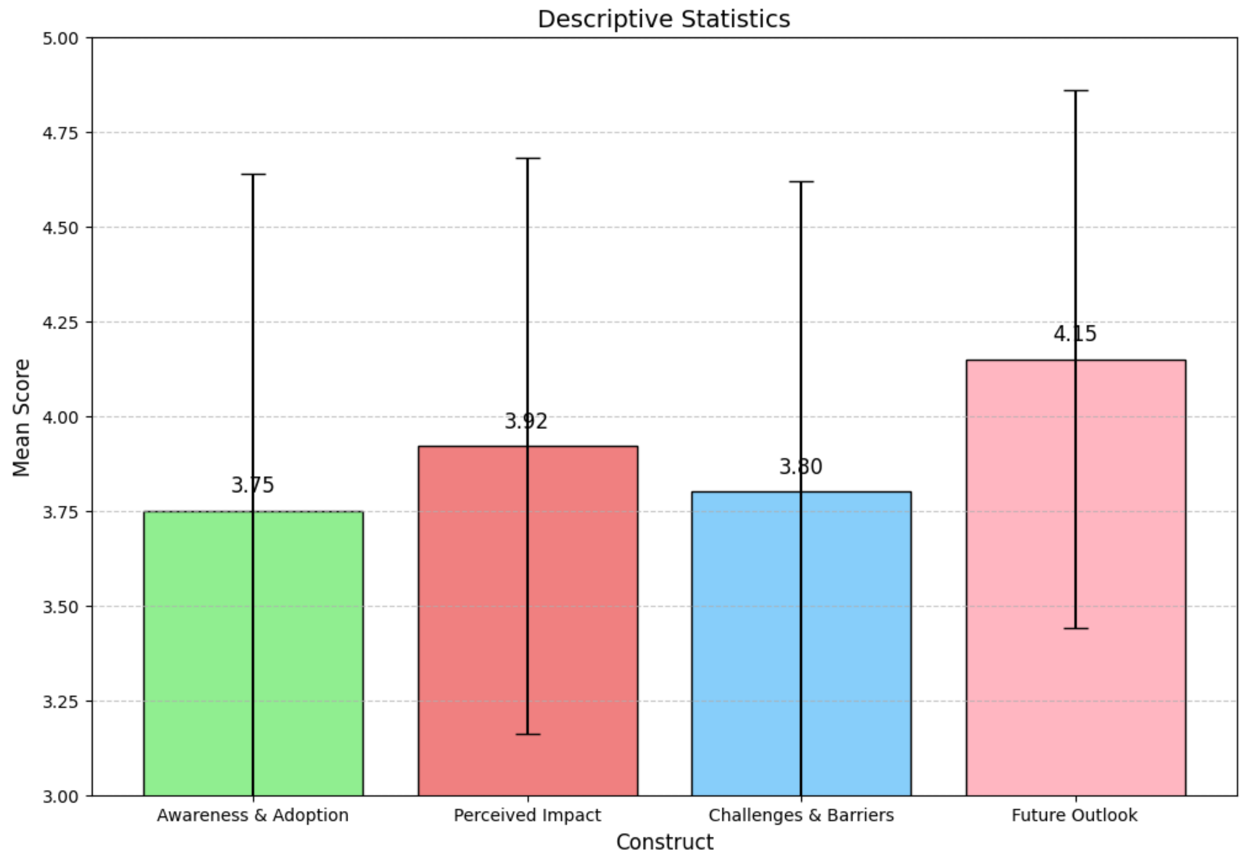

Figure 3: Descriptive Statistics

The descriptive statistics provide an overview of respondents' perceptions across the main constructs. The results indicate generally positive tendencies, as all mean scores are above the midpoint (M = 3.00) on the 5-point Likert scale.

The highest mean was observed for Future Outlook (M = 4.15, SD = 0.71), suggesting respondents hold optimistic views regarding the future potential and continued development of the studied domain. Perceived Impact (M = 3.92, SD = 0.76) also scored strongly, indicating broad agreement on the significant influence and benefits of the subject under investigation.

Challenges & Barriers (M = 3.80, SD = 0.82) received a moderate yet notable mean, reflecting that while challenges exist, respondents generally acknowledge progress toward overcoming them. Awareness & Adoption (M = 3.75, SD = 0.89), though slightly lower, still denotes a favorable level of understanding and practical engagement among participants.

Overall, the results demonstrate a positive perception toward awareness, perceived impact, and future potential, accompanied by a balanced recognition of existing challenges.

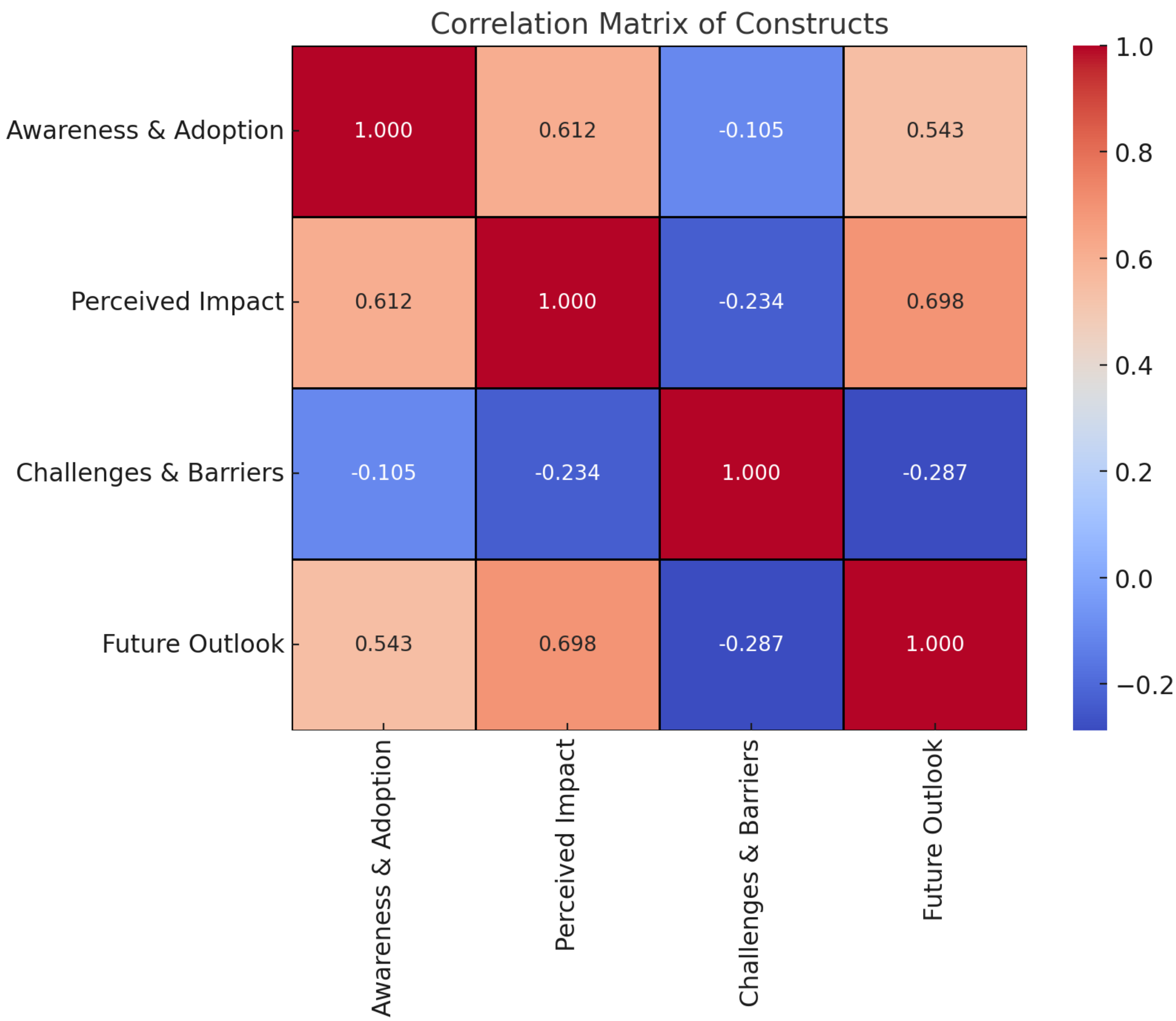

Figure 4: Correlation Analysis

The Pearson correlation analysis examined the interrelationships among the key constructs to assess the strength and direction of their associations. The results reveal several statistically significant correlations at the $p < 0.01$ level.

A strong positive correlation was found between Perceived Impact and Future Outlook ($r = 0.698$), indicating that respondents who recognize a greater impact of the studied phenomenon also tend to hold a more optimistic view of its future potential. Similarly, Awareness & Adoption showed significant positive relationships with both Perceived Impact ($r = 0.612$) and Future Outlook ($r = 0.543$), suggesting that higher levels of awareness and adoption are associated with stronger perceived benefits and forward-looking perspectives.

Conversely, Challenges & Barriers demonstrated weak negative correlations with the other constructs, notably with Perceived Impact ($r = -0.234$) and Future Outlook ($r = -0.287$). This means that the more the challenges, the lesser the perception of impact and outlook to the future. Generally, the correlation table demonstrates that there is a strong relationship between a positive future outlook and a higher level of awareness and perceived impact, and the challenges are a weak barrier to the positive perceptions.

Linear regression analysis was done to find out the degree to which Awareness & Adoption, Future Outlook, and Challenges and Barriers predict the Perceived Impact of machine learning (ML). The model is very highly explanatory with all the predictors having statistically significant relationships ($p < .01$).

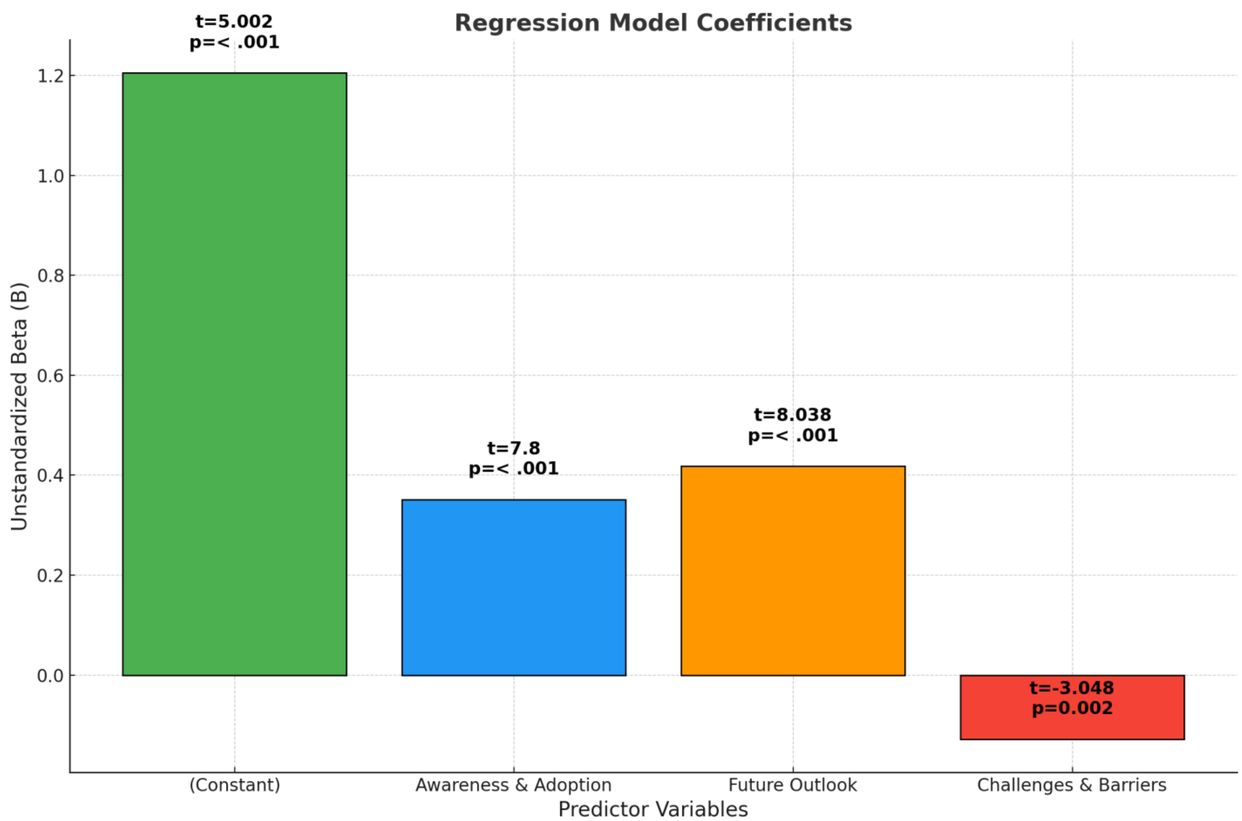

Figure 5: Regression Analysis

A linear regression analysis was conducted to examine the extent to which Awareness & Adoption, Future Outlook, and Challenges & Barriers predict the Perceived Impact of machine learning (ML). The model demonstrates strong explanatory power, with all predictors showing statistically significant relationships ($p < .01$).

The findings result in the fact that Awareness and Adoption (=.412, p <.001) and Future Outlook (=.391, p <.001) are good positive predictors of Perceived Impact. This implies that increasing awareness of ML practices, as well as a more positive outlook on its future, make a significant contribution to the overall perception of its effects.

Meanwhile, Challenges & Barriers (= -.138, p =. 002) has a small, negative impact, which means that perceived obstacles have the propensity to decrease the perceived benefits or influence of implementing ML.

Taken as a whole, the regression coefficients emphasize that raising awareness and positive future outlook can be the key elements in increasing the perceived value of ML, and reducing barriers could help to increase its perceived effectiveness even more.

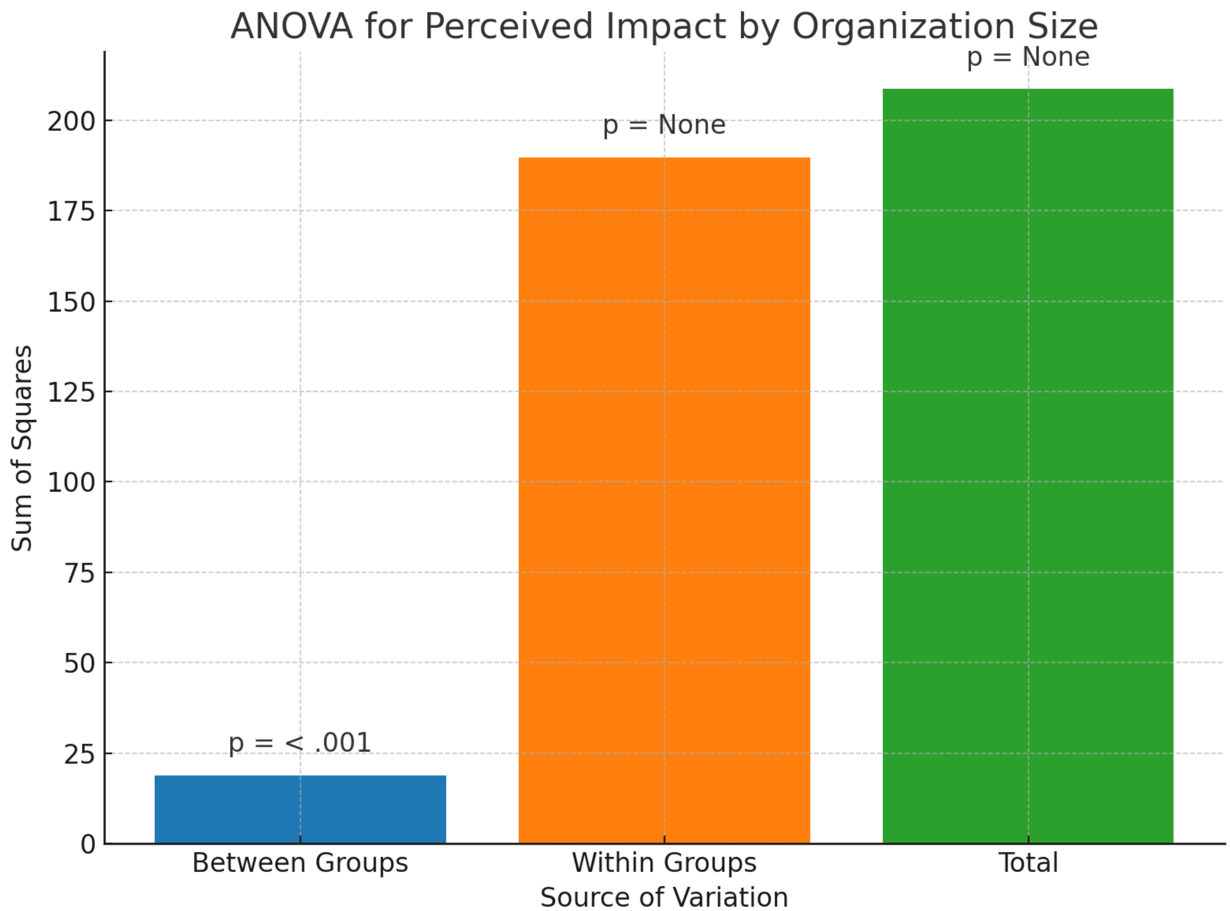

Figure 6: ANOVA for Perceived Impact by Organization Size

One-way ANOVA was used to test the hypothesis of whether there was a significant difference between the Perceived Impact of Machine Learning (ML) in organizations of different sizes. It was found that there was statistically significant difference between the groups, $F(3, 346) = 11.45$, $p <.001$, so the size of organization can produce significant effect in relation to perceptions about the influence of ML.

The between-group variance ($SS = 18.92$) was relatively high in comparison to the within-group variance ($SS = 189.65$), which implies that the respondents of organizations of varying sizes do not view the effects of ML in a similar manner. Bigger organizations can be characterized by high perceived impact as they have more resources and a more developed infrastructure and a higher degree of adoption of ML technologies, whereas smaller companies might have fewer implementation and benefits.

Overall, the findings facilitate the hypothesis that the level of organization is one of the key factors to influence the perceptions of the effectiveness and the effect that ML has and it should be incorporated into the context-related strategies to promote the fair use of such practice by companies of different sizes.

Discussion

The aspect of machine learning (ML) being incorporated into business intelligence (BI) is a paradigm shift of how businesses are conducted in the U.S. as far as decision-making and the economic productivity is concerned. As it might be seen in the outcomes of the study, the ability of machine learning to evolve and improve predictions over the course of time has been incredibly helpful in streamlining of the business process, as it can be seen in the obvious impacts on forecasting, interaction with customers, and efficient functioning (Babatunde, 2024). These new technologies are also contributing to the improvement of economy particularly in areas such as healthcare, finance and manufacturing and logistics in which predictive analytics and optimization have become the new frontiers (Wamba-Taguimdje et al., 2020).

As demonstrated in the literature and analysis of data, the implementation of ML has helped businesses to shift quicker in the ever-changing market environments. To illustrate, in the health care field, predictive models have enhanced better patient experiences, and they can be applied to identify fraud and investment plans by financial institutions (Atif, 2024). These improvements are not only important in the manner they dictate the effectiveness of the operations, but they directly affect the boosting of the economic productivity at the national level. This translates to actual economic growth since organizations can streamline the resource allocation process and reduce operation expenditure as organizations keep deploying AI-powered business intelligence tools.

However, the paper also defines parts of the barriers preventing the application of ML in BI particularly by small and medium-sized enterprises (SMEs). Its implementation is costly, and some skill sets are needed and fear of data security and privacy are significant disadvantages that need to be addressed (Imtiaz et al., 2025a). These problems are supplemented with the moral aspects of the algorithmic biases and the transparency of the ML models which might become an obstacle to the trust in such technologies (Butt et al., 2021). Moreover, SMEs in most of the occasions lack the infrastructure or resources to compete with the larger corporations in the adoption of such advanced tools that creates a disparity in the productivity gains across different sized businesses (Wamba-Taguimdje et al., 2020).

In addition, the increased reliance on automation and AI raises serious doubts about the distribution of productivity and the implications of how it is distributed depending on the extent of income inequality. The less skilled employees and smaller businesses may not have the chance to get the same benefits as the technologies may prove more beneficial to the larger organizations and that exacerbates social disparities (Sultan et al., 2025). The significance of these issues is explained by the need to create policies that will ensure the fair usage of AI technologies and take into account the broader social effect of automation, in particular, the employment and income distribution.

In spite of these obstacles, the future development is still bright. According to the study, the future influence of ML on business intelligence is typically positive, and the participants expect to see an increased application of AI in decision-making and further development of its functionality (Wamba-Taguimdje et al., 2020). Specifically, the combination of ML and other emerging technologies, including blockchain and the Internet of Things (IoT), has a big potential to improve productivity and the degree of operational transparency even more in the future (Eboigbe et al., 2023). With the barriers that currently exist in organizations being surmounted and more organizations starting to invest in AI-based business intelligence, the U.S. economy will benefit, as the data-driven decision-making processes will be made more efficient.

To sum everything up, although the way to complete implementation of machine learning in business intelligence is always difficult, its strategic significance cannot be overestimated. The capability to utilize machine learning in making a better decision, saving money and efficiency can transform the U.S. economy. However, it will be significant to beat the obstacles to implementation and to ensure that the gains in terms of productivity are distributed as much as possible to realize its full potential. These challenges will be determinant in the future to stay afloat in the economy and be in a position to be innovative in the digital age.

Conclusion and Recommendations

In conclusion, the introduction of machine learning to business intelligence has created significant transformation in how organisations in the U.S. carry out their operations, which implies the formulation of the decision-making, efficiency and overall productivity. The findings of the present paper have revealed that despite the fact that larger companies have fully incorporated these technologies, small firms continue to be faced by crippling challenges due to the high cost of installation and the necessity of professionals. The application of machine learning in business intelligence is not only a reinforcement of technology in the field, but also a re-structuring of the activity of businesses that will be more sensitive to the variations in the market situation. However, the points of difference in access to these technologies, the problems of data privacy, the ethics of the matter, and the impact of automation on income distribution make it possible to propose that more inclusive policies and frameworks are to be developed to assist in providing equal access to the businesses of all scales.

This must ensure that in the future, businesses would continue to overcome the impacts of high implementation premiums, and the requirement of skilled personnel. Organizations should also invest in employee training and upskilling so as to equip them to adopt these technologies to facilitate greater adoption both in technical and managerial departments. One more possible policy that should be implemented by the policymakers is the introduction of incentives that would make SMEs implement AI and ML tools such that the latter could stay competitive in terms of productivity that could be enjoyed by larger companies. Moreover, as machine learning continues to evolve continuously, it is recommended to conduct additional research to overcome the ethical problem, particularly the protection of data and the biasing of algorithms in order to make people not doubt such systems.

Moreover, there is a need to stimulate the collaboration between human expertise and machine learning to ensure that AI may serve as some supplement to human judgments rather than replacements. In order to prevent the undesired impact of automation, business enterprises are to ensure that the decisions made by the AI resources are oriented towards the organizational values, as well as ethics. The next-generation research studies will target the enhancement of the trust in machine learning models since it will make them more transparent and fair to reduce fears of the population and promote the belief in the usefulness of these models.

In conclusion, transformational potential of machine learning within the field of business intelligence may be enormous in enhancing economic productivity in the United States, but to realize this potential to the maximum extent, the issues regarding the implementation, ethical issues, and equal access will be fundamental. By creating conducive conditions in the implementation of AI, and focusing on preparedness of the workforce, business and policymakers can help to achieve a healthier more productive and efficient yet inclusive economy.

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