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Article

The innovation role of artificial intelligence using data analytics to influence sustainable business practices and firms' profitability in cars industry

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Abstract: The cars industry has undergone significant technological advancements, with data analytics and artificial intelligence (AI) reshaping its operations. This study aims to examine the revolutionary influence of artificial intelligence and data analytics on the cars sector, particularly in terms of supporting sustainable business practices and enhancing profitability. Technology-organization-environment model and the triple bottom line technique were both used in this study to estimate the influence of technological factors, organizational factors, and environmental factors on social, environmental (planet), and economic. The data for this research was collected through a structured questionnaire containing closed questions. A total of 327 participants responded to the questionnaire from different professionals in the cars sector. The study was conducted in the cars industry, where the problem of the study revolved around addressing artificial intelligence in its various aspects and how it can affect sustainable business practices and firms' profitability. The study highlights that the cars industry sector can be transformed significantly by using AI and data analytics within the TOE framework and with a focus on triple bottom line (TBL) outputs. However, in order to fully benefit from these advantages, new technologies need to be implemented while maintaining moral and legal standards and continuously developing them. This approach has the potential to guide the cars industry towards a future that is environmentally friendly, economically feasible, and socially responsible. The paper's primary contribution is to assist professionals in the industry in strategically utilizing Artificial Intelligence and data analytics to advance and transform the industry.

Keywords: artificial intelligence; cars industry; data analytics; sustainable business practices; firms' profitability

1. Introduction

Artificial intelligence (AI) is a rapidly developing field of revolutionary technologies that is dramatically changing many areas of people's lives, businesses, society, and the environment (Dwivedi et al., 2023). The rapid growth of AI is largely due to these technologies. The use of AI in business and society is becoming increasingly viable. This is especially important given the widespread use of digital computing devices and the growth of big data. Moreover, like any other industry, the cars sector has also witnessed an expansion in the application of data analytics. Data analytics can be very beneficial to any industry, and the cars industry is not an exception to this rule. In the subject of data analytics, the primary emphasis is on the analysis of raw data and the extraction of valuable insights from it (Wang, 2023).

According to Lee (2020), by 2035, it is anticipated that the world's fuel consumption for transportation will increase by 40%. The transportation industry is currently undergoing a critical transition, and in order to meet the sustainable development scenario (SDS) and reduce greenhouse gas emissions, more clean and environmentally friendly fuel must be used for transportation (Lee, 2020). In order to address climate change and meet the ambitious goal of reducing CO_2 emissions, new types of transport systems must be implemented (Lee, 2020). The necessity of making drastic adjustments to the way we produce and use energy in order to address climate change, the environment, and energy security is becoming more widely recognized (García-Olivares et al., 2018; Jahangir et al., 2019). In response to climate change, there has been a significant global growth in the number of electric vehicles (EVs) on the road, which is an important way to reduce greenhouse gas emissions in transportation (Lü et al., 2020; Mihet-Popa and Saponara, 2018; Skrúcaný et al., 2019). With this advancement, AI has the potential to be extremely important in controlling and improving the technology associated with electric cars as well as more complex power and transportation systems (Lee, 2020).

Several leading journals have published scholarly articles exploring a wide range of AI research topics as a result of the growth in interest among scholars and practitioners in this field. A number of recent studies have shown that AI has profoundly impacted the cars industry on various levels, influencing profit margins, environmental sustainability, and social aspects. From economic aspect for the car's businesses, AI affects and plays a substantial role, it can optimize production processes, minimize errors, and predict maintenance needs which helps save time and minimize downtime, increase efficiency of strategies like analyzing customer data that improves the marketing strategy of the car business, and optimize supply chain operations, all these effects can enhance the business car profit (Dou et al., 2024; Judijanto et al., 2024; Rafiey, 2024). From the environmental aspect, AI plays a pivotal role, especially in the development of electric vehicles (EVs) since a crucial component of the transition toward cleaner and more sustainable transportation (Akter, 2024; Kumar and Altalbe, 2024; Rehan, 2024). From social impact, cars businesses that adopt AI into their operations create a work environment that promotes employees' satisfaction and well-being (Usman et al., 2024; Wang and Uysal, 2024), it also provides customers an experience of advanced driver-assistance systems and autonomous driving technology that optimizes road safety by reducing accidents caused by human error (Duarte et al., 2024; Garikapati and Shetiya, 2024; Kolasani, 2024). These research studies indicates that the innovative role of AI in the cars industry is very attractive, useful, profitable, and beneficial from different aspects. For this reason, this research studies analyze the impact of AI on different aspects and perspectives including economic, environmental, and social aspects through using triple bottom line (TBL) and technology-organization-environment (TOE) frameworks. By leveraging the TBL and TOE frameworks, the research offers a multi-dimensional perspective on the role of AI and data analytics in promoting sustainable business practices and enhancing profitability in the cars industry. This integrative approach provides valuable insights for professionals in the cars industry, academics, and policymakers, executives and managers aiming to foster innovation and sustainability in this sector. Therefore, it is perceived to be a unique study and a pioneering issue because there are no studies on the innovative role of AI when employing data analytics to affect sustainable business practices and firms' profitability in the cars industry arena. Additionally, understanding how AI and data analytics are reshaping sustainable business practices in the cars industry is critical for promoting environmentally friendly solutions. From these angles, this research focused on the innovative role of AI using data analytics to influence sustainable business practices and firms' profitability in the cars industry arena. It is imperative to have an integrated understanding of the conceptual and intellectual structures of knowledge in order to propose an agenda regarding AI's significant future implications on people, corporations, and society in the future. This important research gap is addressed in a timely manner by the current study, which also offers future research prospects. This study aims to answer research questions below by exploring the multifaceted impacts of technology, organizational, and environmental factors on social (people), environmental (planet), and economic (profit) outcomes by examining how these factors influence social well-being, environmental sustainability, and economic performance. The research queries (RQs) of the study are:

- RQ 1: What is the effect of technology factors on social (people), environmental (planet) and economics (profit)?
- RQ 2: What is the effect of organizational factors on social (people), environmental (planet) and economics (profit)?
- RQ 3: What is the effect of environment factors on social (people), environmental (planet) and economics (profit)?

From these research questions, the objectives of the research can be derived as follows:

1) To examine the effect of technology factors on social (people), environmental (planet) and economics (profit).
2) To examine the effect of organizational factors on social (people), environmental (planet) and economics (profit).
3) To examine the effect of environment factors on social (people), environmental (planet) and economics (profit).

The research fills a gap in the existing literature by specifically focusing on the intersection of AI, data analytics, sustainability, and profitability in the cars industry. By integrating TOE framework and TBL theory, this study provides a new theoretical perspective for the application of artificial intelligence in the cars industry, and provides directional guidance for future related research. The study offers strategic insights for professionals, academics, policymakers, executives and managers in the car industry on how to implement AI and data analytics to achieve both sustainability and profitability goals.

This study has been structured as follows: section 2 analyses artificial intelligence (AI) and its novel use of data analytics to impact businesses' profitability in the cars industry and sustainable business practices; section 3 addresses the research methodology; section 4 shows the data analytics used for the study; section 5 covers the findings; and section 6 summarizes the conclusions.

2. Review of the literature and theoretical framework

2.1. Dissecting the innovation role of artificial intelligence (AI) using data analytics

2.1.1. Background of artificial intelligence (AI)

AI has seen extensive scientific, technical, and developmental progress over the last several decades (Hassan et al., 2022; Ofosu-Ampong, 2024; Salhab et al., 2023). According to Fleck (2018), the word "artificial intelligence" was first used in the 1940s and 1950s. It was coined in 1956 during the Dartmouth Conference, which is seen as the beginning of AI research, and computer scientist John McCarthy is believed to have been its developer. There were a lot of problems that required fixing in the 60s and 70s before AI research could go further, despite the early enthusiasm. Reductions in financing for AI research, known as the "AI winter," caused a slowdown in research efforts (Groumpos, 2023). The development of expert systems in the 1980s sparked a new wave of AI research. These machines could undertake tasks once performed by humans by using knowledge representation and inference methods. Expert systems have proven useful in several fields, including as healthcare and finance. Popularity of machine-learning algorithms in the 1990s paved the way for AI systems to learn from data and become better over time. The resurgence of research into neural networks—which attempt to model the structure of the human brain—has led to remarkable advancements in AI. AI research and applications have grown significantly in the twenty-first century due to the availability of massive datasets and processing power (Liu et al., 2018), computer vision, and natural language processing are just a few of the fields that have benefited greatly from advanced machine learning techniques, especially deep learning. Applications of AI are becoming more and more common in many sectors, including healthcare, finance, transportation, and entertainment (Alawadhi et al., 2022; Foud et al., 2022). What is the definition of artificial intelligence (AI)?

Despite its age, the idea of AI has been trending heavily recently. Worldwide and in a variety of sectors, AI may affect businesses (Davenport and Ronanki, 2018). For a better grasp of AI, it is necessary to have a firm grasp of the words "artificial" and "intelligence" on their own (Enholm et al., 2022). Intelligence refers to the mental abilities of thinking, reasoning, and learning. "Artificial" is used in contrast to everything that does not originate from nature but is instead made by humans (Mikalef and Gupta, 2021). The capacity of robots to imitate intelligence is what AI is all about, according to Wamba-Taguimdje et al. (2020), which combines the two ideas. AI is the process of creating a computer that can mimic human intellect, or do jobs that would normally need human intelligence (Enholm et al., 2022). Think, comprehend, and solve issues are all part of this (Mikalef and Gupta, 2021). That is not all, however. The ability of AI systems to replicate human performance is achieved by acting as intelligent agents that make choices based on a specific understanding of environmental information (Eriksson et al., 2020). On the other hand, to rephrase, AI aims to imitate human cognition by modelling the way humans take in and process data (Enholm et al., 2022).

An AI's operating mechanism is built upon multiple processes. First, automatic learning constructs the analytical model through an automated process that employs specialized approaches such as neural networks, statistics, and research to uncover hidden information in data without explicit programming of where to look or what processes to perform (Dobrescu and Dobrescu, 2018). Second is learning based on a neural network, which is made up of interconnected units (like neurons), processes information by reacting to external inputs, which are then communicated to each unit. To establish relationships and derive meaning from undefined data, the method necessitates several data flows (Dobrescu and Dobrescu, 2018). Third, deep learning which is based on massive neural networks with several processing units that give computing capacity and sophisticated approaches for analysing vast volumes of data using complex models. Image recognition and speech recognition are two common uses (Dobrescu and Dobrescu, 2018). Fourth process is cognitive computation. It is a human-machine interaction that incorporates the use of AI algorithms and human cognitive computation, with the ultimate objective of having a computer imitate human processes by being able to comprehend pictures and speech (Dobrescu and Dobrescu, 2018). In order to identify objects in images and videos, computer vision comes on the fifth process, which relies on model recognition and deep learning that is powered by AI. These technologies enable machines to process, interpret, and comprehend images as well as detect their environment and take real-time images or videos (Dobrescu and Dobrescu, 2018). The last process is natural language processing (NLP). This process refers to the ability of computers to comprehend, create, and evaluate spoken human languages. Dobrescu and Dobrescu (2018) claim that while computers perform tasks, natural language processing enables users to communicate with the computer via ordinary language.

AI supports industries with the creation of ideas, idea screening, idea development and idea commercialization—the four stages of innovation (Fredström et al., 2021). AI encompasses a variety of functions, such as robotics, data-driven learning, optimization, pattern recognition and language understanding (Cebollada et al., 2021; Delipetrev et al., 2020). Through such capabilities, machines may learn, understand language and visuals, create views, interact physically, recognise patterns and optimize procedures (Cebollada et al., 2021). AI is revolutionising industries and reshaping the world to be smarter and more efficient. Its broad capabilities drive breakthroughs in a variety of fields, including language processing, robotics, healthcare, and manufacturing. Organisations have also begun to delegate critical functions to AI, such as decision-making, recruitment, and customer relationship management (Cao et al., 2024; Dwivedi et al., 2023; Pietronudo et al., 2022).

The focus of AI is constantly changing from being a multipurpose digital technology with the ability to revolutionize important business operations to a technology that is extremely significant for people, society, and the environment (Dwivedi et al., 2021; Kopka and Grashof, 2022). Researchers are becoming more interested in the prospects and problems surrounding AI as a technology that might facilitate social empowerment and growth in the economy (Kopka and Grashof, 2022). Digital technologies like AI and big data disrupt business models, increase productivity, decrease waste, and make businesses more flexible to improve stakeholder experiences. These are just a few of the economic consequences of AI that have been extensively covered in the past (Chauhan et al., 2022).

AI has a wide-ranging impact on many industries, helping firms make better decisions, save costs, and increase productivity (Enholm et al., 2022). Patient care and diagnostics are improving in the healthcare industry (Dwivedi et al., 2021). Customers benefit from the ease and customized experiences. Furthermore, Personalized learning helps education, and government service optimization promotes both. AI facilitates research, advances finance, boosts industry, promotes environmental initiatives, and changes agriculture. Organizations and governments are searching for simple, safe technology to uphold accountability as a result of technological advancements (Mbaidin et al., 2023). Its adaptability transforms decision-making, operations, and innovation across a variety of industries, creating a world that is more efficient (Mhlanga, 2021). As various types of applications and levels of automation improve, AI technology in all its forms is expected to see increased levels of acceptance within organizations (Dwivedi et al., 2021). According to (Bughin et al., 2018), 70% of companies are probably going to have implemented AI technology in some capacity in their manufacturing or commercial processes by 2030.

Technology has an impact on almost every aspect of daily life and has changed our lives in a profound and varied way (Al-Rawashdeh et al., 2023; Thuneibat et al., 2022; Yang et al., 2022). Because of AI's symbolic thinking, flexibility, and explanation capabilities, AI is being developed and used globally in a wide range of applications (Barredo Arrieta et al., 2020) such as:

Healthcare sector: The emergence of AI has resulted in a favourable shift in the healthcare sector by giving reliable data-driven decisions. With an increasing amount of healthcare data and the quick development of analytics tools, AI is revolutionizing the healthcare industry (Secinaro et al., 2021). The primary goal of AI applications in the medical field is to examine the connections between patient analyses and methods of therapy and prevention. AI programmes have been created and used in a variety of fields, including medication research, personalized medicine, patient monitoring, and therapy protocols (Dobrescu and Dobrescu, 2018).

Educational sector: There are new ways to learn and old ways to teach that are both altered by e-learning. There has been a significant influence of AI on education in the areas of administration, teaching, and learning within the education sector or educational institutions. Improved or enhanced education is the result of teachers' increased productivity and efficiency made possible by AI platforms and technology. Additionally, learning experiences for students have enhanced given that AI can customize course content to each individual's strength or deficiencies (Chen et al., 2020). Therefore, online education has become as a top option (Mbaidin, 2024).

Businesses and organizations: AI is a tool which enables enterprises to create new ideas and transform their method of operations. Mishra and Pani (2021) asserts that the objective of any business is to convert inputs into essential output, and the emerging technologies is projected to significantly improve these procedures. The development of AI has made it possible to reconsider organization's processes and significantly change methods of accomplishing tasks (Mishra and Pani, 2021). AI is re-engineering and rebuilding the current organizational structure using these techniques (Wamba-Taguimdje et al., 2020). The impact of organizational structure and business practices on the usage of human resources may facilitate changes to those practices (Enholm et al., 2022). The crucial aspect is to have an HR information system that can monitor employee performance and make some necessary adjustments (Mbaidin, 2020). With AI aid, industry managers, and employees may work together more efficiently with the innovation of new skills and knowledge (Makarius et al., 2020). Businesses may restructure their resources allocation with the help of AI, which could result in a new organizational structure (Eriksson et al., 2020). To put it in another words, AI has the potential to change either how businesses run, now or in the near future (Enholm et al., 2022).

Sustainable business models development it could be stimulated by AI potential (Toniolo et al., 2020). Sustainable business models highlight the measure that organizations take to generate, allocate, and retain value in a way that ultimately serves the interest of both the society and the company (Toniolo et al., 2020). Social and environment issues should also be priorities just as much as business operations (Enholm et al., 2022). AI has the ability to transform society and have a long-lasting effect on people. AI may benefit the environment in a variety of ways, one of which is by reducing energy costs and usage, which in turn lowers pollution and other damaging effects (Borges et al., 2021; Toniolo et al., 2020). AI solutions may help organisation in cutting down waste and lowering pollution. (Rajput and Singh, 2019) claim that AI applications enable companies to enforce regulations that encourage recycling, cut emissions, and reuse materials; all of which contributes to the circular economy.

Car business: AI is revolutionizing the car business, altering production processes, operations, and the whole customer experience (Javaid et al., 2022). According to Jun et al. (2018), the ultimate objective of AI in the cars industry is to provide vehicles with highly practical and intelligent AI capabilities that enable them to mimic human behaviour or surpass it. Oh and Kang (2017) and other aspects are integrated with AI methods including route planning, environmental sensing, and map construction to allow intelligent decision-making (Jun et al., 2018). The use of AI is revolutionizing the cars industry, leading to safer, more efficient, and more personalized vehicles. As a result, it powers AVs, makes collision detection safer, predicts when maintenance will be needed, allows for UI customization, simplifies supply chains, backs eco-friendly car development, and increases customer happiness (Khayyam et al., 2020).

AI in the cars industry plays a critical role as it has many applications across many fields that profoundly reshape the entire cars sector, some of these applications are autonomous driving, intelligent manufacturing, and customer service. Autonomous driving with AI enables driving vehicles, to navigate and operate without human intervention, which gives a totally new experience with safety features (Garikapati and Shetiya, 2024; Nazat et al., 2024). AI also can affect manufacturing processes by utilizing AI-driven automation and predictive analytics to optimize production processes (Rehan, 2024). AI-powered systems in customer service provide personalized experiences, minimize errors, and predict maintenance needs which helps save time and minimize downtime (Dou et al., 2024; Judijanto et al., 2024; Rafiey, 2024). These applications and other technologies utilized by AI will profoundly transform how vehicles are designed, produced, operated, and serviced, leading to significant advancements in efficiency, safety, and customer service in the cars industry. AI is revolutionizing the transportation sector, opening the door to future mobility that is safer, more efficient, and more environmentally friendly (Abduljabbar et al., 2019). Electrification, automation, digitalization, and standardization are advancements that bolster the digital transition. Based on these transportation patterns, the need for ECAS cars has been identified.

2.1.2. Artificial intelligence (AI) and data analytics: The innovative role

As a whole, technology affects almost every facet of our lives and has brought about many different kinds of changes. Papadopoulos et al. (2020) shows that new tech, especially data analytics and AI, are crucial for business continuity. Dwivedi et al. (2022) stress the revolutionary implications of AI in production within the framework of Industry 4.0, drawing attention to the importance of smart agents, expert systems, big data analytics, blockchain, and the internet of things (IoT). The goal of data analytics is to provide decision-makers with useful information by systematically analysing structured and unstructured data using different methods, such as quantitative and statistical analysis, explanatory and extrapolative models, and so on (Bose et al., 2023). Greater efficiency and pinpoint precision in processing are prerequisites for delving into such enormous data sets. According to Rahmani et al. (2021), AI methods including evolutionary algorithms and machine learning may speed up, improve accuracy, and scale big data analytics. It takes complex data analysis to find the feature-to-feature correlations and to predict future observations. Analytics on large amounts of data have the potential to improve organizational performance and decision-making (Rahmani et al., 2021). AI drives transformative innovation via data analytics in many different sectors (Akter et al., 2022). It helps businesses with many things: making better decisions in real time, optimizing processes, personalizing experiences, managing risks, gaining insight from large datasets, and improving productivity (Bharadiya, 2023; Gurjar et al., 2024). Business strategies and operational excellence may be boosted with the use of data-driven insights.

2.2. The innovation role of artificial intelligence (AI) when using data analytics to influence sustainable business practices and firms' profitability

Implementing the most advanced technological solutions to enhance internal organizational performance. As a result, exterior performance, competitiveness, spread, and customer appeal are all enhanced (Al-Mobaideen, 2014). AI is advancing quickly, which is having far-reaching consequences for both the economy and society at large (Mbaidin, 2022). The goal of the change was to improve organizational performance by making it easier for the company to achieve its goals and adjust to new circumstances (Al-Mobaideen et al., 2013). Directly affecting the characteristics and production of several commodities and services, these advancements may significantly affect competitiveness, productivity, and employment (Cockburn et al., 2018). According to Peng et al. (2023), AI and data analytics are crucial in many different sectors for improving profitability and sustainable business practices. Through the exploration of vast amounts of data, AI finds inefficiencies and suggests fixes to solve issues that may be faced so that processes are more efficient and have less waste which leads to higher profitability and cost savings (Goralski and Tan, 2020). According to Toniolo et al. (2020), AI stimulates innovation and creativity in the business environment by providing new markets and company strategies. According to Vaio et al. (2020), developing sustainable products, and services, using new technologies has the potential to boost competitiveness and generate new streams of revenue. As stated by Li et al. (2022) in massive amounts of data, trends, and patterns can be found more rapidly and efficiently with AI-powered data analytics. Developing a better knowledge of the needs and desires of consumers might be beneficial and essential for organizations to create better products and more effective marketing campaigns. In order to verify the ideas of this research, this study was built on the integration of the TBL and TOE frameworks via the use of a quantitative research approach. The function of the TBL framework is to emphasize three dimensions which are social (people), environmental (planet), and economic (profit), using this framework can aid this research in analyzing the impact of technological, organizational, and environmental factors on the sustainable development of enterprises systematically and purposefully. While the function of TOE framework focuses on technological, organizational, and environmental factors, using this framework provides a more comprehensive perspective for assessing and analyzing how these factors impact and influence the integration of innovations within a business. Using these approaches can help in ensuring for this research the effectiveness in providing a contrast between the theoretical concepts with empirical data and the capability to examine the correlations between various variables in an accurate, valuable, and efficient manner.

2.3. Impact artificial intelligence on sustainable business practices and firm profitability when using data analytics

Streamlining processes by using AI is critical to promote profitability and sustainable business practices. Analytics enabled by AI can improve production processes, inventory management, and supply chain management in the cars sector (Sakala and Bwalya, 2023). By evaluating massive volumes of data, AI finds ways to improve, decreases waste, and maximizes resource use; this promotes sustainability while decreasing costs (Javaid et al., 2022). In addition, analytics powered by AI may foretell when equipment will go down and when a vehicle would require repair, paving the way for proactive maintenance via predictive maintenance. Vehicles have longer lifespans, maintenance costs are lower, and this helps with sustainable development (Chen, 2021). Smart manufacturing contributes to innovation in a third way. AI is able to optimize energy consumption, decrease waste, and enhance manufacturing process efficiency (Jamwal et al., 2021). The real-time process adjustments made possible by this technology, which are based on data inputs achieves sustainable production practices. Making decisions based on data is the fourth function of innovation. AI analyses large databases to assists with better decision-making. Based on the findings of Javaid et al. (2022), possible strategies to achieve this goal might involve investing in energy-efficient technologies, utilising eco-friendly materials, or implementing sustainable initiatives within the cars industry. Lastly, AI has the potential to reveal undiscovered streams of profit for the car arena. The organisation could apply AI to manufacture self-driving cars or offer other businesses predictive maintenance services, which would increase revenue and foster innovation (Cherviakova and

Cherviakova, 2018). AI and data analytics have the potential to increase revenue through increased productivity and support the cars industry's sustainability initiatives.

2.4. Technology-organization-environment (TOE) framework and triple bottom line (TBL)

2.4.1. Organization factors

The organization's readiness to adopt and incorporate AI, including skills, culture, and resource accessibility. Getting an organization ready for AI requires having the right skills technical and domain expertise (Shang et al., 2023), cultivating innovation and adaptability, and ensuring adequate resources (financial, technological, and leadership support) aligned with its AI strategy (Neumann et al., 2022). AI effectively incorporated and leveraged within an organization, this applied if the workforce is prepared, a supportive culture is developed, and the resources are sufficient (Yu et al., 2023).

The alignment of AI adoption with the company's strategic goals. A company's ability to use its resources effectively can determine its ability to fulfil its goals (Mer and Srivastava, 2023). AI orientation stimulates managers to apply AI to address business challenges, helps managers make decisions about essential investments, and informs stakeholders about the benefits and reasoning behind the strategic application of AI. All of these things are made possible by the articulation of common objectives (Li et al., 2021). According to Wamba-Taguimdje et al. (2020), AI orientation can thereby minimize associated costs and risks while optimizing the opportunities afforded by bringing AI to corporate processes.

2.4.2. Environment factors

Characteristics of the cars industry, including competitive pressure and market demand. In today's corporate world, companies face intense competition and conflict over limited resources. This means that in order to keep their position, they must be flexible, adaptive to changes, and focused on their future growth (Jung et al., 2020). According to Zameer et al. (2020), an organization is motivated to accept an innovation by competitive pressure, which is the threat of losing its competitive advantage. The cars industry is characterized by a shift from traditional to innovative business models. Ridesharing, electric mobility, autonomous cars, and automated factories are just a few of the groundbreaking inventions that are significantly transforming this unpredictable and dynamic industry (Acciarini et al., 2022). Because it is a highly sophisticated example of modern manufacturing, the cars industry is in a leading position to adopt Industry 4.0 in nations with substantial manufacturing sectors (Alenizi et al., 2023). In a highly competitive market like the cars industry, businesses need to adopt innovative technology to either stay a step ahead of their competitors or meet client needs (Acciarini et al., 2022).

Government policies and regulations related to AI and cars industry. Regulations that put full transparency first are essential to ensuring the ethical and safe application of AI in modern human civilization (Li et al., 2019). These laws ought to set basic technological guidelines that satisfy the bare minimum security, morality, and legal standards for the creation, investigation, manufacturing, and application of AI (Li et al., 2019). Thus, it should be in the interests of both companies and regulators to make sure that AI and autonomous car systems offer a stringent and high degree of protection for ethical rules (Walz and Firth-Butterfield, 2019).

2.4.3. Technology factors

A complete understanding of quality as perceived by the customer is fundamental to the development of a high-quality product (Ali, 2022; Alqaraleh et al., 2022; Jawabreh et al., 2022; Shan et al., 2022). High-performance companies will be able to consistently deliver high-quality, high-performance products to customers by combining digital technologies with techniques that are more sophisticated and intelligent processes. These can lead to more sustainable operations, higher internal productivity, and better protection (Javaid et al., 2021). Predictive analytics and big data assist businesses in cutting expenses (Dubey et al., 2019), producing goods more quickly (Dubey et al., 2018), and developing new goods and services to satisfy the changing needs of customers (Choi et al., 2018).

Advancements in technology have been found to have a significant impact on how productive employees are at work and how they function as a team (Braganza et al., 2021). Employee support for digital transformation will increase if they believe that working in a digital environment will make it easier for them to achieve higher performance, more satisfaction, and personal well-being (Selimović et al., 2021). Therefore, this indicates that advances in employee well-being are supported by suitable technology infrastructure in auto companies.

2.4.4. Social

Consumer perception: How consumers view the company in terms of social responsibility and AI use. According to Alsheibani et al. (2018), policy analysts' and decision-makers' responsibilities will be more impacted by the emergence and growing interest in AI. An organization will not be accepted and supported by society if it just thinks about itself does not take other people into account (Zhao, 2018a). Companies frequently ignore these realities in the age of AI and overemphasize the interests of individuals, organizations, and the group as a whole. It is insufficient to merely emphasize the significance of economic interests. In addition to social and moral obligations, a firm also has legal and financial responsibilities. Companies have greater social and moral responsibilities to society as they grow. Businesses that actively engage in social responsibility will be the most vital and competitive businesses that attract their consumers. As stated by Zhao (2018b) a company implementing AI may adhere to a set of principles, including accountability, transparency, ethical behavior, respect for stakeholder interests, adherence to legal requirements, and adherence to international norms of behavior. This could result in the establishment of a comprehensive social responsibility management system that effectively encourages the implementation of corporate social responsibility in order to achieve both social and economic benefits (Zhao, 2018b).

2.5. Hypotheses development

Adoption of new technologies can be strongly influenced in a favourable way by top management commitment (Shahadat et al., 2023). AI plays a significant role in improving the quality of work life for employees by contributing to equitable pay, healthy and safe working environments, instant access to human potential, security and growth opportunities, work and life space, and the social relevance of work life (Mer and Srivastava, 2023). Top management support is essential for successful AI deployment because of the many organizational requirements connected to AI implementation. Specialists emphasized that a company can only fully commit to adopting AI if the senior leadership sends out a signal to the entire company (Jöhnk et al., 2021). Fostering AI awareness and expertise (Baslom and Tong, 2019) as well as incorporating AI deployment into strategy (Bughin et al., 2018) are strong markers of senior management support for AI.

The effectiveness of organizational change is significantly influenced by the leaders' support (Wulandari et al., 2023). Top management decisions that encourage staff engagement, a change in culture, better knowledge management, motivated staff, and greater employee empowerment can provide the foundation for success (Mayan and Nor, 2017). When sustainability is given top priority by leadership, a culture of environmental sustainability is promoted (Roscoe et al., 2019). There is a favourable association between sustainability activities and managerial support in the cars industry because of the integration of green processes into production processes, the development of environmentally friendly goods, and the reduction of environmental effects (Schöggl et al., 2017).

Yang et al. (2017) highlighted that one of the most important intangible resources in guiding an organization towards higher environmental management and sustainable development is its organizational culture. Developing a great culture requires a willingness to embrace new procedures, technology, and training (Pumplun et al., 2019). Business organizations' workforce demographics, the nature and significance of jobs, the relationship between employers and employees, the interaction between people and technology, customer experience, and competitive advantage in a dynamic market environment will all be profoundly altered by the implementation of AI-based systems (Olan et al., 2022). However, in order to evolve and engage with the realities of existing difficulties in a specific organization, IA requires an enabling intelligent systems (IS) environment (Huang and Rust, 2018). As a result, one of the strategies used by corporate organizations is to continuously create innovative concepts that will inspire innovation at all operational levels and influence how employees interact with one another to further improve performance (Olan et al., 2022).

Hradecky et al. (2022) stated, "A company's size is directly connected with the adoption of innovation". Encouraging the organization's AI preparedness before implementing AI can help ensure its effective adoption (Alsheiabni et al., 2019). Studies have revealed that businesses with greater levels of digital maturity are growing their revenue at a rate that is six times faster than that of their less advanced digital competitors (Acciarini et al., 2022). This has a beneficial effect on more than just financial performance; workers in digitally enabled companies reported a 50% higher measure of job satisfaction. In fact, in the upcoming years, digitization might result in a 20% boost in revenue and an efficiency gain (Parida et al., 2019). Organizations must set up the right framework and implement management techniques for the successful adoption of AI due to the technology's diverse range of applications.

Wessel et al. (2021) highlighted digital transformation may have a significant impact on the identities and aspirations of organizations as well as their fundamental structure. Achieving organizational goals including operational excellence, financial aims, and client satisfaction depends on the role that technology plays in enhancing organizational performance (Olan et al., 2022). The protection of the environment and economic growth are two tasks that should interest the industry as a whole in the context of sustainable development (Yang et al., 2017). Under the umbrella term of sustainable development, “green innovation” refers to green-driven innovation that encompasses all facets of knowledge, technology, goods, processes, and systems and can assist businesses in creating a distinct competitive edge (Gürlek and Tuna, 2018). Businesses’ performance is significantly impacted by their capacity to shift from their current state to a more suitable management plan as the environment changes (Faulks et al., 2021).

Cars companies show that they are committed to enhancing the products they sell by strategically and openly incorporating AI into their goods and services (Wodecki, 2019). When consumers believe AI will be useful and serve a purpose, they are more likely to be favourable about it. AI adoption supports the idea that technology is being used to meet specific customer needs and provide real benefits (Gryth and Rundberg, 2018) since it is in line with strategic goals like boosting safety features, improving driving experiences, or producing more environmentally friendly and energy-efficient cars (Günther et al., 2020).

Many industries depend on technology to help them achieve their sustainability goals. The cars industry is among those. Technological developments in fields like edge computing, AI, and the internet of things (IoT) could accelerate the adoption of policies intended to protect the environment and fight climate change, as well as have a bigger overall impact. A study was done by (Moslehpour et al., 2022) indicates that when authorities create a culture that enhances and encourages sustainable business practices, the long-term of organizational performance will get improved. Moslehpour et al. (2022) clarified that the cars industry’s long-term success connected positively with the business’s sustainable practices, technology use, and workplace culture.

The environmental rules that go under the umbrella of using sustainable energy sources to power electric vehicles have a forward impact on climate change (Llopis-Albert et al., 2021). Liu et al. (2017) elaborate that around the world, multiple countries have an interest in concentrating on programs that take the attention of both consumers and manufacturers to promote and enhance the rapidly expanding market. To ensure compliance with the government policies it is crucial to formulate strategies regarding sustainability in the future of competitiveness of the cars industry, and to achieve this it is necessary to have technological advancements to minimize vehicles energy consumption and reduce the emissions of greenhouse gas (GHG) (Rubio et al., 2020).

In the current era of the industrial revolution, people around the whole world from customers, and entrepreneurs, to society as a whole are capitalizing on potential for gaining opportunities to embrace digital transformation (Paluch et al., 2020). Llopis-Albert et al. (2021) clarified that the cars industry is changing because of digital technologies, which are also posing challenges to establish business strategies and developing strong, dynamic capabilities to quickly develop, implement, and change business models in order to stay relevant in the emerging digital economy. In order to promote and integrate AI components that are relevant to consumers, automakers must answer consumer inquiries, clarify to users the benefits of AI, be readily accessible about how they utilize data, and adapt AI features in light of these socioeconomic trends (Sachdeva et al., 2023).

The well-being of employees impacted by the auto industry's adaptation to socioeconomic developments (Eldem et al., 2022). Businesses that adopt these trends into their operations frequently create a work environment that promotes employee satisfaction and well-being (Lukin et al., 2022). Employee morale and well-being greatly increased by, for instance, providing training programs to keep up with technology changes, supporting work-life balance, and resolving worries about job security (Reu, 2023). On the basis of the above and to propose the ideas of this research, the following model represents the suggested study model built on the integration of the TBL and TOE framework as illustrated in **Figure 1**.

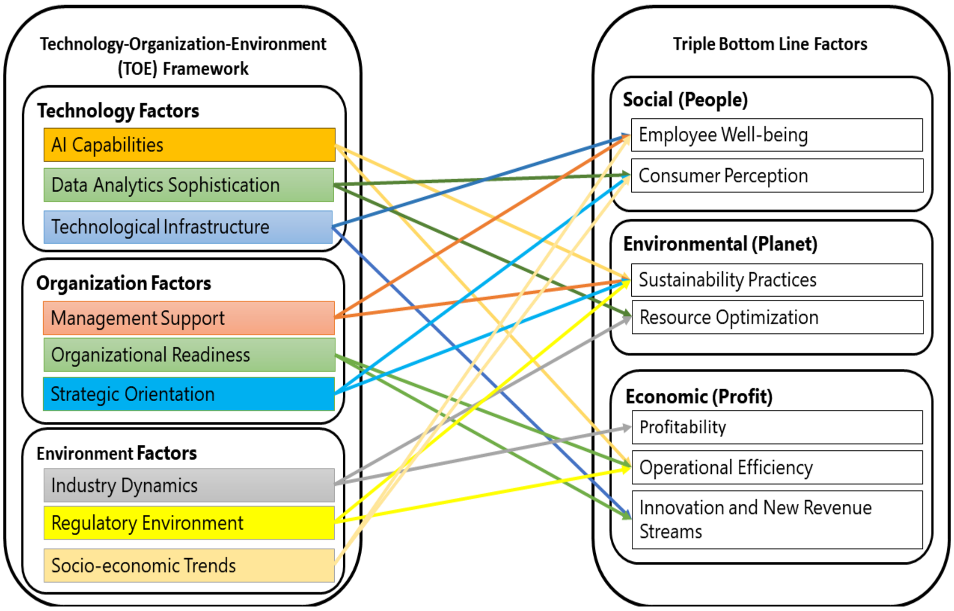

Figure 1. Study model.

H1: There is a strong correlation between improved operational efficiency (economic profit) and higher levels of AI capability in the cars industry.

H2: The use of sustainable business practices is positively impacted by advanced AI capabilities in the cars industry (environmental-planet).

H3: Customer satisfaction rises in tandem with an organization's data analytics prowess (social-people).

H4: Vehicle manufacturers are able to better optimise their resources thanks to data analytics techniques that are becoming more sophisticated (environmental-planet).

H5: When the cars industry's technological foundation is strong, new economic profit streams can be easily created.

H6: Improved staff well-being is supported by adequate technology infrastructure in car firms (social-people).

H7: The morale of workers is boosted when AI projects have the full backing of upper management (social-people).

H8: There is a positive correlation between management support and the application of sustainability strategies in car firms (environmental-planet).

H9: Enhanced operational efficiency (economic-profit) is strongly correlated with an organization's preparedness to embrace AI.

H10: The ability to innovate and create new revenue streams (economic-profit) is impacted by an organization's readiness for AI.

H11: Sustainable business practices are in line with a strategy approach towards AI (environmental-planet).

H12: In the cars sector, customer perception is positively affected by a strategic focus on artificial intelligence (social-people).

H13: The economic profit of a corporation is positively affected by its ability to respond dynamically to AI in the cars industry.

H14: Efficient resource optimisation is highly tied to the dynamics of the cars industry (environmental-planet).

H15: The adoption of sustainable practices in car firms is enhanced by a legislative framework that is supportive of these efforts (environmental-planet).

H16: The operational efficiency of cars firms is affected by the regulatory environment (economic-profit).

H17: The way consumers view the employment of artificial intelligence in the cars industry is heavily influenced by socio-economic factors (social-people).

H18: Car sector employees' well-being is positively impacted by adapting to socio-economic developments (social-people).

3. Methodology

The focus of this study revolves around examining how the relationship between AI may improve the profitability and sustainable business practices in the worldwide cars industry. In order to verifies the ideas of this research, this study was built on the integration of the TBL and TOE frameworks via the use of a quantitative research approach for two reasons. First, because of its effectiveness in providing a contrast between the theoretical concepts with empirical data. Secondly, the capability of this framework to allows us to examine the correlations between various variables in an accurate, valuable, and efficient manner.

3.1. Research design

There were multiple processes involved in designing the research. In order to create the theoretical framework, prior research was first examined. The study focuses on an exhaustive view that contains several technological, organizational, and environmental factors in the global cars industry. For this research, we built and analysed the hypothesis using a deductive approach with the aid of TBL and TOE frameworks. Through the use of a quantitative research approach, this study was able to verify the theories of this research using the integration of the TBL and TOE frameworks. Using the TBL framework, three dimensions are stressed, which are human (people), environmental (planet), and economic (profit). By utilizing this framework, the research can systematically and purposefully analyze the impact of technological, organizational, and environmental factors on sustainable enterprise development. While the function of TOE framework focuses on technological, organizational, and environmental factors, applying this framework enables a more comprehensive examination of how these factors influence and impact the integration of innovations within a company. Using these approaches can help ensure the validity of the research by providing a contrast between theoretical concepts and empirical data as well as the ability to analyze correlations between various variables in an effective, efficient, and accurate manner. The outcomes were acquired using these analytical tools. By using this approach, it can stimulate and enable a full understanding of how AI influences markets and geographical areas from different aspects.

3.2. Data collection

For collecting the data of the variables of our research we used a structured questionnaire with closed questions as the major tool. An online questionnaire was used for the survey, and it was distributed by email and official social media platforms. This study employs stratified random sampling to select 327 professionals from the global cars industry, ensuring the representativeness of the sample. This method enhances the reliability and validity of the study by capturing diverse perspectives and experiences within the cars sector. By selecting a sample of 327 professionals, the study aims to achieve a balance between statistical significance and practical feasibility. The sample size is chosen by taking into consideration statistical power to assure that the outcomes are valid and reliable. No incentives of any kind were provided to promote involvement. The confidentiality of the respondents and the anonymous processing of their answers were assured. The target audience for this questionnaire is the professionals from across the world's cars industry. Also, before conducting the main questionnaire, initial testing is conducted to verify and attain the best performance and effectiveness of the survey instrument.

3.3. Procedure and sampling

The hypotheses of the research were developed by using TBL and TOE frameworks to examine the multifaceted effects of AI across technological, organizational, and environmental dimensions, and their influence on social (people), environmental (planet), and economic (profit) outcomes. These hypotheses aid in providing a detailed comprehension of how the relationship between AI may improve profitability and sustainable business practices in the worldwide cars industry. The sampling strategy for this study aimed to obtain a representative sample of professionals working in the cars industry arena in order to investigate and examine the influence in the relationship of AI and data analytics on sustainable business practices and profitability. 327 responses in total have been taken in the final sample in order to guarantee reliable analysis using structural equation modelling and to produce statistically significant results.

The study included a stratified selection of participants based on attributes like age, gender, and level of education. 252 males (77.1%) and 75 females (22.9%) made up the total of 327 responses. The participants of the study were divided into groups; each group contains a specific range of ages. The first group which is falling into under 25 age range represents 1.8% of the total sample which means 6 respondents. In the second group which is the age from 25 to 34, there were 121 participants which demonstrate 37.0% share of the sample. the third group has had 154 respondents which perform 47.1% of the total sample. The fourth group which is between 45 and 54 age take 11.9% from the sample which act for 39 participants. The last group of the sample which is the of 55 age and upper, involve just 7 or 2.1% of the total participants.

In terms of educational attainment, 243 participants, or 74.3% of the sample, held bachelor's degrees. 18.0% of the sample, or 59 respondents, had master's degrees. Of these, or 7.6% of the total, 25 had doctorate (Ph.D.) degrees. **Table 1** illustrates a detailed demographic breakdown that provides a comprehensive image of the study participants, highlighting intriguing aspects of the sample's diversity with regard to age, gender, and educational attainment.

Table 1. Demographic analysis.

Demographic	Elements	Frequency	%
Gender	Male	252	77.1
	Female	75	22.9
Age	Under 25	6	1.8
	25–34	121	37.0
	35–44	154	47.1
	45–54	39	11.9
	55 and above	7	2.1
Educational	Bachelor's degree	243	74.3
	Master's degree	59	18.0
	Doctorate (Ph.D.)	25	7.6
	Total	327	100%

3.4. Variables

The independent variables of the study are categorised into three groups based on the TOE framework: technology, which includes AI capabilities and data analytics sophistication; organisation, which includes management support and organisational readiness; and environment, which includes industry dynamics and regulatory landscape. Concentrations of the environmental (resource optimisation, sustainability practices), social (employee well-being, consumer perception), and economic (innovation, profitability, and operational efficiency) components can be found in the dependent variables that align with the TBL dimensions.

3.5. Ethical considerations

The main area of interest for this study is ethics. Prioritising the confidentiality and anonymity of survey responses is essential, and before any data is gathered, all participants are asked for their informed consent. Strict privacy and data management procedures are implemented to guarantee the security of participant information.

4. Data analytics

Our focus on this section is to express the data analysis that was done for our study which is about investigating how AI may promote the profitability and sustainable business practices in the cars industry arena. 327 participants' data were collected from the questionnaire that was conducted for this study. Using Smart PLS which is a well-known technique for PLS-SEM we analyse these data that has been collected. Our essential goal for this study was examining the measuring model which is involved looking at the outer loadings of various constructs that is related to customer perception, AI capabilities, and other relevant factors. The study primarily focused our investigation on the measurement model depicted in **Figure 2**. The measuring model incorporates many assessments to assess the dependability and accuracy of constructs pertaining to consumer perception, AI capabilities, and other pertinent elements. More specifically, study analysed the external loads of the various architectures to verify that they satisfy the predetermined criteria. The tests in question involve evaluating the reliability of internal consistency (using composite reliability), the validity of convergence (using average variance extracted, AVE), and the validity of discrimination (through the use of the Fornell-Larcker criteria for reliability and cross-loading).

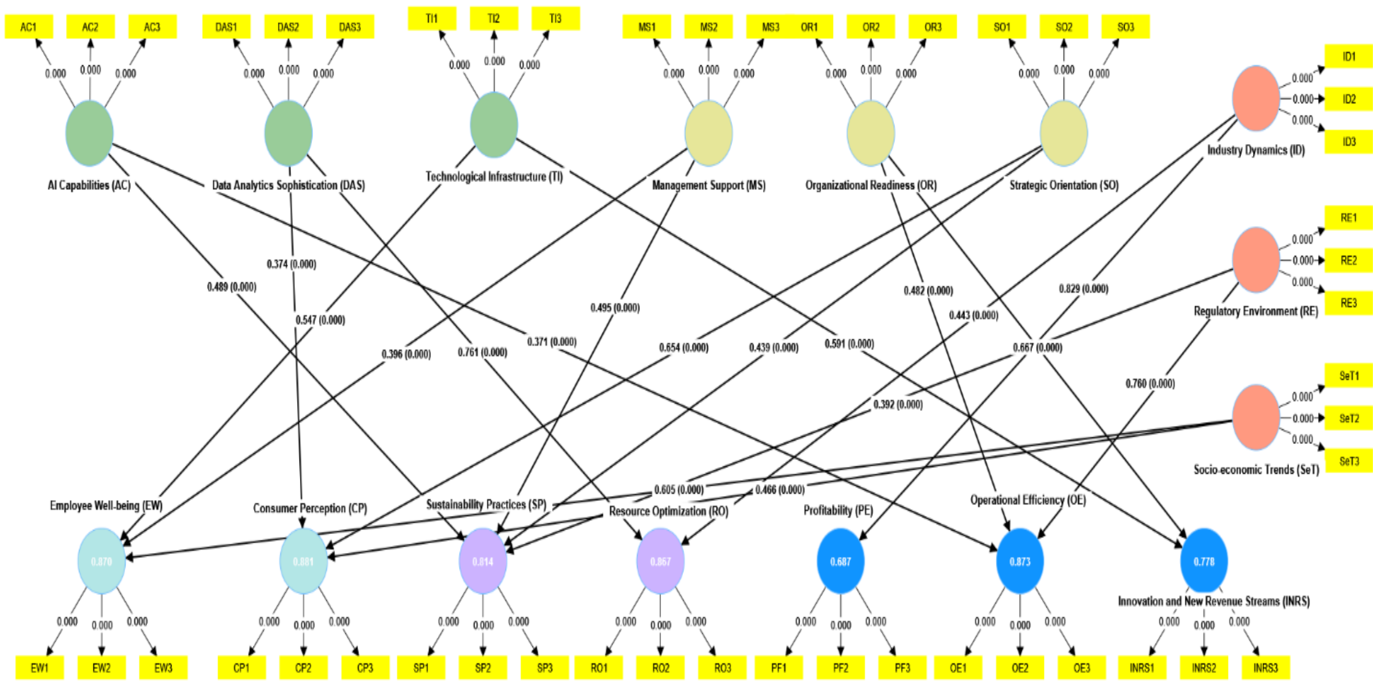

Figure 2. Measurement model.

In the following parts, study gives a comprehensive explanation of these tests and their outcomes, emphasizing how the measuring model reinforces the research question and the overall credibility of the study.

4.1. Outer loadings

This part view examines the outer loadings of each item with their relative components, the items that indicate of high outer loading value represent good measures of their respective structures. These outer loadings which are shown in **Table 2** assess the measuring process of the model's reliability and validity.

Table 2. Construct loading.

Constructs	Loadings	Constructs	loadings
AC1 ← AI Capabilities (AC)	0.928	OR1 ← Organizational Readiness (OR)	0.906
AC2 ← AI Capabilities (AC)	0.912	OR2 ← Organizational Readiness (OR)	0.897
AC3 ← AI Capabilities (AC)	0.904	OR3 ← Organizational Readiness (OR)	0.887
CP1 ← Consumer Perception (CP)	0.824	PF1 ← Profitability (PE)	0.835
CP2 ← Consumer Perception (CP)	0.873	PF2 ← Profitability (PE)	0.743
CP3 ← Consumer Perception (CP)	0.854	PF3 ← Profitability (PE)	0.780
DAS1 ← Data Analytics Sophistication (DAS)	0.896	RE1 ← Regulatory Environment (RE)	0.897
DAS2 ← Data Analytics Sophistication (DAS)	0.918	RE2 ← Regulatory Environment (RE)	0.905
DAS3 ← Data Analytics Sophistication (DAS)	0.908	RE3 ← Regulatory Environment (RE)	0.876
EW1 ← Employee Wellbeing (EW)	0.884	RO1 ← Resource Optimization (RO)	0.888
EW2 ← Employee Wellbeing (EW)	0.807	RO2 ← Resource Optimization (RO)	0.836
EW3 ← Employee Wellbeing (EW)	0.697	RO3 ← Resource Optimization (RO)	0.878
ID1 ← Industry Dynamics (ID)	0.880	SO1 ← Strategic Orientation (SO)	0.879
ID2 ← Industry Dynamics (ID)	0.887	SO2 ← Strategic Orientation (SO)	0.873
ID3 ← Industry Dynamics (ID)	0.898	SO3 ← Strategic Orientation (SO)	0.866
INRS1 ← Innovation and New Revenue Streams (INRS)	0.836	SP1 ← Sustainability Practices (SP)	0.868
INRS2 ← Innovation and New Revenue Streams (INRS)	0.879	SP2 ← Sustainability Practices (SP)	0.855
INRS3 ← Innovation and New Revenue Streams (INRS)	0.766	SP3 ← Sustainability Practices (SP)	0.887
MS1 ← Management Support (MS)	0.858	SeT1 ← Socioeconomic Trends (SeT)	0.872
MS2 ← Management Support (MS)	0.874	SeT2 ← Socioeconomic Trends (SeT)	0.886
MS3 ← Management Support (MS)	0.863	SeT3 ← Socioeconomic Trends (SeT)	0.894
OE1 ← Operational Efficiency (OE)	0.866	TI1 ← Technological Infrastructure (TI)	0.914
OE2 ← Operational Efficiency (OE)	0.854	TI2 ← Technological Infrastructure (TI)	0.905
OE3 ← Operational Efficiency (OE)	0.900	TI3 ← Technological Infrastructure (TI)	0.901

4.2. *R*-square analysis

Our study's structural model in this section takes the measurements of the strength of the relationship between the independent factors on each of the dependent variables with the aid of using *R*-square analysis. A study done by Hair et al. (2017) describes that the modified version of the *R*-square that has been modified for the number of predictors in the model which is called the *R*-square adjusted presents a more highly exact estimate when several predictors are shown.

The *R*-square analysis in **Table 3** illustrates that the variance in consumer perception demonstrates 88.1% of the model based on the *R*-square score of 0.881 (adjusted 0.880) which is considered a high score. The high success rate indicates that the model does a very good job of predicting this particular component. The model of the variability in employee well-being describes 87.0% with an *R*-square of 0.870 (adjusted 0.869). Also, this high rate demonstrates that the predictors of this outcome variable have a significant influence. For innovation and new revenue streams, the *R*-square is 0.778 (adjusted 0.777) this showed that the model explains 77.8% of its variation. This is relatively high, indicating that the model predicts this construct very well. With an *R*-square of 0.873 (adjusted 0.872), the model explains 87.3% of the variance in operational efficiency, indicating that the independent variables have a significant influence on OE. Profitability has an *R*-square of 0.687 (adjusted 0.686), indicating that the model explains 68.7% of the variance in PE. Despite being lower than for other constructs, this accounts for a large portion of the variance. The model explains 86.7% of the variance in resource optimisation, based on an *R*-square of 0.867 (adjusted 0.866). This indicates that RO has a high level of explanatory power. With an *R*-square of 0.814 (adjusted 0.812), the model accounts for 81.4% of the variation in sustainability practices, demonstrating a strong relationship between the independent variables and this outcome.

Table 3. *R*-Square analysis.

Constructs	***R*-square**	***R*-square adjusted**
Consumer Perception (CP)	0.881	0.880
Employee Well-being (EW)	0.870	0.869
Innovation and New Revenue Streams (INRS)	0.778	0.777
Operational Efficiency (OE)	0.873	0.872
Profitability (PE)	0.687	0.686
Resource Optimization (RO)	0.867	0.866
Sustainability Practices (SP)	0.814	0.812

4.3. *F*-square analysis

F-square analysis in **Table 4** is used to assess the actual size of the influence of independent variables on dependent variables, revealing the critical role of factors such as data analysis, regulatory environment, and strategic orientation in the cars industry. *F*-square quantifies the strength of the relationship between variables in the model, helping to identify which factors have a significant impact on the outcomes being studied. Calculating the effect size can determine the relative importance of each factor and prioritize interventions that can drive meaningful improvements in economic, environmental, and social outcomes.

In (PLS-SEM), *F*-square values are used to estimate the extent of the independent variables' effect on the dependent variables. Beyond statistical significance, this metric aids in understanding the practical significance of the correlations. An *F*-square value greater than (0.02, 0.15, 0.35) in PLS-SEM indicates a minor effect, a medium effect, a big effect, respectively (Hair et al., 2017).

The *F*-square values across constructs indicate the practical significance of the model's interactions. The substantial effects of data analytics sophistication on resource optimisation, regulatory environment on operational efficiency, and strategic orientation on consumer perception are particularly noteworthy. The studies highlight critical areas in the cars sector where AI and related factors have a considerable impact on operational, strategic, and sustainability outcomes.

Table 4. *F*-square analysis.

Path	*F*-square
AI Capabilities (AC) → Operational Efficiency (OE)	1.081
AI Capabilities (AC) → Sustainability Practices (SP)	1.286
Data Analytics Sophistication (DAS) → Consumer Perception (CP)	1.165
Data Analytics Sophistication (DAS) → Resource Optimization (RO)	4.272
Industry Dynamics (ID) → Profitability (PE)	2.198
Industry Dynamics (ID) → Resource Optimization (RO)	1.451
Management Support (MS) → Employee Well-being (EW)	1.204
Management Support (MS) → Sustainability Practices (SP)	1.313
Organizational Readiness (OR) → Innovation and New Revenue Streams (INRS)	2.004
Organizational Readiness (OR) → Operational Efficiency (OE)	1.812
Regulatory Environment (RE) → Operational Efficiency (OE)	4.502
Regulatory Environment (RE) → Sustainability Practices (SP)	0.823
Socio-economic Trends (SeT) → Consumer Perception (CP)	1.816
Socio-economic Trends (SeT) → Employee Well-being (EW)	2.814
Strategic Orientation (SO) → Consumer Perception (CP)	3.545
Strategic Orientation (SO) → Sustainability Practices (SP)	1.022
Technological Infrastructure (TI) → Employee Well-being (EW)	2.297
Technological Infrastructure (TI) → Innovation and New Revenue Streams (INRS)	1.575

4.4. Reliability and validity analysis

Table 5 shows that conducted a complete reliability and validity analysis for each concept to assess the durability of the measurement model.

Table 5. Reliability and validity analysis.

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AI Capabilities (AC)	0.903	0.904	0.939	0.837
Consumer Perception (CP)	0.809	0.814	0.887	0.723
Data Analytics Sophistication (DAS)	0.893	0.894	0.933	0.823
Employee Well-being (EW)	0.713	0.735	0.840	0.639
Industry Dynamics (ID)	0.867	0.871	0.918	0.789
Innovation and New Revenue Streams (INRS)	0.770	0.783	0.867	0.686
Management Support (MS)	0.832	0.833	0.899	0.748
Operational Efficiency (OE)	0.845	0.847	0.906	0.763
Organizational Readiness (OR)	0.878	0.880	0.925	0.804
Profitability (PE)	0.692	0.699	0.830	0.619
Regulatory Environment (RE)	0.873	0.883	0.922	0.797
Resource Optimization (RO)	0.836	0.839	0.901	0.753
Socio-economic Trends (SeT)	0.860	0.861	0.914	0.781
Strategic Orientation (SO)	0.844	0.844	0.906	0.762
Sustainability Practices (SP)	0.840	0.840	0.903	0.757
Technological Infrastructure (TI)	0.892	0.893	0.933	0.823

For this study, to measure the reliability we adapted two measurements Cronbach's alpha and composite reliability (rho_a and rho_c). Cronbach's alpha which is a measure of internal consistency, indicated that most constructs had satisfactory levels of dependability with values regularly over the acceptable cutoff of 0.7. Based on the outcomes of the survey questions, show that they exactly measure the underlying constructs since they contain a high value of internal consistency. To support this consideration, the second measurement which accounts for inter-item correlations, the composite dependability scores also strengthen the support of the reliability of the survey questions. According to the study of Hair et al. (2017), a significant proportion of the results were higher than 0.7, demonstrating significant reliability.

To assess the validity and confirm the amount of variance that was collected by each construct correlative to the variation that is generated from the measurement error we have used the average variance extracted (AVE) approach. (Hair et al., 2017) state that the values of AVE for this study represents that the constructs explain over half of the variance in the observed variables which are frequently higher than the suggested threshold of 0.5. This outcome illustrates that since each construct's items accurately converge to measure the intended notion a high degree of convergent validity would be achieved.

4.4.1. Discriminant validity

Table 6. Discriminant validity analysis.

	(AC)	(CP)	(DAS)	(EW)	(ID)	(INRS)	(MS)	(OE)	(OR)	(PE)	(RE)	(RO)	(SeT)	(SO)	(SP)	(TI)
(AC)																
(CP)	0.06															
(DAS)	0.05	0.54														
(EW)	0.08	0.46	0.09													
(ID)	0.04	0.04	0.15	0.12												
(INRS)	0.13	0.10	0.05	0.43	0.08											
(MS)	0.04	0.13	0.09	0.60	0.04	0.05										
(OE)	0.42	0.09	0.04	0.07	0.05	0.28	0.03									
(OR)	0.03	0.12	0.10	0.07	0.02	0.79	0.13	0.48								
(PE)	0.03	0.07	0.15	0.13	0.87	0.09	0.07	0.06	0.09							
(RE)	0.03	0.08	0.06	0.06	0.06	0.10	0.06	0.82	0.11	0.05						
(RO)	0.04	0.44	0.84	0.10	0.65	0.05	0.09	0.04	0.10	0.62	0.06					
(SeT)	0.10	0.62	0.04	0.80	0.03	0.08	0.07	0.10	0.05	0.06	0.07	0.05				
(SO)	0.06	0.86	0.12	0.09	0.05	0.06	0.09	0.11	0.08	0.04	0.09	0.10	0.07			
(SP)	0.53	0.45	0.07	0.37	0.07	0.13	0.63	0.50	0.14	0.07	0.40	0.09	0.14	0.51		
(TI)	0.16	0.02	0.02	0.70	0.13	0.69	0.06	0.07	0.05	0.15	0.03	0.05	0.03	0.06	0.05	

For accurately assessing the unique and independent contribution of each construct to the overall model is critical. Differential validity analysis is crucial aspect of construct validity as it ensures the uniqueness of constructs within the model are truly unique and not overly correlated with each other. Thus, differential validity ensures that each construct is distinct from others, leading to support for the robustness, validity, and reliability of the research findings. The differential validity analysis shows that each construct is independent of the other, which verifies the measurement validity of this research model. The discriminant validity of the constructs is validated by the HTMT analysis which is presented in **Table 6**. The values of HTMT analysis are less than 0.85 indicating that most construct pairs are unique from each other (Hair et al., 2017). In contrast, when the HTMT values approach or marginally exceed this threshold, the constructions are more closely interconnected and this is rare to happen. Based on these results, it shows and verifies that every construct describes a distinct aspect of the phenomenon that is being studied. Thus, these measurement strategies of analysis that have been used to emphasize our examination of the potential uses of AI in the cars industry.

4.4.2. Collinearity statistics (VIF)

Multicollinearity is not a major problem in the dataset, according to the VIF analysis of the constructs in our model. There appears to be no undue association between the independent variables (items) within each construct if the VIF values for each item in **Table 7** are less than 5 (Hair et al., 2017). This result is important because it supports the findings of our study on the impact of AI on the cars industry by validating the accuracy of the regression estimates in the SEM model. The lack of significant multicollinearity in our model assures that the detected correlations and effects are not distorted by interdependencies across variables, adding to its robustness.

Table 7. Collinearity statistics (VIF) analysis.

Constructs	VIF	Constructs	VIF	Constructs	VIF	Constructs	VIF
AC1	3.253	ID1	2.291	OR1	2.583	SO1	2.069
AC2	2.764	ID2	2.138	OR2	2.329	SO2	2.058
AC3	2.717	ID3	2.369	OR3	2.349	SO3	1.933
CP1	1.646	INRS1	1.683	PF1	1.462	SP1	1.965
CP2	1.856	INRS2	1.844	PF2	1.281	SP2	1.872
CP3	1.827	INRS3	1.413	PF3	1.358	SP3	2.168
DAS1	2.479	MS1	1.903	RE1	2.357	SeT1	2.067
DAS2	2.806	MS2	2.086	RE2	2.346	SeT2	2.212
DAS3	2.718	MS3	1.818	RE3	2.303	SeT3	2.264
EW1	1.827	OE1	2.004	RO1	2.134	TI1	2.844
EW2	1.644	OE2	1.895	RO2	1.727	TI2	2.541
EW3	1.229	OE3	2.333	RO3	2.143	TI3	2.595

4.5. Hypothesis testing

Table 8 shows the route coefficients from the structural equation modelling analysis using smart PLS, and the results show that many factors have a substantial impact on different outcomes in the cars industry. **Figure 3** displays the full bootstrapping model, illustrating the relationships identified in the study. A summary of these findings is provided in the following paragraph:

Table 8. Path analysis.

H	Path	Original sample (*O*)	Sample mean (*M*)	Standard deviation (STDEV)	*T* statistics (|O/STDEV|)	*P* value
H1	AI Capabilities (AC) → Operational Efficiency (OE)	0.371	0.370	0.025	14.679	0.000
H2	AI Capabilities (AC) → Sustainability Practices (SP)	0.489	0.489	0.027	18.189	0.000
H3	Data Analytics Sophistication (DAS) → Consumer Perception (CP)	0.374	0.374	0.023	16.383	0.000
H4	Data Analytics Sophistication (DAS) → Resource Optimization (RO)	0.761	0.761	0.023	32.780	0.000
H5	Technological Infrastructure (TI) → Employee Well-being (EW)	0.547	0.549	0.035	15.686	0.000
H6	Technological Infrastructure (TI) → Innovation and New Revenue Streams (INRS)	0.591	0.592	0.034	17.320	0.000
H7	Management Support (MS) → Employee Well-being (EW)	0.396	0.395	0.025	15.788	0.000
H8	Management Support (MS) → Sustainability Practices (SP)	0.495	0.496	0.031	15.841	0.000
H9	Organizational Readiness (OR) → Innovation and New Revenue Streams (INRS)	0.667	0.667	0.029	23.097	0.000
H10	Organizational Readiness (OR) → Operational Efficiency (OE)	0.482	0.482	0.028	17.249	0.000
H11	Strategic Orientation (SO) → Consumer Perception (CP)	0.654	0.654	0.025	25.993	0.000
H12	Strategic Orientation (SO) → Sustainability Practices (SP)	0.439	0.439	0.028	15.867	0.000
H13	Industry Dynamics (ID) → Resource Optimization (RO)	0.443	0.443	0.026	17.024	0.000
H14	Industry Dynamics (ID) → Profitability (PE)	0.829	0.830	0.015	54.860	0.000
H15	Regulatory Environment (RE) → Sustainability Practices (SP)	0.392	0.392	0.029	13.524	0.000
H16	Regulatory Environment (RE) → Operational Efficiency (OE)	0.760	0.760	0.029	26.122	0.000
H17	Socio-economic Trends (SeT) → Employee Well-being (EW)	0.605	0.605	0.026	23.414	0.000
H18	Socio-economic Trends (SeT) → Consumer Perception (CP)	0.466	0.466	0.026	18.099	0.000

In the context of technological considerations in the cars sector, AI capabilities were discovered to have a strong correlation with operational efficiency and sustainability practices, with path coefficients of 0.371 and 0.489, respectively (H1 and H2), indicating a major influence on monetary and ecological factors. The path coefficients for consumer perception and resource optimisation were 0.374 and 0.761, respectively, indicating that Data Analytics Sophistication affected these social and environmental variables. In addition, the path coefficients for Technological Infrastructure (H6) and employee well-being (H5) were 0.547 and 0.591, respectively, demonstrating its essential significance in social and economic consequences.

The path coefficients for management support (H7) and employee well-being (H8) were 0.396 and 0.495, respectively, suggesting that it influences both the social and environmental domains within the organisation. Coefficients of 0.482 and 0.667 (H9 and H10), respectively, for operational efficiency and the ability for innovation and new revenue streams, indicate that organisational readiness is crucial for attaining economic advantages.

Coefficients of 0.654 and 0.439 (H11 and H12), respectively, for strategic orientation and AI, demonstrated that the former had a beneficial effect on consumer perception and sustainability practices, with implications for social and environmental aspects. Finally, looking at environmental factors, we find that regulation and industry dynamics are strong predictors of operational efficiency and resource optimisation, and that industry dynamics has a substantial effect on profitability (H13, H14, and H16). Sustainability practices (H15) were also significantly impacted by the regulatory environment. Socioeconomic trends significantly influenced the path coefficients for staff well-being and consumer perception, which were 0.605 and 0.466, respectively (H17 and H18).

The findings demonstrate how critical advancements in data analytics, artificial intelligence, and infrastructure support are to fostering innovation, environmentally friendly business practices, and operational excellence in the cars sector. This illustrates the relationship between organisational, technological, and environmental factors and the consequences of the TBL.

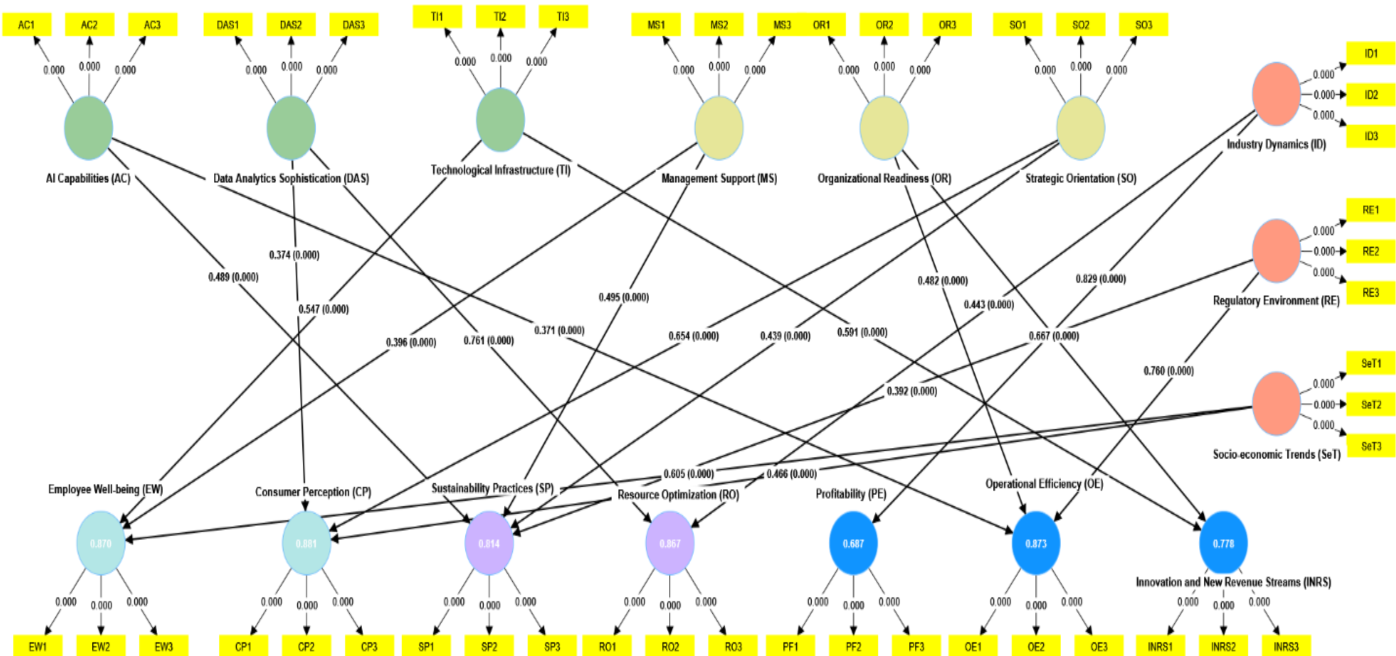

Figure 3. Bootstrapping model.

5. Discussion

Our paper investigates the relationship between how AI has an effect on the cars industry's TBL and how the factors are relevant to each other regarding the TOE. By adopting the TOE framework, the authors have been able to comprehend the external factors that influence the success or failure of AI and data analytics projects in this field in an effective manner, furthermore determining the complex relationship through technology factors and organizational dynamics.

The study results indicate that the incorporation of artificial intelligence and data analytics into the automobile sector might have significant and wide-ranging practical consequences. By using AI capabilities, enterprises may improve operational efficiency, leading to streamlined processes, cost reduction, and optimized resource use, eventually resulting in improved economic return. Furthermore, sophisticated AI technology may enable the implementation of sustainable business practices, including the reduction of environmental impact and the improvement of resource efficiency. In order to capitalize on these discoveries, automobile corporations should contemplate allocating resources towards artificial intelligence technology to augment operational efficiency and sustainability endeavours. This may include using artificial intelligence (AI)-driven technologies for manufacturing, supply chain management, and customer support in order to enhance overall profitability and minimize environmental footprint.

Recommendations of the study based on these consequences include giving priority to the use of artificial intelligence in the automobile industry. Companies should strive to incorporate artificial intelligence (AI) into their fundamental business strategy, with a particular emphasis on predictive maintenance, consumer insights, and resource management. Integrating these systems may result in better decision-making, more customer satisfaction, and a competitive edge in the market. Moreover, it is essential for organizations to allocate resources towards enhancing their data analytic skills in order to get a deeper comprehension of client preferences and industry trends. Through the use of artificial intelligence and data analytics, automobile businesses have the ability to enhance their financial gains while also making a positive impact on the environment for future generations.

5.1. Technology factors

The huge and large-scale AI capabilities and Data Analytics Sophistication (DAS) of the technological entity of the TOE model have strongly promoted sustainability practices (SP) and operational efficiency (OE). This illustrates how technical advancement plays a crucial role in establishing economic benefits and facilitating environmental preservation, which leads our study to discover how crucial is to have strong technical infrastructure in boosting employee satisfaction and foster creativity, both of which drive the potential to generate new revenue streams.

5.2. Organization factors

From an organisational perspective, it was features how crucial management support is to the effective use of AI technology. Enhancements in employee well-being (EW) and the adoption of sustainable practices (SP) seem to be strongly linked to this support. Likewise, it discovered that organisational readiness (OR) significantly affected both operational effectiveness (OE) and innovation and new revenue streams (INRS). This indicating that a company’s readiness may have a very praising effect on its investments in technology.

5.3. Environment factors

Environmental aspects that affect resource optimization (RO) and operational efficiency (OE) include industry dynamics (ID) and regulatory environment (RE). That serves as illustration of how external factors influence business strategies and lead firms towards profitable and sustainable alternatives.

6. Conclusion

This study shows how the cars industry might engage in a significant transformation in terms of sustainable and profitable business practices through the integration of AI when using data analytics. Through use, manufacturers now able to manufacture cars more efficiently, create additional unique designs, and attend to the specific wants of every consumer. Where these innovations help to speed up development of autonomous driving while transforming customer support and retail.

Results indicate that AI and data analytics have the power to totally change the cars industry sector if used effectively within the TOE framework and with an emphasis on triple bottom line (TBL) outputs. In order for the arena to fully benefit from these advantages, new technologies need to be implemented while maintaining moral standards, following legal requirements, and continuously developing. This strategy has the potential to steer the cars industry arena towards a future that is considerate of the environment, economically achievable, and socially responsible. The conclusion of the paper can assist professionals in the cars industry arena in strategically utilising Artificial Intelligence when using data analytics to advance and modify the industry.

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