AI-Enabled Business Models and Innovations: A Systematic Literature Review

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Abstract

Artificial intelligence-enabled business models aim to improve decision-making, operational efficiency, innovation, and productivity. The presented systematic literature review is conducted to highlight elucidating the utilization of artificial intelligence (AI) methods and techniques within AI-enabled businesses, the significance and functions of AI-enabled organizational models and frameworks, and the design parameters employed in academic research studies within the AI-enabled business domain. We reviewed 39 empirical studies that were published between 2010 and 2023. The studies that were chosen are classified based on the artificial intelligence business technique, empirical research design, and SLR search protocol criteria. According to the findings, machine learning and artificial intelligence were reported as popular methods used for business process modelling in 19% of the studies. Healthcare was the most experimented business domain used for empirical evaluation in 28% of the primary research. The most common reason for using artificial intelligence in businesses was to improve business intelligence. 51% of main studies claimed to have been carried out as experiments. 53% of the research followed experimental guidelines and were repeatable. For the design of business process modelling, eighteen AI mythology were discovered, as well as seven types of AI modelling goals and principles for organisations. For AI-enabled business models, safety, security, and privacy are key concerns in society. The growth of AI is influencing novel forms of business.

Keywords: Artificial Intelligence; Business Process; Machine Learning, Explainable AI, Ethical AI, Business Intelligence.

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1. Introduction

The changes and development in technology is a driving force for innovation and economic progress. The industry 4.0 is considered as a revolution with AI enabled business strategies and a growth rate of 20,000 billion dollar for next one and half decade[1]. The trading and business practices enabled, governed, managed, facilitated and operated by using Artificial Intelligence (AI) are said to be AI enabled business. The AI business models are described, the way organizations doing business by using AI services, applications and technologies. The examples include online sales, marketing, trading, banking, healthcare, education, governance, transportation, industry and many more types of the business. The collective term coined for such type of the business is industry 4.0 [2]. The major components of AI enabled business includes marketing strategy, customer engagement, industry assessment, cross-functional assessment, AI infrastructure, AI enabled business models, AI management capability, organizational training and ethical policy enforcement[2]. AI enabled organizations are performing at very fast rate like Amazon, Microsoft, Google, Twitter, Facebook and many others. The many research studies try to conduct a critical review on AI enabled business, productivity and its projected progress goals. The reasons behind such investigations is that the business organizations spend huge investments. The major investments are spent in service standardization, robotics, Open AI and Natural Language Processing (NLP). The results from literature claims that more than 50% AI enabled services are not matured enough yet [1]. The literature also claims that more than 70% AI technological products are not fulfilling's their requirement goals [1].

In 1990, the term business model was first reported in literature as a business planning tool for industrial and service-providing companies [3]. The phrase business model appears in technology firms documents to attract findings. The companies of all halves were using the term business model. It is found that 27% of Fortune 500 companies wrote the term business model in their quarterly and annual reports in 2000 to 2001 [4]. The business firms are facing rapid technology growth, labor rates, buyer-and-seller markets, supply chains of goods and services, environmental challenges, and local and international business laws. Business models play an important role in business strategy, business planning, and the making money process. So, it is required that you will understand the term business model. It is also required to know what the basic components of a business model. The main uses of a business model are statistical analysis, communication methods, and strategic decision-making for business firms [5].

Artificial intelligence (AI), a branch of computer science, offers solutions for many problems, including data analysis, management, organization of knowledge, and decision-making in an effective and automated manner. The AI provides solutions with computational and mathematical modeled algorithmic based intelligent class of problems. AI-enabled business models or frameworks offer many business solutions with knowledge-based decision-making. The AI methods and technologies enhance business competitiveness and business process frameworks. The major outcomes are shared economies, competitive pricing, and improved brand outreach through modern concepts like circular economies.

AI solutions play a vital role in business activities at the top layer of other digital systems. The AI works with Enterprise Resource Planning (ERP), Customer Relationship Management (CRM), databases, websites, and communication systems. The advent of cloud services and the Internet of Things (IoT) creates opportunities for businesses and industrial firms, as well as new challenges for traditional business models such as security, safety, and ethical, national, and international legal regulations.

In this research study, we focus on identifying the components and organization of AI business models with the intent of uncovering the challenges facing industry and academia in order to implement the business models. The method to identify the current state-of-the-art research in the target domain is a systematic literature review. The existing available literature is collected and analysed with the framed research questions. The rest of the study is organised as follows: section 2 presents the background and related work; section 3 illustrates the results of the study; section 4 consists of the discussion; and section 5 presents the conclusion for the systematic literature review.

2. Background and Related Work

The business model (BM) domain evolved over the last 30 years, and we found 12 different definitions with 42 components reported in the literature. The integration of AI with traditional business processes further expanded the research domain, adding new dimensions.[3]. The advent and usage of computer science, data science, AI, and data analytical technologies add many more components to BP models. The AI enabled business models includes supply chain management, decision support systems, cloud storage, data analytics, business intelligence, knowledge management and data driven decision making[5]. The business systems that deploy AI for their process implementation, management, execution, and maintenance are termed AI-enabled systems. The AI-enabled BP is complex and also multi-dimensionally deployed to improve business value. The main success parameters for BP are its definition, reality, and strategic alignment. The key issues in AI-enabled BP are its understanding, business logic, and integration into strategic planning.

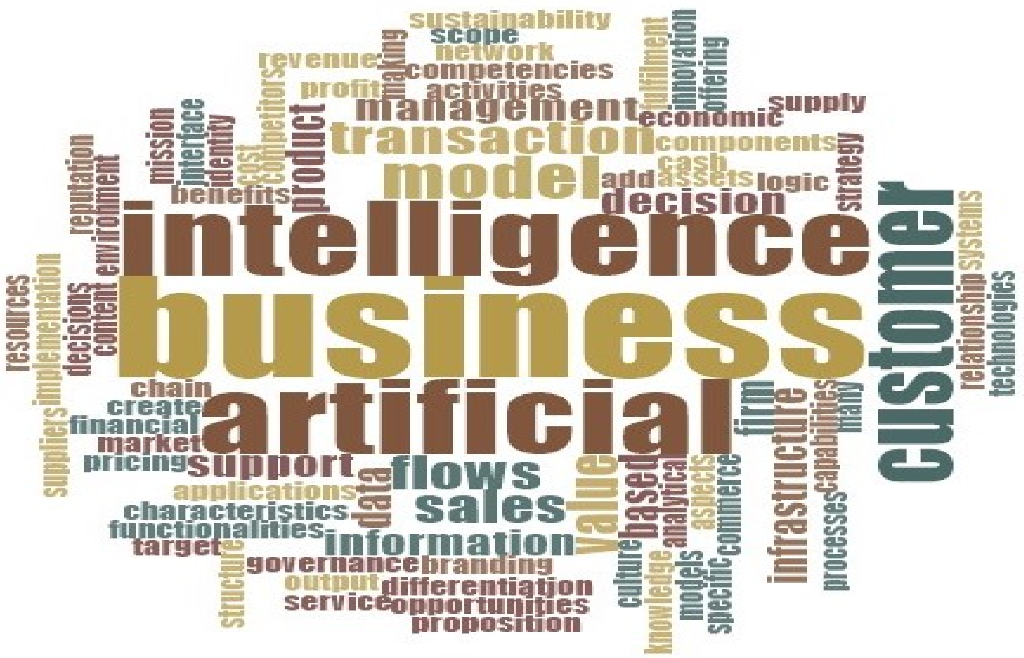

Fig. 1. Word Cloud Representation of BP Components

Fig. 1 depicts a word cloud of the components of business process models published in the literature.

These models also have many different uses and components. AI represents the class of programs in the technology field which emulate human knowledge through sensing, reasoning, and interaction with the real world. AI technology is a game-changer revolution in modern society, giving organizations and businesses competitive powers and huge transformational benefits in the production, marketing and management processes.

Table 1. Summary of Related Studies in AI Enabled Business Models

Study	Reference	Focus Area	Publication Year	Primary Studies	Time Period of Primary Studies
SLR	[6]	BM in sustainable Development	2020	73	1990-2019
	[7]	Ethics of AI	2022	27	Not Reported
	[8]	AI Business strategy	2020	76	2015-2019
	[9]	AI innovation and conceptual Framework	2023	1448	Till 2021
	[10]	AI in the field of justice	2022	69	Till 2021

Table 1 summaries the most relevant SLRs conducted by researchers in AI enabled or business process models. The SLR [6] focus area was business process model development with sustainable development goals projected by the UN. The study spans the time period from 1990 to 2020. The research study selects 73 primary studies with their SLR search protocol. The research study investigates the dependency between AI and rapid development. The evolving domains are machine learning, deep learning, knowledge management, risk management, neural networks, and knowledge-based decision-making. The study reports that ethical, social, economic, and legal aspects of online business models are the key challenges in the coming years. The research study [7] focuses on ethical considerations in adopting AI as technology. The research reports 22 ethical principles and 15 challenges facing industry regarding AI adoption. The research study proposes a maturity model to overcome the lack of knowledge regarding ethical principles. The research study [8] focus on AI business strategy. The SLR consist of academic and non-academic publications which may impose some partiality over the conclusion of the research study. The research study reports that AI-enabled systems consist of algorithms, computational resources, and huge data repositories. The study reports that prediction is the key role of an AI infrastructure. The AI-enabled business covered services like assistance, self-driving vehicles, automated credit, and business transactions. These products and services impose new challenges over traditional business process models, like ethical, legal, and security issues. The research study [9] covers a very large number of published documents on the area of AI innovation and business firms adoption themes regarding technology. The research study conducted a bibliometric analysis to identify the domain topics and their themes as they evolved with time. The research study identified themes like economic, technological, and social development within the prospective of AI innovations. The research study claims a more theoretical understanding of the academic community, and the dataset chosen for such claims is very huge. The analysis performed in this research may not uncover the potential opportunities reported in 1448 research studies. The research study [10] discussed the development of AI in public sector organizations in general and judicial systems in particular. The major themes covered are decision support systems (DSS), knowledge-based systems, surveillance systems, and machine learning. The research study claims that it provides a way forward for justice systems and the management of public policies. This research study also performed a bibliometric analysis due to the large time period for the selection of primary studies. This analysis may neglect the technical findings of the primary studies selected for the analysis. The SLR is structured in a way to narrow down the domain to identify bottom-line concepts in a systematic fashion, which leads to a better understanding

for in-depth analysis. The time period limit also plays an important role in synthesizing the major and minor concepts within the domain.

3. Systematic Literature Review Methodology

Systematic Literature Review (SLR) is a systematic method of identifying and synthesizing the research problems. The SLR provides a systematic method to collect data, formalize the evidence, evaluate the results, syntheses the findings and remove the biases. The SLR guidelines described that SLR have three phases, planning, conducting and documentation[11]. The **Fig. 2** shows the procedural view of the SLR work breakdown with phases, tasks in the phases and subtasks. The tasks executed for an accurate SLR are research significance, research specification, research question formulation, selection of primary studies, data collection, inclusion/exclusion criteria of primary studies, data extraction methods, and results for the SLR.

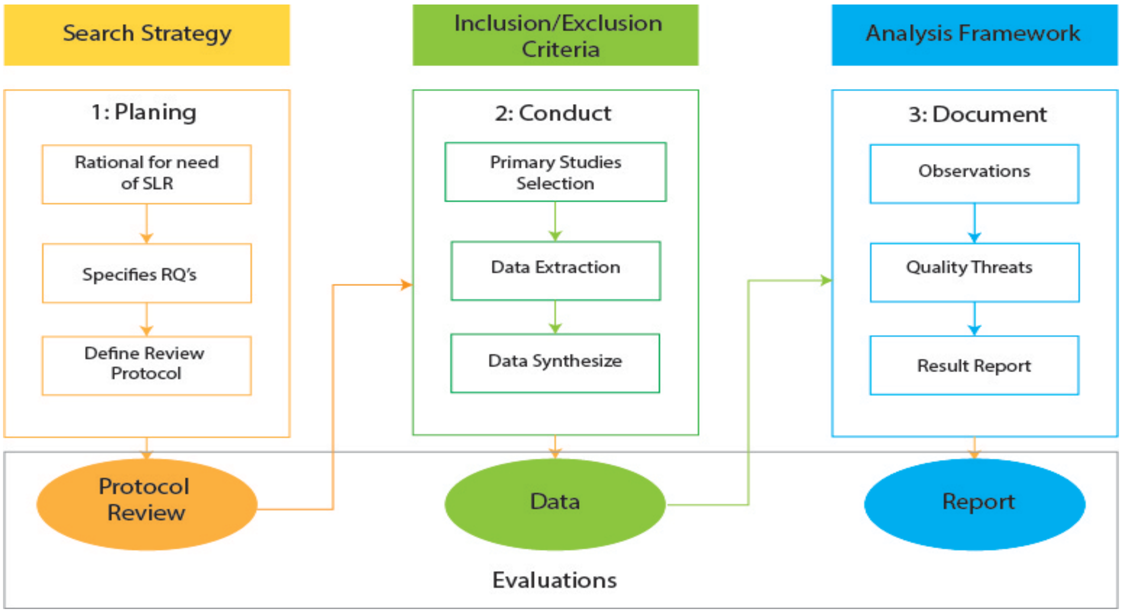

Fig. 2. Generalize Research Methodology of SLR

3.1 Research Questions

The research questions are very important step for an accurate research result in SLR studies. The research questions are framed with the analysis of previously published studies in the particular domain and also further refined by the discussion with experts and peer researches. The research questions also framed by using Population, Intervention, Comparison, Outcome and Context (PICOC) method. In this research study, population refers to AI enabled business models and frameworks. The intervention refers to the social and legal aspects of AI enabled models and frameworks. Comparison refers to the characteristics of the primary studies. The outcome refers to the challenges, solutions and recommendations provided in primary studies. Context refers to the methodology adopted by the primary studies to provide justifications to the results.

Table 2. Research Questions for the SLR

No	Research Question
1	What are the AI methods and techniques used in AI-enabled businesses?
2	What are the meaning and role of AI-enabled organizational models and frameworks?
3	How do academic research studies design parameters in the AI-enabled business domain?

3.2 Search Procedures

The databases sources are in a big number while searching the relevant research studies. The research databases are used in this research study are listed in the **Table 3.** The selection of these databases is also based on the research [12] studies and also based on observations of many research studies already published in the domain of AI enabled business models and framework. The search strings are designed with the help of peer researchers experience and discussions.

Table 3. The Search Databases for searching research studies.

Database	Web Source
ACM	https://www.acm.org/
IEEE	https://ieeexplore.ieee.org
SCIENCEDIRECT	http://www.sciencedirect.com

The search keywords are used to search the primary and relevant research studies. The most relevant research studies are further selected by using inclusion\exclusion criteria. This method also provides us the opportunity to find relevant SLRs, Mapping studies and Literature reviews. The search key words are applied with the intent to find all possible research studies in order to answer the research questions.

3.3 Inclusion and Exclusion Criteria for Primary Studies

The phase is consists of the activities to select the primary studies from the search list of the research studies from the databases. The objective is to narrow down the collection of the research studies to the most relevant research studies. The studies are selected on the basis of the research questions already framed. The criteria for inclusion or exclusion of the search studies are based on the fact that the selected studies could use to answer the research questions. It is possible that some of important studies may be not covered due to the titles or the keywords published by the authors. But to be simple, the most of the relevant studies should be used and included for the analysis of the research study. The inclusion and excluded criteria in each phase is provided in **Fig. 3**.

Table 4. Distribution of Studies After/Before Inclusion/Exclusion

Repository	Studies Found	First Level Selection	Second Level Selection
ACM	71	11	11
IEEEXplore	194	46	23
SCIENCEDIRECT	91	30	5
Total	336	83	39

Table 4 depicts the studies' phase-wise exclusion. We prepare three sets of the searched studies and analyse the titles, abstracts, and keywords. We make sure that each selected study must contain one or more keywords from AI, artificial intelligence, A In this phase, we prepare three sets of research studies by executing the search queries on targeted research repositories. The analysis of titles, abstracts, and keywords is performed to identify the most relevant

research studies as per research questions. These studies are then completely analysed so that they propose AI-enabled business models and reporting methods, such as experiments, case studies, or simulations.

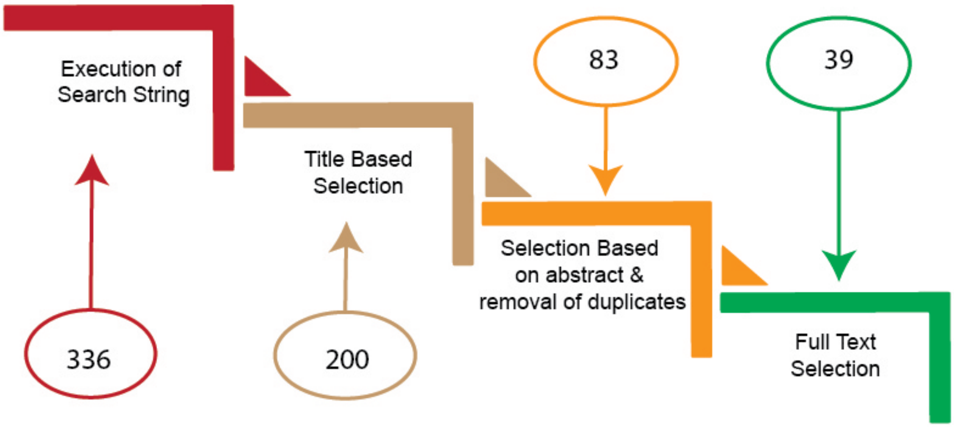

Fig. 3. Inclusion/Exclusion Process for Primary Studies

Fig. 3 demonstrates a step-by-step inclusion/exclusion criterion with the number of studies chosen for each phase. We apply the following additional criteria to our study selection process in order to identify the most appropriate studies that answer the research questions of this SLR:

1. Posters, technical papers, doctoral dissertations, and research with fewer than 8 pages were not accepted. The key objective of this research is to provide a synthesis of peer-reviewed papers that includes appropriate technical specifications.
2. The studies that did not reports any empirical evidence were excluded.
3. The studies that were not based on any business domain were excluded.

Table 5. Primary Studies, Business Model/Framework and Domain

Paper ID	Study Reference	Business Model	AI Tech	Business Domain
S1	[13]	Framework	AI	Education
S2	[14]	Framework	AI	Bureaucratic decision-making
S3	[15]	Framework	ML	Real Estate
S4	[16]	Framework	ML	Social Media
S5	[17]	Framework	ML	Social Media/Fake news
S6	[18]	Framework	HCI	Music Game Design Story Telling Digital Art Industrial/Product Design
S7	[19]	Framework	Data Mining	WikiPedia
S8	[20]	Framework	Deep Learning Cloud/Edge/AI	Health Care
S9	[21]	Framework	Deep Learning CPS IoT	NIL

S10	[22]	Framework		Code Generators
S11	[23]	Framework	Explainable AI	Sales Health Care
S12	[24]	Framework	AI	NIL
S13	[25]	Model	Big Data AI IoT	E-Commerce
S14	[26]	Model		Github
S15	[27]	Framework	Cloud/Edge/AI	Trading
S16	[28]	Model	Block- Chain	Data Publication
S17	[29]	Model	Computer Vision	Consumer Drones Entertainment Logistics
S18	[30]	Framework		NIL
S19	[31]	Model	Explainable AI	Health Care
S20	[32]	Guideline	Explainable AI	Online Education
S21	[33]	Guideline	Ethical AI	NIL
S22	[34]	Framework	Deep Learning	Healthcare Social Media
S23	[35]	Framework	Explainable AI	Social Media
S24	[36]	Model	AI	Health Care
S25	[37]	Framework	AI	Health Care
S26	[38]	Framework	ML/DL	Health Care
S27	[39]	Model		Intelligent Transportation
S28	[40]	Framework	Responsible AI	Health Care
S29	[41]	Model	Hard AI	NIL
S30	[42]	Framework	DL	Health Care
S31	[43]	Framework	Block-chain	Insurance/Fraud Detection
S32	[44]	Framework	DL	Health Care
S33	[45]	Framework	CyberSecurity	Internet of Vehicles
S34	[46]	Framework	ML/NLP	Online Education
S35	[47]	Framework	ML	Health Care
S36	[48]	Framework	ML/DL	Software Auto Sales Package Food
S37	[49]	Framework	ML	Manufacturing
S38	[50]	Framework	AI/ML	Chat-Bot in customer service
S39	[51]	Framework	AI	NIL

We were unable to decide whether to include numerous studies in this SLR in certain situations during the second level. We addressed this critical choice with other researchers, and decisions were taken based on consensus. We were left with 39 studies at the end of phase two. Three of the 39 studies were expanded versions of conference sources that had previously been published in journals. We consider these three articles to be one in this situation. **Table 5** contains a list of our selected primary studies, with necessary information in each column to address the SLR's research questions.

4. Results

This section reports the results as per the data collected from the primary studies collected by the SLR search protocol.

4.1 What are the AI methods and techniques used in AI-enabled businesses?

The purpose of this research question was to identify the main methods, concepts, and techniques under use in AI-enabled business models. The information helps us reveal the current state-of-the art trends in the research domain. There were a total of 39 studies found through the SLR search protocol. We identify 18 main concepts and more than 50 techniques to implement AI-enabled business models and frameworks. The main methods are AI, Deep Learning (DL), Machine Learning (ML), Human Computer Interaction (HCI), Data Mining (DM), Cloud Computing (CC), Edge Computing (EC), Internet of Things (IoT), Cyber Physical Systems (CPS), Explainable AI (XAI), Big Data (BD), Block Chain (BC), Computer Vision (CV), Ethical AI, Responsible AI, Hard AI, Cyber Security, and Natural Language Processing (NLP). The distribution of methods are shown in **Fig. 4** below.

The most reported methods were AI [S2, S8, S12, S13, S15, S24, S25, S38, S39] and ML [S3, S3, S4, S5, S26, S35, S36, S37, S38], which found 19% each out of total research studies. AI is a branch of computer science that studies intelligent software systems. These systems perform tasks that are normally performed by humans. The study area of AI is very broad term due to its conceptual background and applications, but typically it includes decision-making, logical reasoning, language processing, language understanding, problem design, problem solving, prediction, forecasting, monitoring, data analysis, knowledge representation, and many more. The classic AI methods reported in the studies under analysis were linear regression, neural networks, deep neural networks, decision trees, k-nearest neighbors, and logistic regression analysis. The primary objectives of using these AI methods are automated decision-making, data analytics, resource optimization, problem selection, problem prioritization, and problem reduction. The applications of these algorithms are finance management, forecasting, customer behavior prediction, sales, fraud detection, risk assessment, risk management, risk mitigation, credit scoring, image classification, image recognition, spam filtering, sentiment analysis, feature extraction, feature segmentation, data visualization, and image analysis.

ML is an equally popular method reported in our primary studies for the development of AI-enabled business models. ML is a subdomain of AI that helps design methods, techniques, and concepts to design solutions that enable machines to learn from data, information, or knowledge. The basic difference between AI and ML lies in their capability of learning. The systems designed with ML are capable of learning from data and improving their performance through continued knowledge discovery. The most common methods of ML reported are regression analysis, dimensionality reduction, decision tree models, time series analysis, and support vector machines. These methods are commonly used in biology, chemistry, social science, marketing, signal processing, finance, image analysis, environmental solutions, and stock markets. The most common techniques of ML are bagging, boosting, extreme gradient boosting, voting, stacked ensembles, and arbitrarily-oriented spatial pooling.

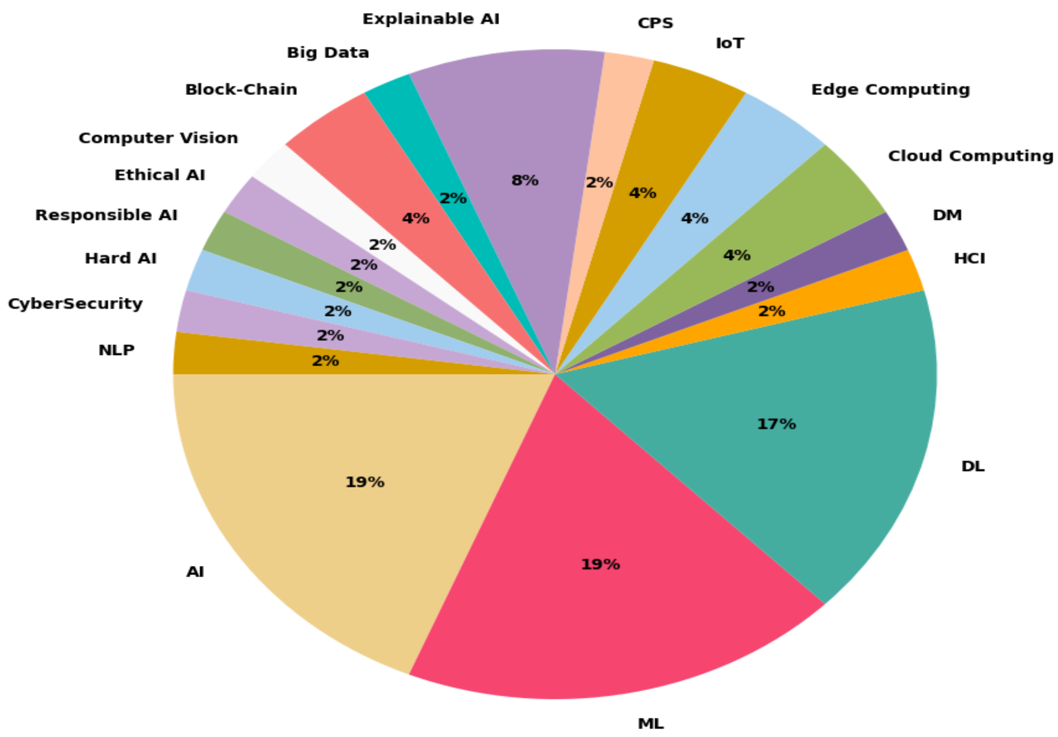

Fig. 4. Distribution of AI Methods over Primary Studies

The third most reported method was DL [S6, S9, S22, S26, S30, S32, S34, S36], found in 17% of the total studies under analysis. DL models layered abstractions of data with more detailed layers of neurons. These neurons represent the complex arrangements of unstructured transformations. DL is a special type of ML in its design and applications. The simplest representation of DL is deep neural network. The DL extends the capabilities of ML methods and achieves reasonable maturity in many data analytical problems due to the inbuilt capability of hierarchical data distribution over multiple layers. The reported methods of DL are convolutional neural networks, recurrent neural networks, anomaly detection, collaborative filtering, and deep neural networks. DL solutions are widely used for image recognition, facial recognition, object detection, medical image recognition, autonomous vehicles, voice assistance, e-commerce, video streaming methods, fraud detection in financial systems, health care imagery solutions, logistical drones, and autonomous cars.

The fourth method of AI-enabled business model reported in primary studies was explainable AI [S11, S19, S20, S23], which reported 8% of the research studies under analysis. XAI are sociotechnical systems that complement the limitations of AI and ML by embedding their components in social environments. The XAI promised to deliver human-understandable solutions, which were not provided with the AI and ML solutions and somehow also missing in the DL solutions due to their complex and layered architecture design. The XAI as a research domain gained momentum due to the popularity of solutions like critical systems, healthcare systems, finance, and criminal justice. The XAI solutions are also increasing transparency, accountability, and trust due to their interactive design of solutions for users and regulatory and governance bodies. The XAI methods are rule-based systems, decision trees, local interpretable model-agnostic explanations, counterfactual explanations, and layer-wise relevance propagation. The applications of XAI are expert systems, decision support systems, credit scoring decisions and risk assessments, chatbots, recommender systems, autonomous vehicles, security drones, surveillance systems, automated HR systems, image recognition, and speech recognition systems.

The fifth reported method was cloud computing [S8, S15], appeared in 4% of the research studies. Cloud computing is described as a platform that provides any kind of computing service, like databases, hardware, software, storage, analysis support, and intelligence, to its users. The traditional clouds were available on the intranet, while modern cloud systems are available on the internet. Cloud users may use cloud services on a rent basis without coping with the maintenance of the physical resources of the system. Cloud computing methods are named Infrastructure as Service (IaaS), Platform as Service (PaaS) and Function as Service (FaaS). The AI, ML, DL, and XAI solutions are hosted on cloud infrastructures and made available globally to users, which upscales the availability of these services. The reported primary studies propose a facial expression recognition system as a service and a computer power trading network as a service on a cloud platform. These two studies used ML technologies to provide these business applications to their users.

Edge computing-AI [S8, S15] is reported in 4% of the primary studies. Edge computing overcomes the limitations of cloud computing to reduce the latency of the network by bringing computational resources close to the user's computers, known as data generators. Edge computing may not rely on a central server for hosting services in the cloud. Similar to cloud computing, edge computing also provides platforms for AI, ML, DL, and XAI applications for global distribution. Edge computing plays a very vital role in partnership with AI, ML, DL, and XAI for industrial IoT, smart homes, autonomous vehicles, and health care systems. IoT [S9, S13], The IoT is a network of networks that provides connectivity to millions and millions of devices. These devices are from public, private, business, and government-owned networks. The IoT with AI and ML is used for analytics, anomaly detection, remote monitoring of objects, home devices, patient monitoring, tracking medical equipment, and intelligent transportation.

The block chain [S16, S31] is an important method, which reported 4% of the total research studies under analysis. A ledger technology that decentralizes and distributes is called blockchain. The main features of a block chain include secure transactions on multiple devices. The transactions are organized into multiple blocks that are linked in a chronological order, which is termed the block chain. The blockchain is gaining importance due to its applications in cryptocurrency, information security, privacy, security, and technology-biased removal mechanisms. The major domains of blockchain are insurance, e-commerce, banking, healthcare, and education.

The AI enabled business models also identified HCI [S7], DM [S8], CPS [S9], Big Data [S13], and computer vision [S17]. HCI is a multidisciplinary domain that includes interface design, interaction design, usability modeling, and accessibility modelling between machines and humans. It is also worth mentioning that NLP and machine learning are playing a procedural role within HCI applications. Modern HCI systems focus on gesture recognition, brain-computer interfacing, and mobile and touch interfaces, virtual and augmented reality, and speech recognition models. Data mining is also an AI, ML, and DL-based technology that deals with large amounts of data and information. Its primary purpose is to extract knowledge from very large repositories of data, which is further refined for decision-making processes in business, governance, and strategic planning. The knowledge discovery process is carried out by identifying trends and patterns in data repositories. CPS is a collection of algorithms, techniques, and methods deployed for physical processes like monitoring, controlling, real-time data analysis, and decision-making. The characteristics of CPS are integration with the physical environment, tight control, accuracy, time-bound response, and geographically scattered input processing. AI and ML are the procedural components of CPS models to achieve their goals. The applications of CPS models are security systems, smart grids, autonomous vehicles, the industrial Internet of Things, healthcare, smart buildings, smart cities, precision agriculture, aerospace, and defense. Big Data is a data processing technology that is applied to a huge volume of data with adequacy issues, undetermined complexity, and diverse data representations. The algorithms for big data are MapReduce, Hadoop, Spark, NoSQL, ML algorithms, graph processing algorithms, and stream processing algorithms. The applications of big data are business analytics and intelligence, smart cities, finance and fraud detection, social media analysis, e-commerce personalization, supply chain optimization, and cybersecurity. Computer vision is a subdomain of AI that investigates the methods, techniques, and frameworks for interpreting and representing visual information for intelligent systems. In simple words, computer vision helps to analyses and provides decision-making mechanisms for data, which consists of images and videos. The algorithms for computer vision are image classification, object detection, semantic segmentation, face recognition, optical character recognition, pose estimation, and image generation. The applications of computer vision are medical imaging, autonomous vehicles, security and surveillance, retail, e-commerce, agriculture, and quality control in manufacturing.

The ethical AI [S21] and responsible AI [S28] are reported in 4% of the primary studies. The ethical and responsible AI terms are used to refer to the concepts used to enforce the development of AI solutions with the principles of fairness, transparency, accountability, restoration of privacy and security, inclusiveness, explainability, and human-centred design. These studies are providing guidelines and design principles for the development of AI enabled business models and frameworks.

The hard AI [S29] was reported in 2% of the primary studies. Hard AI is the notion of having a comprehensive grasp of the technology being used while building an intelligent solution. It shares a domain with AI, machine learning, deep learning, and blockchain. The basic goal of hard AI solutions is to create models that can comprehend, learn, and use information to address future issues. General intelligence, adaptability, reasoning, problem solving, autonomy, natural language comprehension, and common sense reasoning are all components of the hard AI viewpoint. The areas are still growing, with concepts and approaches borrowed from other sectors like as blockchain, computer vision, and cybersecurity.

The cyber security [S33] was reported in 2% of the primary studies. Cybersecurity is a study field that develops approaches, methodologies, and frameworks to prevent unauthorised access, damage, or theft of software systems, networks, and computing resources. Network security, endpoint security, identity and access, encryption, application security, and event security are the primary goals of cybersecurity. The well-known ML algorithms, together with blockchain technology and cryptography, functioned as cybersecurity procedural components. The NLP [S34] is reported in 2% of the primary studies. NLP is a subdomain of AI that investigates the techniques, methods, and technologies for understanding natural language for computers and vice versa. The NLP models enable computer systems to understand, interpret, and generate human language with meaningful contextual presentations. The algorithms of NLP are hidden Markov models, conditional random fields, long short-term memory, and transformer architecture. The main applications of NLP are chatbots and virtual assistants, sentiment analysis, speech recognition, text summarization, text generation, and document classification.

4.2 What are the meaning and role of AI-enabled organisational models and frameworks?

AI-enabled business models elevate business operations and embed innovation across a wide range of sectors. The AI and BP relationships optimise BP efficiency, decision-making, and the generation of novel products and services. In this research topic, we attempt to examine current business models, their distinctive features, and their application in different sectors of AI-enabled business entities. **Fig. 5** demonstrates the spread of AI-enabled business sectors.

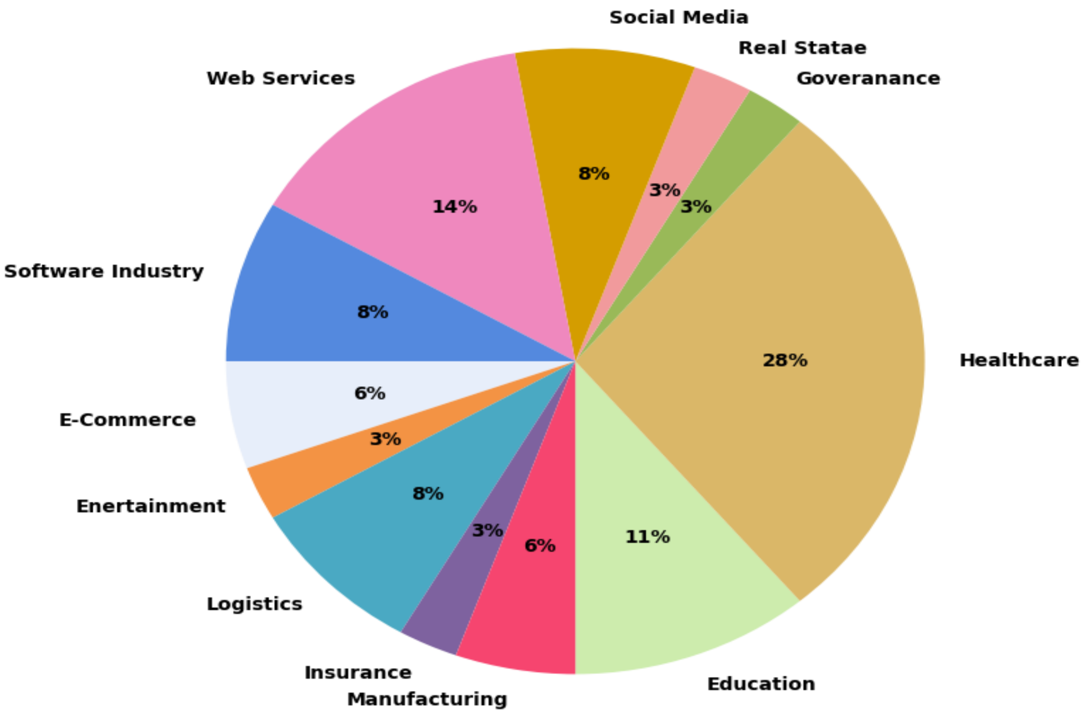

Fig. 5. Distribution of Primary Studies over Application Domains

Following a thorough execution of the SLR search strategy, 39 primary studies were chosen. These research studies uncovered a wide range of business areas and industries as shown in **Table 6**. To make the procedure simple, if a research study reports more than one business domain, we simply add it to our list of businesses against our research study. Healthcare was the most investigated business domain reported in our primary studies [S2, S9, S11, S18, S24, S25, S26, S28, S32, S35], accounting for 28% of all primary studies. Diagnostic imaging, medication discovery and development, virtual health assistants, predictive analytics, clinical decision support systems, patient data protection, administrative process optimization, and health monitoring wearables are all uses in the healthcare industry. Web services [S6, S7, S14, S15, and S16] were the second most commonly reported business domain, appearing in 14% of primary studies. Code generators, communication and collaboration, file storage and sharing, web development, hosting, and streaming services are all examples of web services firms. It is worth to mention that e-commerce, transportation, and insurance have BPs that are comparable to web services, but we classified them separately owing to their AI model properties. Education [S1, S19, S22, and S34] is the third of all identified business domain, contributing to 11% of our primary studies. Online education platforms, higher education, and basic and secondary education are among those domains. Social media [S4, S6, S7, S23, S5], software industry [S10, S29, S36], and logistics [S17, S27, S33] were the fourth most reported business domains, at 8% each. Twitter, Facebook, job search and recruiting, online markets, news, and content aggregation are examples of social media applications. Software development and software project management packages and tools are typical software industry applications. Automated and intelligent transportation, intelligent cars, and commercial logistic drones are all part of the logistics business industry. With 6% each, the manufacturing industry [S37, S38] and e-commerce [S13, S38] are the sixth most reported business domains. Shopify, WooCommerce, Magento, BigCommerce, retail, and sales services are a few of the e-commerce systems. Collaborative robots (chatbots), robotics, revenue management, inventory management, and supply chain traceability are typical manufacturing applications. Insurance [S31]. Real estate [S3] and entertainment [S17] were 3% of our primary studies. The focus of insurance applications was on detecting fraud in insurance claims. The real estate case studies focused on market analysis and prediction. The entertainment industry includes games, storytelling, and digital art.

The second part of this research question was to identify and classify the features of these models and frameworks which were designed in the business domains shown in **Fig. 5**. The characteristics of models and frameworks are shown in **Table 6**.

Table 6. Model Framework Classification with Goal and Limitations

Model Domain	**Primary Studies**	**Model Characteristics**	**Model/Framework Class**	**Model Limitations**
Education	S1, S19, S22, S34	Predictive Feedback Oriented Giddiness, Performance assessment	Explainable decision-making	Time constraints Data quality bias AdversarialAttacks
Health Care	S2, S9, S11, S18, S24, S25, S26, S28, S32, S35	Predictive Analytic Resource Optimization Accuracy Effectiveness	Predictive	Noisy Data High Resource Management
Governance	S2	Decision Making Accountability AI Adoption	Business Intelligence	
Real Estate	S4,S3	Forecasting Real time data	Business Intelligence	Data Quality
Social Media	S4,S6, S7, S23, S5	Data Driven Social Broadcasting Forecasting Intent Classification	Business Intelligence	Noisy Data Large Memory Requirement
Web Services	S6, S7, S14, S15, S16	Groupware Communication Interaction Based Data Traceability Decentralized	Collective Intelligence	Privacy Issues
Software Industry	S10, S29, S36	Security Transparency Activity Tracking	Data-Centric	Privacy Issues Data Dependencies Lack of Generalization
e-Commerce	S13, S38	Generlision People Oriented	Process Oriented	Complexity High Costs

		Value Based		
Entertainment	S17	Security, Privacy Communication Efficient	Predictive	Large Data-sets
Logistics	S17, S27, S33	Value, optimization, consensus, Failure Layered-workflow	Predictive	Resource-intensive
Insurance	S31	Anomaly detection Incremental Learning Distributed Data Sharing Data Classification	Secure Transaction Data Driven	Privacy Concern Lack of Governance Delays in Communication channels
Manufacturing	S37,S38	Cognitive ability Quality Control	Process Oriented	Standardization

Table 6 represents the business domain, primary studies mentioning that business, model/framework, model/framework characteristics, model/framework goal, and their limitations in each column, respectively. In this analysis, there were a total of seven classes found. These distinct classes are predictive models, explainable decision-making models, business intelligence models, collective intelligence models, data-centric models, process-oriented models, and data-driven models. Predictive systems are AI-enabled business models that take data as input and employ AI, ML, and DL algorithms to predict or anticipate future events, behaviors, or situations. These systems analyze previous data to detect trends and patterns, and then build knowledge-based predictions for the future. The major goal of the systems is to improve a company's decision-making process. Data analysis, algorithms, model training, and real-time or batch processing are all common components of a predictive system. As shown in Table 6, many other predictive system components are dependent on business domains, such as decision-making, accountability, AI adoption, predictive analytics, resource optimization, accuracy, effectiveness, security, privacy, communication efficiency, value, optimization, consensus, and layered workflow. Large data sets, resource-intensive solutions, and noisy data were the constraints of predictive systems highlighted in our primary investigations. Overall, predictive systems use data and sophisticated analytics to deliver significant insights and aid decision-makers in planning for future forecasting and process optimization.

The models for explaining decision-making are based on XAI, AI, or ML models. The fundamental design goal of these models is to give interpretable explanations for the models' complicated decision-making process. The objective is to make complicated models more visible and accessible to users, stakeholders, and decision-makers so that they can understand the logic behind the model's output. Business intelligence models are a set of tools, approaches, procedures, and processes that are used to collect data and display it in a way that allows for automated decision-making. These models are distinguished by their capacity to extract value from data and incorporate it into operational efficiency. Data warehousing, data integration, data analysis and reporting, online data analysis, data mining, and a performance management unit are the main components.

To address an issue, collective intelligence models rely on the knowledge and experiences of a group of people. The goal of these strategies and procedures is to produce a better solution by making decisions based on the collective wisdom of a group. This notion is applicable in social, organizational, and technical contexts and spans several disciplines. AI-enabled models are data-centric models that emphasize the role of data in the creation and execution of business processes. Through data management, data analysis, data processing, and data visualization, these models provide business value. Decision-making in business operations is the major goal of data-centric models.

These models and frameworks have many features in common with their common goals, as well as a few unique features depending on their implantation choices and domain requirements. We try to classify these models on the basis of their use and working methods. This is necessary because the AI methods discussed in **Fig. 4** have so many different implementations that are both context-dependent and domain-dependent.

4.3 How do academic research studies design in the AI-enabled business domain?

The type and design of the model or framework employed in testing empirically in a certain business domain are critical. The usefulness of a technique does not guarantee its appropriateness to fulfil a business objective. Thus, in order to perform a successful experiment case study, guideline, and simulation, empirical principles for the design of experiments, case study, guidelines and simulation must be followed. In this research question, we look into the designs, reproducibility, as well as the size of the reported studies.

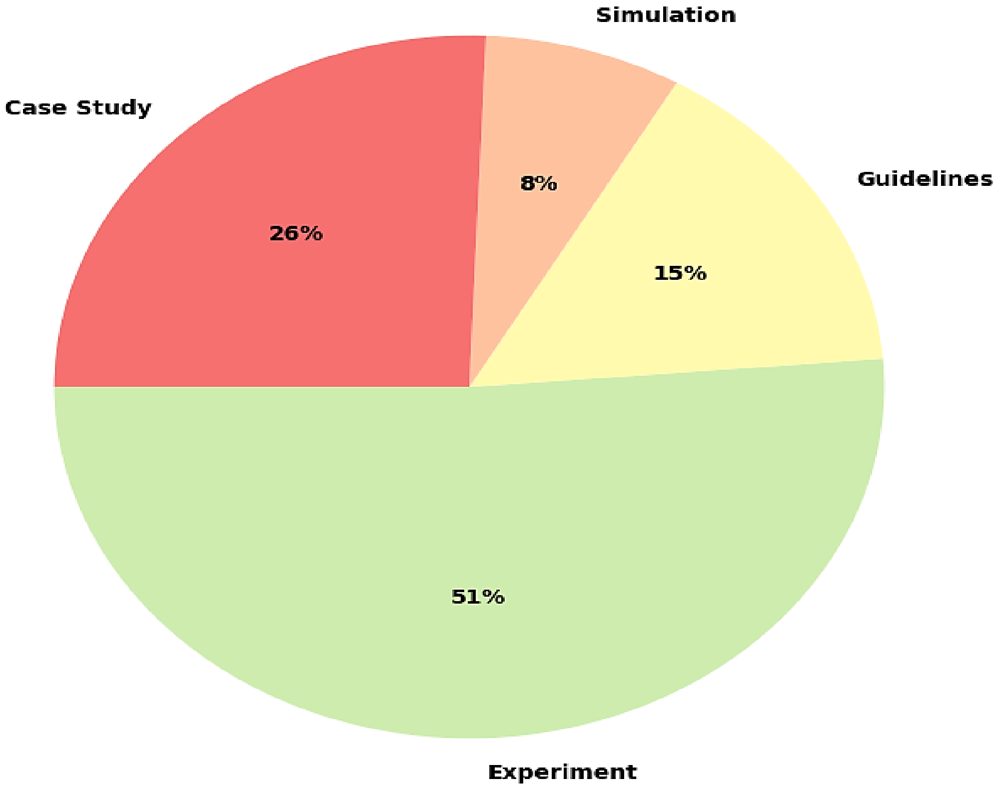

Fig. 6. Primary Studies Design Distribution

To answer the question we use following definitions to assess the primary studies.A research in which an intervention is deliberately executed with the objective to examine its repercussions [52]. A scientific investigation into an ongoing occurrence in its intended setting existence context, in which the differences between manifestations and the environment become fuzzy clearly prominent [53].

The primary studies were evaluated by these definitions and discovered that 51% of the research claimed to be experimental [S4, S5, S8, S9, S10, S16, S18, S19, S22, S23, S24, S25, S26, S27, S29, S30, S31, S32, S33, S34, S35, S38], and 26% of the studies claimed that they were conducted as case studies. It was also found that 15% of primary studies proposed guidelines. There were also 8% of studies that presented simulations. **Fig. 6** depicts the distribution of key study design features. It is also noticed that 21 of the 39 primary studies clearly indicate their research questions, whereas 8 of the 39 primary studies mention their research aims only partially, and 10 studies do not include their research questions or research goals at all. The second finding was that 19 of the 30 primary studies did not identify their threats to validity, 6 partially expressed their threats to validity, and 13 did not discuss or express their limits. The third design criteria of the study was its reproducible results. It was found that 27 of the 39 primary papers utilized public datasets, 6 used private datasets, and 6 did not give information on their datasets. **Table 7** shows specific information for each research design parameter.

Table 7. Primary Studies Design Structure Assessment

ID	Question	Yes	Partially	NO
1	Are the research questions mentioned explicitly?	21 (53.6%)	8 (20.7%)	10 (25.7%)
2	Were the threats to authenticity conveyed clearly?	19 (48.6%)	6 (15.7%)	13 (33.7%)
3	Is the study replicable (using publicly available datasets)?	27 (69%)	6(15.5%)	6 (15.5%)

5. Discussion

Following a thorough study of the literature, it is also critical to note that AI has spawned several misunderstandings among the scientific and academic sectors. AI is seen to be an excellent fit for nearly every problem. In truth, the situation is not as it is often assumed or portrayed. Because the creation of AI solutions is very context-dependent in its design and applications, it is important to note that AI solutions have yet to be generalized. The AI solution for book sales may not be applicable to the auto-sales procedure. AI solutions are also seen to be a replacement for human cognitive decision-making processes. We feel that after examining these 39 research articles, AI solutions are confined to many of the challenges and their contextual contexts.

AI is also a very broad term, and somehow it is mixed with IoT, edge computing, big data, and cyber security. There were many research studies that claimed and justified the evidence that there were different methods in their use and design. It is also believed that AI models may not explain themselves, such as in knowledge creation and knowledge representation domains. It is also hard to understand that AI models may not provide their own justifications and explanations about their internal data processing and analysis procedures.

It is clear that the use of AI and its related fields is growing by the day. Because of this growing popularity, AI technology has both advantageous and undesirable repercussions. The most common concerns regarding AI include security, privacy, safety, ethics, and AI legislation for business, as well as the governance of AI technology across various parts of society. The legislation and regulations may fall under the jurisdiction of governments, and regulatory bodies actively develop and enforce the laws through law enforcement agencies. The framework of ethics, security, safety, and privacy has two aspects that must be enforced and evaluated. According to one point of view, the implementation of security, safety, privacy, and regulations is enforced through technology such as blockchain methods, which are attempting to deliver secure solutions; XAI is attempting to provide understandable solutions; and responsible AI provides solutions that address society's privacy and regulatory concerns. The second point of view is that these technologies must be implemented with legitimate competence, and more research is required to explore these problems in society.

In terms of technology implementations, AI subdomains such as ML, DL, traditional AI, blockchain, and cloud computing have become established, while ethical AI, XAI, hard AI, and responsible AI require significant attention from academia and industry. Models such as business intelligence were shown to be common aims in the majority of AI approaches, although models and frameworks such as collective intelligence and process-oriented models have gained momentum in academia in recent years and provide the potential for further research. Last but not least, while designing empirical investigations, research study design and organisation must be carefully considered. It was identified that we discovered 339 papers, only 39 of which followed certain experimental guidelines, and only 27 of the 39 research studies were reproducible.

6. Conclusion

The findings of our systematic review of empirical studies on AI-enabled business models have been presented. The SLR concentrated on AI methodologies and techniques utilised in various business areas. Three research questions were developed, the following are the conclusions based on these study questions:

RQ1: A total of 39 studies were chosen from a total of 336 research based on AI-enabled business models published between 2010 and 2023. AI, DM,ML, HCI, DM, cloud computing, edge computing, IoT, CPS, explainable AI, big data, blockchain, computer vision, ethical AI, responsible AI, hard AI, cyber security, and NLP were among the eighteen (18) unique methodologies and techniques. Based on their context and the problems they tackle, these strategies and techniques differed in different ways. The intelligence and automation shared by various approaches and methods. AI and machine learning were the most popular methodology or techniques among academics, accounting for 19% of all main studies. The cybersecurity and NLP were found in 2% of the studies selected for the SLR. The emerging crossroad among the AI business solutions were explainable AI, responsible AI and hard AI.

RQ2: The objective of this research question was to identify business areas and key goals for adopting AI-enabled models and frameworks in those domains. According to 28% of the research studies, the most popular domain researched by researchers was medical and healthcare. The most common goal of AI models and approaches built for business models is business intelligence. Collective intelligence and explainable decision making were found emerging trends among the research community.

RQ3: We discovered that 51% of the research chosen were experimental. 21% of studies explicitly stated their research questions. A threat to validity was stated in 19% of the research. 27% of research papers used publicly available datasets, making them reportable. The majority of studies did not adhere to the research methodology and experimental standards outlined in their research methodology section. To maintain maturity in the AI-enabled business model area, empirical research must be designed with adequate experimental guidelines.

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