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AI advancements – scary or hand holding for employees? A systematic literature review

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Abstract: The knowledge gained from a thorough literature analysis that was carried out to identify, categorise, and analyse recent developments in artificial intelligence (AI), its business applications, and its effects on the labour force is presented in this paper. Ninety-four papers are analysed and categorised as AI-related, business-related and domain-specific. AI developments and their applications in different functions of business and sectors of industry, and the possible impact on workforce are discussed. Robotic process automation, machine learning and natural language processing, along with their recent features that find use in business functions are presented. This study contributes to both technical and managerial literature. Future studies irrespective of their discipline can use this study as a roadmap from both technical and business perspectives. The paper also discusses the impact of AI on workforce in a futuristic and optimistic perspective. This study's practical implications include illuminating the path towards individual self-evaluation and skill acquisition, organisational skill development and forecasting, and societal welfare policy framing.

Keywords: AI advancements; AI and business applications; AI and workforce impact; AI and employees; Systematic literature review.

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1 Introduction

In the modern world, artificial intelligence (AI) has gained popularity and caught the interest of researchers and industry professionals (Hutchinson, 2020; Sestino and De Mauro, 2022). Today, AI use represents 80% as strategic opportunity and 85% to achieve competitive advantage (Enholm et al., 2022). Economies continue to express overwhelming interest in investing on AI for the future, and there have been leaps in such investments in recent years (Furman and Seamans, 2018). The world is awaiting the predicted transformation through AI revolution, especially in business functions (Gil et al., 2020; Muhloth and Grottko, 2020). This transformation is expected to create considerable social and economic opportunities (Harari, 2017) and transform work culture around the world (Acemoglu and Restrepo, 2018). AI is reshaping organisational expectations by promising efficient performance of various tasks, contributing to innovation, and enabling accuracy and speedy completion of tasks (Huang and Rust, 2018). Amidst excitement about the advancements promised by AI, there have been concerns as well. The threat to human manpower/jobs has raised fear of employment among people (Siau and Wang, 2018).

AI is a well-researched topic in various disciplines (Taulli, 2020; Mohri et al., 2018). From the business angle, the impacts and benefits of AI to various end-use applications have been analysed (Droll et al., 2017; Campbell et al., 2019). The importance of exploring the interplay of AI and business is many-fold. First, AI is associated with better accuracy and speed, both of which bolster the business ecosystem and therefore warrants more extensive exploration (Furman and Seamans, 2018; Harari, 2017). Second, AI can conceivably alter the lifestyle and standards of living in the same way that the industrial revolutions of the past centuries altered the fabric of social living (Harari, 2017). Finally, the employment of technology can be challenging due to a variety of reasons (Peters, 2017). However, there have been less discussions spreading out both technical and business aspects of AI (Loureiro et al., 2020). It is thus important to study AI from all these aspects, and not merely from the technology and science angle, in order to prepare societies to participate in the change heralded by AI advancements.

This paper aims to analyse recent progress in AI and their implications in the business domain. It also investigates the impact of AI advancements among human workers.

2 Overview of the study

AI has developed quickly in recent years and has numerous applications in a variety of industries (Ali et al., 2023). AI interventions enhances the business resilience (Zamani et al., 2023), supports digital transformation and hence societal transformation (Sestino

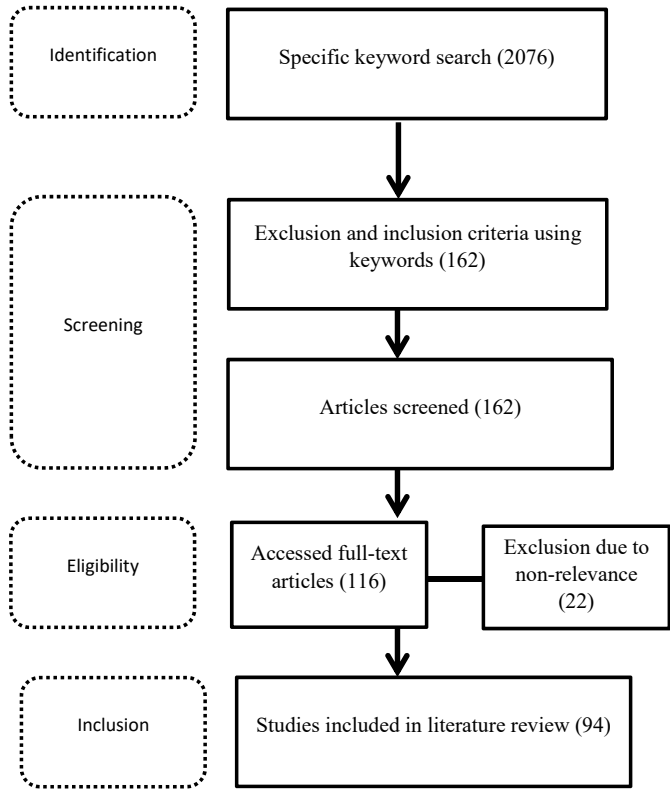
et al., 2023). Though studies have attempted to discuss role of AI in business and technical terms separately, an interplay of both of these rarely discussed (Han et al., 2021; De Mauro et al., 2022). Moreover, the human elements such as emotions and their concerns were rarely discussed in the previous works (Glikson and Woolley, 2020). In order to fill in these research gaps, the following research questions will be addressed in this paper:

- RQ1 What are the recent advancements of AI and what are their applications/implications in business?
- RQ2 How do these AI advancements influence/affect employees in an organisation?

3 Method

An extensive examination of the reported AI tools and technologies, as well as their present or anticipated application in the workforce, can address the research issues. In order to do this, a thorough literature study was carried out, and the PRISMA criteria were used to create the framework (Moher et al., 2009).

Figure 1 Steps of the systematic literature review



A systematic literature review analyses all related earlier primary studies to collate and evaluate the information/knowledge that have been gained in the area of interest (Barata

et al., 2018). Such reviews provide a theoretical framework and methodological rigour to academicians and a reliable knowledge-base for practitioners (Boland et al., 2023). Although there are numerous frameworks for conducting systematic literature review in social sciences (Tranfield et al., 2003; Jesson, 2011), we have applied the framework recommended by Jesson (2011) due to its wide acceptability in techno-managerial studies (Tezel et al., 2016; Spilker et al., 2019; Al-Kurdi et al., 2018). Such an approach starts with conducting a comprehensive search of literature in the relevant area of research.

The overall review approach comprises three steps. The first step is the identification of the need for the review and development of the review principle. The second step is the identification of the research domain, selection of research studies in the domain and synthesis of data from these studies. The final step is the report of the result of the review. Figure 1 shows the steps of systematic literature review used in this study.

3.1 Identification and search process

To address the research questions, a systematic research review was conducted during February 2020 and the results were subsequently updated in May 2020.

Table 1 Inclusion and exclusion criteria

<i>Inclusion/exclusion</i>	<i>Criteria (codes)</i>	<i>Explanation</i>
Exclusion (Screening stage-1)	Non-English files (EX-N-ENG)	Paper with abstract available in English, not full text
	Non-Accessible files (EX-N-ACC)	Full text of paper is not accessible
	Non-relevant files (EX-N-REL)	File contents from blogs and media platforms
Exclusion (Screening stage-2)	Non-matching content files [AI advancements] (EX-N-MAT-AI)	AI appears only as example or in future research directions or in keywords or reference
	Non-matching content files [AI impact on employees] (EX-N-MAT-EMP)	AI impact on workforce appear s only as example or in future research directions or in keywords or reference
Inclusion (Screening stage-3)	Matching content files [AI advancements] (IN-MAT-AI)	AI is one among the many topics discussed in the article, or article discusses AI without specifically mentioning the term
	Matching content files [AI impact on employees] (IN-MAT-EMP)	AI impact on workforce is one among the many topics discussed in the article, or article discusses it without specifically mentioning the exact term
Inclusion (Screening stage-4)	Explicit matching content files [AI advancements] (IN-EXMAT-AI)	These articles clearly related to AI advancements or its impact on employees or both

The databases used for this search were Scopus, IEEE, ProQuest, EBSCO, ScienceDirect and Web of Science. The snowball effect was also used as additional searches were performed based on the articles referenced in the primary search articles. The papers discussed English-language conferences, books, and publications in peer-reviewed journals. We also had access to several reports from international and national

organisations that deal with AI. For acquiring more insights into this area, we accessed different websites related to AI, media reports and expert talks. To locate the research articles related to the research questions, the keywords ‘artificial intelligence’, ‘AI’, ‘AI and employees’ and ‘machine learning’, etc. were used in the search. The journals from which the articles were culled were chosen based on their contribution to the area of AI.

To ensure all papers could be assessed with few or no subjective opinion(s), two fundamental review principles were adopted, viz. explicit inclusion and exclusion criteria, and a two-level review strategy. The criteria for including or excluding the papers that were gathered were specified in clear inclusion and exclusion criteria. Table 1 represents detailed inclusion and exclusion criteria.

In the review strategy, each paper that was chosen was reviewed by both authors and assigned codes as mentioned in the inclusion and exclusion criteria. These were cross checked and a decision was reached to include or exclude the paper. In case of any difference of opinion, decisions were taken based on consensus and external expert opinion.

3.2 Article classification criteria

For classification of included papers, a concept-centric approach (Webster and Watson, 2002) was used, and the papers were divided into AI-related, business-related and domain-specific categories. In the AI-related category, studies that are more of technical in nature, including AI, RPA, ML, etc. were included (Van Der Aalst et al., 2018; Moffitt et al., 2018). For the business-related category, we included papers in the area of impacts of AI in the business arena (Bickel et al., 2019; Feng et al., 2018). The domain-specific category included papers relating to AI impact on workforce (Levy, 2018; Makridakis, 2017). This classification of reviewed papers is shown in Figure 2. The source journals of the selected articles under each classification are shown in Table 2.

Figure 2 Distribution of papers for systematic review process (see online version for colours)

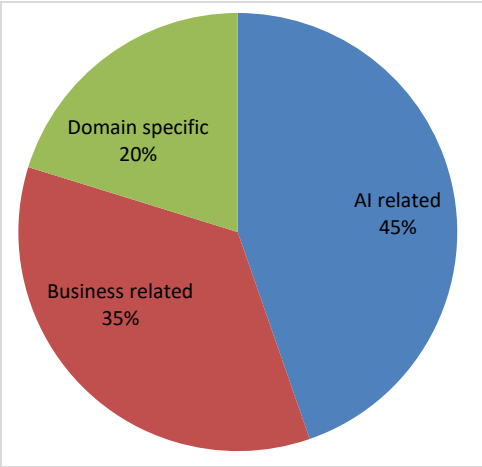


Table 2 Year-wise distribution of papers

Year	Number of papers published	Number of papers published based on classification		
		AI related	Business related	Domain specific
2015	2	1		1
2016	8	3	4	1
2017	16	7	6	3
2018	27	11	10	6
2019	32	14	11	7
2020	9	6	2	1
Total	94	42	33	19

4 Results

The analyses of the results were divided into three sections. In the first, characteristics of the papers were analysed. Methodological aspects were also included in this section. The second section focused on AI advancements and its applications in the business domain. The final section analysed the impact of AI on the workforce.

4.1 Characteristics of the papers

The study analysed 94 articles published between 2015 and 2020. The criteria of descriptive analysis for characteristics of the paper are distribution of publication over time based on classification and its type. Hence, we explored several articles published over years. Table 2 shows the year-wise distribution of articles.

A noticeable increase in the number of articles over the years shows the growing interest in the topic among practitioners and researchers. As the study was conducted in the beginning of the 2020 and completed in middle, the data for the year is incomplete to make an evaluation for that year. The papers selected under the classifications have also shown the same trend of increase over the years. Under the classifications, the business-related papers included different sectors such as insurance, BPO, auditing, manufacturing companies, supply chain firms and design/architecture companies. These papers discussed various management functions including finance, marketing, production and HRM.

The second criterion considered was the type of the article over years. We divided the papers into journal articles, conference proceedings, and others. Reports, books and newspaper articles were included in the ‘others’ category. Of the 94 papers, 92% (86 papers) were from peer-reviewed journals and 4% (four articles) were from conference proceedings. The remaining 4% (four articles) consisted of books, news articles and reports (see Figure 3).

Table 3 shows the journals in which the 94 papers that were reviewed in this work appeared.

We analysed the relevance of the journals to the aim of the current review and found the following journals to have the most number of relevant papers: *Artificial Intelligence Review*, *British Journal of Management*, *Business Horizons*, *Computers in Human*

Behavior, Harvard Business Review, IEEE Transactions on Engineering Management, Information Fusion International Journal of Information Management, International Journal of Production Research, Journal of Artificial Intelligence Research, Journal of Enterprise Information Management, and MIS Quarterly Executive Technological Forecasting and Social Change.

Figure 3 Types of articles per year (see online version for colours)

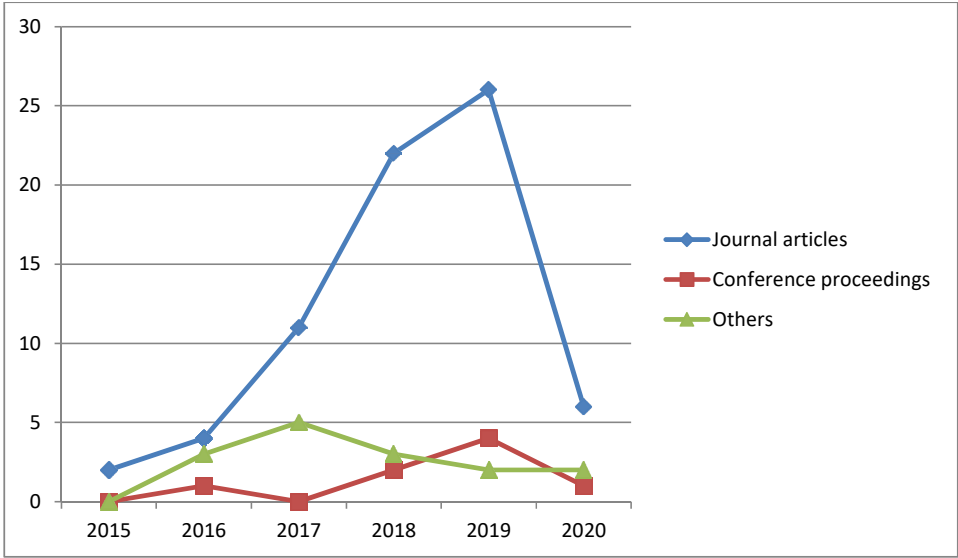


Table 3 Sources of contribution

Source	Number of papers
<i>Journals</i>	
<i>ACM Computing Surveys (CSUR)</i>	1
<i>AI & Society</i>	1
<i>Artificial Intelligence Review</i>	2
<i>arXiv preprint arXiv</i>	1
<i>Automated Software Engineering</i>	1
<i>British Journal of Management</i>	2
<i>Business & Information Systems Engineering</i>	1
<i>Business Horizons</i>	3
<i>California Management Review</i>	1
<i>Central European Business Review</i>	1
<i>Cognitive science</i>	1
<i>Computational Linguistics</i>	1
<i>Computers and Industrial Engineering</i>	1
<i>Computers in Human Behavior</i>	2
<i>Current Opinion in Behavioral Sciences</i>	1

Table 3 Sources of contribution (continued)

<i>Source</i>	<i>Number of papers</i>
<i>Journals</i>	
<i>Cutter Business Technology Journal</i>	1
<i>Digitalisierung von Staat und Verwaltung</i>	1
<i>Futures</i>	1
<i>Harvard Business Review</i>	3
<i>IEEE Computational Intelligence Magazine</i>	1
<i>IEEE Transactions on Engineering management</i>	5
<i>Information Fusion</i>	2
<i>Information Processing and Management</i>	1
<i>International Journal of Information Management</i>	2
<i>International Journal of Production Research</i>	2
<i>Journal of Artificial Intelligence Research</i>	2
<i>Journal of Financial Perspectives</i>	1
<i>Journal of Emerging Technologies in Accounting</i>	1
<i>Journal of Enterprise Information Management</i>	2
<i>Journal of Information Technology Teaching Cases</i>	1
<i>Journal of Labor Economics</i>	1
<i>Journal of Manufacturing Technology Management</i>	1
<i>Journal of Participation and Employee Ownership</i>	1
<i>Journal of Quantitative Linguistics</i>	1
<i>Journal of Service Research</i>	1
<i>Machine Learning</i>	1
<i>Management</i>	1
<i>Minds and Machines</i>	1
<i>MIS Quarterly Executive</i>	2
<i>Nature News</i>	1
<i>Oxford Review of Economic Policy</i>	1
<i>PLoS One</i>	1
<i>SSRN Electronic Journal</i>	1
<i>Strategic HR Review</i>	1
<i>Supply Chain Management: An International Journal</i>	1
<i>Synthesis Lectures on Artificial Intelligence and Machine Learning</i>	1
<i>Synthesis Lectures on Human Language Technologies</i>	1
<i>Technological Forecasting and Social Change</i>	2
<i>Technology Innovation Management Review</i>	1
<i>The Journal of Financial Perspectives</i>	1
<i>VLDB Journal</i>	1
<i>Workshop on Engineering Applications</i>	1

Table 3 Sources of contribution (continued)

<i>Source</i>	<i>Number of papers</i>
<i>Other sources</i>	
<i>AI: Augmentation so more so than Automation</i>	1
<i>Amazing progress in AI and Automation</i>	1
<i>Artificial intelligence: a modern approach</i>	1
<i>BBC News(News report)</i>	1
<i>Cognitive Computing for Big Data Systems Over IoT</i>	1
<i>EAI international conference on smart objects and technologies for social good</i>	1
<i>Foundations of machine learning</i>	1
<i>ICSE-SEIP 2019(Conference proceedings)</i>	1
<i>Innovation Policy and the Economy</i>	1
<i>International Conference on Applied Technologies</i>	1
<i>International Conference on Economics and Finance Research (ICEFR)</i>	1
<i>International Conference on Information Systems</i>	1
<i>Managing Technology and Middle- and Low-Skilled Employees</i>	1
<i>National Bureau of Economic Research(Report)</i>	1
<i>NBER Summer Institute(Report)</i>	1
<i>New Horizons for a Data-Driven Economy</i>	1
<i>Proceedings of International Design Conference</i>	1
<i>Proceedings of the AAAI Conference on Artificial Intelligence</i>	1
<i>Proceedings of the International Conference on Engineering Design</i>	1
<i>The Executive Guide to Artificial Intelligence</i>	1
<i>The Future of Management in an AI World</i>	1
<i>The Guardian</i>	1
<i>The Robotic Process Automation Handbook</i>	1
<i>World Economic Forum</i>	1
Total	94

4.2 *AI advancements and its application on business*

4.2.1 *Artificial intelligence – future awaits*

AI, which was first named in 1956 (Russell and Norvig, 2016), is one of the newest fields of study and it deals with the emulation of human intelligence processes by computers, particularly computer systems (Russell and Norvig, 2016). These processes include learning, reasoning and self-correction. Today, AI is used in multiple disciplines and fields (Saidi Mehrabad and Fathian Brojeny, 2007; Park et al., 2019). It is anticipated to bring about significant changes in many facets of our culture and way of life in the near future, leading to highly integrated businesses with decision-making processes predicated

on the examination of ‘big’ data and heightened international competition (Makridakis, 2017). However, AI might also result in higher levels of unemployment and income disparities (Makridakis, 2017).

Professor Stephen Hawking once told the BBC that “the development of full artificial intelligence could spell the end of the human race” (Cellan-Jones, 2014). While considering the legend’s words in the area of workforce, it is predicted that artificial intelligence can surpass human performance in many jobs and replace human workers (Siau and Wang, 2018). More precisely, more than 800 million workers, about a fifth of the global labour force, could lose their jobs soon due to the AI revolution (Gray, 2017).

4.2.2 Importance of AI in business

The benefits of AI to the employer and employee are many-fold, which would drive its adoption in future.

4.2.3 Product/service aspect

Over the next decade, AI methods will become increasingly significant in product development processes that can complement numerical simulations and increase their accessibility, thereby enabling economic viability (Zimmerling et al., 2019). AI is widely used for the product development process that helps in reducing the time for any development and in enhancing product quality (Bickel et al., 2019). AI also explores and maximises customer value (Feng et al., 2018). A recent change in the area of consumption is that many customers are now willing to use AI devices in customer delivery as well (Gursoy et al., 2019).

4.2.4 Functional aspect

Marketing applications of AI include expert systems for sales promotion, automation of reporting, predictive modelling of customer behaviour and case-based reasoning for decision-making (Orriols-Puig et al., 2010; Jarek and Mazurek, 2019). Another area for AI application is human resource management (HRM). In HRM, the use of AI can span the entire range of operation, from hiring of employees to retention, management and termination and naturally, many organisations have started using AI in HRM (Cappelli et al., 2018; Gulliford and Dixon, 2019). The major finance applications of AI are in block chain technology, areas such as portfolio construction and return forecasting (Emerson et al., 2019). Supply chain risk management and supply chain optimisation are the areas that have the most scope for AI integration because they make use of genetic algorithms (Baryannis et al., 2019; Calatayud et al., 2020). AI helps in enhancing customer service, optimising processes and internal business operations, and generating insights (Burgess, 2018).

Despite the above advantages, as the challenges faced by AI include difficulty in integrating with existing systems, expensive technology, dearth of knowledge about the technology, lack of expertise in the technological area, immature technologies, etc. (Davenport and Ronanki, 2018).

4.2.5 *Types of artificial intelligence – a business view*

AI is divided into three types:

- 1 process automation
- 2 cognitive insight
- 3 cognitive engagement.

4.2.5.1 *Process automation*

Process automation is also known as robotic process automation (RPA). This a collective term for tools that operate at the user interface of computer systems in the way a human would do (Van Der Aalst et al., 2018). This technology aims to perform tasks that are repetitive and mundane and involve a lot of human time (Asatiani and Penttinen, 2016). This is currently the most frequently used type of AI in businesses due to its low cost and high return on investment (ROI) and is also the least complex one among the lot (Moffitt et al., 2018). This idea of automation has existed for long, such as in screen scraping, and current technological improvements have significantly expanded the scope of RPA. Using these tools and technology allows employees to focus on more creative and productive tasks. RPA works best for automating repetitive and tasks that require zero to low-levels of thinking. Automation is performed using software bots (bots run using software on personal computer device). Automation can be achieved by code scripts written by a developer or using application user interface (API).

An overall picture of process automation is as follows – in a normal office setup, a data entry operator could receive some details by mail every day, which will be entered into a customer relationship management (CRM) software of the company. This is a time consuming chore that is prone to errors. Software bots can be employed to extract data from the mail and input them into the CRM software, with 100% accuracy and 0% human intervention (percentages might vary depending on the nature and complexity of the task). While the above example is simplistic, RPA can be used for more complex activities. One advantage of RPA is that unlike an office employee who requires a table, computer, and other materials to work, a software robot can perform the task in a virtual environment or on the cloud, making it easy for companies to adapt it to their business objectives (Santos et al., 2020).

There are many fields in which the scope of RPA is significant, such as banking and finance, lending and mortgage processes, customer care, online shopping merchandising processes, optical character recognition (OCR) applications and data entry and extraction activities (Aguirre and Rodriguez, 2017; Lamberton et al., 2017; Kedziora and Kiviranta, 2018; Taulli, 2020). Some uses for process automation are report generation and distribution, transferring of files, orders handling, e-mail sending/attachment extraction, claims process and customer support (Aguirre and Rodriguez, 2017; Hallikainen et al., 2018).

Due to the current pace of technological advancements and the decreasing budgets required to deploy RPA, we can expect an RPA 2.0 scenario or unassisted RPA. Implementing AI technologies into RPA would reduce the need for periodic checking of the functioning of the bots. But for the realisation of such AI-enabled RPA, clear process path, objectives and contingencies need to be put in place. ‘Hyperautomation’ – a fusion

of different latest technologies like RPA, AI, data mining, etc. can potentially mimic human workers to create more impact than just automation (Park, 2017).

RPA has its own drawbacks as well. The cost-burden is one of them, and only 3% organisations have deployed more than 50 bots until now, because of the expenses involved (Houy et al., 2019). Frequent or periodic changes in regulations and data collection could render a programmed bot useless for the task, unless reprogrammed (Taulli, 2020). Reprogramming to suit the new regulations/procedures could be time consuming and complex. Some large companies using RPA are Walmart, Walgreens, AT&T, Vanguard, Ernst & Young, Deutsche Bank, Anthem and American Express Global Business Travel, etc. The current leading software providers for enterprise-level RPA deployment are Automation Anywhere, Blue Prism, UiPath.

4.2.5.2 Cognitive insight

This is another domain in which businesses seek to incorporate AI and other new age technologies to make the most out of the data they currently have. The objective of this field is to derive inferences/meaning/decision-suggestions from large amounts of data (Duan et al., 2019). As it deals with a large volume of data, it is dominated by technologies like machine learning (ML), deep learning (DL) and algorithmic learning. Such application can help in areas such as predicting consumer preference of products, identification of profitable clients for insurance, fraud detection, analysis of warranty data to find safety and quality issues in products and personal digital marketing (ads relevant to the person) (Davenport and Ronanki, 2018).

Although cognitive insight may appear to be similar to business/data analytics, but there is a fundamental difference with the in that the former uses ML and is heavily dependent and requires large amounts of data to perform well (Droll et al., 2017). The algorithms/models are trained on part of the data (generally 70%) and tested and validated using the remaining data; thus, the more data used to train, the better the model performs, i.e., it can predict things more accurately.

One type of ML technique is ‘DL’. DL attempts to mimic the human brain by replicating the working of neurons to find patterns in data (Mohri et al., 2018). DL is powerful enough to be used to recognise objects, numbers, signs, speech, etc. Using ML we can create new data for better analytics (Ratner et al., 2020).

Data curation is a crucial and challenging task for large companies and ML has enabled identification of data that belong to a same entity (person or company) (Sakr et al., 2018). This is done in a probabilistic manner, which means data that relates to the same entities but in different formats can be grouped together for better analysis (Freitas and Curry, 2016). Many companies have used this technique and saved money in the process (Fakher et al., 2017; Parthy et al., 2019).

To exemplify the business impact of this technology, we will look at two examples. General Electric matched supplier data using this technique and save a whopping 80 million dollars by clearing duplicate records and re-negotiating contracts that were managed at lower levels earlier. Deloitte’s Audit agency is using cognitive insight technology to gather the terms and conditions from contracts to automatically complete the audit process without a human auditor, which reduces the document processing time and eliminates the engagement of humans in this mundane task.

A current application in this field which is taking the marketing world by storm is ‘extreme/depth personalisation’; it uses DL to create customer profiles that are accurate and can be used for ad targeting and product curations (Campbell et al., 2019).

There are many benefits of using cognitive Insight in a company. It provides detailed and accurate data analysis (Pramanik et al., 2018). This accuracy in data analysis helps for increased productivity and efficiency in business processes and enhanced customer/client interaction (Duan et al., 2019). It not only provides highly probabilistic client profiling, but also mimics human thinking (Collins, 2019).

Most applications that benefit from cognitive insights are tasks that can be completely be carried out machines such as large data mining and data optimisation that are challenging and/or time consuming to be performed by human endeavour (Elmousalami, 2020). Thus, it does not pose a significant risk to employees and their job security. Despite its advantages, companies are yet to adopt it to understand their customer base, thereby and losing out on profits that could be gained through such insights (Trela et al., 2020).

4.2.5.3 Cognitive engagement

This area of AI uses natural language processing (NLP) and ML to engage customers and employees (Miller, 2017). The applications in this field include chatbots, intelligent agents, virtual assistants, etc.

Many companies now use cognitive engagement technologies to interact with employees of their organisation instead of customers/clients mostly because these tools are not mature enough to handle complex queries and solve a wide array of queries (Gil et al., 2020). Once the tools are capable, companies would start using it for customer-faced interactions. Some companies have developed virtual assistants capable of answering all IT-related questions of employees, thus acting as an IT support employee itself (Spencer et al., 2018).

This system of AI has not elicited much interest by companies because of the limited expertise. For example, Facebook discovered that its messenger chatbots could not solve 70% of the customer’s issues, and so limited the use of chatbots to very specific domains, and a narrow set of questions. Airtel uses this technology for its customer care support; it is implemented in the for IVR, where the customers can use the Dialpad on their phone to navigate the menu and resolve their queries. However, all queries cannot be resolved in this method, and for complex situations, human intervention is mandatory. Target uses customers order data to predict items that can be bought together and sends out these recommendations.

Although it may appear that this field is a threat to jobs, the lack of expertise has not yet realised the threat. However, improvements in chatbots and intelligent agents could replace current customer care services. The goal of the companies must be to handle the increase in customer and employee interactions without adding new employees and not eliminating current employees. Companies can use these tools to transfer simple and easy issue-resolving part to chatbots whereas complex ones can be handled by employees.

Cognitive engagement has many applications in different fields. It plays a role in health care recommendation systems and can help doctors provide customised care to their patients based on previous medications and treatments (Lawry, 2020). It is also used to resolve queries regarding IT, HR, company policy for the employees (Tarafdar and Beath, 2018). Many organisations use it as intelligent agents (or systems) to provide

customer service to customers on different topics and also in the local language of the client/customer (Spencer et al., 2018). It serves as recommendation systems that curate products or services for customers, this tool can be used for suppliers/retailers (Kumar et al., 2019).

4.2.6 Natural language processing

It is a field or subset of AI, that predominantly deals with textual, language or speech data (Sun et al., 2017). It can be summarised as an attempt to enable better collaboration between computers and humans in a natural language (NL) that includes the local languages or known languages (Young et al., 2018). The goal of this field is to understand human language and additionally mimic human speech and response to support linguistic communication.

The steps involved in the interaction with machines using NLP are as follows. When a person talks to the computer/machine, the machine records the audio. In the machine, audio to text translation process is initiated, and then the text is then refined and processed. Finally, the machine's text data is converted into audio data and the machine then plays the audio as a response (Goldberg, 2017).

Some of the common applications of NLP are:

- 1 text translation (Google translate)
- 2 personal virtual assistants such as Siri (apple), Google assistant, Alexa (Amazon)
- 3 IVR (interactive voice response) in customer care call centres (used by Airtel)
- 4 Applications like Grammarly to help in grammar and spelling corrections.

NLP is not a simple text processing tool as it appears and is more complex due to a variety of reasons. First, the rules and principles followed by humans in NL is difficult for computers to understand; human language uses semantic relationships to group words and meanings together in our brain, and it is challenging to program this feature into computers. Human beings understand not only the sounds/but also emotions through words and tone, whereas computers currently lack this specialty (Goldberg, 2017). Second, human speech is of high level, i.e., various elements of speech such as sarcasm, comedy, etc. are incorporated in it. Human beings can identify and analyse these aspects, and computers cannot just yet (Alulema Flores, 2020). As an example, translating 'Google is cool' using the Google Translate feature to the Hindi language, results in 'Google Shaanth Hai', wherein, the word 'cool' in English that is supposed to indicate it's awesomeness, is translated to a word that means 'peace' in Hindi. Third, for a machine to understand human language, we need to program the meanings of words and how they are structured into sentences to form a message or intent, and this has thus far, proven to be extremely difficult given the diversity and complexity of human language (Ponti et al., 2019). Fourth, there many ambiguities and inaccurate properties in our human language, which makes it hard for computers to understand as computers follow a rule-based approach to solve problems (Ferrari and Esuli, 2019)

NLP uses algorithms and different ML techniques to retrieve information from unstructured text, which is then converted into a form that computers can understand. The computer will parse through the text line-wise and derive the intent from each of the

sentences. When it fails to get the meaning (or the correct meaning) then the results will be poor.

The most important and widely used techniques in NLP are syntactic and semantic analysis.

4.2.6.1 Syntactic analysis

Semantic analysis deals with the syntax of the sentences. Syntax refers to the arrangement or structuring of words so that they are grammatically correct. Algorithms are applied to grammatical rules to get meaning from the text (Vani and Gupta, 2018). Popular techniques in this domain are parsing, word segmentation, lemmatisation, stemming, sentence breaking, morphological segmentation and parts of speech (POS) tagging. Parsing is the inspection of the text using grammar rules; this can be used to detect grammatical ambiguities and to determine if the appropriate syntax has been followed (Gómez-Rodríguez et al., 2017). Word segmentation deals with the splitting of large and continuous alphabet sequences into meaningful words (Lyu et al., 2012). Some languages do not have spaces as in English, and in such cases, word segmentation can be helpful. Lemmatisation helps in finding the root word from words that are of plural or other grammatical forms (Vassallo et al. 2019), e.g., ‘eating’, ‘eat’, ‘ate’, and ‘eaten’ have the root verb of ‘eat’. Stemming is similar to lemmatisation but with minor differences, in that it reduces the word into valid low level words (Singh and Gupta, 2016). Sentence breaking uses punctuations to identify the start, end and pauses in a sentence. This is tricky as punctuations are used not only for ending sentences but also as parts of words (e.g., ‘Mr.’) and abbreviations (e.g., ‘USA’). Morphological segmentation deals the breaking of words into components called as morphemes, ‘reader’, for example, can be spit into two morphemes, ‘read’ and ‘er’ (Cotterell et al., 2019). This field assumes that words are created by the combination of different morphemes. POS tagging deals with identifying the correct tag (verb, noun, adjective, etc.) to a word based on its context (Vulanović and Miangah, 2018).

4.2.6.2 Semantic analysis

Semantic analysis attempts to understand the meaning conveyed by the text using computer algorithms that analyse how the words are organised (Zupanc and Bosnić, 2017). This is a challenging part of NLP and research is ongoing to perfect it. Some good techniques are NL generation, named entity recognition and word sense disambiguation. NL generation involves gathering data from large knowledge bases (databases in general) to get semantic inferences and translate them to human language (Gatt and Krahmer, 2018). Named entity recognition deals with recognising words and putting them into categories like names, things, emotions, places, etc. (Lample et al., 2016). Word sense disambiguation helps in finding the correct meaning of the word using context if a single word has different meanings; for example, the word ‘bat’ can mean the animal bat or the sports item ‘cricket bat’ (Navigli, 2009). Sentiment analysis is a booming application used by businesses to find emotions or biases of their customer from data such as tweets, reviews and ratings.

4.2.7 Machine learning

ML enables computers to learn without being explicitly programmed (Alpaydin, 2020). It falls under Artificial Intelligence and originated as early as 1950's but it is more relevant and has high scope in today's world due to the availability of large amounts of data and significant computing capabilities. In simple terms, it is the science of making computers understand how to make decisions without human assistance. This is enabled through provision of large volumes of good data to the machine and training it so that the machine creates a model of this information and uses it to make decisions on the testing data; the accuracy of the decision is set to improve over time. There are many algorithms for training the data, the selection of which depends on the type of data available and the task to be carried out.

ML works through the following steps:

- 1 Collection of data in forms that are suitable for processing (text, images, videos, audio, etc.). The larger the amount and better the quality of data, better are the results of ML.
- 2 Processing of the collected raw data into forms that can be supplied as input to the ML model. This is often called as pre-processing.
- 3 Dividing the data into three sets - training set, validation set, testing set. The ratio generally used is 6:2:2. The split is random to avoid bias.
- 4 Iteratively testing of different techniques to choose the suitable ML model on the training data.
- 5 Testing the chosen model for performance on the training set using different metrics such as F1 score, recall and precision.

While dividing into five stages may appear trivial, it must be remembered that each stage/step takes time to complete and must follow the preceding one, except for steps 4 and 5 that are performed in tandem.

Some popular ML methods are supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning (Mohri et al., 2018).

4.2.7.1 Supervised learning

This method trains the data on known input and output, i.e., the set of desired outputs is pre-known (Jordan and Rumelhart, 2013). During the training, the model checks whether its prediction is correct or not and modifies the model accordingly to achieve better results. Applications like grouping mechanical components into 'F' (fail) or 'P' (Pass) based on some parameters can use supervised learning as the output is discrete ('P' or 'F'). Supervised learning can also be used to predict the validity of credit card transactions. This learning method is commonly used when past/previous data are used to predict future events. Some common methods are gradient boosting, regression, prediction and classification.

4.2.7.2 *Unsupervised learning*

This type of learning is often used when the data has no pre-set labels, i.e., the model must determine the nature of the data on its own (Hofmann, 2001). The goal is to find patterns or structure in the data. These techniques are generally deployed on financial and transactional data, to group or cluster customers based on different parameters and direct the company's marketing efforts according to the type of customer. It also can be used to identify the characteristics that differentiate certain group of customers from others. These techniques are generally used to group/cluster data points. Popular techniques are K-nearest neighbours (KNN), and K means clustering and maps.

4.2.7.3 *Semi-supervised learning*

This is a mixture of both supervised and unsupervised learning, i.e., the training data contains both labelled and unlabelled data (Zhu and Goldberg, 2009). Usually, a small amount of labelled data is used as unlabelled data and is cheap and easily available. This method can be used when the cost of labelling the data is high (expert labelling needs high payment). This learning method is used for regression, classification and prediction. One example is facial recognition through webcam video feed.

4.2.7.4 *Reinforcement learning*

Reinforcement learning is often used in robotics, navigation and gaming. The algorithm identifies a set of actions that give the maximum result, through trial and error (Sutton and Barto, 2018). Typically, there are three important components – the agent (the machine taking the decision), the environment (basically all that the agent interacts with), and the action (events the agent can do). The agent tries to find a sequence of actions to maximise the performance criteria (time/money/productivity). Thus, the objective of this learning method is to identify a set of rules that when incorporated, yield the best results.

There are many applications for this field in business. One may have observed that after searching or browsing for something in a search engine or shopping site, social media sites feature advertisements related to the search or shopping history. This phenomenon, called personalised ad targeting, occurs automatically in the background using ML and employs customer profiling. Data from different sites/sources can be used to profile the customer. Customer profiling and personalised targeting have revolutionised the field of advertising and marketing; while earlier one was exposed to general advertisements meant to the public at large through media such as television and newspapers, today, the advertisements that one comes across are personalised in almost all platforms

ML has been successful in the healthcare industry as well, there are ML models that can predict the type of cancer based on image scans, with tolerable accuracy. This has eased the burden of image analysis for doctors. However, doctor assurance is required if the model predicted with low confidence. These models are trained on high quality image data (mostly scanning images) and on high computing machines using state-of-the-art algorithms to achieve high accuracy. This reduces the wait time for people to get their diagnostic results.

Some applications such as Google Photos, Netflix, and Gmail also have inbuilt ML models. Google Photos uses ML to recognise people and animals in pictures to group them; this is illustrated by the 'find by face' feature. Netflix uses watching history and

other parameters to curate the content. This has, in fact, been reported to be the most desirable feature of Netflix in that it is able to predict user interests and likes fairly accurately. Google mail services use ML to implement an auto-spam classifier to filter spam e-mails from the inbox into the spam folder. This ML provides the opportunity for the user to classify a particular mail as spam or not, and this data is used to train the model and make it more accurate.

Important algorithms in this field are neural networks, decision trees, random forests, associations and sequence discovery, gradient boosting and bagging, support vector machines, nearest-neighbour mapping, k-means clustering, local search optimisation techniques (e.g., genetic algorithms), expectation maximisation, multivariate adaptive regression splines, Bayesian networks, Kernel density estimation, principal component analysis, singular value decomposition, Gaussian mixture models and sequential covering rule building.

4.3 Impacts of AI on existing work force

4.3.1 Is AI a threat for employees?

It is possible that AIs that out-perform humans will become a reality in the next few decades and may disrupt human employment opportunities (Levy, 2018). Positions like bank tellers, medical transcriptionists, janitors and building cleaners, lawyers face threat from advancements in AI (Levy, 2018).

Autonomous long-distance trucks, automated customer service responses and industrial robotics are three evolving AI technologies that may lead to more job replacement (Levy, 2018; Ford, 2017; Presidente, 2017). Such applications could destroy middle range jobs while increasing those on the low and high ends, thereby increasing social inequality as the pay gap between low and high end jobs is increased (Makridakis, 2017). AI raises concerns that it would take over many of tasks performed by currently human-centric sectors like BPO, and this has led to increased stress about job loss among employees (Hallikainen et al., 2018). Accountants, auditors, and tax preparers also perceive risk due to implementation of AI technologies (Frey and Osborne, 2017).

Employees in organisations that are not currently affected or not expected to be affected in future, have other kinds of concerns in terms of sustainability, pay checks, etc. (Wilson and Daugherty, 2018). As part of the AI revolution, employees must engage in continuous skill development to stay relevant, and this has added to their concerns (Kaplan and Haenlein, 2018). Organisations may also face issues like absenteeism and turnover intensification (Gulliford and Dixon, 2019). Increasing substitution of employees by AI technology could reduce the cost of production of machines and this will change the comparative advantage of machines relative to people and will end up in increase of the income earned by machines relative to human workers (Freeman, 2018).

4.3.2 AI – a handholding colleague

An analysis of job loss possibility due to automation shows that many companies that have adopted AI in their workspaces have not replaced their employees but have given them jobs that require more creative and thinking skills, i.e., the employees are now given tasks that are not mundane and repetitive (Egash et al., 2019). This would lead to more innovative ideas and human capital investment in new opportunities (Manyika, 2017).

It must be remembered that the aim of AI is not to eliminate employees but to increase productivity and value to customers. AI would, undoubtedly, eliminate a few jobs, especially in the business process outsourcing (BPO) sector, but would also lead to an increase in requirement for skilled process designers in the coming years. It would also increase work satisfaction among managers due to accuracy and speed (Hughes et al., 2019). When AI is used to automate tasks, employees can focus on work that requires real-time judgment and empathy and this would increase work engagement and lead to intention to stay longer in the organisation (Smith, 2018). Moreover, AI would be a significant contributor to the productivity boost of organisations and thus would enhance the GDP of nations (Manyika, 2017).

4.4 How to prepare for an optimistic future?

In order to moderate job replacement by AI, governments must enact policies to minimise inequalities either by guaranteeing a minimum universal income, raising taxes for the superrich and/or increasing inheritance taxes (Makridakis, 2017). Development of anticipatory policies to assist people who lose jobs and other people who, under earlier circumstances, would have expected to take those jobs would mitigate the impact of job replacement (Levy, 2018).

It is predicted that more developments in AI would require professional expertise and this would enhance the demand on people who are educated and skilled in the various areas of AI (Metz, 2016). Employees or organisations can choose training on such job opportunity areas, which would enhance professional survival. In addition to specialised AI professions, employment opportunities would continue to exist in areas that require social and interpersonal skills as well as creativity and innovation. The demand for novel jobs that caters to the needs of higher income people such as personal trainers, coaches, beauty advisors, diet consultants, nutritionists and teachers for their children, etc. may be augmented. These and similar jobs would offer employment opportunities and adequate payment, and could compensate for the jobs lost through replacement by AI technologies (Makridakis, 2017).

5 Discussion

5.1 General implications

The first insight that may be gleaned from this review is that advancements in AI promise a future with more accuracy and precision and can potentially replace existing applications and manual work. The survey of literature in this area shows that it is difficult to find a paper that includes both AI advancements and their impacts in the business arena and workforce implications. In every paper, the AI aspects deal with technical innovations and applications for a particular scenario. This, on one hand, provides a pointer to the richness and vastness of the area and on the other, opens many aspects for further exploration. The impact of AI on workforce is a classic example of under-investigated topics.

This study analyses two different concepts viz. AI advancements and workforce impact, that are apparently disparate, but in reality, impact the contemporary world in synergy. While AI advancements are purely technical and workforce issues are purely

managerial, this study brings them under one umbrella, given the increasing prevalence of concerns from people on both sides of an organisation (Levy, 2018; Hill et al., 2015).

We have conducted a systematic review and have categorised the papers into AI-related, business-related and domain-specific, and the details are shown in Figures 1 and 2, and Table 1. The study adopted an in-depth analysis of the characteristics of papers before answering the research questions. The year-wise distribution of papers (Table 2), types of papers per year (Figure 3) and sources of contribution were analysed (Table 3).

The first research question was on the identification of recent advancements of AI and their applications in business. As stated earlier, although many papers have discussed AI advancements and their business applications separately, there have been no attempts to connect the two. Indeed, in-depth technical discussions have focussed on introducing the developments to the public (Van Der Aalst et al., 2018; Collins, 2019). The transition of a production-orientated field, which focuses on profit making, to a holistic approach of applications and concerns was visible as advancements moving to different levels (Moffitt et al., 2018; Aguirre and Rodriguez, 2017). From the business angle, this paper has explained the types of AI with developments and applications in different functions of business and sectors of industry. It has provided detailed description of RPA, ML and NLP with their possible business applications and how they work. It also presented the drawbacks of these developments and their future prospects.

An understanding of the impact of AI advancements on employees was the second aim of the paper. The papers considered for this were more management-oriented or generalist in nature (Levy, 2018; Presidente, 2017; Ford, 2017). It is understood from the review of literature that jobs that involve precision and accuracy are at risk of being replaced by AI while those that involve logical decision making, inter-human interactions, etc., would not be affected to a great extent. Design, artistic and creative skills are irreplaceable and be in great demand in a future job market in an AI-integrated world.

5.2 Theoretical implication

The theoretical implications of the study are many-fold. First, the study provides a detailed description on AI advancements and drawbacks in business scenario. The combination of these two areas of AI would offer a roadmap for the researchers in this area. Second, although the study has combined both technical and business aspects, each scenario is enriched in such a way that individual researchers can work on specific areas. Third, the study provided an analysis of impact of AI advancement in workforce. While the concerns among employees is justified, the study shows an optimistic future.

5.3 Practical implication

The practical implications of the paper are significant. For an individual, it provides knowledge of AI advancements, in addition to pointers to skillsets required of employees in the near future. Appropriate choice of skillset acquisition would lead to human capital development (Murphy and Topel, 2016). For organisations, the study would help in determining the training and motivation methods to be adopted for human employees for holistic progress within the organisation (Smith, 2018). Organisations could work based

on the skill of the employees and AI technologies, and this would lead to time and energy savings and productivity. For society, the study would provide a path for to address the advancements and concerns related to AI. Such rapid changes in technology may tamper the socio-politico-cultural processes (Floridi et al., 2018). This study provides an insight to policy makers on framing policies that are adaptable for both acceptance of technology and changing environment. For example, technological unemployment will be a bigger challenge for the policy makers, as technology and workforce interest go hand in hand for the benefit of the economy (Peters, 2017). The study also offers pointers to ideas on skill development required for such a situation that can be worked upon further to frame policies. Another policy challenge would be in the ethical aspects of AI implementation (Hagendorff, 2020). Policy makers can work upon policies that ensure ethical practices, privacy and human dignity.

5.4 Limitation and future research direction

The study did not assess the attitude of employees in different industries towards AI advancements. Future studies can investigate employee attitude sector-wise or region-wise. Different personality types and their response to AI advancement would also add new avenues for future research. Studies could be conducted in service-driven industries like hospitals, military, police, education, etc., and in industries like BPO, IT, etc. to bring about a difference in perception among employees. Empirical analysis and case studies would afford insights and inferences for the study. Hence, it is suggested that empirical studies be conducted on employee views on AI acceptances.

6 Conclusions

Artificial Intelligence is often perceived as a boon to mankind. This paper described the advancements of AI and its applications in business, considering different business functions and sectors. AI is also considered a bane by the worker because of the threat it poses to his/her job. This paper analysed the concerns of employees and presented an optimistic perspective that some human skills such as empathy and cognitive skills can never be replaced by machines. Hence, amidst concerns, it is heartening that AI would enhance the human cognitive and creative skills of employees, who would now not need to spend their time and life repetitive, mundane and uninspiring tasks. Working hand in hand – AI and human skills- would lead to more successful individuals, organisation, and thereby society and mankind.

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