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To cite this article: Wael Hadid, Satoshi Horii & Akinori Yokota (2025) Artificial intelligent technologies in Japanese manufacturing firms: an empirical survey study, International Journal of Production Research, 63:1, 193-219, DOI: [10.1080/00207543.2024.2358409](https://doi.org/10.1080/00207543.2024.2358409)

To link to this article: <https://doi.org/10.1080/00207543.2024.2358409>



Published online: 28 Jun 2024.



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Artificial intelligent technologies in Japanese manufacturing firms: an empirical survey study

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ABSTRACT

Motivated by conflicting arguments/claims in the AI literature on its implementation, motivations, and practical impact, we combine interview data from a case company with questionnaire data from eighty-five Japanese manufacturing firms to examine seven AI technologies at firm, function, and technology levels. We find that one-third of the sample firms did not employ any of the seven AI technologies. Over 50% of the remaining firms implemented one or two technologies only. Visual recognition, machine learning and natural written language processing were the most commonly implemented technologies. AI implementation was the highest in production and research and development compared to other functions. The main motivations for implementing AI were to enhance operational efficiency, improve defects detection and prediction, automate processes, and reduce labour hours/costs. Among the firms that implemented AI, improvements in operational efficiency were more frequently reported, followed by reductions in labour hours/costs and enhancements in product/process quality. Lack of business needs, suitability to the business, expertise in implementation, and confidence in generating significant benefits were the main reasons for not experimenting with AI technologies. Our detailed analysis improves our understanding of the current state of AI adoption in manufacturing firms, its practical impact and highlights avenues for future research.

ARTICLE HISTORY

Received 30 May 2023
Accepted 14 May 2024

KEYWORDS

Artificial intelligence technologies; case study; survey; manufacturing industries; Japan

SUSTAINABLE DEVELOPMENT GOALS

SDG 9: Industry; innovation and infrastructure

1. Introduction

The literature on artificial intelligence (AI) has exploded in the last decade (Baryannis et al. 2019; Gebhardt et al. 2022; Grover, Kar, and Dwivedi 2022; Pietronudo, Croidieu, and Schiavone 2022; Sahu, Young, and Rai 2021). Some scholars expected AI to revolutionise business processes/operations and produce significant benefits to its adopters (Chen et al. 2021; Demlehner, Schoemer, and Laumer 2021; Olan et al. 2022; Sharma et al. 2022). Others warned that AI could lead to mass lay-offs and unprecedented levels of unemployment with significant negative impact on the society (Giermindl et al. 2022; Haenlein and Kaplan 2019; Malik et al. 2021).

However, as highlighted by a number of researchers (Brock and Von Wangenheim 2019; Duan, Edwards, and Dwivedi 2019; Johnson et al. 2022), much of the discourse on AI and its impact has been based on conceptual/theoretical research and literature review articles (e.g. Baryannis et al. 2019; Gebhardt et al. 2022; Grover, Kar, and Dwivedi 2022; Holmström 2022; Paschen, Wilson, and Ferreira 2020; Sahu, Young, and Rai 2021). Currently, there is a lack of sufficient empirical evidence regarding the practical impact of AI especially in the

manufacturing context (Brock and Von Wangenheim 2019; Giermindl et al. 2022; Lee et al. 2023). Although recent studies have attempted to empirically examine the determinants of AI or its impact, they have primarily focused on aggregate-level measurements of AI or examined a single technology such as robotics or expert system (e.g. Cadden et al. 2021; Chowdhury et al. 2022; Mikalef and Gupta 2021). Such studies have overlooked the fact that AI is a term usually used to represent a group of different technologies such as (in addition to robotics and expert systems) natural language processing systems, voice recognition systems, visual recognition systems, machine learning etc. These technologies (1) may not necessarily be all implemented by organisations and (2) may be implemented in different organisational functions, and hence their impact may depend on where they are implemented.

Moreover, for the expected AI impact to materialise and be researched, AI has to be first implemented and used by organisations. Yet, our knowledge of whether AI has been implemented in practice and the scale of that implementation is very limited (Duan, Edwards, and Dwivedi 2019; Johnson et al. 2022; Lee et al. 2023;

Mikalef and Gupta 2021). This perhaps explains why some scholars have claimed that AI penetrated many companies and functions (e.g. Arnaboldi et al. 2022; Liu et al. 2020) while others have argued that AI is still at the infancy stage and its progress into companies is slower than expected (e.g. Bedué and Fritzsche 2021; Chen et al. 2021; Ghobakhloo 2020; Johnson et al. 2022).

Consequently, while previous studies have contributed to our understanding of AI's relevance and potential impact across industries and processes, we believe there is an urgent need, at this stage of the AI literature development, for more empirical research which aims to address the following essential, yet underexplored, questions:

- (1) How extensively have organisations implemented AI technologies, and which specific technologies are more commonly adopted?
- (2) Which organisational functions have experimented with AI technologies, and do certain technologies have a higher likelihood of adoption within these functions?
- (3) What are the reasons for implementing (or not implementing) AI technologies?
- (4) Do AI implementing companies achieve their AI-related goals/objectives?

Our current study aims to address the aforementioned gap in the AI literature by conducting an exploratory study in which we collect and analyze detailed empirical, questionnaire-based data from Japanese manufacturing companies on seven AI technologies (i.e. expert systems, neural networks, natural spoken language processing system, natural written language processing system, visual recognition systems, intelligent robots, and machine learning).¹ We further adopt a descriptive case study approach to provide deeper insights into the survey results which collectively enable us to address our four research questions.

We believe that our current study is timely and needed for three reasons. First, given the current contradictory arguments presented in prior research regarding the impact of AI, our study offers empirically driven insights into such impact as perceived and reported by the implementing organisations. Second, a number of scholars have claimed that AI invaded many industries and companies (e.g. Arnaboldi et al. 2022; Liu et al. 2020; Zeba et al. 2021) while others argued that AI is still in its infancy and is spreading among companies slower than what was previously predicted (e.g. Chen et al. 2021; Ghobakhloo 2020; Johnson et al. 2022). These contradictory statements about the actual use of AI technologies in practice, not supported by empirical evidence yet, necessitate more academic research with the aim to document

empirical evidence of the status of AI implementation in practice. Third, our study responds to a number of scholars' recent observations regarding the lack of large-scale empirical research on the impact of AI, its enablers and scale of implementation in practice (Brock and Von Wangenheim 2019; Chiarini 2021; Chowdhury et al. 2022;; Duan, Edwards, and Dwivedi 2019; Giermindl et al. 2022; Jaiswal, Arun, and Varma 2022; Johnson et al. 2022; Merhi and Harfouche 2023; Ngai and Wu 2022; Venkatesh, Raman, and Cruz-Jesus 2023; Vrontis et al. 2022).

Our study contributes to the AI literature in different ways. First, we provide fresh empirical evidence of the scale of AI implementation in the manufacturing sector, which is currently underexplored. Second, we provide a detailed analysis on the implementation of seven AI technologies across different organisational functions. By doing so, we add to the AI literature by identifying the most conducive functions for AI technologies and the most commonly implemented ones in each function. Third, our study improves our knowledge of the potential impact of each of the seven AI technologies by offering a list of forty-six distinct impacts. Forth, we supplement the existing AI literature with a list of the most important reasons for which companies decided to implement (or not implement) AI technologies. We believe our results provide a valuable foundation for future researchers interested in understanding the determinants and performance impact of AI. Collectively, our findings point to interesting opportunities for further research and should help inform the development of frameworks and models that explain how organisations make decisions about AI adoption along with its impact on different dimensions of organisational performance (i.e. financial, operational, and employees).

The rest of the paper is structured as follows. A review of the relevant literature is presented in section 2 followed by the methodology in section 3. Data analyses and results are presented in section 4. Section 5 is devoted to the discussion of the results and section 6 focuses on the research implications. Section 7 concludes the paper and highlights the research limitations and directions for future research.

2. Literature review

While AI has attracted exceptional interest in the academic literature, there is still no consensus regarding its definition. Early work on AI defined it by making reference to the different technologies it involves such as neural networks, expert systems, voice-recognition systems, natural language systems, visual recognition systems, and robotic systems (Akers et al. 1986; Duchessi,

O’Keefe, and O’Leary 1993). More recently, attempts have been made to produce a formal AI definition. For instance, Duan, Edwards, and Dwivedi (2019, 63) defined AI as ‘the ability of a machine to learn from experience, adjust to new inputs and perform human-like tasks’. According to Li et al. (2021, 1603), AI is the ‘technologies that leverage machine-based intelligence and advanced computing capacity to mimic human “cognitive” functions’. Sharma et al. (2022, 7527) referred to AI as

the use of computers for reasoning, recognising patterns, learning, or understanding certain behaviours from experience, acquiring, and retaining knowledge, and developing various forms of inference to solve problems in decision-making situations where optimal or exact solutions are either too expensive or difficult to produce.

Haenlein and Kaplan (2019, 1) explained AI as ‘a system’s ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation’.

The lack of consensus on AI definition also extends to its potential impact. While some scholars envisaged various benefits from implementing and using AI technologies, others were not as optimistic. Conceptual, case studies and literature review papers argued that AI can improve decision making (Choi et al. 2022; Gupta et al. 2022), increase operational efficiency and productivity (Sharma et al. 2022), detect fraudulent activities (Loureiro, Guerreiro, and Tussyadiah 2021), lead to more accurate operational performance measurement (Loureiro, Guerreiro, and Tussyadiah 2021), speed up the decision making process (Overgoor et al. 2019), cut costs and enhance quality control (Choi et al. 2022; Holmström 2022), predict employees turnover (Chowdhury et al., 2023), reduce human errors (Makarius et al. 2020), identify new suppliers (Choi et al. 2022), reduce inventory levels (Choi et al. 2022), improve new product development processes (Choi et al. 2022), enable real time operational control (Allal-Chérif, Simón-Moya, and Ballester 2021), improve customer engagement and satisfaction (Campbell et al. 2020), and improve sales forecast (Sohrabpour et al. 2021). Survey-based studies, while scarce in the AI literature, extended the list of benefits to include waste reduction and management (Chiarini 2021) and supply chain performance (Belhadi et al. 2024).

The impact and relevance of AI technologies extend beyond specific industries or processes. For instance, visual recognition technology played a pivotal role in assessing CEOs’ emotional responses during capital-raising events (Momtaz 2021), evaluating the credibility of entrepreneurs based on facial cues (Duan et al. 2020), and monitoring suspicious consumer behaviour

in retail environments (Arroyo et al. 2015). Additionally, the critical role of visual recognition in autonomous vehicles should not be overlooked. Machine learning and neural networks proved instrumental in enhancing the accuracy of bond rating predictions (Jabeur et al. 2020), water consumption predictions (Karamaziotis et al. 2020), automating inventory classification processes (Lolli et al. 2019), automating part designs selection based on unique data and user input (Elhoone et al. 2020), developing job shop scheduling systems (Lee, Piramuthu, and Tsai 1997; Park et al. 2021), identifying and diagnosing faults in industrial chemical processes (Ragab et al. 2018), and modelling complex manufacturing operations for optimisation (Coit, Jackson, and Smith 1998), among other applications. While less prevalent in academic literature, natural language processing technology facilitated the measurement of emotional content in textual documents, potentially influencing human decision-making processes (Kratzwald et al. 2018). Moreover, this technology proved effective in detecting fraudulent activities in insurance claims (Wang and Xu 2018). Expert systems empowered process planners to identify critical process parameters for optimisation (Singh and Raman 1992), aided producers of electric vehicles in determining optimal strategies for repurposing car batteries (Kloör et al. 2018), and supported production managers in decision-making processes regarding production scheduling (Webster, Muhlemann, and Alder 2000). In the hospitality industry, robots were deployed to respond to consumer inquiries and process their orders (Tuomi, Tussyadiah, and Hanna 2021), although consumer satisfaction with these interactions was not always assured (Rajaobelina et al. 2021). Similarly, within the automotive sector, robots were instrumental in enhancing efficiency and productivity by facilitating the processing and assembly of vehicles (Lopes et al. 2017).

In contrast to the positive views of AI presented above, some negative consequences associated with the implementation of its technologies were also reported. Corsaro et al. (2022) indicated that AI does not necessarily generate the purported benefits claimed by its proponents. AI may eliminate jobs and increase social inequality (Pan and Froese 2023). It was also found to increase employees stress and job insecurity (Malik et al. 2021). Using data from 119 announcements of 62 listed firms, Lui, Lee, and Ngai (2022) found a negative impact of AI announcement on firm market value.

While considerable attention has been given to identify and report on the potential impact of AI technologies, this was dominated by conceptual, case-based studies and literature reviews (e.g. Choi et al. 2022; Gupta et al. 2022; Johnson et al. 2022; Loureiro, Guerreiro, and Tussyadiah 2021; Overgoor et al. 2019; Sohrabpour et al. 2021). There

has been a lack of large-scale empirical research on AI as noted by some scholars (Brock and Von Wangenheim 2019; Giermindl et al. 2022; Lee et al. 2023). Further, less attention has been devoted to whether AI technologies have been received well in practice and hence implemented by companies as noted by several scholars (Duan, Edwards, and Dwivedi 2019; Johnson et al. 2022; Mikalef and Gupta 2021; Ngai and Wu 2022). To substantiate these observations, we conducted an extensive literature search across two widely utilised databases, namely Scopus and Web of Science. The search criteria employed were as follows:

Scopus code: TITLE-ABS-KEY ('artificial intelligence' OR 'machine learning' OR 'neural' OR 'natural written language' OR 'natural spoken language' OR 'cognitive computing' OR 'decision support systems' OR 'expert system*' OR 'visual recognition' OR 'industry 0.4' OR 'robot*' OR 'cloud computing') AND TITLE-ABS-KEY (use OR implement* OR adopt*) AND TITLE-ABS-KEY (questionnaire OR survey* OR empirical* OR dataset) AND (LIMIT-TO (SRCTYPE, j')) AND (LIMIT-TO (DOCTYPE, ar')) AND (LIMIT-TO (SUBJAREA, BUSI')) AND (LIMIT-TO (LANGUAGE, English'))

Web of Science code: AB = ('artificial intelligence' OR 'machine learning' OR 'neural' OR 'natural written language' OR 'natural spoken language' OR 'cognitive computing' OR 'decision support systems' OR 'expert system*' OR 'visual recognition' OR 'industry 0.4' OR 'robot*' OR 'cloud computing') AND AB = (use OR implement* OR adopt*) AND AB = (questionnaire OR survey* OR empirical* OR dataset). (Research areas: operations research management science and business economics).

Utilising the aforementioned codes, we retrieved a total of 3651 articles. After eliminating duplicates (292), we scrutinised the titles, abstracts, and, in some instances, the full texts of the remaining articles (3359) to ascertain their relevance to AI. Figure A1 provides a summary of this process. Following the application of exclusion criteria, we identified fourteen survey-based articles that reported on the implementation of AI in the manufacturing sector, the primary focus of our study. Table 1 outlines these fourteen studies, highlighting the examined technologies and the level of analysis. While these studies offer valuable insights into the extent of AI implementation in practice, their scope has been limited to individual technologies, firm-level analysis, or conceptual examinations of AI implementation without delving into specific technologies. Since interest in different AI technologies may vary along with their use in different organisational functions, more research is needed to provide more detailed information on the implementation scale of different

Table 1. Summary of AI survey-based implementation/use literature.

Authors	AI technologies	Level of analysis
Torii (1989)	Robotics	Country and industry
Hsieh, Lu, and Pan (1992)	Expert system	Firm
Byrd (1993)	Expert system	Firm
Byrd (1995)	Expert system	Firm
Coakes and Merchant (1996)	Expert system	Firm
Lusk et al. (2005)	Expert system	Firm
Brock and Von Wangenheim (2019)	Concept (without reference to any technology)	Firm
Chmielarz (2019)	Concept (without reference to any technology)	Firm
Jung and Lim (2020)	Robotics	Country
Sheares (2020)	Concept (without reference to any technology)	Firm
Anzolin, Andreoni, and Zanfei (2020)	Robotics	Industry
Singh (2021)	Concept (without reference to any technology)	Firm
Ballestar et al. (2021)	Robotics	Firm
Fu et al. (2021)	Robotics	Country

AI technologies and in different organisational functions.

In response, our study aims to contribute to this stream of the AI literature by reporting empirical evidence on: (1) the extent to which AI has been implemented in practice, (2) the AI technologies which have received more attention and higher implementation, (3) the reasons for implementing (or not implementing) such technologies, (4) the functions which have attracted more AI implementation and the specific AI technologies implemented in each function, and (5) the impact of AI implementation as experienced by the adopters with respect to each of the AI technologies.

3. Methodology

To address our research questions, we adopted a survey methodology in this study. This choice was motivated by (1) the nature of our research questions, (2) the prevalence of conceptual and case studies, leading to a scarcity of survey studies in the AI literature, and (3) calls from several scholars for more large-scale empirical studies on the practical use of AI technologies and their impact (Brock and Von Wangenheim 2019; Chiarini 2021; Chowdhury et al. 2022; Duan, Edwards, and Dwivedi 2019; Giermindl et al. 2022; Vrontis et al. 2022). Data were collected from a sample of Japanese manufacturing listed companies. A questionnaire instrument was developed and mailed, in January 2022, to

Table 2. The distribution of the responding companies per industry.

Industry	Frequency
Machinery	14
Electrical appliances	12
Chemicals/pharmaceuticals	11
Transportation equipment	9
Iron and steel	7
Other products	7
Metal products	6
Textiles and apparels	5
Foods	4
Glass and ceramics products	3
Precision instruments	3
Nonferrous metals	3
Oil and coal products	1
Total	85

senior managers of 1,462 companies in different manufacturing industries. The questionnaire was prepared in English, translated to Japanese and then back to English by two different bilingual researchers to ensure consistency with the original English version. Before distribution, we piloted the questionnaire with five academics and five managers from the manufacturing sector which resulted in minor changes to the wording of some questions. To increase the response rate, we followed common practices by sending participants two reminder letters by post, with approximately a two-week interval between the first distribution date and each subsequent reminder. Of the 1,426 distributed questionnaires, 89 were returned, 4 of which were eliminated due to missing values on many questions leaving a final sample of 85 questionnaires. Respondents held titles such as director (18), executive officer (8), general manager (16), managing director (13), manager (22), and vice president (8). Average age of respondents was 56 years. Respondents had, on average, approximately 16 years of managerial experience and 24 years of experience working in their current company. The average number of employees in the responding companies was 7,626 full time employees and 548 part-time employees. Table 2 summarises the distribution of the responding companies per industry.

3.1. Variables measurement

3.1.1. AI technologies

We measured AI by focusing on seven technologies commonly associated with AI in the respective literature. These include (1) neural network, (2) expert system, (3) natural spoken language processing system, (4) natural written language processing system, (5) visual recognition system, (6) intelligent robots, and (7) machine learning (Akers et al. 1986; Cadden et al. 2021; Duchessi, O'Keefe, and O'Leary 1993). Respondents were asked to indicate the frequency of using each

of the seven technologies in fifteen different organisational functions. The functions include production, production engineering, quality control, maintenance, warehouse, logistics, purchasing, sales, marketing, IT, strategic planning, accounting, human resource management, research and development, and supply chain. Given that not all functions may exist in a typical company, respondents were asked to indicate the functions which do not exist in their company. A seven point Likert scale was used to gauge the frequency of using each of the seven AI technologies where 1: never, 2 very rarely, 3: rarely, 4: occasionally, 5: frequently, 6: very frequently, 7: always. Respondents were also asked to report whether a technology was implemented but later abandoned. A glossary sheet which contains a definition for each of the seven AI technologies was provided.

Further, we collected information with respect to the year each of the seven AI technologies was first implemented. A seven-point scale was used where 1: A year ago, 2: 2 years ago, 3: 3 years ago, 4: 4 years ago, 5: 5 years ago, 6: 6 years ago, 7: over six years ago.

3.1.2. The impact of AI technologies

Through an open-ended question, participants were asked to report the most important impacts (up to three) their company experiences as a result of their AI implementation for each of the seven technologies.

3.1.3. The reasons for implementing (or not) AI

To capture the reasons for implementing or not implementing AI technologies, we asked participants to list the most important reasons (up to three) through two open-ended questions. Given the exploratory nature of our study, we deemed the use of open-ended questions to be more appropriate for capturing the impacts and reasons for (lack of) implementation as this helps to reveal new impacts or reasons, if any, which have not been known in the literature. All the measures used in this study are presented in Appendix A.

4. Data analyses and results

4.1. The use of AI technologies in practice – research questions (RQ) 1–2

To provide useful insights into the use of AI technologies by our sample firms and address our research questions (i.e. RQ1-RQ2) on the use of AI technologies, we carry out analyses at three different levels; organisation level, function level and AI technology level. The analysis at organisation level helps to reveal the number of AI technologies the sample firms experimented with regardless

of the function in which the technologies were implemented. The analysis at the technology level aims to highlight which of the seven AI technologies have received more attention by the sample firms. These two analyses enable us to address RQ1. The analysis at the function level aims to improve our knowledge of the most common AI technologies in each of the fifteen functions examined in this study along with the frequency of using them. This analysis helps in addressing RQ2.

A key consideration in our analyses is how to determine whether a company is using an AI technology or not. Classifying AI technologies into those ‘used’ or ‘not used’ entails some subjectivity. Different scholars may have different opinions with respect to when a technology can be considered to be in use or not. For instance, some may argue that even if a technology is ‘rarely’ used by a company, it should be classified as being in use. Others may raise the bar and require a more frequent use of the technology to be considered in use. To accommodate for these different opinions, we present our results based on three different classification methods.

Given our seven-point measurement scale explained earlier, in the first classification method (never vs. all other points on the AI measurement scale (2–7)), an AI technology is considered to be in use by a firm if it received a score of 2 (very rarely) or higher in any of its functions. In the second method ‘never + very rarely’ vs. all other points (3–7) we require a score of 3 (rarely) or higher to consider an AI technology to be in use while in the third method (‘never + very rarely + rarely’ vs. all other points (4–7)) a score of 4 (occasionally) or higher was used.

4.1.1. The use of AI technologies in practice – organisation level and technology level analyses (RQ1)

Starting with the organisation level analysis, Table 3 displays the number of AI technologies implemented by our sample firms based on the three different classification methods. It is important to note that in constructing Table 3, we count an AI technology only once when it meets the classification criterion under each of the three classification methods even if the technology is used by a company in multiple functions. That is, if company X only uses expert systems in four different functions, this company will fall into the ‘one technology’ group in Table 3.

Based on the more demanding classification method (i.e. method 3), approximately a third (32%) of the sample firms did not use any of the seven AI technologies in any of their functions. 16 (19%) firms used one technology only while 15 (18%) firms used two different AI technologies. Only 14 (17%) firms used more than four

Table 3. The number of AI technologies implemented by the sample firms.

	Method 1 (‘never’ vs. all other points)		Method 2 (‘never + very rarely’ vs. all other points)		Method 3 (‘never + very rarely + rarely’ vs. all other points)	
	No. of companies	%	No. of companies	%	No. of companies	%
None	23	27	24	28	27	32
One technology	12	14	13	15	16	19
Two technologies	9	11	12	14	15	18
Three technologies	7	8	12	14	5	6
Four technologies	13	15	8	9	8	9
Five technologies	7	8	4	5	5	6
Six technologies	8	9	7	8	5	6
Seven technologies	6	7	5	6	4	5
Total	85		85		85	

technologies, 4 of which used all seven AI technologies simultaneously.

The results in Table 3 suggest that approximately two-thirds of the sample firms can be associated with AI. However, in the majority of cases the use of AI was limited to one or a couple of technologies only. This raises the question of whether some AI technologies are more commonly used in practice than others and highlights the importance of the technology level analysis which we present next.

Figure A2 (in Appendix B) reveals how common each of the seven AI technologies is in our sample firms. For the purpose of developing Figure A2, we define ‘common’ as the aggregate count of instances where an AI technology is reported to be in use across all fifteen functions within our sample firms. That is, if company X uses the same AI technology (e.g. machine learning) in three different functions (e.g. sales, production and logistics), this is counted as three different uses in Figure A2 for that particular technology. Keeping that in mind, Figure A2 indicates that visual recognition system is the most common AI technologies in our sample firms followed by machine learning and natural written language processing system. The least common AI technology is intelligent robots.

4.1.2. The use of AI technologies in practice – function level analysis (RQ2)

Our function-level analysis, summarised in Figures A3–A17, provides deeper insights into Figure A2 by examining the frequency of AI technology usage at the function level.² This analysis offers more detailed information about the prevalence of each AI technology in different functions and addresses our third and fourth research questions. In our sample firms, the production function and research and development function dominated the use of AI technologies compared to other

functions as can be seen in Figures A3 and A4, respectively. The nature of work in these functions seems to offer a conducive environment for the use of AI technologies. In both functions, visual recognition system and machine learning received more attention compared to other technologies though visual recognition system prevailed in the production function while machine learning was the most frequently used technology in the research and development function.

Other functions which also made a noticeable use of AI technologies in our sample firms include the IT function, quality control function, production engineering function, and maintenance function. Based on Figures A5–A8, except for the IT function, the use of visual recognition system and machine learning dominated other technologies in the aforementioned functions. In the IT function, however, natural written language processing system was the most commonly used technology followed by machine learning.

The use of AI technologies was apparently lower and less common in the remaining functions, i.e. sales, marketing, human resource management, warehouse, logistics, purchasing, strategic planning, accounting, and supply chain. In the case of the sales function (Figure A9), marketing function (Figure A10), accounting function (Figure A11) and human resource management function (Figure A12), natural written language processing system was used more frequently than other technologies. However, expert systems dominated, compared to other technologies, in the warehouse, logistics and purchasing functions.

Finally, Figure A18 summarises the implementation of AI technologies over time. In general, there is no clear pattern for AI implementation over time in our sample firms. However, we observe that three AI technologies did not receive attention in 2021 and these include neural network, expert system and natural spoken language processing system. In addition, Figure A18 documents evidence of the popularity of the visual recognition system technology where approximately 50% (22) of its implementation rates occurred in 2015 or earlier.

4.2. Reasons for (not) implementing AI technologies – RQ3

Our third research question focuses on the reasons for which companies decide to implement (or not implement) AI technologies. Table 4 outlines the reasons for implementing each of the seven AI technologies as reported by the sample firms. The values in this table represent the frequency of reporting each reason by the

participants. The most frequently reported reasons for implementing AI technologies are improving operational efficiency (mentioned 55 times), detecting/predicting defects (28 times), automating processes (22 times), reducing labour hours/costs (18 times) and improving quality management (16 times).

Regarding the reasons for not implementing AI technologies, Table 5 indicates that the lack of business needs for AI is the most common reason (reported 137 times) for not experimenting with AI. Other companies do not find any of the seven AI technologies to be suitable for their business (43 times). A fewer number of companies do not have expertise in AI technologies (35 times) and hence decided not to engage with them. Another set of reasons concerns the costs and benefits associated with AI. Companies which are uncertain about achieving significant benefits from AI (33 times) or reduce costs (14 times) are less likely to implement it. The high implementation cost of AI (16 times) is also one of the frequently reported reasons for avoiding its implementation. However, the last two items in Table 4 suggest that some companies in the sample are interested in all seven technologies and they are currently being considered while other companies indicated that AI technologies will be considered in the future.

4.3. The impact of AI technologies – RQ4

Information on the impact of AI through was collected through an open-ended question. Table 6 summarises the results for each of the seven AI technologies. It is clear from Table 6 that AI technologies generate various impacts, the majority of which are operational in nature. The number-one impact experienced by AI adopters in our sample is the improvement in operational efficiency followed by the reduction in labour hours/cost and improvement in product/process quality. These three impacts have been reported by participants 46, 41 and 30 times, respectively. Interestingly, the positive impacts of AI on operational efficiency and labour hours/costs are the only ones attributed to each of the seven AI technologies. It is equally interesting to observe that the top four benefits from AI in Table 6 align with the primary reasons for which companies implemented the technologies (Table 4). This suggests that AI-related goals/objectives have been largely achieved by the implementing companies. The last two items in Table 6 also indicate that some companies have been unable to determine the impact from their AI implementation (reported 14 times) while others have not realised any impact from the AI technologies they implemented (reported 5 times).

Table 4. Reasons for implementing AI technologies.^a

Reasons	ES	IR	ML	NSLPS	NWLPS	NN	VRS	Total
Improve operational efficiency	9	5	6	9	12	3	11	55
Defects prediction/detection			7			4	17	28
Automate processes	2	2	3	3	1	2	9	22
Reduce labour hours/costs		7	1	2	1	2	5	18
Improve quality management	1		3		1	2	9	16
Reduce operating costs	3		2			1	3	9
Mitigate labour shortage			2	1	1	1	2	7
Preserve knowledge and expertise	4		2					6
Improve productivity	1	1	1			1	2	6
Compatible/bundled with another system	1		1	1	1	1	1	6
Improve R&D results	1		2			1	1	5
Predict machines/equipment failure			4				1	5
Improve processes			2			1	2	5
Improve production planning	5							5
Enhance product functionality	1		1			1	1	4
Eliminate human's subjectivity		1	1			1	1	4
Check compliance / regulatory violations	3				1			4
Improve customer service	1			2				3
Monitor employees							3	3
Free up employees time		3						3
Improve employees safety		1	1				1	3
Analyze big data			3					3
Predict the useful life cycle of products			1			1	1	3
Fashion/competition						2		2
Language translation					2			2
Predict sales demands	1		1					2
Predict future events						2		2
Control pollution	1						1	2
Improve sales growth				1		1		2
Improve the security management system							2	2
Simulate complex problems			1			1		2
Accumulate data			1	1				2
Improve the product development process	1					1		2
Search for similar documents			1					1
Digitalise forms					1			1
Detect frauds							1	1
Enable the examination/use of past documents					1			1
Identify business opportunities					1			1
Conduct causal analysis of quality and manufacturing requirements			1					1
Monitor emails			1					1
Analyze human resources						1		1
Optimise personnel distribution/allocation at work							1	1
Accurately convey work-related instructions					1			1
Data entry				1				1
Discover new indicators					1			1
Analyze and automatically process malicious emails					1			1
Total	35	20	49	21	26	30	75	256

^aES: Expert system, IR: Intelligent robots, ML: Machine learning, NSLPS: Natural spoken language processing system, NWLPS: Natural written language processing system, NN: Neural networks, VRS: Visual recognition system.

4.4. Case-based evidence (Bolt company)

To provide deeper insights into the adoption process of AI technologies and our survey results, we supplement our survey results with a descriptive case study in which we delineate how a Japanese private manufacturing company has integrated AI into its operations. Aligned with our research questions, we focus on the AI technologies that have been implemented, their deployment locations, the rationale behind their implementation, and the outcomes of these implementations. Data were collected, in August 2023, through a two-hour interview with the digital transformation manager, who plays a pivotal role in driving AI adoption within the company.

The case company, referred to as 'Bolt' for anonymity, operates in the manufacturing sector and it specialises in producing bolts and screws. Based on recent information, the company employs approximately 2500 individuals and generates an annual revenue of around £500 million.

Until two years ago, Bolt perceived AI as complex and irrelevant to its operations. However, interest in AI began to grow for two main reasons. First, one of Bolt's key customers relied on AI and encouraged its suppliers to explore its relevance and consider the long-term benefits it could bring to operations. Second, like many other Japanese companies, Bolt had concerns about labour shortages and believed that AI could help address these concerns.

Table 5. Reasons for not implementing AI technologies.^a

Reasons	ES	IR	ML	NSLPS	NWLPS	NN	VRS	Total
There are no business needs	20	20	17	25	23	21	11	137
It is not suitable to our business	6	12	2	6	7	7	3	43
Lack of expertise in this technology	6	4	4	5	5	10	1	35
Significant benefits are not guaranteed	6	4	4	6	5	4	4	33
High implementation costs	4	3	3	1	1	4		16
Cost reduction is not guaranteed	2	2	2	3	2	2	1	14
Not aware of this technology	2	1	1	1	1	2	1	9
Immature technology	2	2	1	1	1	2		9
No desire to learn about a new technology	1	1	1	1	1	1	1	7
Efficiency and effective operations can be achieved without it	1	1	1	1	1	1	1	7
No examples of successful implementation in our industry	2					2		4
Lack of skilled employees to maintain the technology		1	2					3
Difficult to make significant changes to current practices	1							1
Priority to fixed robots		1						1
Data is not available	1							1
Negative impact on performance	1							1
Currently being considered	3	6	4	4	3	5	2	27
Will be considered in the future	2	5	1	6	4	2	2	22
Grand Total	60	63	43	60	54	63	27	370

^a **ES:** Expert system, **IR:** Intelligent robots, **ML:** Machine learning, **NSLPS:** Natural spoken language processing system, **NWLPS:** Natural written language processing system, **NN:** Neural networks, **VRS:** Visual recognition system.

Two years ago, AI was still unfamiliar to us, and the general perception within the company was that it was complex and irrelevant to our operations.

We seriously need to establish a specialised digital technology unit; production cannot keep up. In fact, since last week, we have been short of on-site workers, and even indirect departments are sending support staff. We need to automate tasks with robots and reallocate people to primary production activities.

However, the desire to implement AI did not mean choosing an AI technology and/or a function/process randomly. It was crucial to identify a problem where AI could assist with in order to create successful use cases within the company, with the aim of promoting wider AI adoption in the future. Therefore, Bolt decided to experiment with visual recognition technologies within its quality function, specifically focusing on the process of inspecting bolt head marks. The inspection process was a natural choice since the quality function was striving to ensure 100% accuracy in bolt head mark inspection due to the role product quality plays in Bolt's market reputation.

Right now, we have implemented it in only one location. What it does is recognise marks on the head of bolts, such as 10 or 11, and at the final inspection point, it checks whether these marks are correct.

The main objective was to reduce errors to zero and to ensure 100% accuracy.

Among the available AI technologies, visual recognition was selected because publicly available examples of algorithms were easier to find, which could be adapted to suit Bolt's needs.

It is better to say there are many examples. When researching on our own, a good number of cases come up, and you can use them by just slightly altering the code. So, the bar is somewhat low in that respect.

Inspired by the successful implementation of visual recognition to automate the inspection of bolt head mark, similar applications of the technology were identified within several manufacturing processes. The perception at Bolt is that quality assurance function and manufacturing function are more conducive to AI technologies due to the nature of processes/activities performance in these functions.

By department, I believe quality assurance and manufacturing can benefit the most. Manufacturing has started to reach out, and it is easy to understand when you go on-site, so you can find where the technology fits.

In the cold forging process, we do routine checks. We inspect the appearance and dimensions. For the appearance, we are using image recognition to detect flaws and stop the equipment.

Bolt is committed to expand the use of AI throughout the company. However, such expansion should be problem driven. That is, AI should address a problem (e.g. quality, labour shortage) as mentioned earlier.

Now we are asking people on the ground if they face any issues that this technology might address. A couple of them seem to have potential use cases for it. We are currently in the phase of collecting pictures.

Experimenting with AI at Bolt was not without its challenges. The main challenges revolved around the availability of data and resources for data collection.

Table 6. Impacts of AI technologies implementation.^a

AI benefits	ES	IR	ML	NSLPS	NWLPS	NN	VRS	Total
Improved operational efficiency	6	5	7	8	8	1	11	46
Reduced labour hours/costs	3	9	5	7	4	2	11	41
Improved product/process quality	4		6		1	6	13	30
Improved defects detection speed/accuracy			2			2	10	14
Reduced human-related errors		2	2	1	1	3	4	13
Freed up staff time	2		2		4	1	4	13
Improved product development speed/capability	2		3		1	3		9
Improved productivity	2		2		1		1	6
Improved prediction accuracy	1		4					5
Improved product competitiveness/functionality	1		2			2		5
Improved sales growth		1	1				2	4
Increased profitability		1	1			1	1	4
Reduced machines/equipment downtime			3			1		4
Improved R&D results			1		1	1	1	4
Reduced operating costs	1		2				1	4
Stabilised the production processes	2		1	1				4
Enabled rapid search for emails and files			1		1	1		3
Improved employees safety/well-being		2					1	3
Reduced the need to employ more workers			1			1	1	3
Helped to preserve knowledge and expertise	1		1		1			3
Improved customer service/satisfaction	1			1				2
Improved production conditions			1				1	2
Improved security checks							2	2
Reduced frauds			1				1	2
Reduced inspection time							2	2
Shortened lead time		1					1	2
Sped up information sharing				1	1			2
Eliminated human subjectivity	1		1					2
Enabled cooperation with the production planning team	1							1
Enabled measurement of complex shapes							1	1
Facilitated the development of new ideas for business expansion					1			1
Improved information input speed					1			1
Improved meetings minutes quality				1				1
Improved operational control	1							1
Improved process capability							1	1
Improved recognition accuracy							1	1
Reduced emails-related attacks reaching employees					1			1
Reduced the loss of future sales contracts				1				1
Sped up negotiations with foreign companies					1			1
Identified new ways for mixing different raw materials						1		1
Reduced inventory	1							1
Reduced the reliance on highly experienced employees	1							1
Helped to become a paperless company					1			1
Helped to quantify sales promotion effects					1			1
Enabled the effective use of employees		1						1
Reduced human response time to queries		1						1
Still early to determine the benefits	2		6	1	1		4	14
No significant benefits	2		1		1		1	5
Total	35	23	57	22	32	26	76	271

^aES: Expert system, IR: Intelligent robots, ML: Machine learning, NSLPS: Natural spoken language processing system, NWLPS: Natural written language processing system, NN: Neural networks, VRS: Visual recognition system.

At first, it was difficult because I had to manually take photos. However, once you have a system that allows you to automatically stream and store photos, I feel like things will suddenly accelerate.

Data from the production side of the equipment is not yet recorded, so we cannot progress to that stage. We need to install new sensors to collect data or make current sensors capable of recording data. It is difficult to get the resources for that.

While the adoption of visual recognition is considered successful by Bolt management, it has not yet yielded significant positive outcomes, especially given its relatively short implementation period and small implementation scale. Nevertheless, there is optimism that broader

implementation in the future will lead to more noticeable positive impacts on the company by enhancing productivity, efficiency, and mitigating labour shortages.

It is not like this has significantly increased productivity or made people's lives easier. The inspection time was shortened by a few seconds. However, the number of employees remained the same because they are needed for transporting the products.

5. Discussion

Prior research on AI, mainly based on conceptual and case-based studies, has expected AI technologies to spread widely in various industries (Belhadi et al. 2024;

Chen et al. 2021; Chiarini 2021; Demlehner, Schoemer, and Laumer 2021; Olan et al. 2022; Sharma et al. 2022). However, our empirical evidence based on data from a sample of Japanese manufacturing firms does not find conclusive supporting evidence in this respect. In our sample, almost a third (32%) of the companies did not engage with any of the seven AI technologies examined in this study. This percentage is in line with Brock and Von Wangenheim (2019) who also found 30% of their sample to have no experience with AI at all. Among the two-thirds of companies which reported the use of AI, over 50% had their use of AI limited to one or a couple of technologies only. Our case study further supports this finding as the use of AI in the case company we studied was constrained to only one technology (i.e. visual recognition). Therefore, if the spread of AI in practice implies the simultaneous use of multiple AI technologies, we did not find strong evidence in this respect. In our sample, only fourteen (17%) companies used more than four technologies, four of which used all seven AI technologies simultaneously.

Further, a number of scholars have discussed the relevance of AI to different organisational functions including production function (Helo and Hao 2022), production engineering function (Yoo and Kang 2021), logistics function, sales function (Paschen, Wilson, and Ferreira 2020), marketing function (Campbell et al. 2020), human resource management function (Pessach et al. 2020), purchasing function (Allal-Chérif, Simón-Moya, and Ballester 2021), research and development function (Keding and Meissner 2021), maintenance function (Helo and Hao 2022), and supply chain function (Dora et al. 2022). As such, there has been a clear expectation in the literature that AI can be found in all organisational functions. Our findings confirm this expectation though we found that certain functions seem to largely dominate the use of AI technologies. Our survey results indicate that the production function and research and development function make a significantly more use of AI technologies. These are followed by the IT function, quality control function, production engineering function, and maintenance function. Our case study evidence confirms this finding and further suggests that the nature of processes in the production function and quality assurance function makes it easier for decision makers to see the relevance and applicability of some AI technologies especially visual recognition. However, despite the growing interest in the application and potential of AI in the sales function, marketing function, purchasing function, and human resource management function in the academic literature (Allal-Chérif, Simón-Moya, and Ballester 2021; Overgoor et al. 2019; Pan et al. 2022; Sohrabpour et al. 2021), our empirical survey

evidence points to an apparently lower level of translation of this interest into practical applications. Nonetheless, this should not necessarily be understood as AI technologies are not applicable to these functions. Our case study suggests that AI may be first implemented in functions (e.g. production, quality assurance) where AI is perceived to be more easily implemented and success is more likely to be achieved in order to build success case uses of AI with the intention to expand AI use into other processes and functions. By doing so, companies may gain the necessary practical experience with AI which enables them later to consider the relevance of AI to other processes and functions. Such an implementation strategy could be effective especially because our survey results in Table 5 show that 'lack of expertise in this technology' and 'significant benefits are not guaranteed' are among the most frequently reported reasons for not considering AI.

Proponents of AI have promoted a number of benefits that adopters can gain from using AI technologies, some of which were more frequently reported than others such as improving operational efficiency (Sharma et al. 2022; Zhou et al. 2022), reducing human errors (Makarius et al. 2020), reducing costs and enhancing quality control (Allal-Chérif, Simón-Moya, and Ballester 2021; Choi et al. 2022; Holmström 2022; Zhou et al. 2022). Our survey findings confirm these benefits as shown in Table 6 and place improvement in operational efficiency as the most frequently achieved benefit. However, our survey results also find some merit for the argument about the potential negative impact of AI on employees and employment envisaged by some scholars (Giermindl et al. 2022; Haenlein and Kaplan 2019; Jaiswal, Arun, and Varma 2022; Malik et al. 2021; Vrontis et al. 2022). Table 4 shows that reducing labour hours/costs is one of the top four reasons for which AI technologies have been implemented and it is the second-ranked impact from AI as reported by our sample firms (see Table 6). When this is considered with other reported impacts of AI (reported in Table 6) such as 'reduced the need to employ more workers' and 'reduced the reliance on highly experienced employees', they collectively indicate that AI is used by some companies with the intention to replace some employees. However, our case study evidence suggests that other companies decide to experiment with AI not necessarily to lay off existing employees or because they do not want to recruit more, but rather to mitigate the impact of labour shortage they face in their industry. As such, the use of AI should not always automatically be associated with the management's intention to reduce the existing employment rate. At Bolt, the issue of recruitment was serious enough to motivate the consideration of AI to enable more effective use of currently employed workers in order to meet the demand for its products.

A few studies have recently begun to focus on the reasons for which companies implement AI technologies including reasons such as institutional pressures (Bag et al. 2021), entrepreneurial orientation and environmental dynamism (Dubey et al. 2020), supply chain culture (Cadden et al. 2021), and chief information officers (CIOs) and boards of directors' characteristics (Li et al. 2021). Our survey participants, however, did not clearly refer to these factors. The participants in our study reported a long list of reasons (see Table 4) for their implementation of AI technologies, the majority of which concern either the achievement of operational/financial performance improvements or to address a specific operational issue such as to 'reduce human errors', 'eliminate human's subjectivity', 'predict machines/equipment failure' and 'predict the useful life cycle of products'. Therefore, our survey results lend more support to the findings of Pillai et al. (2022) who reported empirical evidence of the importance of the perceived compatibility of AI with existing practices, perceived benefits and costs of AI implementation and the support from AI vendors. Almost all of these factors have been reported by our sample firms in Tables 4 and 5. As such, the implementation of AI seems to be more goals/targets/problems driven. In our case study, it is interesting to note that even though the initial interest in AI had been driven by one of Bolt's key customers, the company did not blindly select a function/process and AI technology to implement. Rather, an appropriate function/process (i.e. quality assurance) was selected along with an appropriate AI technology (i.e. visual recognition) to address a specific problem (i.e. quality improvement and labour shortage).

Our results in Table 5 are particularly interesting because they not only corroborate our conclusion that the decision to implement AI is primarily driven by goals and problems, but they also provide explanations for the low implementation rate of AI observed in practice as evidenced in our study and Brock and Von Wangenheim (2019). Some companies in our sample refrain from experimenting with AI due to their belief that they lack expertise in AI technologies or because they are skeptical about achieving significant benefits from AI. As shown in our case-study analysis, Bolt has until recently perceived AI to be complex and irrelevant to its operations and refrained from using it. Our analyses empirically confirm the arguments and findings of earlier conceptual and case-based research. These studies have highlighted the complexity of AI (Arnaboldi et al. 2022; Dora et al. 2022; Grover, Kar, and Dwivedi 2022; Lee et al. 2023; Malik et al. 2021; Metcalf, Askay, and Rosenberg 2019), the perceived consequences, rewards, and benefits of AI (Chatterjee et al. 2021; Dora et al. 2022; Ghobakhloo

2020; Grover, Kar, and Dwivedi 2022; Lee et al. 2023; Merhi and Harfouche 2023), and the lack of expertise in AI (Brock and Von Wangenheim 2019; Lee et al. 2023) as potential hindrances to its implementation. Interestingly, our survey study reveals two additional reasons that hinder AI implementation, which have not been emphasised enough in prior research. In our sample, the top two reasons for not experimenting with AI are the perceived lack of business needs and the perceived unsuitability of AI for the operations of some companies. These two reasons are mentioned noticeably more frequently than others in Table 4 though they were not reported in the comprehensive literature review conducted by Lee et al. (2023). We will discuss the implications of our findings in the next section.

6. Research implications

Our study and findings have implications for different parties. For researchers, firstly, AI can be associated with various benefits as reported in Table 6. Therefore, future research intended to examine the AI-performance relationship should take that into account when measuring its impact and ensure sufficient indicators are included in the performance construct. Secondly, the majority of the impacts reported in Table 6 have an operational nature. As such, future studies aiming to document evidence of the link between AI and financial performance should also explore the potential AI's indirect effect through these operational impacts. Thirdly, the impact of AI takes time to materialise as indicated in both our survey results and also case study evidence. It also depends on the scale of implementation as evidenced in the case company we studied. As such, future research on AI impact should account for these two factors in their methodology in order to provide more accurate empirical results in this respect. Fourthly, given the use of AI technologies in different functions documented in this study, scholars interested in the performance impact of a particular technology should also take into account the function(s) in which the technology is implemented. This is so because in a given company; the same technology may succeed in one function but fail to deliver in another function, and hence focusing on the aggregate effect may conceal interesting and useful information. Fifthly, companies in our sample implemented AI for different reasons and they reported specific intended goals to be achieved depending on the technologies implemented. As such, future studies should consider the motivations for implementing AI when designing studies to evaluate the success/failure of AI. Not doing so may raise concerns that such studies evaluate AI using inappropriate or unintended goals, and hence produce erroneous results.

For companies currently using or contemplating the implementation of AI, firstly, by identifying which AI technologies are most commonly used in specific functions, these companies can benchmark their own use of AI and identify areas for improvement. Secondly, our findings should help these companies to prioritise their investments in AI technologies by focusing on the most commonly implemented technologies in specific functions as reported in our study. Thirdly, our research points to the production function and research and development function as the most conducive functions for the implementation of AI. In our sample firms, these functions attracted the highest frequency of AI implementation and hence, they can perhaps be targeted as a starting point by companies considering the implementation of AI technologies. Fourthly, our study has also documented various benefits especially in the form of operational efficiency and reduction in labour hours/costs. These were by far the most frequently reported impacts and the only ones attributed to all of the seven AI technologies examined in our study. Therefore, this should encourage companies which need to make improvements on the aforementioned two indicators to experiment with AI technologies. Fifthly, our findings suggest that AI implementation should start with clear problems that AI can solve. Success in these cases can then inspire broader AI adoption across the business.

For AI developers and consultants, our findings suggest that many companies do not experiment with AI because they believe there are no business needs or AI is not suitable to their operations. As such, there is an opportunity for AI developers and consultants to provide various AI implementation examples suitable for different organisational functions. Such examples could help to highlight the relevance of AI and accelerate AI adoption in practice.

Our findings also reveal the intention of some AI adopters to use AI technologies for reducing labour hours and costs. This should help inform policy and regulatory discussions related to AI. By identifying which AI technologies are most commonly used and in which specific functions, policymakers can now better understand which categories of employees in the workforce are more likely to be affected by AI compared to the others, and begin to develop policies that mitigate the negative consequences.

7. Conclusion, limitations and future research directions

This research set out to supplement the existing literature on AI with fresh empirical evidence of the popularity of

AI in practice, its impact for the adopters and the reasons for its (lack of) implementation. Based on questionnaire data collected from eighty-five manufacturing firms in Japan, we found a third of the sample firms to have no experience at all with any of the seven technologies examined in this study. Among the remaining two-thirds, over 50% had their use of AI limited to one or a couple of technologies only. Only four companies in our sample used all seven AI technologies. The most commonly used technology was visual recognition system followed by machine learning and natural written language processing system. The production function and research and development function dominated the use of AI technologies. In both functions, visual recognition system and machine learning received more attention compared to other technologies. AI companies in our sample mainly implemented the technologies with the aim to improve operational efficiency, enhance defects detection/prediction, automate processes and reduce labour hours/costs. In line with these reasons for implementing AI technologies, the most frequently reported impact by AI companies was the improvement in operational efficiency. It was followed by the reduction in labour hours/costs and improvement in product/process quality. Finally, we found that the number one reason for not implementing AI technologies was the lack of business needs. Other important and frequently reported reasons included the lack of suitability to the business, lack of expertise in the technologies and lack of confidence in generating significant benefits from the technologies.

Like other academic studies, this study has some limitations. First, data were collected from one informant per company. However, while collecting information from two or more informants is argued to be superior, this usually has a detrimental effect on the response rate. Second, whereas we attempted to collect data from a large sample (1426 companies), our final sample is relatively small which has an obvious impact on the generalisability of results. However, we supplemented our survey with a descriptive case study in order to provide deeper insights into our survey results. Future research may address the aforementioned limitations (i.e. relatively small sample) to enhance the quality of evidence for the aspects examined in this study. In addition, our findings should stimulate further AI-related research. For instance, our research reveals the organisational functions in which AI was less common such as marketing, purchasing, sales, accounting, logistics, and human resource management. Future research, particularly field and case studies, on the reasons for which such functions attract a lower level of AI implementation can be a useful addition to the

existing AI literature. Further, more quantitative empirical research is needed on the performance impact of AI technologies at a function level. This will help us better understand whether some AI technologies may have differential impacts depending on where they are implemented. Also interesting would be research on AI technologies at industry level. Because of the relatively small sample size distributed across a number of industries, we were unable to produce a meaningful analysis at industry level. Future research may focus on fewer industries and collect information from larger samples per industry in order to provide insights into the use of AI technologies in each industry.

Despite the acknowledged limitations of our study, we believe it still makes a useful contribution to the AI literature by providing a detailed analysis on the use of seven AI technologies at three different level of analysis, namely firm level, function level and AI technology level. Collectively, our analyses offer a more detailed picture than in prior studies on the scale of using AI in practice, the specific AI technologies which received more attention compared to others along with the organisational functions which attracted more AI implementation.

Notes

1. A definition for each of the seven AI technologies is provided in the glossary sheet in Appendix 1.
2. The sum of values for some AI technologies may not equal eighty-five in Figures A2–A16 either because of missing data or because some functions do not exist in some companies.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

The data that support the findings of this study are available from the corresponding author, [WH], upon reasonable request.

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Appendices

Appendix 1

AI technologies

Using the 0–7 scale below, please type the number which best reflects the frequency of using each of the seven technologies in each function in your company. If a function does not exist in your company, please type ‘X’ under the column ‘function does not exist’. If you do not know whether a technology is used in one or more of the functions, please type a question mark ‘?’ in the respective cell.

0	Implemented but later abandoned	4	Occasionally
1	Never	5	Frequently
2	Very Rarely	6	Very Frequently
3	Rarely	7	Always

Implementation year of AI technologies

Please indicate when your company first began to implement each of the seven technologies even if some were abandoned later. Circle ‘X’ under ‘never implemented’ or ‘0’ under ‘I do know’ for each technology which your company has never implemented or you do not know the implementation year.

Function	Function does not exist	Neural networks	Expert systems	Natural spoken language processing system	Natural written language processing system	Visual recognition systems	Intelligent robots	Machine learning
Production								
Production engineering								
Quality control								
Maintenance								
Warehouse								
Logistics								
Purchasing								
Sales								
Marketing								
IT								
Strategic planning								
Accounting								
Human resource management								
Research and development								
Supply chain								

	Never implemented	I do not know	A year ago	2 years ago	3 years ago	4 years ago	5 years ago	6 years ago	Over six years ago
Neural networks	X	0	1	2	3	4	5	6	7
Expert systems	X	0	1	2	3	4	5	6	7
Natural spoken language processing system	X	0	1	2	3	4	5	6	7
Natural written language processing system	X	0	1	2	3	4	5	6	7
Visual recognition systems	X	0	1	2	3	4	5	6	7
Intelligent robots	X	0	1	2	3	4	5	6	7
Machine learning	X	0	1	2	3	4	5	6	7

Reasons for implementing AI technologies

Please list the most important reasons (maximum three) for which your company decided to implement each of the following seven technologies. Strikethrough the row of any technology which your company did not implement.

	Reason 1	Reason 2	Reason 3
Neural networks			
Expert systems			
Natural spoken language processing system			
Natural written language processing system			
Visual recognition systems			
Intelligent robots			
Machine learning			

Reasons for not implementing AI technologies

If your company has not implemented one or more the following seven technologies in any of its functions, please list the most important reasons (maximum three) behind the non-implementation decision. Strikethrough the row of any technology which your company has implemented.

	Reason 1	Reason 2	Reason 3
Neural networks			
Expert systems			
Natural spoken language processing system			
Natural written language processing system			
Visual recognition systems			
Intelligent robots			
Machine learning			

Impacts of AI technologies

Please list the most important impacts (maximum three) which your company has experienced as a result of implementing each of the following seven technologies. Strikethrough the row of any technology which your company did not implement.

	Impact 1	Impact 2	Impact 3
Neural networks			
Expert systems			
Natural spoken language processing system			
Natural written language processing system			
Visual recognition systems			
Intelligent robots			
Machine learning			

Glossary sheet

AI technology	Definition/description	Reference
Neural network	Neural network is one of the machine learning methods. It is a computing system or software which attempts to mimic the actions of the human brain. Neural network can recognise patterns, classify data, and forecast future events based on learning from the data.	Chase and Shim (1991)
Expert system	Computer software or system which captures the reasoning and decision-making processes of human experts, providing, in effect, computerised consultants. An expert system (1) uses specialised knowledge about a particular problem area (such as optimising production plans, product components configuration) rather than just general purpose knowledge that would apply to all problems and (2) uses symbolic (and often qualitative) reasoning rather than just numerical calculations.	Sharma, Conrath, and Dilts (1991), Akers et al. (1986)
Natural spoken language processing system	Software or system which is able to recognise human voice and natural spoken words. Such software can execute actions based on the orally given order (e.g. perform a search, stop/run a machine or other tasks).	Sutton, Holt, and Arnold (2016)
Natural written language processing system	Software or system which is able to recognize, analyse and/or process textual data (i.e. written words) (e.g. emails, reports, websites, handwritten documents etc.).	Sutton, Holt, and Arnold (2016)
Visual recognition system	Visual recognition systems allow a machine to tag or recognize human faces, objects or products, and identify the contents and scenes in pictures or videos.	Sun (2019)
Intelligent robots	Machines that are mobile and can perform a complicated series of tasks automatically. Intelligent robots may or may not necessarily resemble (in appearance) human beings.	Oxford dictionary
Machine learning	The use by machines/equipment to algorithms to analyze data, learn the underlying patterns, and apply the learned data pattern or trend to make predictions/decisions.	Sun (2019)

Appendix 2

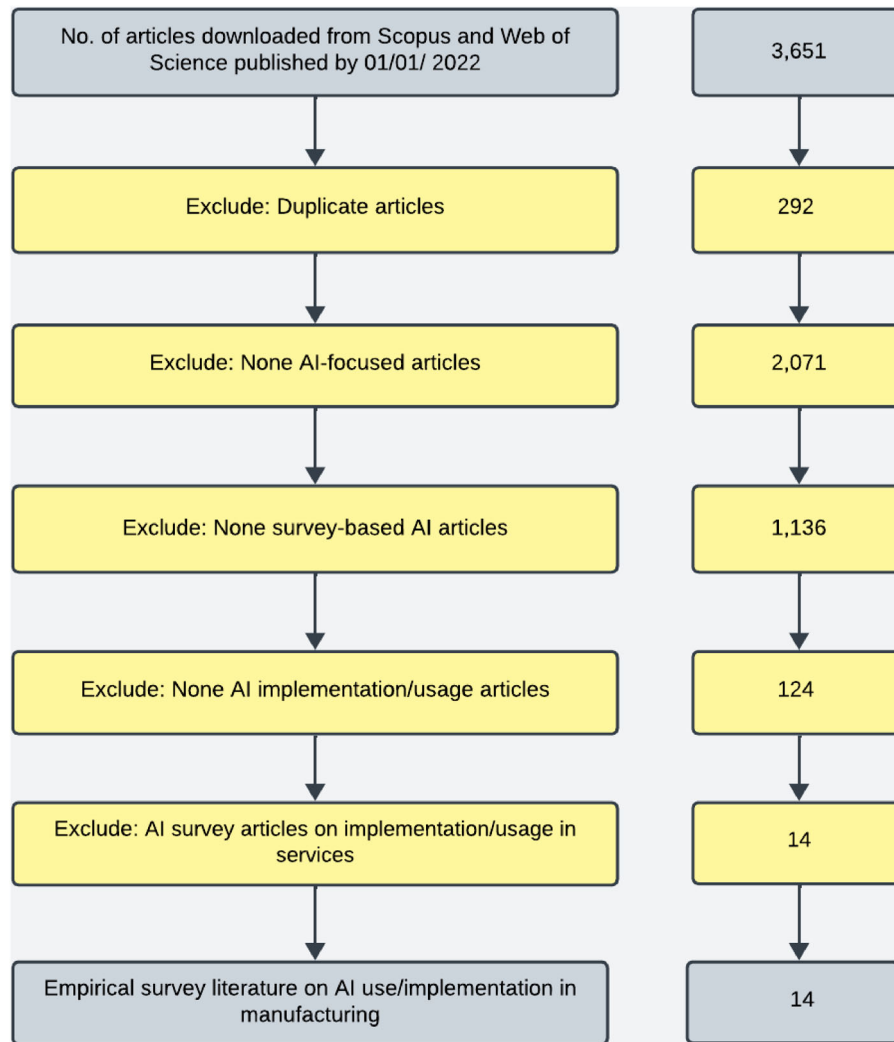


Figure A1. AI empirical survey literature on its use/implementation

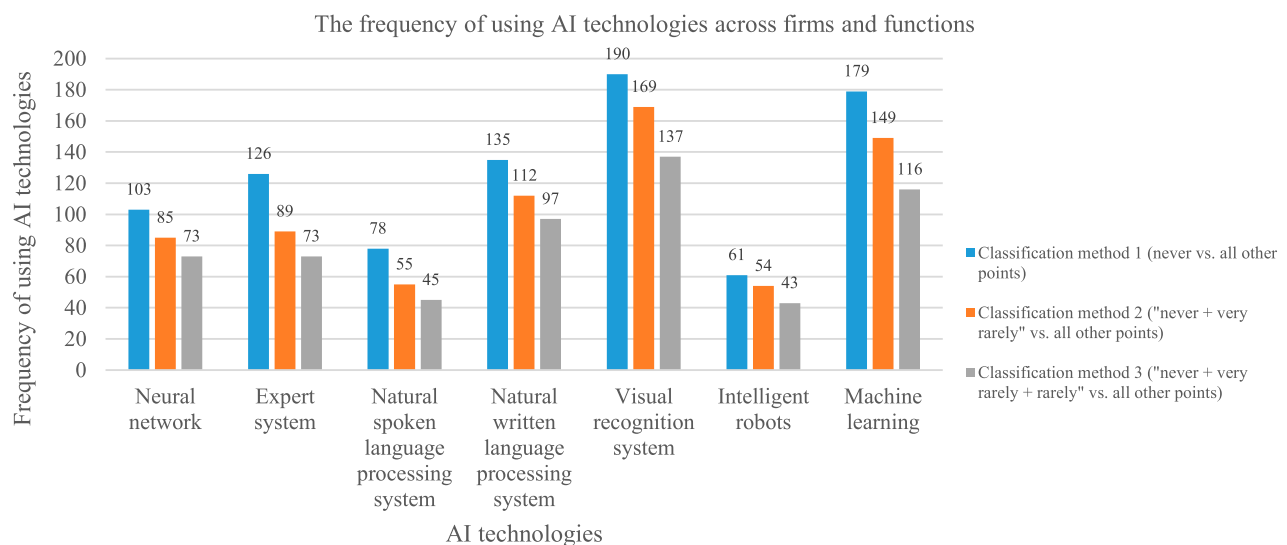


Figure A2. The frequency of using AI technologies across firms and functions.

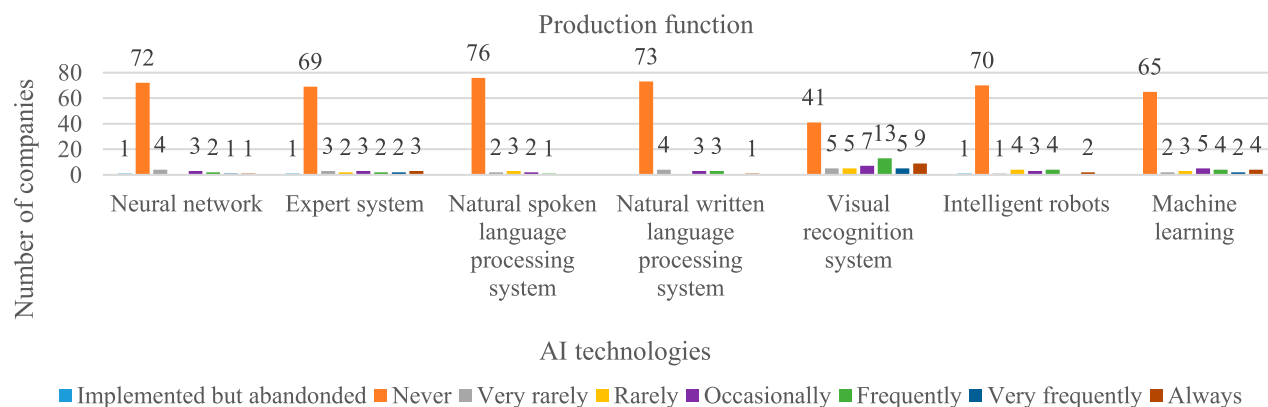


Figure A3. The frequency of using AI technologies in the production function.

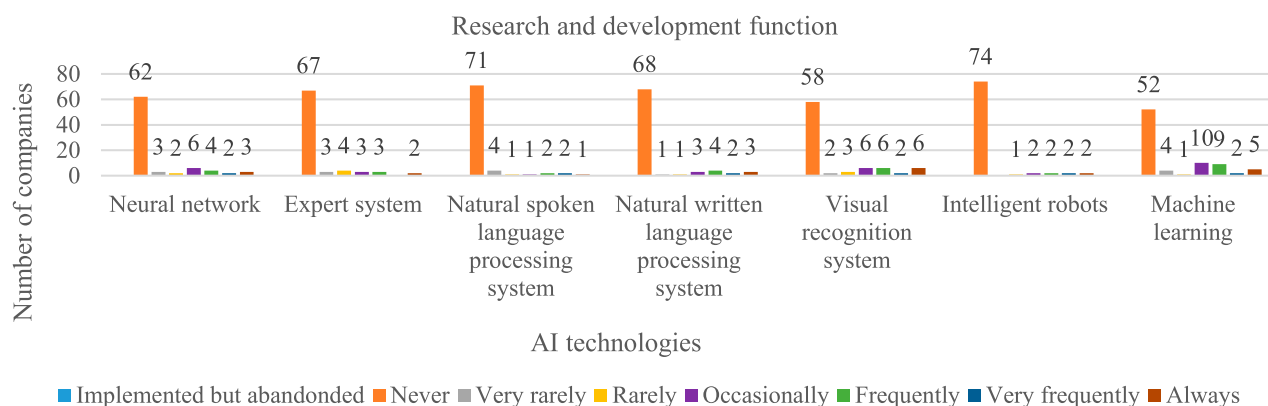


Figure A4. The frequency of using AI technologies in the R&D function.

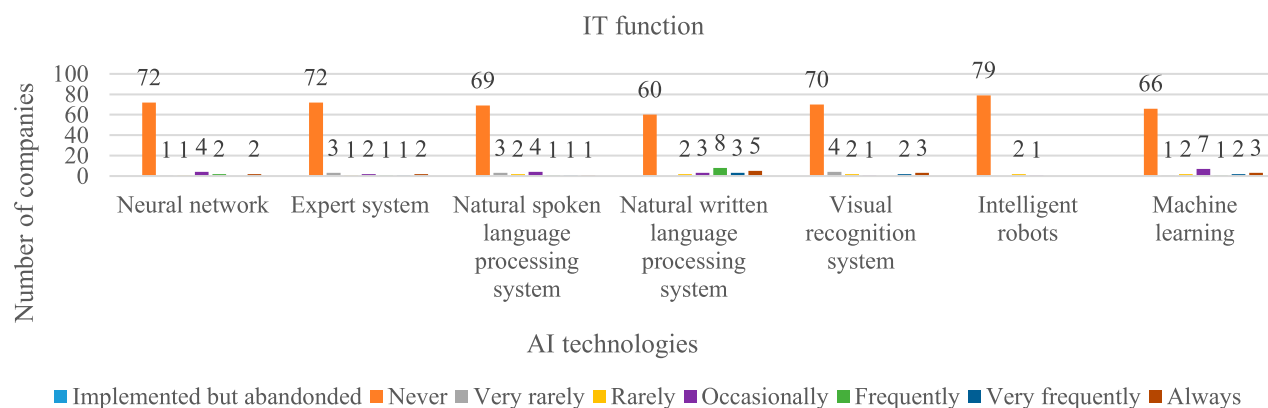


Figure A5. The frequency of using AI technologies in the IT function.

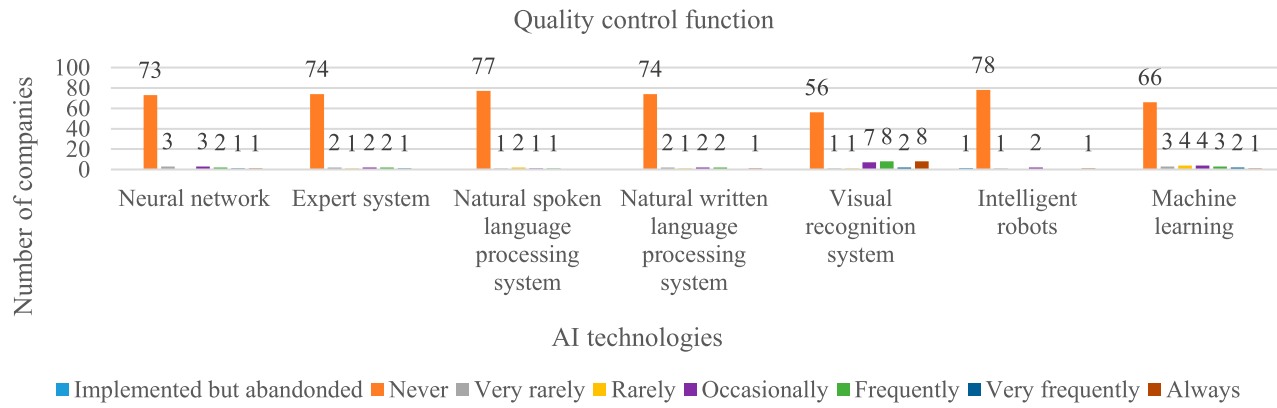


Figure A6. The frequency of using AI technologies in the quality control function.

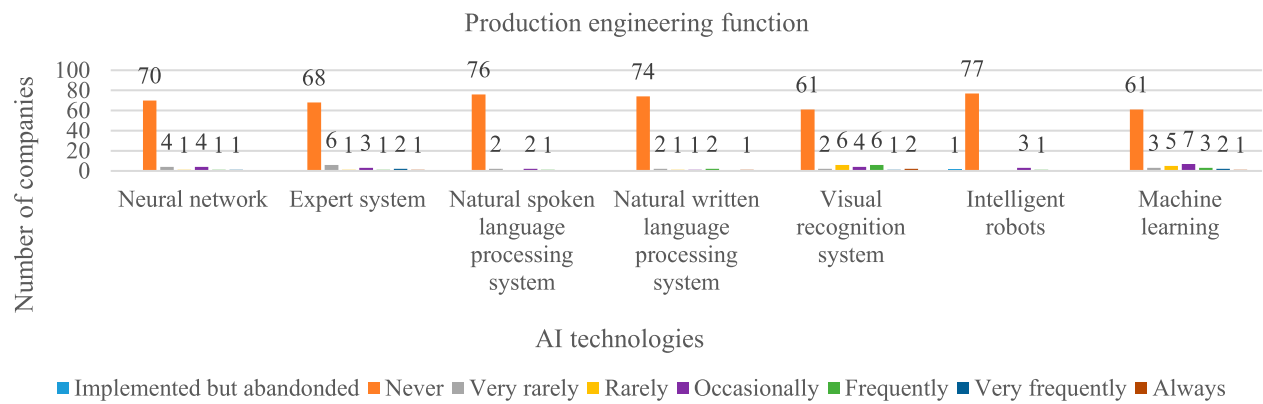


Figure A7. The frequency of using AI technologies in the production engineering function.

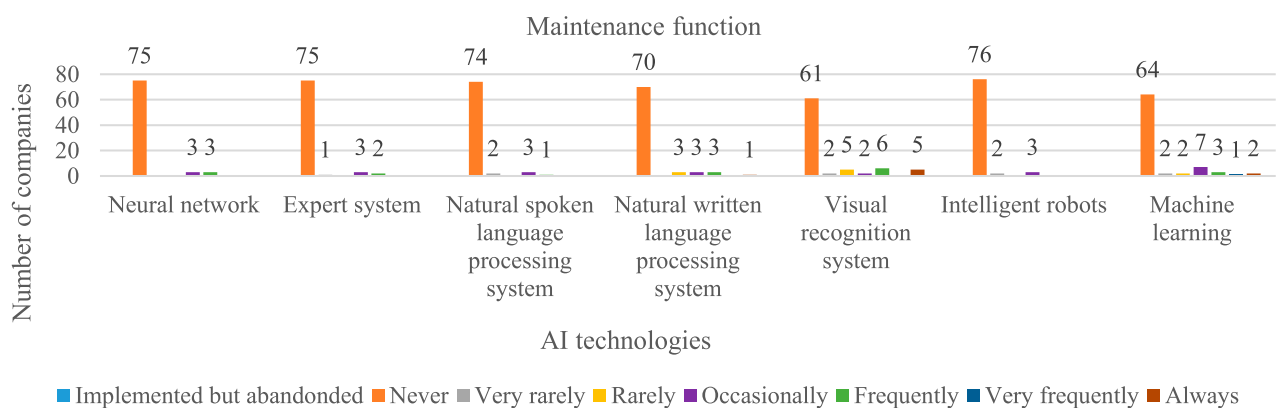


Figure A8. The frequency of using AI technologies in the maintenance function.

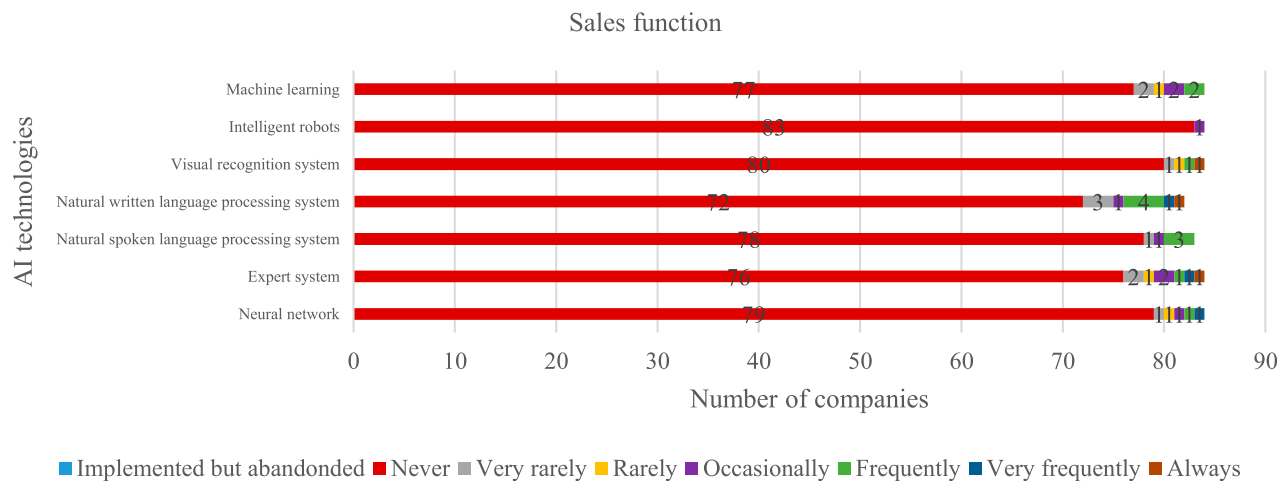


Figure A9. The frequency of using AI technologies in the sales function.

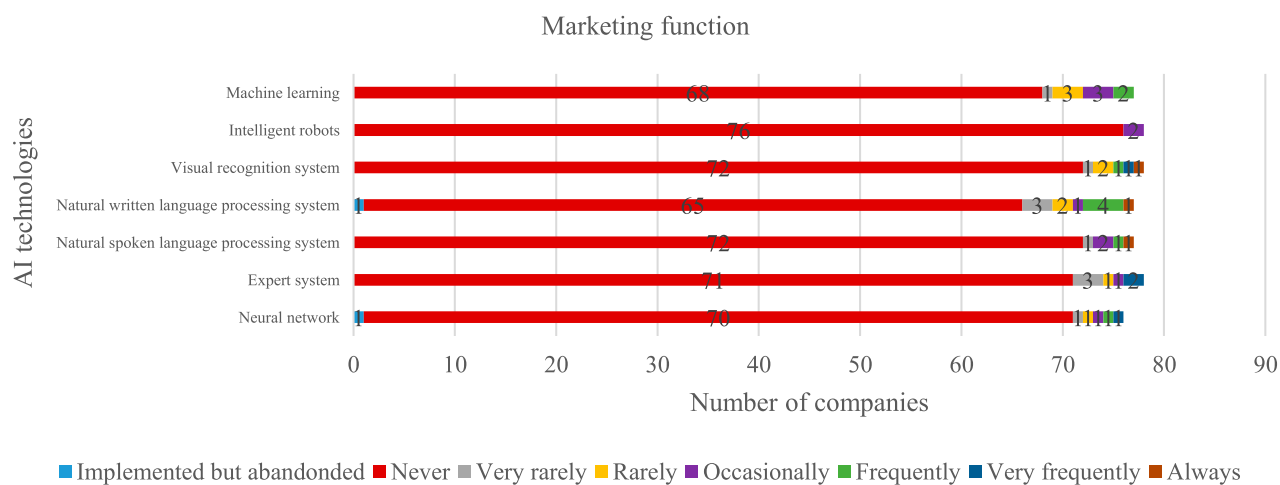


Figure A10. The frequency of using AI technologies in the marketing function.

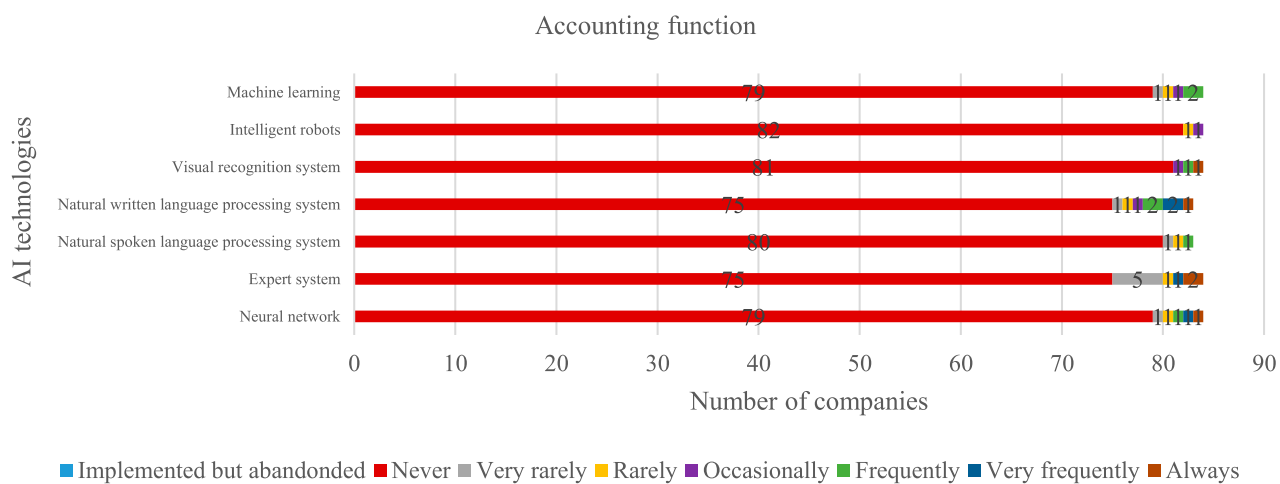


Figure A11. The frequency of using AI technologies in the accounting function.

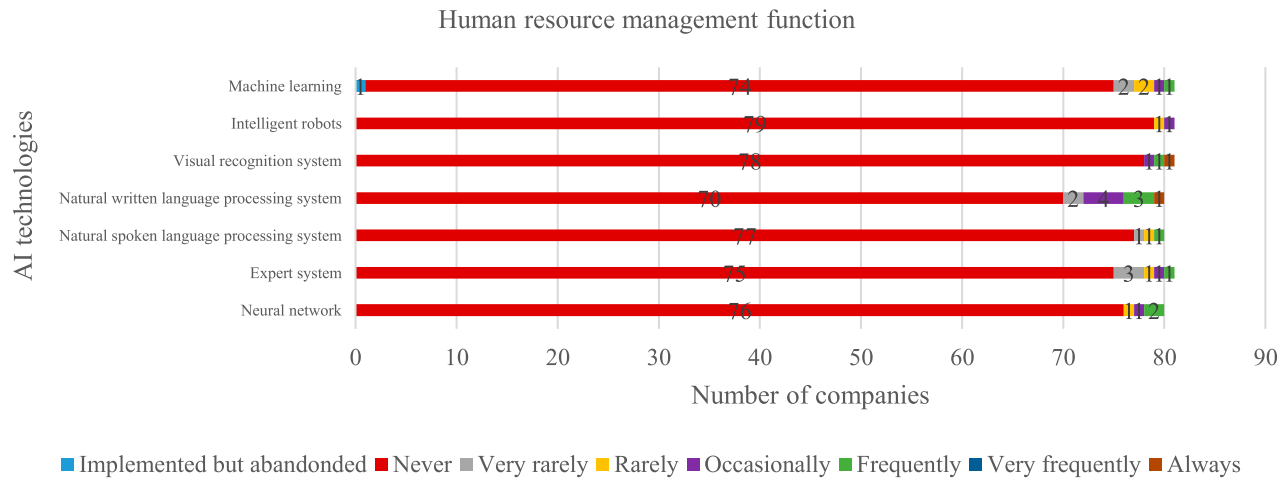


Figure A12. The frequency of using AI technologies in the human resource management function.



Figure A13. The frequency of using AI technologies in the warehouse function.

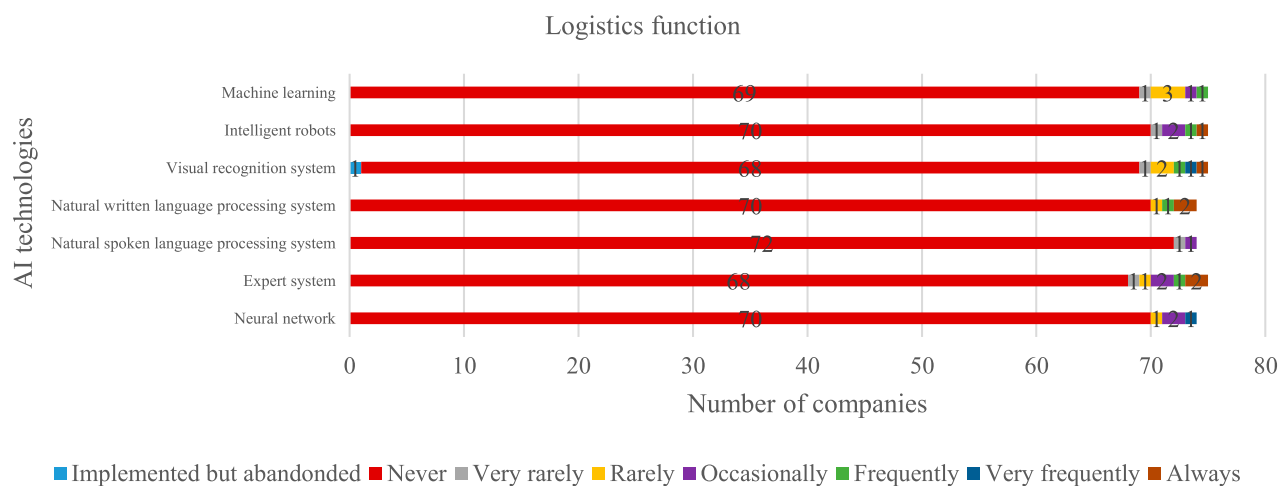


Figure A14. The frequency of using AI technologies in the logistics function.

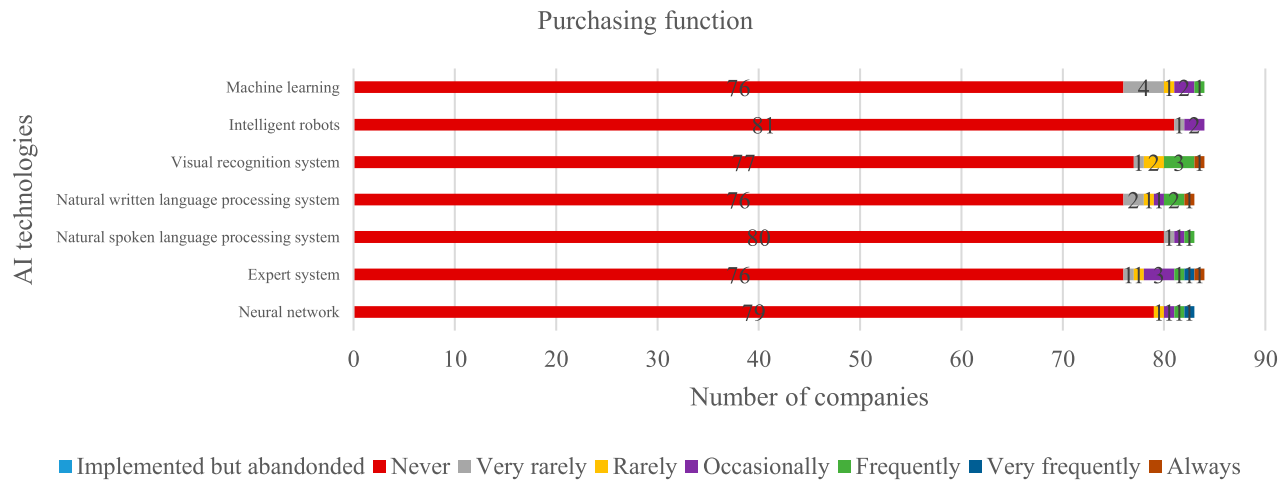


Figure A15. The frequency of using AI technologies in the purchasing function.

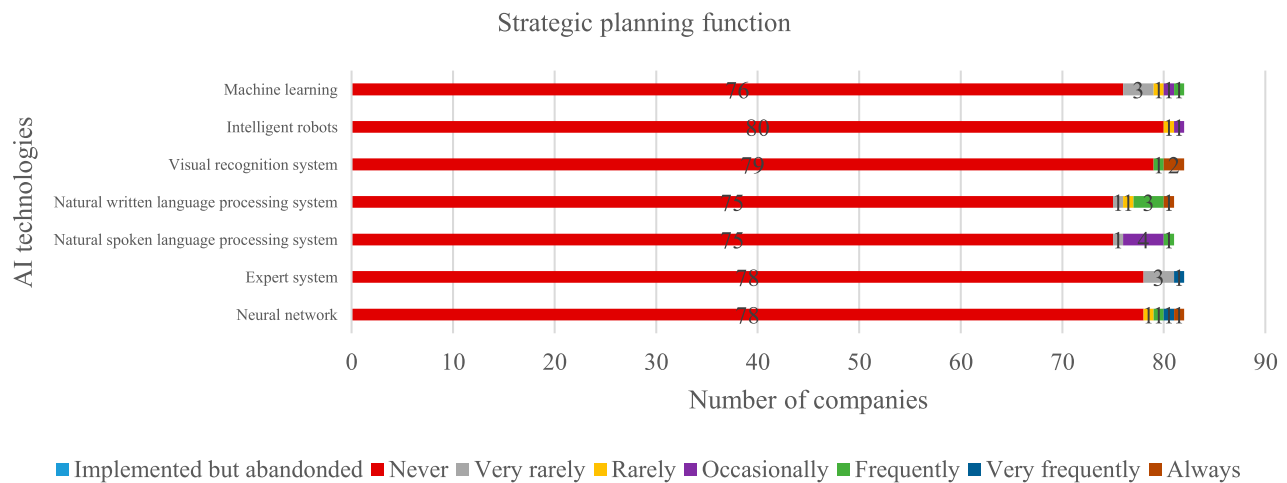


Figure A16. The frequency of using AI technologies in the strategic planning function.

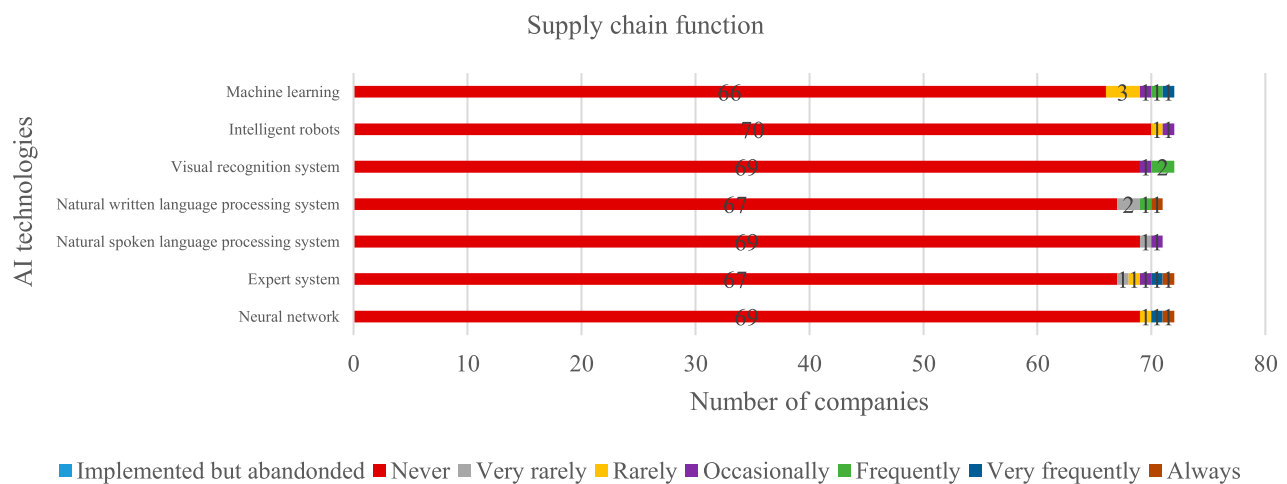


Figure A17. The frequency of using AI technologies in the supply chain function.

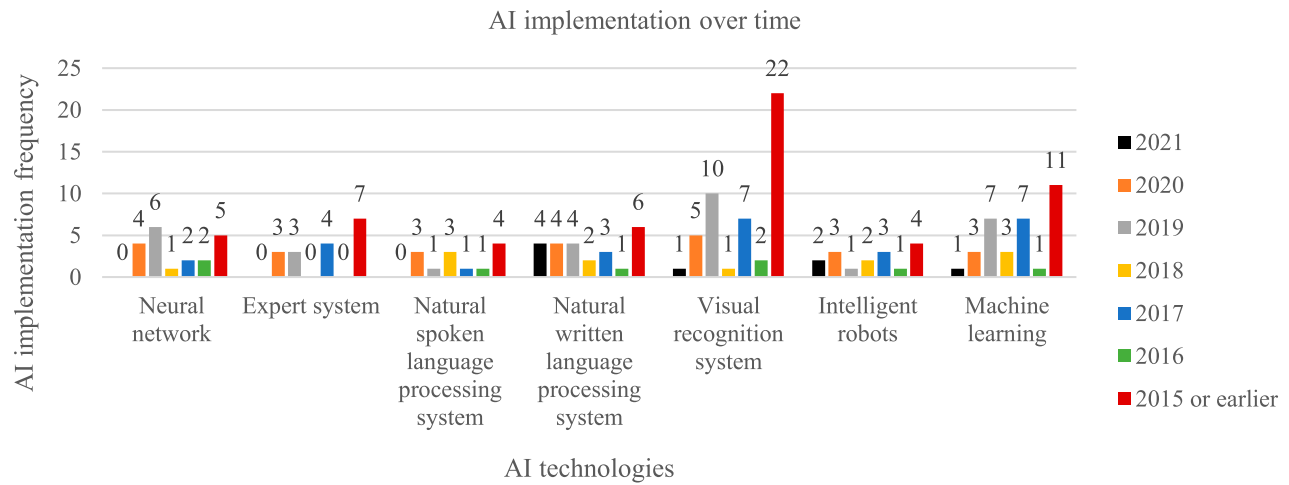


Figure A18. AI implementation over time.