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Drivers, Barriers and Social Considerations for AI Adoption in Business and Management: a Tertiary Study

Abstract:
The number of academic papers in the area of Artificial Intelligence (AI) and its applications across business and management domains has risen significantly in the last decade, and that rise has been followed by an increase in the number of systematic literature reviews.
The aim of this study is to provide an overview of existing systematic reviews in this growing area of research and to synthesise their findings related to enablers, barriers and social implications of the AI adoption in business and management.
The methodology used for this tertiary study is based on Kitchenham and Charter's guidelines [14], resulting in a selection of 30 reviews published between 2005 and 2019 which are reporting results of 2,021 primary studies. These reviews cover the AI adoption across various business sectors (healthcare, information technology, energy, agriculture, apparel industry, engineering, smart cities, tourism and transport), management and business functions (HR, customer services, supply chain, health and safety, project management, decision-support, systems management and technology acceptance).
While the drivers for the AI adoption in these areas are mainly economic, the barriers are related to the technical aspects (e.g. availability of data, reusability of models) as well as the social considerations such as, increased dependence on non-humans, job security, lack of knowledge, safety, trust and lack of multiple stakeholders' perspectives.
Very few reviews outside of the healthcare management domain consider human, organisational and wider societal factors and implications of the AI adoption.
Most of the selected reviews are recommending an increased focus on social aspects of AI, in addition to more rigorous evaluation, use of hybrid approaches (AI and non-AI) and multidisciplinary approaches to AI design and evaluation.
Furthermore, this study found that there is a lack of systematic reviews in some of the AI early adopter sectors such as financial industry and retail and that the existing systematic reviews are not focusing enough on human, organisational or societal implications of the AI adoption in their research objectives.

Keywords: artificial intelligence, business, machine learning, management, systematic literature review, tertiary study

1. Introduction

The motivation for this study is twofold, and it is based on an increase in Artificial Intelligence (AI) research publications and the importance of AI for global economy.

According to the latest AI index report [33] the number of academic papers in the area of AI has risen more than 7 times since early 2000s reaching more than 0.6M publications by 2018. This rise has been followed by an increase in a number of literature reviews published on the topic of AI and its applications across different domains. The search performed for this study found 1,544 systematic reviews. These reviews are based on empirical studies on AI and its components such as machine learning (ML), robots and intelligent agents, covering methods, applications, adoption patterns, impact on business and very rarely (e.g. [6]) on wider social implications.

The research by McKinsey Global Institute from September 2018 [5] estimates potential value of AI for the global economy as additional $13 trillion by 2030, which amounts to 16% rise in cumulative GDP compared to 2018, or 1.2% additional GDP growth per year . PWC analysis from 2017 [30] predicts that AI contribution to the global economy in 2030 could be more than the current output of China and India combined. Accenture report from 2016 [29] indicates that in 2035, AI could double annual growth rates of gross value added (a close approximation of GDP) in 12 developed countries that make up 50 percent of global GDP in 2016. To realise this unprecedented potential for economic growth, it is important to understand the drivers and barriers for the adoption of these technologies in business and management (B&M) domain.

With a notable exception of Metaxiotis and Psarras' review from 2004 [19] which considers AI applications across different business functions, most of the reviews focus on a specific business sector (e.g. IT, engineering, energy or healthcare), or a specific business functions (e.g. marketing, supply chain, business process, systems management). Despite the evident increase in the number of reviews on this topic, up to now, there has been no attempts to aggregate and categorise the results of these reviews in a systematic way.

The aim of this research is to produce a tertiary study that will provide an overview of the results from the existing systematic literature reviews on AI adoption across different business sectors, and B&M functions and to identify areas for further research.

The focus of the study is on identifying drivers and barriers for adoption of AI in B&M domain, and what recommendations the reviewers have put forward for practice and research. In particular, the review will attempt to capture the level of current awareness of the issues surrounding the AI adoption, and the proposed ways forward. These issues include not only technical and economic challenges but potentially serious social implications resulting from bias, which can arise when human preferences direct the choice of the training data and the design of machine learning algorithms. The negative repercussions include not only poor management decisions and misleading financial forecasts, but also wider societal implications related to trust, social inclusion, justice, ethics and human rights.

The rest of the paper is organised as follows: the next section includes the description of the methodology used in the review, followed by a section on the findings and discussion structured according to research questions is presented the methodology section. The final two sections include conclusions and the list of papers considered in the review (P1-P30).

2. Methodology

Systematic literature review (SLR) is a type of a literature review that follows a specific review protocol and quality procedures to select relevant (primary) studies, extract and analyse appropriate information from the selected studies in order to answer specific research questions. The SLRs have been used in medical research since early nineties to support the evidence-based practice and help clinicians in decision-making [9]. Since then, the evidence-based approach to practice has expanded from medicine to other areas, and the SLR guidelines from medicine [11] have been adapted to other disciplines, most notably in Information Systems ([13]-[15]), management [35], and social research [1].

Similar to SLRs are mapping studies, and scoping studies, which aim to find and classify the research in a particular field i.e. answer the questions such as, what is known about a specific topic, and where the gaps are in the specific knowledge area. As the distinction between these and SLRs is not always clear [15], in this review we consider both of these to be a special case of SLRs. Unlike these, the meta-analysis reviews collect data from individual studies to be statistically analysed in order to provide more precise estimates of effect sizes [35]. Although very important tool in medical research [7], meta-analysis has been used less in B&M domains because of diversity of primary studies in this area and difficulty to find a sufficient number of comparable primary studies with quantitative measurements ([15],[35]). However, in recent years more reviews based on meta-analysis have started to emerge in the B&M domain, and therefore they have also been included in this review (see P2 and P15 in Section 5).

This review is a tertiary study, as it compiles evidence from other SLRs, using them as primary studies for further analysis. This type of review is also known as 'umbrella study', 'overview of systematic reviews', 'systematic review of systematic reviews' or 'meta- review' [25].
This study is based on the guidelines from [14] and [4] and on other examples of tertiary studies such as [15] and [11].

2.1. Research questions

The research questions addressed in this study are combination of questions recommended in [15] for all tertiary studies (RQ1-2 and RQ6) and other more specific questions that this study is set to answer (RQ3-5).

> *RQ1: How many SLRs on AI in B&M were published since the re-birth of AI (2000) to date (2019) and what is their quality?*
> *RQ2: What research areas are being addressed in the SLRs on AI in B&M?*
> *RQ3: What are the drivers and the barriers for AI adoption in B&M?*
> *RQ4: What importance is placed on human and social factors in AI applications in B&M?*
> *RQ5: What recommendations are made for future research on AI in B&M?*
> *RQ6: What progress has been achieved with respect to prior recommendations for AI in B&M?*

The only question recommended in [15] that is not included in the question list is: Which individuals, organisations, and publication venues are most active in the research on AI in B&M? This is because of the broadness of the B&M scope that spans across different disciplines, application and research areas, and relatively small number of SLRs published in each of these areas.

2.2. The search process

Two searches were performed on the 18th of July 2019 using the University of Hertfordshire Online Library (UHOL) search facilities. The UHOL performs a search over 278 different library databases, including Scopus which has the widest coverage of peer-reviewed journals [20].
The search strings used for the two searches are shown in **Figure 1**.These strings were developed using the AI terms from the most recent AI index report [33], typologies of systematic reviews ([9], [25]) and Thomson Reuters [34] business sector qualifiers. The latter was used only in the second search.

Search string 1:
("systematic review" OR "systematic literature review" OR "systematic map" OR "systematic mapping" OR "mapping study" OR "scoping review" OR "meta-analysis") AND
("AI" OR " artificial intelligence" OR "machine learning" OR "neural network" OR "robot" OR "intelligent agent" OR "deep learning")

Search string 2:
<Search string 1> AND
("business" OR "management" OR "finance" OR "financial services" OR "high tech" OR "information technology" or "IT" OR "tourism" OR "hospitality" OR "travel" OR "transportation" OR "logistics" OR "energy" or "resources" or "healthcare" OR "education" OR "retail" OR "media" OR "entertainment" OR "automotive" OR "assembly" OR "smart cars" OR "smart cities" OR "consumer goods" OR "building" OR "accounting" OR "insurance")

Figure 1 Search strings

2.3. The study selection process

The selection process is shown in **Figure 2.** The first search using *the search string 1*, resulted in 1,544 peer-reviewed SLRs on AI published between 2000 and 2019 in English language. This list was reduced to include only publications from the B&M-related disciplines resulting in 436 papers (step 2a). After reading the abstracts, and applying the exclusion criteria listed below, 33 publications were selected for further analysis (step 3a). Due to the potential 'false negatives', i.e. exclusion of publications listed under the research disciplines not directly linked to B&M, another search was performed using the *search string 2*, this time on all disciplines, but using the selection of B&M keywords from Thompson and Reuters business sector classification [34]. This new search resulted in 337 papers (step 1b) and after exclusion of the overlaps with the first search, the total number of new papers from the second search was reduced to 8 (step 2b), or in total with the first search to 41 publications. This set was supplemented with additional 4 studies that were found in the references of selected articles, resulting in total of 45 papers. After the quality assessment described in section 2.4, 15 articles were excluded resulting in final 30 publications listed in Section 5.

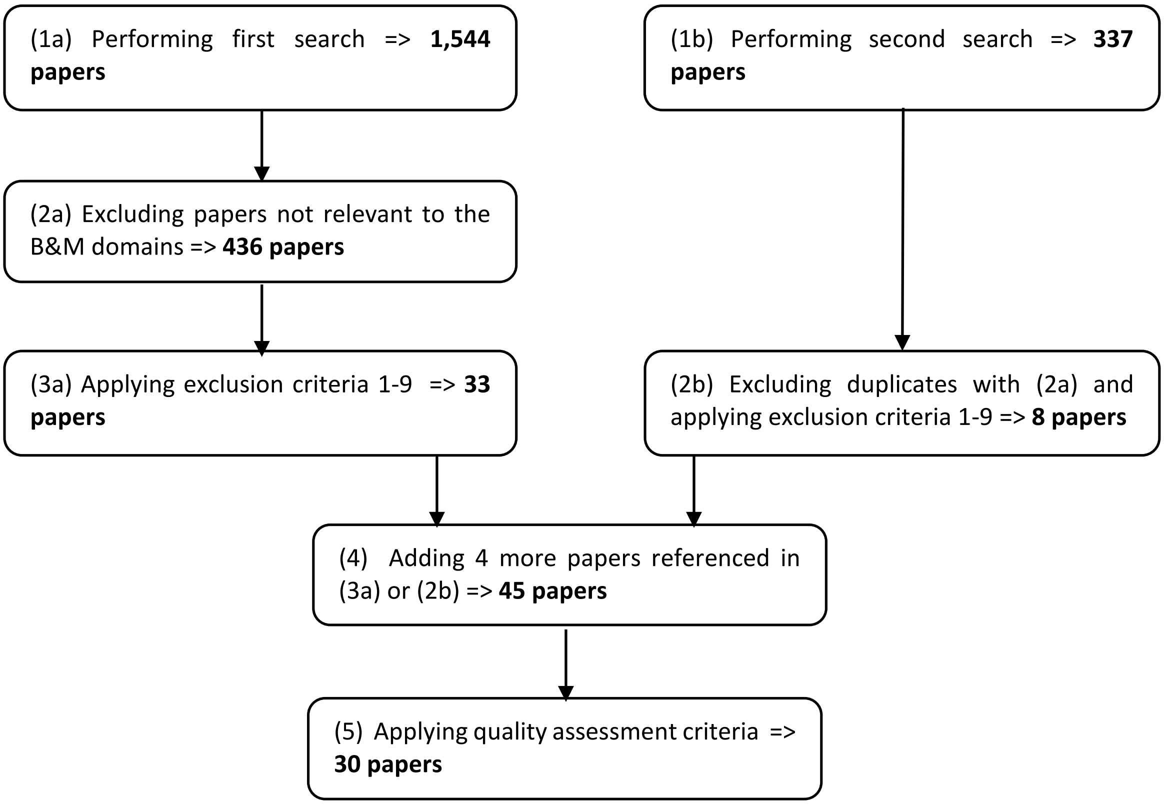

Figure 2 Paper selection process flow

The specific inclusion and exclusion criteria applied in the selection process are summarised below.

2.3.1. Inclusion criteria

1. Studies published after 01/01/2000.
2. Publication type is journal article or conference proceeding.
3. Publication language is English.
4. Studies that are directly related to AI use B&M domain e.g. use of AI in SCM (P3).
5. Systematic reviews, scoping studies and mapping studies. Reviews that contain meta-analysis in addition to the SLR, where SLR was not accurately named in the title, the abstract or under the subject terms e.g. "review" in P23.
6. Papers cited in some of the previously selected papers that are directly relevant to the topic of the review e.g. P4, P16, P21, P27.
7. Studies that consider AI in a context of B&M topics such as quality, cost, risk management or optimisation of business processes e.g. AI based software project estimation and fault prediction models (P30).
8. Studies that consider AI technology acceptance from a management perspective, even in a non-business context such as elderly wellbeing e.g. P12.
9. Secondary studies that are systematic in their methodology e.g. realistic evaluation study (P27).

2.3.2. Exclusion criteria

1. Publications that are not peer-reviewed such as: newspapers, book reviews, dissertations.
2. Repeated entries in the search output.
3. Papers that contain “false positives” e.g. term ‘neural network’ could be found in biology papers.
4. Publications where only abstract is available e.g. [2].
5. Non-systematic literature reviews e.g. [36], comparative studies e.g. [39], or surveys of AI techniques e.g. [37].
6. Papers not specifically related to AI but to technology in general e.g. [6].
7. Specific AI-technology reviews, but with no links to B&M subject e.g. [28].
8. Technology reviews in a specific B&M area e.g. [18].
9. Papers on AI subject which do not relate to B&M area e.g. AI used for rapid production of SLRs e.g. [16].

2.4. Quality assessment

Ten quality assessment questions have been devised to assess the credibility, relevance and rigour of the 45 studies obtained in step 4 of the selection process (**Figure** 2) :

1. Is the publisher reputable? E.g. Elsevier, Springer, Taylor & Francis, Emerald, SAGE, Oxford University press were considered to be amongst the top publishers.
2. What role has AI played in the review? E.g. primary technology under consideration, one of the two (or many) technologies considered
3. What type of review has been performed?
4. Has number and quality of primary studies been reported?
5. How many online databases were searched?
6. Are years covered in the review known?
7. Have specific SLR guidelines been reported to be followed in the review?
8. Have the search strings been reported and how detailed they are in describing the AI?
9. Has the data analysis method been described?
10. Have the research questions been clearly defined?

Most of these questions (3-10) are assessing rigour and they are derived from the SLR guidelines provided in [4], [12], [15] while the questions 1 and 2 are added for additional assessment of credibility and relevance respectively. First question has been added since business and management researchers rely more on the implicit quality rating of journals, rather than formal quality assessment of the articles [35]. Second question is used to classify articles according to their relevance with respect to the role that AI plays in the subject of the article.

Table 1 Quality ranking criteria

Q	*Yes (1.0 score)*	*Partial (0.5 score)*	*No (0 score)*
1	Top publishers	Reputable open access and professional bodies	Other
2	Primary	One of the two main techniques compared	One of many techniques
3	SLR	Mapping or scoping study	Other
4	Yes (all peer-reviewed)	Yes (not all peer-reviewed)	No
5	3 or more	2 or less, or top journals/conferences	Not reported
6	Yes	Could be derived	No
7	Yes	No, but the review was based on existing SLRs	No
8	Yes (3 or more terms)	Yes (1-2 terms)	No
9	Yes	Could be derived	No
10	Yes	No, but the objectives of the review are implicit	No

Similarly to [11], the quality scores of the reviews were calculated using a simple scheme: 1, 0.5 and 0 for 'yes', 'partial' and 'no' answers, which was applied to 10 quality criteria shown in **Table 1.** The total score was calculated as a sum of the scores from the 10 questions. The distribution of the quality scores ranging between 1.5 and 8.5 with an average score of x=6.33 (s=2.26) is shown in **Figure 3.**

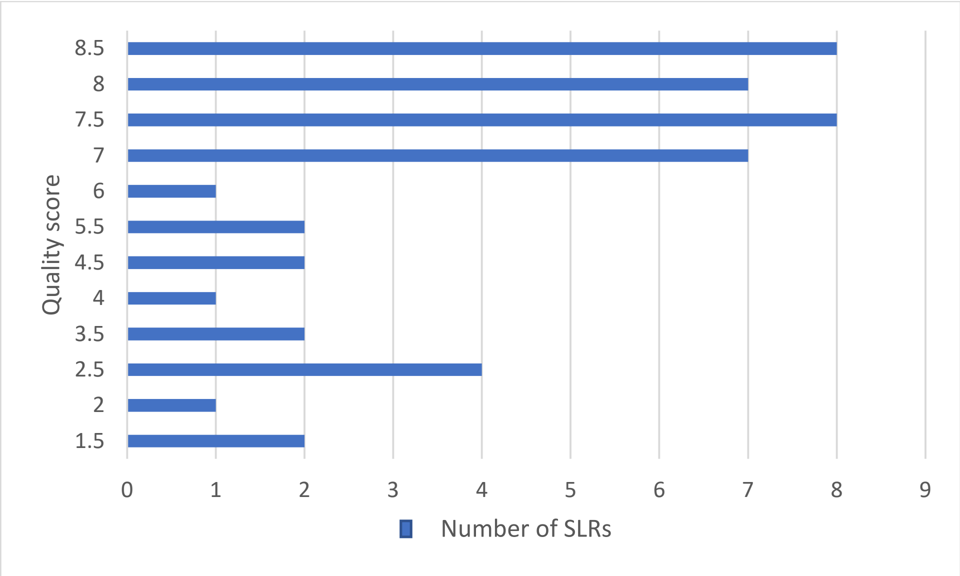

Figure 3 Total number of SLRs per quality score

The reviews with the quality scores below the average value were excluded from the sample, resulting in 30 studies with the quality scores between 7 and 8.5 shown in **Table 2.**

2.5. Data extraction and analysis

The data extracted from the selected 30 studies included the following items:

- Bibliographic information such as: citation, title, abstract, publication year, publication type, publication title, and keywords.
- SLR quality related information: publisher, the AI role, type of review, number of primary studies, online databases, years covered, SLR guidelines, search string (only the AI-related substring), data analysis method, research questions. For more details, see Section 2.4.
- Research questions related information: business sector/ or business function, main findings, consideration of bias, consideration of ethics, other human and social consideration such as trust or privacy, barriers for the AI adoption, drivers for the AI adoption, and recommendations.

The extracted data were stored in an excel spreadsheet table (total of 25 columns), and prepared for further analysis by categorising non-numerical values where possible (e.g. type of review, data analysis method), to enable statistical analysis of results. This was followed by a thematic analysis of qualitative data extracted for answering the research questions RQ3-RQ6. Due to the exploratory nature of the research, the analysis process was based on the inductive approach [31]. In an inductive approach, the starting point in the analysis are the data and the themes are emerging from the data through an iterative process comprising reading, interpreting, summarising and grouping (categorising) the data. The resulting categories and themes (higher level categories) are presented in the following section.

3. Findings and Discussion

In this section the results of data extraction are presented in tabular and graphical form and they are discussed relative to the research questions. Limitations of the research are included at the end of the section.

3.1. RQ1: How many SLRs on AI in B&M were published since the re-birth of AI (2000) to date (2019) and what is their quality?

Thirty SLRs on the use of AI in B&M domains were found to match the selection criteria with a quality score between 7 and 8.5 out of 10 (x=7.77, s=0.57). These SLRs were published between 2005 and 2019, and their main quality characteristics are shown in **Table 2**.

Table 2 AI in B&M SLRs published between 2005 and 2019

SLR #	Quality score	Publication year	Publication type	Publisher[1]	Type of review[2]	Primary studies	Years covered	SLR guidelines[3]	Data analysis Methods[4]
P1	8.5	2011	Journal	Elsevier	SLR	23	1995-2008	KC	narrative
P2	8.5	2019	Journal	Elsevier	SLR+MA	15	2005-2017	KC	narrative +MA
P3	7	2019	Journal	T&F	MS	276	1996-2018	NR	narrative+CA
P4	7	2009	Journal	Springer	SLR	68	1998-2009	NR	narrative
P5	8	2019	Journal	Emerald	SLR	126	2007-2018	Other SLRs	narrative
P6	7.5	2018	Conf.	Springer	MS	29	2013-2017	KC	CA
P7	7	2019	Journal	MDPI	SR+MS	39	2009-2018	PKR	narrative+NA
P8	7.5	2019	Journal	AAMC	SLR	69	1993-2017	PRISMA	narrative+CA
P9	7.5	2011	Journal	SAGE	SLR	95	1995-2009	NR	CA+TA
P10	8.5	2015	Conf.	Springer	SLR+MS	49	1987-2015	K	narrative+VC
P11	8	2018	Journal	SAGE	SLR	32	1996-2018	BPS	CA+TA
P12	8	2017	Conf.	Springer	SLR	95	2003-2013	HG	narrative
P13	8	2014	Journal	T&F	SLR	86	2002-2012	HG	narrative
P14	7	2018	Journal	Elsevier	SLR	38	2013-2017	NR	narrative
P15	7.5	2017	Journal	Elsevier	SLR+MA	41	1997-2015	TDS	MA
P16	8	2018	Journal	OUP	SLR	17	2003-2017	HG	narrative+CA
P17	7.5	2018	Journal	STT Int.	SS	69	1991-2017	AO	narrative+CA
P18	8	2015	Journal	Emerald	SLR	11	2004-2014	KC	narrative+CA
P19	8.5	2015	Journal	Elsevier	SLR	64	1995-2013	KC	narrative+CA
P20	7.5	2019	Journal	Springer	SLR	65	2000-2018	KC	narrative+CA
P21	7.5	2015	Conf.	AIS	SLR	52	1994-2013	WW	narrative+CA
P22	8.5	2019	Journal	Elsevier	SLR	40	2008-2018	PR	narrative+CA
P23	8	2005	Journal	T&F	SLR+MS	398	1980-2004	Other SLRs	MA+CA
P24	7	2019	Journal	MDPI	SLR	70	2000-2018	NR	narrative+CA
P25	8.5	2019	Journal	IEEE	SLR	105	2008-2019	KC	CA+TA
P26	8.5	2018	Journal	Elsevier	SLR	25	2013-2017	KC	narrative+CA
P27	7	2016	Journal	Springer	SLR	228	1996-2015	PT	narrative+RE
P28	7.5	2018	Journal	Springer	SLR	42	2006-2016	NR	narrative+CA
P29	7	2019	Journal	Online OA	SLR+SS	80	1997-2018	AO	narrative+CA
P30	8.5	2012	Journal	Elsevier	SLR	84	1992-2010	KC	narrative+VC

[1] T&F=Taylor & Frances, OUP=Oxford University Press, STT = Sigma Theta Tau;
[2] MA= Meta-Analysis, MS= Mapping Study, SS=Scoping Study;
[3] AO [1], BPS [3], HG [11], K [13], KC [14], NR=Not Reported, PKR [23], PR [26], PT [27], PRISMA [17],[21],[32], TDS [35], WW[38].
[4] CA=Content Analysis, NA=Network Analysis, RE=Realistic Evaluation, TA=Thematic Analysis, VC=Vote Counting.

Number of SLRs published each year (**Figure 4**) is showing an increasing trend, especially in the last two years when 17(56.67%) reviews are publishes.

Four (13.3%) SLRs were published in conference proceedings and the remaining 26 (86.67%) in 22 different journals (**Table 3)** of which 23(76.67%) were from major publishers, 4(13.33%) from professional bodies (AAMC, AIS, IEEE, STT Int.) and remaining 3(10%) from online open access (OA) collections (MDPI and online OA).

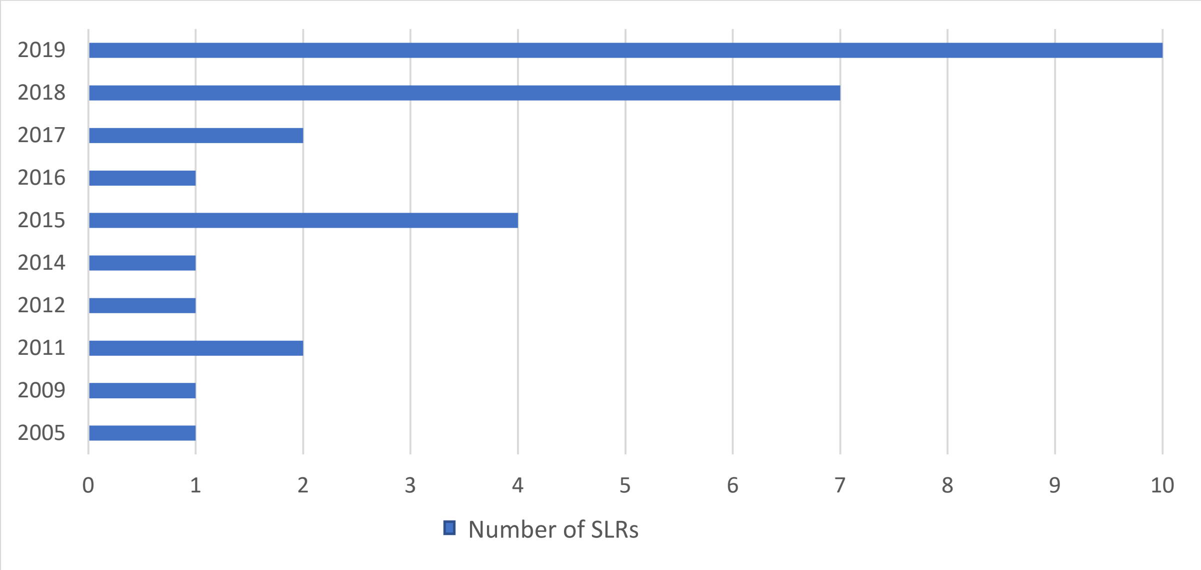

Figure 4 Total Number of SLRs per year

Table 3 Number of SLRs per publication (journal or conference proceedings**)**

Lecture Notes in Computer Science	3	10.00%
Expert Systems with Applications	2	6.67%
Information and Software Technology	2	6.67%
International Journal of Social Robotics	2	6.67%
Academic Medicine(1), Applied Software Computing Journal(1), Business Process Management Journal(1), Cognition, Technology & Work(1), Computers and Electronics in Agriculture(1), Computing, Energies(1), European Conference in IS(1), IEEE Access, International Journal of Human-Computer Interaction(1), International Journal of Production Research(1), Journal of Creating Value(1), Journal of Decision Systems(1), Journal of the American Medical Informatics Association(1), Journal of Nursing Scholarship(1), Mechanical Systems and Signal Processing, PloS one(1), Supply Chain Management: An International Journal(1), Sustainability(1), Sustainable Cities and Society(1), Textile Research Journal(1).	21	69.99%
Total	30	100.00%

In addition to the SLRs, the reviews included 5(16.67%) mapping studies (MS), 2(6.67%) scoping studies (SS), and 2(16.67%) meta-analysis (MA).

The total number of primary studies considered in the reviews was 2,021 (x=76.25, s=80.99), ranging between 11 and 398 per review paper. This number was obtained after excluding duplicates (114) across the same sector/or discipline. An online open-source application http://cermine.ceon.pl/ was used for extracting the references from the SLRs.

- Three SLRs (P23, P3 and P27) include the largest number of primary studies: 398, 276 and 228 respectively. This is due to the following reasons:
- The scope of the research questions is very wide e.g. P23 aim was to assess if the capabilities and limitations of AI-enabled decision support in organisations.

- The primary studies included wide range of publication types e.g. due to the nature of research questions in P23, it was necessary to include in the search not only academic sources but also professional journals and professional websites.
- The definition of AI used in search is too broad, e.g. in P3 it included various techniques that rely on some form of mathematical optimisation and automated reasoning in addition to the machine learning techniques.

Six studies (20.00%) did not report the source of the SLR guidelines, two (6.67%) were based on other similar reviews from the field and the remaining 22 (73.33%) were using some of the recognised SLR protocols. Majority of these (n=10, 33.33%) have used Kitchenham's guidelines ([13],[14]).
With regard to the data analysis techniques, 11(36.67%) studies used a combination of content analysis (CA) and narrative, 8(26.67%) combination of narrative with other techniques, 5(16.67%) narrative only, 3(10.00%) content analysis combined with thematic analysis (TA), and the remaining 3 (10.00%) content analysis, meta-analysis or the combination of the two. In majority of the studies the data analysis methods were not self-reported, but were derived from the analysis of the SLRs.

Figure 5 shows the years covered in the primary studies included in the SLRs. Please note that the "years covered" refers to the publications of the primary papers covered in a particular SLR, rather than the years used in the search criteria for the primary papers within the SLR. The years covered by majority of SLRs fall within the 1991-2019 period, with the exception of two reviews: P23 and P10 which cover the period prior to 1991 (1980-2004 and 1987-2015 respectively). In P23, the authors distinguish between the papers published before and after 1990, the first (earlier) group contributing significantly smaller percentage (20.10%) of the total number of primary studies considered (N=398). In P10, that number is even smaller, with only 1 paper (2.04%) out of 49 was published before 1990. Half of the papers are considering period starting in 2000 or after.

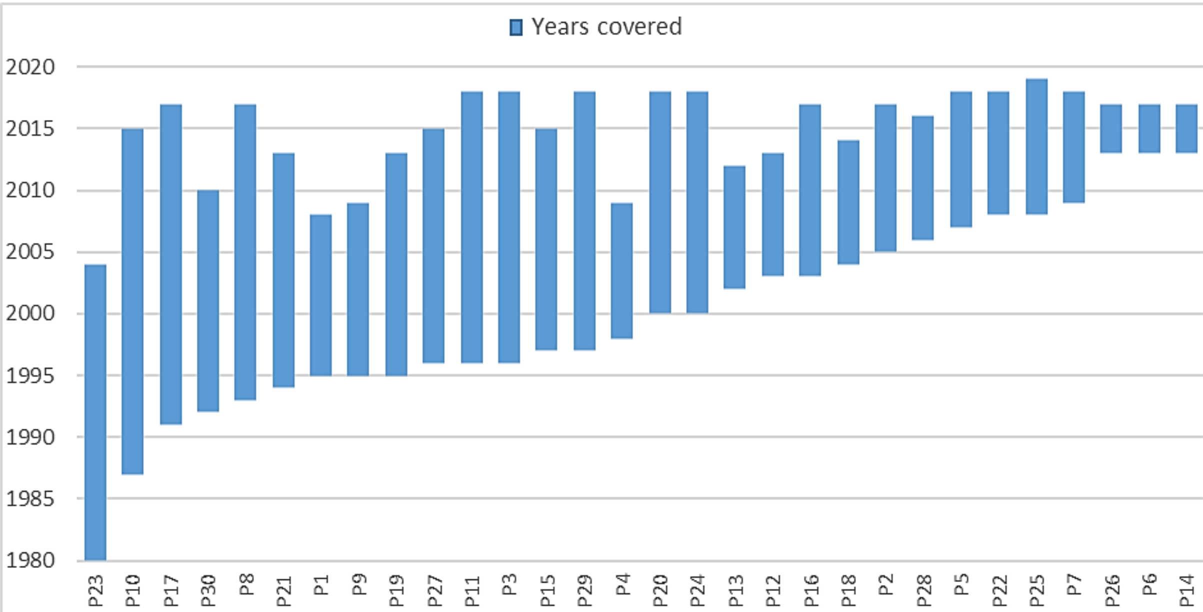

Figure 5 Years covered in primary studies of the SLRs (P1-P30)

Fifty three percent of the SLRs are covering the last three years (2017-2019) and when comparing the types of the AI considered in these and other SLRs (Table **4**) it is clear that the focus in the last three years has been on the ML techniques compared to other types of AI. Also, new AI techniques such as conversational agents and deep learning are starting to be considered. These techniques have been enabled by the changes in the information environment in the 21st century such as increasing the amounts of data from the multitude of different sources and rapidly expanding social demands for AI [23].

Table 4 Types of AI considered in different periods

Years covered	*#SLRs*	*#Primary studies*	*Robots*	*ML*	*AI misc*	*ANN& SVM*	*GP*	*Conv. Agents*	*Deep Learning*
Up to 2016	14	1335	6	3	2	2	1	0	0
2017 and after	16	1095	2	8	2	1	0	2	1
Total	30	2430	8	11	4	3	1	2	1

It is important to notice that although the SLRs themselves start in 2005, the earliest year of publication of primary studies is 1980, which is quite some time ago from the perspective of AI evolution. However, while the types of AI considered in the primary studies (**Table 4**) have considerably changed over time, the SLRs, which are much more recent, are reviewing the primary papers from the perspective of the more recent time and not from the perspective of the time of the primary papers' publication.

3.2. RQ2: What research areas are being addressed in the SLRs on AI in B&M?

Table 5 shows the distribution of the reviewed SLRs across different business sectors , AI types, business functions and research areas.

Nine (30.00%) reviews are from the healthcare sector, focusing on the use of robots (3) or conversational agents (2) in the healthcare, acceptance of robots by the healthcare users (1), impact of robots on the teamwork of healthcare practitioners (1), and use of ML algorithms in the healthcare HRM (1) and decision making (1).

Eight (26.67%) reviews do not consider a specific business sector, but instead focus on the use of robots (3) , AI in general (2) or ML algorithms (3) for specific business function such as decision support (2), supply chain (2), customer services (1), business process improvements (1), health & safety (1) or consider social acceptance of robots in different occupational fields (1).

The SLRs from the IT domain focus on the assessment of different ML (4) and Genetic Programming (1) techniques in the areas of software quality (2), cost (2), and performance (1) management.

Energy sector is represented by 2 SLRs (6.67%) covering ML models for effective management of energy systems.

The remaining 6(20.00%) SLRs are each from a different business sector, including agriculture, apparel industry, engineering, smart cities, tourism and transport focusing on different ML (3), deep-learning (1) or general AI techniques (2) for supporting decision-making (3), systems' management (2) and customer services (1).

The following business sectors were not specifically covered in any of reviewed SLRs: Automotive and assembly, Building materials and construction, Financial Services, Media and Entertainment, Professional services.

Table 5 Business sectors, functions and research topics of reviewed SLRs[1]

Bus. sector	*AI type*	*Bus. Fun./res. area*	*Review topic*	*SLR#*
Healthcare	Robots	HSM	The role of SARs in elderly wellbeing	P12
	Robots	HSM	SAR in elderly care	P13
	Robots	HSM	Robotics in nursing	P17
	CA	HSM	Conversational agents in healthcare	P16
	CA	HSM	Conversational agents in healthcare	P22
	Robots	Tech. acceptance	Acceptance of healthcare robots for the older population	P4
	Robots	Teamwork	Comms and dec. making in robot-assisted surgical teams	P27
	ML	HRM	ML for assessing physician competences	P8
	ML	DSS	Applications of ANN in healthcare org. decision-making	P29
Various	Robots	Customer service	AI and robots in value co-creation	P11
	Robots	Health & Safety	Safety certification practices in robots s/w development	P10
	Robots	Tech. acceptance	Social acceptance of robots in different occupational fields	P28

	AI	DSS	Application of AI in decision support systems	P23
	AI	SCM	AI potential and use in ("self-thinking") supply chain	P5
	ML	DSS	Application of ML in decision support systems	P21
	ML	SCM	Use of AI in supply chain risk management	P3
	ML	BPI	Process mining through ANN and SVM	P18
IT	ML	SW Project Mgmt.	SW code smell detection	P2
	ML	SW Project Mgmt.	ML techniques for software fault prediction	P19
	ML	SW Project Mgmt.	ML for software optimization of parallel comp. systems	P20
	ML	SW Project Mgmt.	ML-based sw development effort estimation models	P30
	GP	SW Project Mgmt.	Effectiveness of GP for quality/cost predictions/estimations	P1
Energy	ML	Systems Mgmt.	ML models in energy systems	P24
	ML	Systems Mgmt.	Electrical load forecasting models	P15
Agriculture	AI	DSS	AI in precision agriculture for grain crops	P26
Apparel ind.	AI	DSS	Applications of AI in the apparel industry	P9
Engineering	ML	Systems Mgmt.	Application of DL in mech. systems' health management	P14
Smart cities	ML	Smart cities	ML techniques for supporting smart cities	P7
Tourism	ML	Customer service	Online reviews on sustainability of hotels	P6
Transport	ML	Systems Mgmt.	Intelligent intersection management systems with AV	P25

[1] ANN=Artificial Neural Networks; AV= Autonomous vehicles; BPI=Business Process Improvement; CA=Conversational Agents; DL=Deep Learning; DSS=Decision Support Systems; GP=Genetic Programming; HSM=Health Systems Management; HR=Human Resources Management; IT=Information Technology; ML=Machine Learning; SAR = Socially Assistive Robots; SW=software; SCM=Supply Chain Management.; SVM= Support Vector Machine.

3.3. RQ3: What are the drivers and the barriers for AI adoption in B&M?

Table 6 and **Table 7** summarise and categorise the main drivers and barriers for the AI adoption in B&M found in the reviewed studies. The drivers for the AI adoption in these areas are mainly economic, such as reduction in cost and time, increased performance and customer satisfaction, more accurate predictions and decision making; and less so social (sustainability and wellbeing). While the economic drivers are common to all sectors, social drivers are reported only in the agriculture and the healthcare domains.
The barriers for the AI adoption include economic and technical aspects, related to the prohibitive cost of implementation and maintenance, the need for support infrastructure, lack of useable data, non-reusability of models, limited applicability for some class of problems. But equally important are social barriers, such as increased dependence on non-humans, job security fears, lack of knowledge and understanding of potential benefits, safety issues, lack of trust and difficulty in obtaining multiple stakeholder perspectives. However, these social barriers are frequently formulated as lacking in some capacity (knowledge, trust) that, if carefully managed can be overcame and the technology will be accepted by those who will need to use it or be replaced by it.

Table 6 Drivers for AI adoption

Area	*Category*	*Description (code)*	*SLR#*
Economic	Innovation	Potential for deep learning based innovation (interest in academic community driving innovation).	P14
	Productivity	Increased productivity and efficiency in business processes.	P18,P21,P26
	Cost	Deep learning may not require extensive human interaction and knowledge for feature design.	P14
		Reduced equipment costs.	P26
		Reduced human error.	P26

		SAR can potentially reduce cost of the health provider.	P13
		Governments and care funders favour 'aging in place' to mitigate the expanse of the growing number of aged in care.	P4
	Customer satisfaction	Enabling resource integration between service providers and beneficiaries (by learning customer preferences).	P11
	Accuracy	Automatic classifier can prevent human errors in the quality assessment process, making it an alternative to manual inspection.	P26
		(Manual) grain inspection and disease assessment is laborious and susceptible to human failure.	P26
	Time	Reduce traffic congestion by using intelligent traffic management systems at intersections.	P25
	Decision making, and predictions	AI techniques more capable in providing decision making, predictive and learning capabilities.	P3
		Assisting clinicians during the consultation.	P16
		Supporting consumers with behaviour change challenges.	P16
		The growing utilisation of data collectors in energy systems has created a vast number of opportunities and challenges for informed decision-making.	P24
		Machine learning technology is well-suited for analysing medical data and providing effective algorithms in diagnosis and disease monitoring.	P29
		More accurate forecasting, other cognitive support for decision making, understanding customers, improving division of tasks.	P11
		Uncertainty, flexibility in production planning and control, strong non-linearity, and seasonality in apparel retailing, are hard to solve by conventional techniques.	P9
Social	Sustainability	Sustainable agricultural processes are required in order to fit consumer demand.	P26
	Well-being	SAR can potentially decrease the workload on caregivers, provide them with more free time and less stress.	P12,P13, P17
		SAR can potentially enhance elderly well-being (autonomy, move from private to nursing home).	P12,P13, P16, P17
		Supporting beneficiaries' wellbeing through safeguarding, social contact and cognitive support.	P11
		Often human contact is in short supply, and of poor quality.	P4

Table 7 Barriers for Ai adoption

Area	**Category**	**Description**	***SLR#***
Economic	Cost	Human assistance was needed to improve ML	P21
		Labelling data, can be an exceedingly expensive effort.	P14
	Support infrastructure	Support infrastructure required for wide-scale implementation.	P29
Technical	Data	Availability of large training datasets.	P3,P16, P20,P21,P30
		Inability of AI to read unstructured data.	P29
		Lack of training data may result in performance degradation.	P20
		Most of the data in health care is unstructured and difficult to share.	P29
		Project data sets are difficult to collect and maintain.	P30

		Project data sets usually contain confidential information.	P30
		Reproducibility/generalisability of data/results (“the black-box problem”).	P8
	Model	Difficult to reuse AI models for different problems.	P9
	Problem selection	Less effective than non-ML approach in some cases.	P21
		Task of (image) classification is more challenging in some domains (e.g. agricultural domain).	P26
Social	Lack of knowledge	Lack of knowledge about the potential capability of ML techniques for specific type of problems.	P3, P18, P21
		Unrealistic expectations of technology.	P4
	Stakeholders' perspectives	Practitioners not only need to be aware of the estimation contexts, but also need to understand the characteristics of the candidate ML models.	P30
	Safety	Potential safety issues, leading to harm to humans.	P10, P16
	Trust	Many nurses distrustful of the technology.	P4
	Dependence on non-humans	Emotional attachment to non-human caregivers.	P17
		Too much dependence on the robotic helpers.	P17
	Jobs	Many nurses felt that their job security was threatened.	P4, P17

3.4 RQ4: What importance is placed on human and social factors in AI applications in B&M?

A starting point in considering human and social factors relevant to the use of AI in B&M area is the role that bias can play in harming individuals or specific groups and the role the ethics play in designing and using AI.

3.4.1 Bias

Many SLRs (N=19, 63.33%) do not consider bias in the primary studies.
Five studies (16.67%) (P6, P12, P14, P25, P28) report on potential "cultural bias" due to a large percentage of primary studies been from a certain region or only a few countries, and one (P27) reports on the sample bias: "While the literature identified in the review was concerned with the experience of surgical teams, the included papers were almost exclusively written by surgeons. "
One study (P2) suggests that the findings need to be re-evaluated because 93% of the primary studies analysed relied on a biased validation strategy that likely led to interpretation errors. In the same study the authors recommend taking a closer look into the way ML techniques are configured in order to properly interpret their results and avoid bias.
Another study (P21) reports that "none of the articles has directly attempted to evaluate the proposed models. This is in particular remarkable since it is well understood that decisions are biased by psychological and social factors".
Two studies, both from the healthcare sector (P13, P16) recognise the importance of minimising the consequences of bias, and also assessing the effects of hidden bias: "Given the potential for bias in the design of these applications (i.e. conversational agents), they may contribute to reinforce stereotypes or disproportionally affect groups that are already discriminated against, based on gender, race, or socioeconomic background"(P16).

3.4.2. Ethics

Even lesser number of studies (N=6, 20.00%) considers (or recommends) ethics as an important element in AI design.
Four of these are from the healthcare domain (13.33%):

- P4 recommends allowing the user to choose the gender of the robot, or its personality as that could "help give the older person a sense of personal autonomy and control over the robot and their own health".
- P17 emphasises the importance of ethical considerations in dealing with patients with dementia.
- P8 highlights that only seven percent of studies from the sample recommend that adherence to ethical principles should be included in the assessment of physicians' competences.
- P29 concludes that a successful application of ANN in healthcare organizational decision-making requires an improved understanding of the ethical, societal, and economic implications.

In other domains, P10 emphasises that in addition to be safe, a robot needs to be ethical for trustworthiness. which relies on modelling the robot as well as the environment, which is an issue notably in dynamic environments in which field robots operate; and P11 recommends future research on the ethical considerations when using AI-based decision-making in marketing and customer services.

3.4.3. Other human and social considerations and implications

Seven (23.33%) studies do not consider any human/or social factors or implications in their research objectives or recommendations. They all focus on technical aspects such as most commonly used AI/ML or ANN techniques or models in particular domain or scenario (P6, P9, P18, P19, P23, P26), evidence of effectiveness of these techniques for prediction, estimation and classification problems (P1), and identification of the tasks where these techniques are particularly suitable (P18).
All of these studies are from the non-healthcare sectors such as: Apparel industry, Agriculture industry, Energy, IT, Tourism, or business disciplines such as DSS and Business process improvements.
Reporting of the results in these studies is overly optimistic, while evaluation methods reveal a degree of immaturity (P18). The latter observation coincides with the informal observations from practice; according to Andrew Ng, a well-known AI practitioner and researcher, the following conversation can be heard in multiple companies: “Machine learning engineer: Look how well I did on the test set! Business owner: But your ML system doesn’t work!” [22].
All studies from the healthcare domain recommend increased focus on human and social factors, such as, stakeholders’ (patents, nurses, doctors, family) perspectives, needs and expectations in designing SAR (P4, P13), conversational agents (P16, P22) or robotic surgery assistants and procedures (P27).
Given the potential for bias in the design of conversational agents, it is particularly worrying that a social-systems analysis is currently missing from research on these application (P16). The same study points out that patent safety is rarely evaluated, and that there are currently no agreed methods to assess the long-term effects of this technology on human populations, including the “unintended consequences". The study recommends that the social impact of conversational agents should be consistently considered, from conception to real-world dissemination, given the potential to negatively influence the health of particular population.
Similar recommendation for "more concentrated cooperation between developers and caregivers" is made in P17 in a context of a SAR design.
Negative effect that SAR can have on elderly are reported in P12: "for instance, it could increase the level of anxiety due to fear of breaking or doing something wrong with the robot " while P17 emphasises the potential issues when dealing with patents with dementia. The same study reports on the negative attitudes of nurses who perceive robots as competitors rather than helpers. In both cases further training is recommended to better cooperate with robots.
Two studies report on the need to Increase understanding of the ethical, societal, and economic implications when choosing ML and ANN models and techniques for healthcare organizational decision-making (P29) and in the assessment of competencies of clinical staff (P8).
To explicitly acknowledge the sociotechnical nature of technologies such as robotic surgery, P27 uses the "realistic evaluation" framework [27] in combination with the SLR. This framework seeks to answer not only the question of ‘what works?’ but ‘what works for whom, in what circumstances, and how?’ The study identifies challenges in addition to the benefits of the robot-assisted surgery. E.g. increased operation duration, which has implications for patient safety; the separation of the surgeon from the team can compromise communication etc. The strategies to deal with these challenges such as, appropriate support from hospital administration and nursing management, and use of standardised communication respectively, are also identified in the review.

3.5. RQ5: What recommendations are made for future research on AI in B&M?

The reviewed studies make 56 recommendations for future research that can be classified in seven distinct categories, as shown in **Table 8.**
More rigour in research methods of the primary study is recommended in 17(30.36%) of SLRs. That includes, better evaluation methods, use of hybrid, mixed or integrated approaches, multidisciplinary approaches, shared datasets and standardised presentation of results so that comparisons can be made.
More focus on people, organisational and social aspects of AI technologies is suggested in 16 (28.57%) SLRs, and that includes researching factors for acceptance or adoption of AI, human-AI interactions, more links with practice and new paradigms such as 'technology has agency' (P11).
New application areas are recommended in 8 (14.29%) studies, that could further support decision making, SCM and HRM in various sectors.
Remaining 15 (26.79%) recommendations call for more research (primary studies) specifically in the areas of IT, business processes, smart cities and use of robots outside of healthcare; improvements in AI techniques, including explanations and reuse of models; and more consideration of the impact of the AI, such as its performance, benefits and social implications.

Table 8 Recommendations from the reviewed SLRs on AI in B&M domain

Recommendation categories	***Count***	***%***	***SLR#***
Methodology improvements	17	30.36%	P3,4,8,9,12-14,16,18,19,21,23,26,28-30
Focus on org. and people aspects	16	28.57%	P4,5,7,11,13,17,20,21-23,27,30
New application areas for AI	8	14.29%	P3,6,8,9,22,25,26,28
More research (primary studies)	6	10.71%	P7,10,18,19,28,30
AI technique improvements	6	10.71%	P1,2,5,14,23,24
Quantification of the impact	3	5.36%	P2,5,16
Total	56	100.00%	

Compared to [19] there are many more recommendations made outside of the methodology, impact and new applications areas, suggesting increased awareness of the social implications of the AI, the need to improve the techniques and to increase the number of empirical (primary) studies.

3.6. RQ6: What progress has been achieved with respect to prior recommendations for AI in B&M?

Since there is no prior tertiary study on the subject of AI use in B&M, it is not possible to make an exact comparison. Instead, Metaxiotis and Psarras [19] semi-systematic literature review that consider the contribution of AI techniques such as ANN and GP in the context of business decision making is considered for comparison purposes. Their review reports on the benefits from the use of ANNs and GAs in business in the following areas: increased accuracy, consistency, and flexibility, improved quality, and effective training. In their recommendations they are calling for:

1. Integration of various AI technologies and operations research (OR) techniques, especially simulation, in order to solve increasingly complex problems facing business managers (methodology)
2. Comparison of AI techniques and non-AI optimisation techniques in order to identify advantages and disadvantages of each technology (impact)
3. Benefits of using AI in marketing optimization problems (new applications).

Comparison of these recommendations with the evidence from this study, reveals small progress regarding the use of hybrid technologies (P22, P29), comparing the AI with other techniques (P19, P30) and benefits of AI use in marketing field (P11).
Majority of the selected SLRs in this tertiary study focus on describing the current use of AI i.e. most applicable areas or tasks, and most used techniques in a specific business sector or within a specific B&M function.

3.7. Limitations

Many of the limitations of this study are a direct consequence of the nature of tertiary studies, and mentioned in similar studies ([15], [12]).
For example, a small overlap in primary studies (114 duplicates) in the reviews related to the same topic (e.g. P16 and P22; P21 and P23) could have led to a slightly skewed reporting of frequencies in RQ3 and RQ4. However, the focus in these questions was to find the important themes, rather than count the occurrences of specific words. Moreover, the potential overlap re-enforces the conclusions as they are generated from multiple sources.
Although the quality of the original primary studies considered in the SLRs was not re-evaluated in this study, the quality of the selected SLRs was subject to a rigorous quality assessment.
The research questions addressed in the selected SLRs have not always matched the research questions in this study. Therefore, more time was spent in finding and extracting relevant information from the SLRs' findings and recommendations.
Since SLRs have much longer tradition in the healthcare and IT research, it is possible that in other sectors (e.g. financial service, media and entertainment, retail) those reviews are not published yet, although the primary studies might exist. This suggests some new research areas for SLRs.
The broadness of the B&M scope has made the selection process quite difficult, as some of the commercial and management aspects such as quality, time and cost of product/service development, support for decision making, technology acceptance by different user groups, have been included in many publications that are outside of the B&M domain. It is therefore possible that some SLRs have not been included if they have been published in the areas outside of the Scopus B&M related disciplines or have not included any of the Thomson Reuters [34] business sector classification qualifiers in their abstracts, titles or keywords. This implies the importance of including appropriate qualifiers in titles, abstracts and keyword lists so that the publications are not missed in future reviews.
Only one person (the author) has been involved in the selection and the review process, which has made the findings prone to subjective judgment. To mitigate the impact, the author has maintained an extensive list of inclusion and exclusion criteria (section 2.3) so that the process can be challenged by the reviewers.
The aim in this study was to consider only the publications where AI (tools, techniques and methods) have played a primary role in a context of B&M area. Therefore, the SLRs that have aimed to identify different techniques (including the AI-based) in a specific research area (e.g. software maintainability [18]), were not included in the search. The SLRs that considered technical improvements in a specific AI tool or technique (e.g. recommender systems in [28]) were not included either. This might have reduced the scope of the findings as some of the excluded papers might contain some relevant information that could support answering the research questions of this study.
Since this is a first tertiary study in this research area (AI in B&M) it was not possible to provide more accurate judgment of the progress made in the field (RQ6).

4. Conclusions

This tertiary study includes a review of 30 systematic literature reviews published between 2005 and 2019 on the subject of AI adoption across various B&M domains. The quality of these SLRs has been assessed to be 70% and over using a pre-defined quality ranking scale. More than half of the SLRs are covering primary studies published in the last three years (2017-2019), and they include new AI techniques such as conversational agents and deep learning that have been enabled by the rapid increase in big data and data driven innovation. (RQ1).
These reviews cover the AI adoption across healthcare, IT, energy, agriculture, apparel industry, engineering, smart cities, tourism and transport sectors, as well as across B&M functions such as HRM, DSS, customer services, health and safety, SCM, project management, systems management and technology acceptance (RQ2).
The drivers for the AI adoption in these areas are mainly economic (cost, time, performance, customer satisfaction, accuracy in decision making and predictions) and less so social (sustainability and wellbeing). The barriers for the AI adoption are of economic (cost, support infrastructure) and technical nature (data availability, reuse of models, support infrastructure and problem selection), but include equally social considerations, such as dependence on non-humans, job security, lack of knowledge, safety, trust and lack of multiple stakeholder perspectives. (RQ3)
Very few SLRs outside of the healthcare sector consider human, organisational and wider social factors relevant to AI production and adoption in the B&M domain. These studies focus on technical and economic aspects of

the AI technologies, report in an overly optimistic way and frequently do not include evaluation of the results in practice. The critical perspective on the values that drive the production and adoption of AI technologies [10] is missing from these SLRs. The level of awareness of the wider social impact of these values is higher in the studies from the healthcare domain where it is recognised that the social-systems analysis is currently missing from research on these applications (RQ4).

The recommendations from the reviewed SLRs are suggesting increased focus on human, organisational and social aspects of AI, in addition to methodological improvements in primary studies such as more rigour on evaluation methods, use of hybrid approaches (AI and non-AI) in problem-solving and multidisciplinary approach to AI design and evaluation (RQ5).

As the knowledge in this area continues to grow at an unprecedented rate, it is important to continue in parallel with its systematisation and categorisation using the proven SLR protocols. This study recommends more systematic reviews across other sectors, in particular Retail and Financial Industry which have been early adopters of the AI technologies [8], and across business functions that could benefit more from the AI techniques such as accounting, quality management and human resources management. In addition to that, the SLRs should include in their research objectives social considerations and implications of AI technologies.

Despite the limitation of the research, this study provides a very timely identification and categorisation of some important findings on AI adoption in business and management field from 30 SLRs (directly) and 2,021 primary studies (indirectly) and it helps in raising awareness on human, organisational and wider societal considerations and implications of the AI adoption.

5. Reviews included

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