The Impact of Smart Technologies on the Management and Strategic Control: A Structured Literature Review

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Abstract

This research proposes a systematic literature review (SLR) of the application of big data, analytics, business intelligence, and artificial intelligence to company management and strategic control. Thus, this paper attempts to answer the following research questions: 1) How is the literature on the application of big data, analytics, business intelligence, and artificial intelligence to management and strategic control developed in the business, management and accounting fields? 2) On which aspects of this application does the literature focus? 3) What are the implications that arise for companies?
In this paper, we used a longitudinal study of research documents in the form of last-decade literature collected from Scopus database as the leading source for the international scenario. After, we selected business, management, and accounting areas, and screened the titles and abstracts of the research documents, we based the final result on 60 scientific documents as sources relevant to the aim of this SLR. The findings highlight four main topic clusters. We specifically explain smart technologies' usefulness for each analyzed business function, and, while adopting a critical perspective, we point out the interesting current streams of research resulting from the application of new sources of technology. We conclude by proposing valuable insights gleaned from the study. Thus, our results are useful for both the academic and the professional community.

Keywords: Big data, Analytics, Business intelligence, Artificial intelligence, Management and strategic control, Decision-making.

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1. Introduction

"Nowadays, firms work in a very complex and dynamic environment, in which different forces interact, as new technologies, new ways to look at the future, new principles and values, new regulations" (Mancini, 2018). During the last years, companies had to adapt their business processes to the disruptive impact of new technologies (Krumeich et al., 2014). All economic fields and organizations are influenced by technological transformation (Hossnofsky and Junge, 2019; Kohnová et al., 2019; Schimperna et al., 2020; Lombardi et al., 2021). Particularly, all company's business processes are affected by new technologies such as artificial intelligence (AI), big data, analytics and business intelligence (BI) (Mahraz et al., 2019; Bordeleau et al., 2020).

In this scenario, managers' strategic decisions are directly or indirectly affected by smart technologies, up to the complete replacement of the final decision-maker (Eriksson et al., 2020). Additionally, corporate planning and the scenario analysis (Vacík et al., 2014), budgeting processes and management control systems will be strengthened through these technologies (Warren et al., 2015). Thus, companies ready to face this technological revolution could achieve relevant competitive advantage (Liu et al., 2014; Lombardi et al., 2020a; Peters et al., 2016).

This paper aims to review the impact of smart technologies on corporate management and strategic control. The research questions are answered through a systematic literature review (Tranfield et al., 2003; Kraus et al., 2020), based on a longitudinal study from 2009 to 2020. To achieve this objective we use Scopus database as prominent source in the international scenario to find business administration documents.

Our findings show how BI, AI, business analytics and big data significantly affect decision-making process, planning and control by organizations. This paper is novel in providing the current stage of development and implementation of these new technologies in the field of management and strategic control. Our results address to the academic and professional community as theoretical and practical advances also supporting the digital revolution into organizations.

The remainder of the paper is structured as follows: section 2 provides the theoretical background, section 3 the research methodology, whereas section 4 shows results. Lastly, section 5 points out the conclusions and future research agenda.

2. Theoretical background

2.1 The decision-making process

The decision-making process adopted by owners, managers and people deputed to several functions inside organizations moves the business complex and according to which the organization is structured (Trequattrini, 2004). According to Mella (2001), the decision made by a decision-maker is *"a choice, conscious or voluntary, among several alternatives, implemented to achieve a goal or to solve a problem"*. A decision can be affected by several factors among which the following are the most valuable (Trequattrini, 2004): I) complexity; II) conciseness; III) changeability; IV) probabilistic nature; V) systematization. Decisions are made from complex decision-making processes (Simon, 1960), based on the following subsequent and logically-connected phases (Dewey, 1997; Trequattrini, 2004; Lombardi et al., 2014; Lombardi et al., 2020b):

1. *"identification of the problem to be solved or specification of the objectives to be achieved;*
2. *collection of information regarding the external and internal environment in order to establish and define the problem or clearly highlight the objective;*
3. *development of alternative courses of action;*
4. *identification and assessment of consequences associated with alternatives according to the assessment system of the person making the decisions;*
5. *choice of the very best alternative"* (Trequattrini, 2004; Lombardi et al, 2014).

The objective rationality theory and limited rationality theory represent the two main schools of thought defining the decision-making process (Simon, 1958). According to the objective rationality theory, the Economic Man knows perfectly all the alternatives to solve each problem, identifying exactly every consequence associated with each alternative. The Economic Man is capable of evaluating these consequences and chooses the alternative that maximizes his/her utility function (Trequattrini, 2004). Conversely, according to the limited rationality theory, the Administrative Man does not know all the alternatives to solve a problem, cannot identify exactly all the possible consequences associated with each alternative and does not know his utility function perfectly. Thus, the Administrative Man cannot choose the best alternative. The Administrative Man does not make optimised choices because of informative nature limitations, mainly due to lack of understanding, attention, memory and communication (March and Simon, 1958; Cyert and March, 1963; Trequattrini, 2004; Lombardi et al., 2014).

2.2 Some elements by the strategic planning and control

Strategic planning represents the process of defining and implementing the strategy by each organization (Marasca et al., 2013). The essential objectives of corporate management are defined by the strategic planning processes and the strategic ways to achieve them are identified. This process is based on a time horizon that exceeds a single financial year (Marasca et al., 2013). Conversely, the term "programming" is applied to short-term choices, typically annual periods (Brusa, 2012). In this scenario, a crucial role is filled by the budget, *"a business management program, translated into economic-financial terms, which guides and empowers managers towards short-term objectives, defined as part of a long-term strategic plan"* (Brusa, 2012).

Management control can be defined as a system of methodologies, tools and processes (Marchi et al., 2018) through which managers verify compliance with objectives defined in the strategic planning and budgeting stage, as well as with the criteria of efficacy and efficiency (Marasca et al., 2013; Pavan, 2019). Even if management control is traditionally considered as an internal process inside organizations, it is evolving toward three external perspectives. *"The first one is the information perspective: integrating internal and external data, i.e. combining internal with external measurements, for strategic control purposes. The other perspectives are related to the new management control external issues. The second perspective deals with: monitoring relationships, integrating objectives and measuring shared value for the network. The third perspective refers to managing external reporting, together with external roles and responsibilities, for an extended model of governance"* (Marchi, 2011).

2.3 The advent of smart technologies

In recent years, organizations (e.g. private companies, public companies, SMEs and so on) are more and more influenced by the advent of smart technologies. In this direction, companies are adapting their business processes to the disruptive impact of new technologies (Krumeich et al., 2014) to gain significant benefits (Marchini et al., 2019). Thus, all economic fields and organizations are influenced by technological transformation (Hossnofsky and Junge, 2019; Kohnová et al., 2019; Schimperna et al., 2020; Lombardi et al., 2021).

The most relevant smart technologies are classified by the national government under the Industry Plan 4.0 using nine relevant categories: I) advanced manufacturing solutions; II) additive manufacturing; III) augmented reality; IV) simulation; V) horizontal/vertical integration; VI) industrial internet; VII) cloud; VIII) cyber-security; IX) big data and analytics. However, artificial intelligence (AI), big data, analytics and business intelligence (BI) are relevant smart technologies (Mahraz et al., 2019; Bordeleau et al., 2020) able to contribute to the competitive advantage (Liu et al., 2014; Peters et al., 2016).

In light of the above, our research questions are the following:

- *RQ1: How is big data, analytics, business intelligence and artificial intelligence application to management or strategic control literature developed in the field of business, management and accounting?*
- *RQ2: What is the literature's focus on big data, analytics, business intelligence and artificial intelligence applied to management or strategic control sector?*
- *RQ3: What are the implications that arise for organizations?*

3. Research method

We develop our systematic literature review (SLR) analysing how big data, analytics, business intelligence and artificial intelligence are applied to management or strategic control and their impact on planning and control processes. Thus, this section aims to define research protocol and criteria to develop the SLR (Tranfield et al., 2003; Petticrew and Roberts, 2008; Kraus et al., 2020). We build up the analytical framework of our analysis in accordance to the summary by Secundo et al. (2020) by analysing the following items: a) publications' timing; b) geographical distribution of articles; c) citations of authors; d) articles citations and connected journals; e) emerging keywords and topics. Lastly, we identify future research, developing "*insights and critique through analysing the dataset*" (Massaro et al., 2016).

We analyse some research documents, providing strong theoretical support to our study. Afterwards, we adopt a longitudinal study of research documents from 2009 to 2020. We try to avoid the highest number of false positives and negatives (Petticrew and Roberts, 2008) and we base our queries on the groups of keywords we obtained by a specific bullet point included in the call launched by Management Control Workshop 2020: I) (“big data” or “analytics” or “business intelligence”) and (“manage* control” or “strategic* control” or “strategic* plan*” or “planning and control”); II) “artificial intelligence” and (“manage* control” or “strategic* control” or “strategic* plan*” or “planning and control”).

We use Scopus database as the leading source to get access to the documents, ensuring the best transparent process. Our search is based on “Article title, Abstract, Keywords”. Additionally, we adopt the Boolean operator (AND) as connection. This systematic literature review refers to the so-called “grey analysis” (Kraus et al., 2020). Our first stream of search provides 491 documents for the first query and 422 for the second one.

We limit the investigation field to the business, management and accounting area. The results are based on 120 documents for the first query and 77 for the second one. After the cut-off of those non-English language documents and the screening of titles and abstracts of retrieved documents, we develop our final result based on 60 relevant documents as crucial sources of the development of the SLR. The full list of these documents is presented in the Appendix (www.sidrea.it/smart-technologies-control).

The high number of documents suggests that the analysed field is a mature one with a new interesting stream of research due to the application of new sources of technology. Our SLR provides the theoretical background connecting management and strategic control and new technological tools, such as big data, analytics, business intelligence and artificial intelligence. Additionally, we develop many bibliometric analyses (Secundo et al., 2020) based on keywords and content analysis. This bibliometric analysis, provided by VOSviewer software (Van Eck and Waltman, 2017), bases on citations of documents, co-occurrence of keywords and bibliographic coupling in order to obtain clusters. Thus, the following section presents our findings.

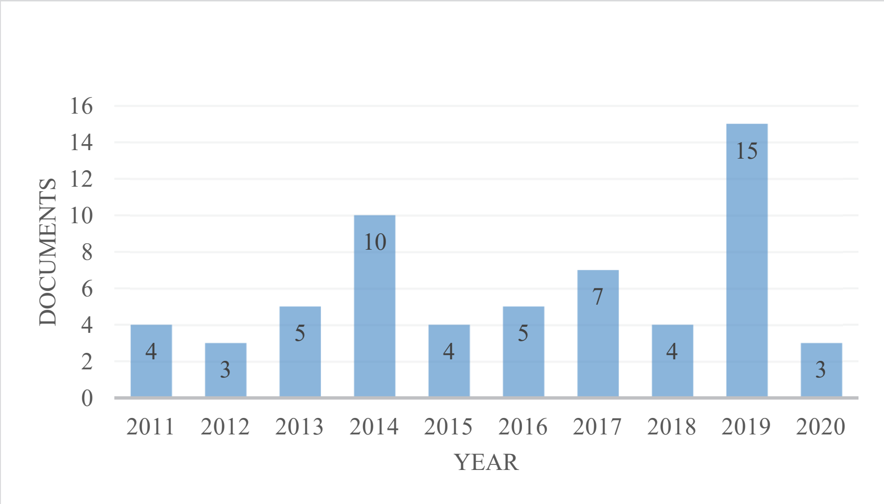
4. Results

We show our findings in the following sections, answering our research questions. Section 4.1 provides insights in order to answer RQ1 and RQ2. Section 4.2 aims to answer RQ3, providing relevant findings for this SLR.

Descriptive and bibliometric analysis

Figure I shows the number of published documents from 2009 to 2020 highlighting a very irregular trend. Additionally, the 2014 year and the 2019 year are the most significant years in terms of publications. Indeed, in 2014 10 documents were published, while 15 during 2019.

Figure I – Publishing trend



Source: our elaboration from Scopus data

Assuming the perspective of countries (Tab. I), the highest number of documents comes from the USA (15 documents). The USA is followed by the United Kingdom (9 documents) and Italy (7 documents). We also provide an analysis of related citations. The USA (601 citations) and the United Kingdom (250 citations) are again at the top of the list, followed by Australia (413 citations).

Table I - Top six countries (citation)

Country	N° of Documents	N° of citations
United States	15	601
United Kingdom	9	250
Italy	7	94
Australia	6	413
Germany	5	61
Russia	5	3

Source: our elaboration

In this scenario, the USA, the United Kingdom, Italy and Australia can be seen as leading countries in the analysed topic. Additionally, the number of citations per source is found as follows: I) *Decision Support Systems* (88 citations; 2 documents); II) *Journal of Information Systems* (67 citations; 3 documents); III) *International Journal of Accounting Information Systems* (27 citations; 2 documents); IV) *Lecture Notes in Business Information Processing* (19 citations; 4 documents); V) *Journal of Manufacturing Technology Management* (15 citations; 2 documents). We also adopt other specific measures, such as the citation index (CI) and the citations per year (CPY). Table II shows the top five cited articles.

Table II – Top five cited articles

Authors	**Title**	**Citations**	**CPY**	**Source**
Akter et al. (2016)	How to improve firm performance using big data analytics capability and business strategy alignment?	187	37.4	*International Journal of Production Economics*, 182, 113-131.
Elbashir et al. (2011)	The role of organizational absorptive capacity in strategic use of business intelligence to support integrated management control systems	111	11.1	*The Accounting Review*, 86(1), 155-184.
Warren et al. (2015)	How Big Data will change accounting	67	11.17	*Accounting Horizons*, 29(2), 397-407.
Chae et al. (2014)	The impact of advanced analytics and data accuracy on operational performance: A contingent resource-based theory (RBT) perspective	62	8.86	*Decision support systems*, 59, 119-126.
Schläfke et al. (2013)	A framework for business analytics in performance management	57	7.12	*International Journal of Productivity and Performance Management*

Source: our elaboration

Business, management and accounting is the main journal sector. However, we found a frequent co-presence of: computer science; decision sciences; engineering; economics, econometrics and finance; mathematics; social sciences; arts and humanities; environmental science; psychology; energy.

Starting from 2011 there is a strong increase in citations (Fig. I). The total number of citations is 832. We also identified the most relevant keywords in the 60 documents analyzed through the occurrence analysis. The most relevant all keywords (with 4 as the minimum number of occurrences of a keyword) are provided by table III. Thus, strategic planning, artificial intelligence, decision-making, big data, business intelligence and decision support systems are relevant words answering our research questions.

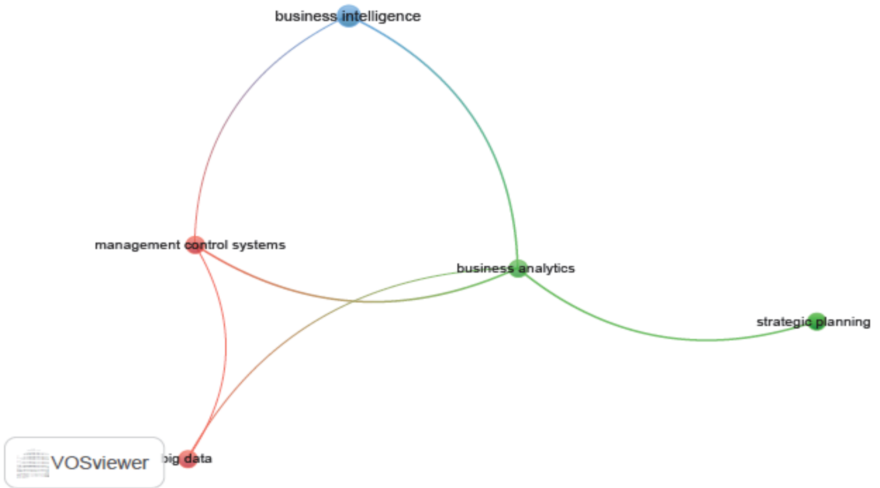
Table III – All keywords occurrence

Keywords	**Occurrence**
Strategic planning	18
Artificial intelligence	13
Decision-making	12
Big data	12
Business intelligence	10
Decision support systems	8
Information management	7
Competitive intelligence	7
Information systems	6
Supply chain management	6
Business analytics	6
Management control systems	6
Information analysis	5
Information use	5
Performance management	4
Sustainable development	4
Management science	4
Planning and control	4
Performance measurement	4

Source: our elaboration

The authors' keywords analysis through the occurrence (selecting 5 as the minimum number of occurrences of a keyword) shows three main clusters: cluster 1) is composed of big data and management control system; cluster 2) is composed of business analytics and strategic planning; cluster 3) is composed of business intelligence (Fig. II).

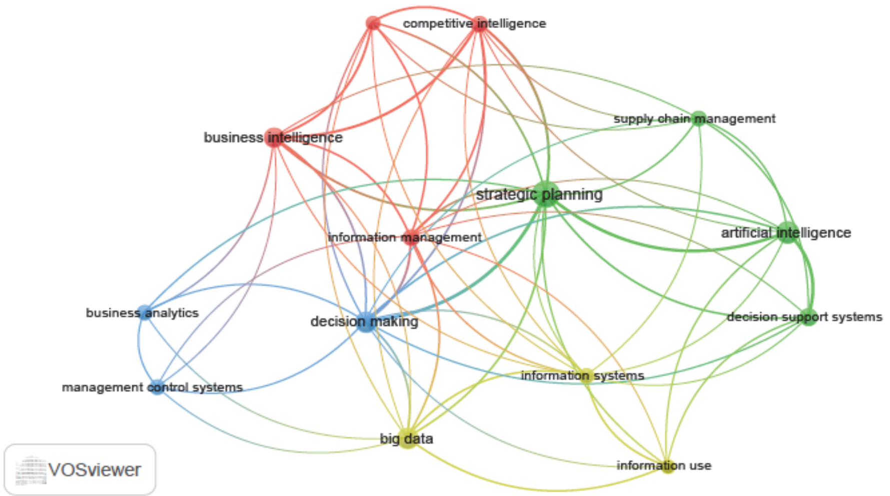
Figure II – Authors Keywords' occurrence



Source: VOSviewer

We also investigate all keywords clusters through the co-occurrence, selecting 5 as the minimum number of occurrences of a keyword. 14 keywords meet the threshold (Fig. III). We choose the full counting method assuring the documents' reliability, without weighing the authors.

Figure III – All Keywords' occurrence



Source: VOSviewer

We identify cluster 1 with 4 items adopting the red colour, cluster 2 with 4 items adopting the green colour, cluster 3 with 3 items adopting blue colour, cluster 4 with 3 items adopting yellow colour. Interestingly, results highlight the role of technological tools and their connection with I) business intelligence, competitive intelligence, information analysis, information management; II) artificial intelligence, decision support system, strategic planning, supply chain management; III) business analytics, decision making, management control systems; IV) big data, information systems, information use. Each cluster emphasizes the role of new technologies in business applications. In this scenario, cluster 1 focuses on business intelligence, cluster 2 on artificial intelligence, cluster 3 on business analytics and cluster four on big data.

Emerging topics by clusters

The development and the need for new technologies, such as BI, AI, business analytics or big data, emerged from the cluster analysis, with special reference to decision-making, strategic planning and control systems. Several conflicting objectives, different stakeholders, little relevant data, different decision alternatives and long horizons affect strategic decisions (Kunc and O'Brien, 2019). In this scenario, the implementation of digital technologies, big data, business analytics and AI provides intelligent support to decision-making process and improves the quality of business processes management (Wang et al., 2011; Lněnička et al., 2017; Aleksandrova et al., 2019). In the current digital revolution, big data plays a relevant role, improving rational decision-making through databases, better measurement and statistical models developed to improve transparency, forecast individuals' wishes and steer future actions (Arnaboldi et al., 2017).

Additionally, business analytics is useful to support a broader range of strategy making, transforming data into a more valuable strategic resource and bringing strategic change in organisations (Kunc and O'Brien, 2019). In the current dynamic and complex environment, managers could get competitive advantage from business analytics improving their decision-making as follows (Klatt et al., 2011):

- Disclose assumptions: business analytics allows managers to understand and build their business dynamics;
- Test strategy impact: business analytics is useful to test strategy strength, revealing whether the desired results derive from specific strategic actions;
- Leverage efficiency: the analysis of critical interfaces or operations through business analytics reduces the risk of time-consuming mistakes,

speeds up task execution and improves operative efficiency by cutting unnecessary costs;
- See and learn from changes: business analytics helps managers to understand market and customer behaviour;
- Objectify decisions: the decision-making process can be characterized by more formal reporting through business analytics.

Also, AI is currently present in the business context (Eriksson et al., 2020), bringing deep changes to companies and affecting how they compete and thrive (Paschen et al., 2020). AI allows the identification, summarization and extraction of information useful for strategic decisions without solicitation. Together with the identification of required information, *"AI has already started to modify, directly or indirectly, the strategic decision taken by companies"* even going so far as to replace managers in making a final decision (Eriksson et al., 2020). In order to remain competitive, companies are trying to fully automate their strategic planning process, replacing human discretion with AI up to the decision-making managerial positions (Tokic, 2018).

According to Paschen et al. (2020), AI enables competence-enhancing process innovations, competence-enhancing product innovations, competence-destroying product innovations and competence-destroying process innovations. Analysing which products or processes are influenced by AI and the kind of outcomes (competence-enhancing or competence-destroying), managers can completely understand their exposure to AI opportunities and risks and plan accordingly. Additionally, managers can map AI to impact on their strategic partners' competencies and discuss their organization's strategic innovation portfolio (Paschen et al., 2020).

In several companies, AI is so mature that it makes strategic decisions. No less important are tactical uses, *"playing an operational role in data analysis, conducting sentiment analysis, executing customer interactions (e.g. chatbot) and making immediate, autonomous non-strategic decisions (e.g. making short term investment decisions)"* (Eriksson et al., 2020). However, some companies refuted any current AI use for strategic decisions (Eriksson et al., 2020). Table IV summarizes how each technology affects the decision-making process.

Managers are currently facing the challenge of corporate planning in a time of technological and economic upheaval, where intelligent systems, such as AI, Internet of things (IoT), advanced analytics, big data analytics represent an essential input to organizational strategic planning (Chae et al., 2014; Akter et al., 2016; Zarrin and Daim, 2019; Schröder and Geldermann, 2019; Pasichnyi et al., 2019, Culver, 2019). Particularly, a holistic application of business analytics facilitates managers' knowledge of essential interdependencies between inputs, processes, outputs and outcomes (Klatt et al., 2011; Schläfke et al., 2013). Thus, business analytics provides managers with valuable information about key performance aspects, avoiding data overload and consequently inefficient decisions. Additionally, business analytics leads to a more objective decision-making process (Klatt et al., 2011).

Table IV – Technological impact on the decision-making process

Technology	**Functions**
Big data	It plays a relevant role, improving rational decision-making through databases, better measurement and statistical models developed to improve transparency, predict individuals' wishes and steer future actions (Arnaboldi et al., 2017).
Business analytics	It supports managers to understand and build their business dynamics, it is useful to test strategy strength, reduces the risk of time-consuming mistakes, speeds up task execution, improves operative efficiency and allows more objective decisions (Klatt et al., 2011).
Artificial intelligence	It allows the identification, extraction and summarization of information useful for strategic decisions without solicitation. AI has already started to modify, directly or indirectly, the strategic decision taken by companies even going so far as to replace managers in making a final decision (Eriksson et al., 2020).

Source: our elaboration

Corporate planning has recently been affected also by BI and becomes relevant to provide strategic scenarios, useful for: i) elaboration of strategic plan variants; ii) assessment of strategic variants; iii) risk management. *"The scenario application, while respecting risks known, significantly enhances the quality of strategic management which contributes to better company's stability, determination of realistic goals and, finally, to the increase of its market value"* (Vacík et al., 2014).

Together with the previous technologies, planning – and control too – is characterized by the use of the following technologies: fuzzy logic (FL), knowledge-based systems (KBS), case-based reasoning (CBR), genetic algorithms (GA), neural networks (NN), data mining and hybrid AI – a hybrid combination of previous AI technologies – (Kobbacy and Vadera, 2011). Among the countless fields of application, FL is useful for change management in construction (Motawa et al., 2007) and for cost-volume-profit analysis under uncertainty (Yuan, 2009), KBS for sheet metal operations (Kumar and Singh, 2008), for metal cutting-punching combination processes (Pan and Rao, 2009) and for national defence budget planning (Wen et al., 2005), CBR for marketing plans (Changchien and Lin, 2005) and for block assembly in shipbuilding (Seo et al., 2007), GAs for coordinating dispersed product development in the fashion industry (To et al., 2009) and for computer-aided process planning in preliminary and detailed planning (Salehi and Tavakkoli-Moghaddam, 2009). Lastly, neural networks are applied in cost estimation for sheet metal parts (Verlinden et al., 2008), precision casting process planning (Vosniakos et al., 2009) and automated CAD/CAM integration for die manufacture (Ding and Matthews, 2009), while data mining in planning support system for biomass-based power generation (Ayoub et al., 2006). Table V summarizes how each technology affects the strategic planning.

Table V – Technological impact on the strategic planning

Technology	**Functions**
Business analytics	It facilitates managers' knowledge of essential interdependencies between inputs, processes, outputs and outcomes (Klatt et al., 2011; Schläfke et al., 2013).
Business intelligence	It is used for scenario analysis that significantly enhances the quality of strategic management, which contributes to better company's stability and determination of realistic goals (Vacík et al., 2014).
Artificial intelligence	It can provide full support to the strategic planning of companies operating in every economic sector.

Source: our elaboration

Companies are increasingly developing BI systems to support their management control activities (Elbashir et al., 2011; Elbashir et al., 2013; Lee and Widener, 2016; Peters et al., 2018) as well. Particularly, the feedback stage could be enhanced by BI reporting systems, through the comparison between actual results and feedforward data calculating feedback variances (Peters et al., 2016). According to Huber (1991), *"advanced information systems can enhance organizational learning in three ways: (1) by broadening information distribution within an organization; (2) by facilitating the elaboration of more varied interpretations; and (3) by enabling more entities to develop uniform comprehensions of the various interpretations"* (Peters et al., 2016). In this scenario, BI and analytics lead to competitive advantage (Liu et al., 2014; Peters et al., 2016).

Management control systems and budgeting processes will be strengthened also by big data (Warren et al., 2015). Particularly, according to Daskalova and Ivanova (2019), control can be characterized by the following four levels – all affected by big data: diagnostic control systems, interactive control systems, beliefs systems and boundary systems. Additionally, analytical methods and software systems are needed for a proactive control, based on the detection and the prediction of important events from collected data (Krumeich et al., 2014). Table VI summarizes how each technology affects control.

Table VI – Technological impact on control

Technology	Functions
Artificial intelligence	It can provide full support to the strategic control of companies operating in every economic sector
Business intelligence	It allows the comparison between the achieved results and the planned ones, calculating the deviations (Peters et al., 2016).
Big data	It improves control systems, also supporting the development of proactive control based on the detection and the prediction of important events from collected data (Krumeich et al., 2014).

Source: our elaboration

5. Conclusions and Future Research Agenda

Latterly, smart technologies such as AI, BI, big data and analytics have been revolutionizing every organization and business process (Mahraz et al., 2019; Schimperna et al., 2020, Lombardi et al., 2021). Companies have to deeply change their actions and processes and innovate (Krumeich et al., 2014). We aim to understand the impact of smart technologies on management and strategic control through an SLR. Answering our research questions, the main findings provide both practical and theoretical contributions to the literature.

Section 4.1 provides the answer to the first two questions. Starting from a first stream of search of 491 documents for the first query and 422 for the second one, we selected 60 documents. Such numbers are relevant evidence that big data, analytics, BI and AI application to management or strategic control literature represents a mature field from a business, management and accounting point of view. Additionally, our cluster analysis points out a strong connection between these smart technologies and the decision-making process, planning and control by organizations.

Section 4.2 answers the third question. Smart technologies support the decision-making process (Kunc and O'Brien), corporate planning, scenario analysis (Vacík et al., 2014), budgeting processes, management control (Warren et al., 2015) and the feedback stage (Peters et al., 2016). In the current scenario, the main challenge to face is the introduction of these technologies in the organization getting as many advantages as possible due to the improvement of the previous processes (Liu et al., 2014; Peters et al., 2016).

This paper has several limitations, among which the use of only one research database (Scopus) to collect papers. In this direction, our future research is directed to oversee limitations, adopting other databases of search (such as Google Scholar, search by sectorial scientific journals; dataset provided by scientific association's website) and focusing on the most top three relevant countries highlighted in our analysis: the United States, the United Kingdom and Italy. Thus, current evidence shows primary data on the impact of smart technologies on management and strategic control and we retain very useful information to cross and develop future analysis to investigate specific issues by the general topic analysed. Lastly, the construction of the future agenda is in progress and directed to deeply investigate: I) (individually) smart technologies and management and strategic control systems; II) (individually) smart technologies and decision-making processes; III) effects and implications by the intersection of smart technologies, decision-making processes and management/strategic control systems.

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