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# From forest to finished products: The contribution of Industry 4.0 technologies to the wood sector

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A B S T R A C T

This study offers a Systematic Literature Review of the main applications of Industry 4.0 technologies in the wood sector, from forest management and raw materials production to the manufacturing of finished wood and paper products. The review, based on a rigorous and structured process, includes 106 papers published between January 2011 and December 2020. The analysis and categorization of the selected papers brings to the creation of a summary framework, which identifies (1) the needs of the wood sector that can be addressed with Industry 4.0, (2) the actions to be implemented to satisfy each need and (3) the specific Industry 4.0 technologies to be adopted for the implementation of the identified actions. Overall, the analyses conducted show that Industry 4.0 is mainly applied in previous literature to collect, share and analyze different types of data through network and data processing technologies, thus supporting decision-making processes along the entire wood supply chain. The aforementioned summary framework, which provides a complete overview of the contribution of Industry 4.0 to the wood sector, is used for the development of promising future research opportunities, deriving mainly from the investigation of underexploited Industry 4.0 technologies (i.e., blockchain, augmented reality, autonomous and collaborative robots). The research provides contributions to both academics and practitioners interested in the application of the new technologies to the different wood supply chain processes.


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## 1. Introduction

Industry 4.0 is one of the most debated topics in recent literature (Frank et al., 2019). Given its strong technological advancements, it is considered by several a disruptive phenomenon that will significantly impact both industry and society (Horváth and Szabó, 2019). Industry 4.0 relies on the adoption of several technologies that allow to collect, share and analyze real-time data, to connect the cyber-space with the real environment and to enable new digital production systems (Culot et al., 2020).

Along with the agri-food industry (see e.g., Annosi et al., 2019; Miranda et al., 2019), one of the sectors where these technologies seem to have a significant potential is the wood one. The huge amount of data generated along the wood supply chain process can indeed be used to extract relevant information and improve the management of the entire supply chain, from forests to wood/paper manufacturing (Zhang et al., 2020). Similarly, the new technologies can also create a cyber-physical environment for the design and manufacturing of wood products, thus optimizing the relative processes (Chang and Chen, 2017). The scholars exploring key features, adoption and benefits of Industry 4.0 technologies in the wood sector are several (e.g., Murmura and Bravi, 2018; Zhang et al., 2019; Guirado et al., 2020).

However, few attempts have been made by previous research to holistically investigate and synthetize extant knowledge on the applications of Industry 4.0 in the wood sector, as summarized in Table 1. From the table, it is immediately clear that previous reviews, besides lacking systematicity, focus on single Industry 4.0 technologies and/or on few processes of the wood supply chain, thus failing to provide a holistic view on the topic. Accordingly, the present study aims at filling this gap by exploring which processes of the wood supply chain can benefit most from Industry 4.0 adoption, through which technologies and in what way.

Providing such analysis is relevant and original for many reasons, summarized as follows:

- First, the wood sector is quite peculiar. Besides having a wide variety of potential uses, wood, as a raw material, is characterized by a wider set of properties and morphologies, if compared to steel, aluminum or plastic. Each wood species has a more appropriate target application (e.g., sawmill vs. pulping process) and, even within the same species, certain characteristics of the wood may change according to the geographical location of forests, making the material more or less suitable to certain uses (Teischinger, 2017). Exploring the role that Industry 4.0 technologies can play in deeply understanding the characteristics of a forest is therefore important to properly manage the raw materials and better allocate them.
- Second, recent contributions have claimed that the technological advancement of companies operating in the wood sector is quite limited. As highlighted by Landscheidt and Kans (2019), the production processes are still characterized by many manual activities and firms are not completely aware of the potentialities offered by automation in this sector. A detailed review on the topic can be helpful not only to confirm or deny this claim, but also to identify the main application areas of Industry 4.0, as well as future uses that may be useful to consider, thus fostering technological advancement in the sector.
- Third, since one of the key principles of the 2030 Agenda for Sustainable Development is the sustainable use of natural resources, including forests, exploring previous literature to understand if and how technological progress can enhance sustainable production and consumption of wood products is important to direct Industry 4.0 investments in the sector.

Considering all the aforementioned benefits, this paper develops a Systematic Literature Review (SLR) on the applications of Industry 4.0 technologies in the wood supply chain, from forests and the production of wood raw materials to the manufacturing of finished wood and paper products. The three questions addressed by the SLR are the following:

*RQ1. What are the general needs of the wood sector that can be addressed through Industry 4.0?*

*RQ2. What actions have to be carried out to satisfy the aforementioned needs?*

*RQ3. Which Industry 4.0 technologies are needed to implement the aforementioned actions?*

Based on the review of 106 papers, selected with a rigorous and structured process, we were able to answer the research questions, identifying an original set of eight needs related to the different wood supply chain processes that can be addressed through Industry 4.0 technologies. We also specified how these needs can be satisfied, defining detailed actions and sub-actions. This result provides both theoretical and managerial contributions. From a theoretical point of view, it offers a complete overview of the applications of Industry 4.0 technologies in the wood sector and identifies fruitful suggestions for future research studies. From a practical viewpoint, it can be helpful for a wide range of stakeholders to better understand the applications of Industry 4.0 and identify the technologies needed to satisfy their potential needs, thus optimizing the investments in Industry 4.0.

The paper has the following structure. In Section 2, we provide a short review of the two relevant concepts of this research, namely Industry 4.0 technologies and the wood supply chain. In Section 3, we describe the methodology used to select and analyze the papers, whereas in Section 4 we examine and categorize the selected papers, developing a summary framework of the applications of Industry 4.0 in the wood sector. Starting from this framework, we develop some suggestions for future research directions (Section 5) and, finally, we conclude the paper highlighting theoretical and managerial implications, as well as limitations of the present work (Section 6).

**Table 1**
Overview of previous literature reviews on similar topics.

| Author (s), year | Review type | Time horizon | Paper focus | Reviewed Industry 4.0 technologies | Reviewed wood processes |
|---|---|---|---|---|---|
| Holloway and Mengersen (2018) | Not systematic | Not available | Review of machine learning methods commonly applied to remote sensing data, focusing on applications in agriculture, forest and water | Artificial intelligence (machine learning) | Forest management: forest cover change |
| Liu et al. (2018) | Not systematic | 2008–2017 | Review of three machine learning methods and analysis of their application in forest ecology | Artificial intelligence (machine learning) | Forest management: species distribution prediction, carbon cycle analysis, forest mapping |
| Müller et al. (2019) | Systematic | 2011–2018 | Analysis of general trends and applications towards Industry 4.0 in the wood supply | RFID, sensors, M2M communication, human-machine interactions, big data, cloud computing, advanced analytics, artificial intelligence | Wood supply: from forest to the timber sale |
| Zhang et al. (2020) | Not systematic | Not available | Analysis and summary of data-oriented solutions to enhance forest and biomass supply chain management | Big data analytics | Harvesting process, manufacturing process, supply chain management |

## 2. Relevant concepts

### 2.1. Industry 4.0 technologies

Presented for the first time at the German Hannover Fair in 2011, the term Industry 4.0 refers to the real-time connection of actors and objects that enables the digitalization and automation of the entire supply chain environment (Galati and Bigliardi, 2019; Horváth, Szabó, 2019). “Smart manufacturing” and “fourth industrial revolution” are alternative terms that are often used to refer to this phenomenon (Culot et al., 2020), which is typically associated to several emerging technologies, listed in Table 2 and described below.

**Internet of Things** (IoT) refers to the creation of a virtual network that allows machines and devices to communicate and interact with each other (Rüßmann et al., 2015; Hofmann, Rüsch, 2017). When a physical network is combined with a cyber network and continuously interact with this latter, a **cyber-physical system** (CPS) can be obtained (Hofmann, Rüsch, 2017; Xu et al. 2018). **Big data** technologies are instead linked to the availability of large volumes of data having different natures and sources; these data can be (real-time) analyzed through appropriate analytic tools to extract relevant information and support the decision-making process (Ghobakhloo, 2018). An important set of advanced computer-based techniques to analyze and process big data is offered by **artificial intelligence** (AI), which includes a wide variety of machine learning algorithms that are able to automatically learn through experience (Moktadir et al., 2018). The storage and computation of this huge amount of data can instead be supported by **cloud computing** programs, which allow to access data from any location in a quick and independent way (Fatorachian and Kazemi, 2018; Xu et al., 2018). The increased connectivity enabled by Internet of Things and cloud computing raises **cybersecurity** needs, which represent a further technology linked to Industry 4.0 (Rüßmann et al., 2015). A secure and trustworthy solution to implement and store transactions is offered by the **blockchain** technology, a distributed and immutable peer-to-peer data infrastructure that offers a decentralized network working without human intervention (Ghobakhloo, 2018). Looking at the process-related technologies, an innovative contribution to the production can be given by **additive manufacturing** (AM), such as 3d printing, that allows to produce small quantities of highly customized products (Ghobakhloo, 2018; Moktadir et al., 2018). As concerns production efficiency and flexibility, they can be improved through the use of **autonomous robots**, which can either substitute or support the workers in the implementation of production processes (Rüßmann et al., 2015; Frank et al., 2019). Finally, **augmented reality**, a visualization technology, can create partial or complete virtual environments that can be useful for training, maintenance, control and product development purposes (Ghobakhloo, 2018; Frank et al., 2019).

### 2.2. The wood supply chain

The wood sector is a major contributor to many economies around the world. The high levels of employment and income generated by this sector can be associated not only to the different finished products that can be obtained from forests (i.e., lumber, wood products, paper and pulp products, biofuels, etc.), but also to the numerous and heterogeneous activities and processes that are carried out in this industry. An overview of these activities, from forest to finished products, is provided in Fig. 1. Five main processes can be distinguished.

**Forest management** deals with all the activities aimed at guaranteeing the health of forests and the availability of trees for all their possible different uses (D'amours et al., 2008). The **harvesting** process consists instead of all the cutting and extraction activities (Zhang et al., 2020), including decisions on the felling sites, trees to be cut and roadside transportation lines (Scholz et al., 2018). As shown in Fig. 1, forest residues, alternatively called forest biomass, are collected in this process. **Storage & transportation** is the third process of the wood supply chain and refers to the transportation of logs and biomass from forest to industrial plants or to intermediate distribution centers for temporary storage (D'amours et al., 2008). Three types of **processing & manufacturing** can follow the transportation activity, depending on the desired final product (see D'amours et al., 2008). Logs can be processed in sawmills and planing mills for the production of wood components (e.g., lumbers, boards, panels, etc.) and finished wood products (e.g., wooden furniture, flooring, roofing systems, etc.). Alternatively, they can be used for the production of paper sheets, rolls and packaging through pulp and paper mills. The last option is the creation of bioproducts through the processing of forest residues, as well as bark and chips discarded by wood and paper manufacturing. Finally, the last process, **sales, distribution & maintenance**, concerns, besides sale, the maintenance activities of the final products during their whole life cycle.

## 3. Methodology

We applied the SLR method proposed, among others, by Tranfield et al. (2003) to select the papers and answer the research questions. We followed a structured process (see Fig. 3) consisting of three steps, as described below.

**Table 2**
Overview of Industry 4.0 technologies (adapted from Culot et al., 2020).

| Technology types | Main Industry 4.0 technologies | Exemplary references |
|---|---|---|
| Physical/digital interface technologies | Internet of Things | Rüßmann et al. (2015); Hofmann, Rüsch (2017); Fatorachian and Kazemi (2018); Ghobakhloo (2018); Xu et al. (2018); Moktadir et al. (2018); Frank et al. (2019) |
| | Cyber-physical systems | Hofmann, Rüsch (2017); Fatorachian and Kazemi (2018); Ghobakhloo (2018); Xu et al. (2018); Frank et al. (2019) |
| | Augmented reality | Rüßmann et al. (2015); Ghobakhloo (2018); Moktadir et al. (2018); Frank et al. (2019) |
| Data processing technologies | Big data analytics | Rüßmann et al. (2015); Fatorachian and Kazemi (2018); Ghobakhloo (2018); Moktadir et al. (2018); Frank et al. (2019) |
| | Artificial intelligence | Moktadir et al. (2018); Frank et al. (2019) |
| Network technologies | Cloud computing | Rüßmann et al. (2015); Fatorachian and Kazemi (2018); Ghobakhloo (2018); Moktadir et al. (2018); Xu et al. (2018); Frank et al. (2019) |
| | Cybersecurity | Rüßmann et al. (2015); Ghobakhloo (2018); Moktadir et al. (2018); Frank et al. (2019) |
| | Blockchain | Ghobakhloo (2018); Wang et al. (2019) |
| Digital/physical process technologies | Additive manufacturing | Rüßmann et al. (2015); Ghobakhloo (2018); Moktadir et al. (2018); Frank et al. (2019) |
| | Autonomous robots | Rüßmann et al. (2015); Ghobakhloo (2018); Moktadir et al. (2018); Frank et al. (2019) |

### 3.1. Conceptual boundaries

The conceptual boundaries were defined considering the review's objectives and research questions. Coherently with our aim of exploring the contribution of Industry 4.0 technologies in the entire wood sector, we did not define any limitations neither to the Industry 4.0 technologies used in the papers, nor to the processes of the wood supply chain where these technologies were applied. Therefore, our study includes papers applying different Industry 4.0 technologies, both in isolation and in combination with other Industry 4.0 technologies and focusing on a wide range of activities associated to the wood industry (i.e., from forest management to sales, distribution & maintenance).

### 3.2. Papers collection: inclusion and exclusion criteria

Papers were collected based on some inclusion and exclusion criteria regarding the selection of sources, time range and articles.

In line with other SLR studies (e.g., Culot et al., 2020), we considered both scientific peer-reviewed and trade journals published in English language. The inclusion of non-academic publications (in particular, reports and practitioner-oriented articles) was deemed appropriate given the influence of industry policymakers on the topic and the possibility of identifying more recent advancements of Industry 4.0. We used the Scopus database for the analysis of scientific literature and ProQuest's Social Sciences, JSTOR Business and EBSCO Business Source Complete for the analysis of trade publications.

As concerns the time range, we followed the approach of previous literature reviews (e.g., Müller et al., 2019; Kipper et al., 2020) and selected only papers published from 2011 onwards, since 2011 is widely recognized as the year of "birth" of the Industry 4.0 concept. To verify the suitability of this choice, we also screened the scientific papers published before 2011 (n = 309). We found that many of them (75%) were linked to artificial intelligence applications and that, besides being mainly related to Industry 3.0, they would have been discarded with our exclusion criteria (see following paragraphs). We thus concluded that 2011 is an appropriate starting year for the research.

The identification of the potential papers to be included in the review was based on the combination, through Boolean connectors, of 18 keywords related to the Industry 4.0 phenomenon and 30 keywords concerning the wood sector (see Fig. 2). Industry 4.0 keywords were adapted from Rüßmann et al. (2015) and recent literature reviews on the topic (e.g., Culot et al., 2020), whereas the wood-related keywords were based on the classification proposed by the Food and Agriculture Organization of the United Nations (1982). The aim was to guarantee the widest possible coverage of previous research on Industry 4.0 in the wood sector. We searched these keywords in the title, keywords or abstract sections of the scientific literature. For the non-academic literature, we opted instead for full-text research in order to maximize the number of sources selected.

The initial search, based on the criteria described above, provided a preliminary sample of 1598 scientific papers and 1547 practitioner papers. The abstracts of these papers were read and analyzed by the authors with the aim of selecting only the contributions relevant for

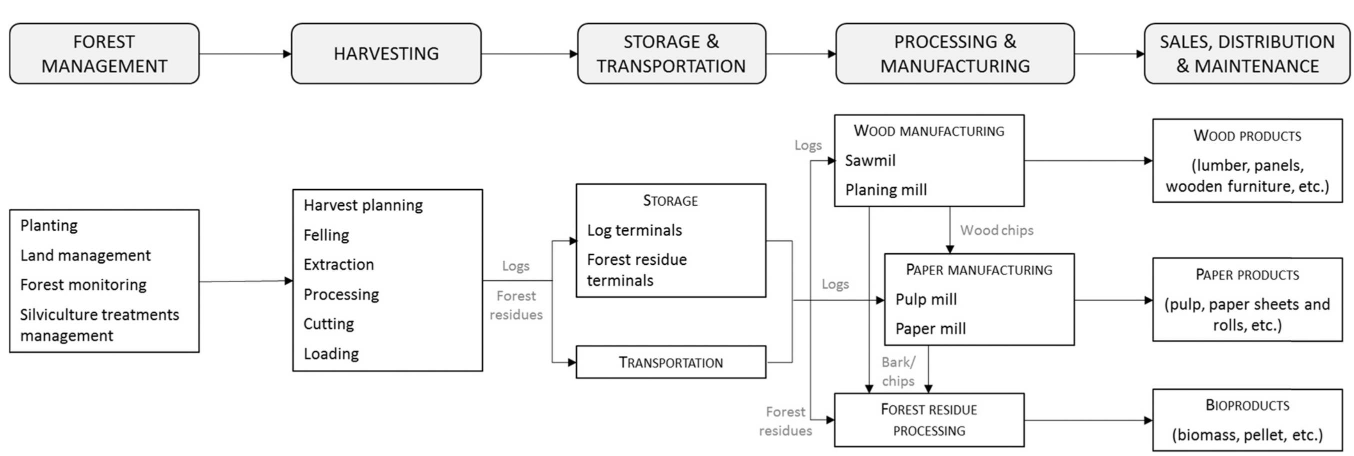


**Fig. 1.** The wood supply chain configuration.
Adapted from D'amours et al. (2008) and Zhang et al. (2020).

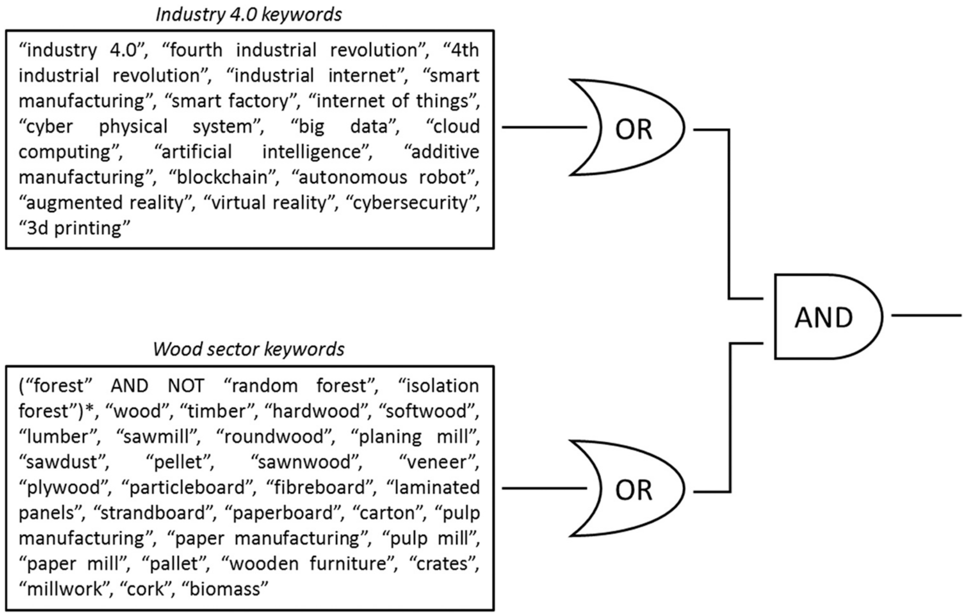


**Fig. 2.** Keywords used for the papers collection in the selected databases
*Note: the keyword "forest" alone leads to the identification of papers that have nothing to do with forests themselves but apply algorithms or ensemble learning methods whose name includes the term "forest". In order to reduce the papers out of scope, we excluded the most recurrent algorithms (i.e., "random forests" and "isolation forest") from the database search using the "AND NOT" connector.

the scope of this research. As a result, 3039 articles were excluded from further analysis. The criteria of exclusion were the following: literature reviews or conceptual studies; articles that consider non-woody pallets or biomass; articles in which the term "forest" indicates only an algorithm and there is no application in the wood sector; articles in which Industry 4.0 technologies are applied to urban forests; articles whose full text is not available; articles in which Industry 4.0 technologies are used to provide restorative experiences in virtual forest environments. Many papers belonging to the preliminary sample, more than 50, discuss the possibility of adding small percentages (i.e., 0.2–1%) of wood fibers to the plastic material used in 3d printing to reinforce the properties of the final product. These papers were excluded from the research as well because the wood material is just a small component of the entire product and it cannot be considered the real object of 3d printing application.

The final sample includes 96 scientific papers and 10 practitioner articles published between January 2011 and December 2020. These papers were read and analyzed as described in the following section.

### 3.3. Content analysis and validation

We analyzed the full content of the 106 papers with the aim of identifying the main applications of Industry 4.0 in the wood sector and synthetizing the results. In particular, the goal was the creation of a framework including: (1) main needs of the wood sector addressed with Industry 4.0 technologies, (2) specific actions implemented to satisfy the identified needs and (3) Industry 4.0 technologies used to execute the identified actions. We followed a precise process to reach this result.

First, using the information included in the abstracts, we inductively associated each paper to one of the five wood supply chain processes (i.e., forest management, harvesting, storage & transportation, processing & manufacturing and sales, distribution & maintenance) and grouped them accordingly. Then, for each process, we quickly read the full content of all the related papers analyzing the actions carried out through the Industry 4.0 technologies. We identified 19 categories of actions, sometimes detailed into more precise sub-actions, and used them to further classify the papers. In addition, we reflected on the needs that these actions aim at satisfying. In some papers, the needs were explicitly mentioned by the authors, while in the other cases we derived them based on the implicit goal of the technologies' adoption. After a brainstorming, we identified and named 8 needs of the wood sector, addressed through one or more categories of actions.

With these results, we created a summary framework of the literature review that is shown in Fig. 4 and discussed in Section 4. An overview of the entire SLR process is instead provided in Fig. 3.

### 3.4. Descriptive sample overview

From a quick overview of the selected articles, it emerges that the number of papers dealing with the application of Industry 4.0 technologies in the wood sector has been increasing since 2012, indicating that the attention of researchers on the topic has intensified during the years, reaching a constant peak in the last three years. The wood supply chain process mainly explored by previous scholars is forest management, addressed by approximately 70% of the papers (n = 75), followed by processing & manufacturing (n = 17). In terms of Industry 4.0 technologies, artificial intelligence is the most used in our sample, with 80 applications. Less attention is instead given to digital manufacturing technologies (e.g., autonomous robots), as well as to augmented reality. Overall, the topic is of interest to both technological and environmental-related publication sources.

## 4. State-of-art of Industry 4.0 research in the wood sector

The analysis of the 106 papers selected in this SLR allowed us to identify 8 different needs of the wood sector that can be addressed with Industry 4.0 technologies, as well as 19 actions and 21 more specific sub-actions that should be implemented to satisfy these needs. Several input data are used in the papers to exploit the technologies, including: environmental data (i.e., soil type, elevation, distance to road, etc.); weather data (i.e., temperature, humidity, wind direction, drought, etc.); forest parameters (i.e., average tree

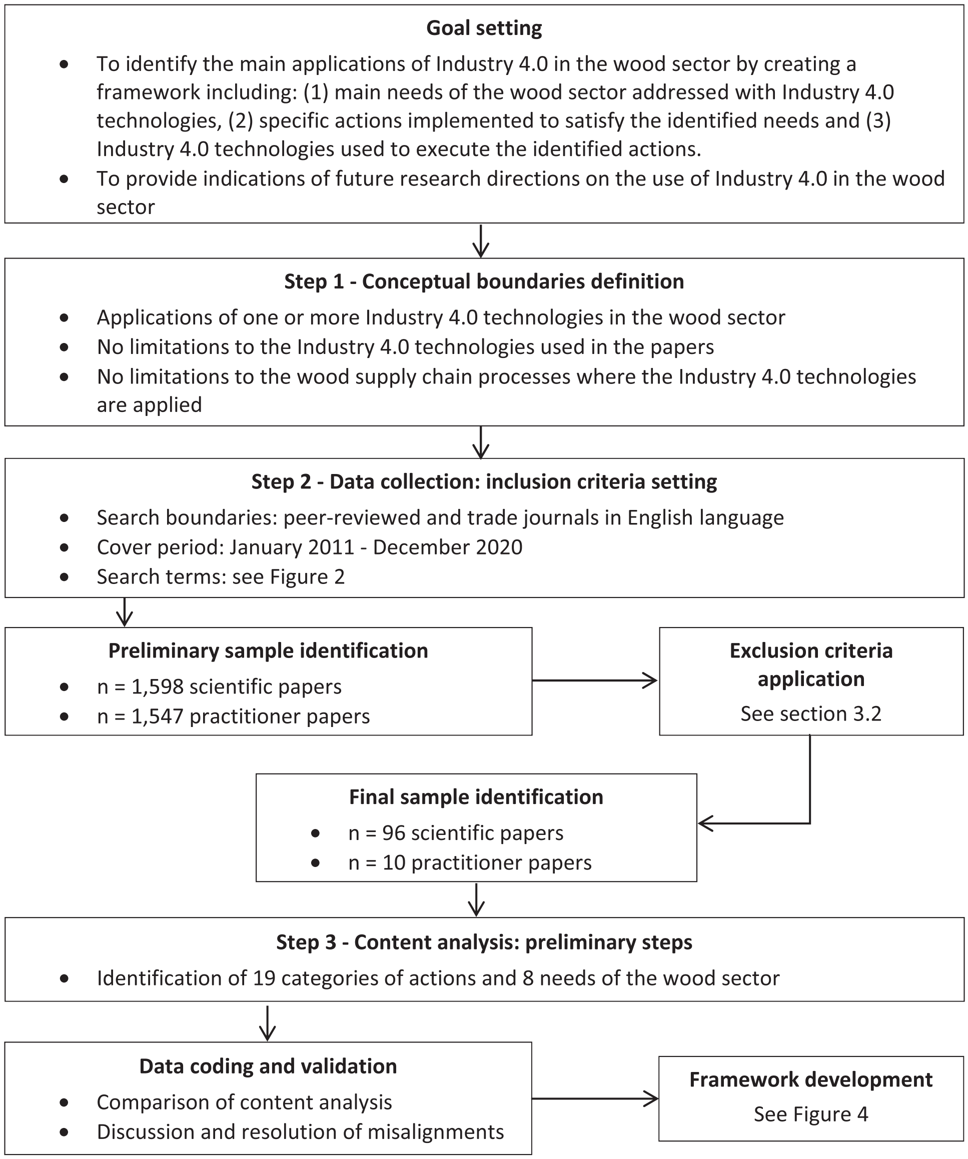


**Fig. 3.** Overview of the SLR process.

volume, number of forest logs, diameter of forest logs, total basal area, etc.); tree parameters (i.e., tree species, tree diameter at breast height, tree height, etc.).

As concerns the Industry 4.0 technologies explored in the papers, they are mainly implemented to collect, manage and analyze the huge amount of data that are available in the different wood supply chain processes to support decision-making processes. The majority of the papers can indeed by classified into three categories:

- Papers using Industry 4.0 technologies to build an appropriate architecture for the collection and storage of data: this goal is reached using network and/or interface technologies, such as cloud computing and IoT, while the analysis of data is carried out with traditional methods;
- Papers using Industry 4.0 technologies to analyze data and exploiting the potential offered by data processing technologies, such as artificial intelligence;
- Papers combining the previous goals and using data processing, network and/or interface technologies together to build complete Industry 4.0 models able to store, manage and process data.

Process-related technologies (additive manufacturing and autonomous robots) are instead less common in the selected sample.

In the following sections, we provide a detailed description of the literature dealing with the identified needs, while in Fig. 4 and Table 3 we present an overview of the main SLR results.

### 4.1. Need 1 – protect the forest

Protect the forest, which is addressed by 30 papers, is the first need identified in this review. Five different actions that can help protecting the forest emerge from the analysis (see Table 4).

**Forest fire prediction**, obtained through occurrence and propagation analysis, is the most common activity proposed by the authors. The aim is to predict forest fire occurrence and/or to develop dynamic fire spread models. The papers carrying out this action belong to all the three categories previously identified: (1) four of them use Industry 4.0 to create appropriate environments to store previously collected weather and environmental data, which are then analyzed with traditional methods to forecast the fire occurrence (Kalabokidis et al., 2014; Ozaki et al., 2019; Kang et al., 2020; Zheng et al., 2018b); (2) five papers (Sakr et al., 2011; Vahidnia et al.,

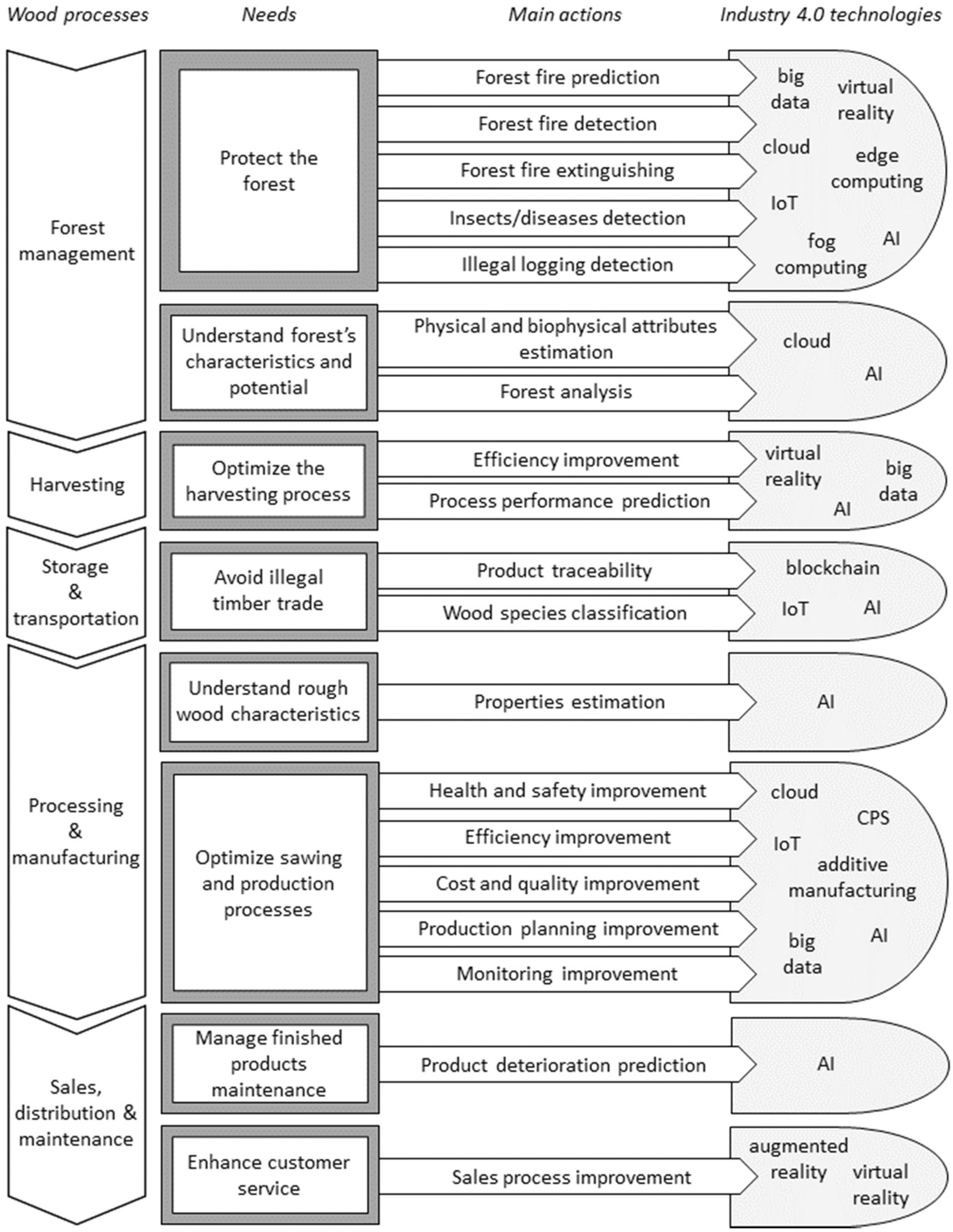


**Fig. 4.** Summary framework of the SLR.

2013; Castelli et al., 2015; Ganapathi Subramanian and Crowley, 2018; Tien Bui et al., 2019) apply artificial intelligence algorithms to process different data types and predict forest fire danger patterns and occurrence; (3) five papers use Industry 4.0 both to store and process input data for fire risk predictions (Benzekri et al., 2020; Sharma et al., 2020a; Kaur and Sood, 2019a, 2019b, 2020).

When a forest fire cannot be avoided, it becomes fundamental to identify it as soon as possible for an effective and timely reaction. **Forest fire detection** is thus the second action linked to forest protection. As for fire prediction, network, interface and/or data processing technologies are used to store and/or process input data. These latter include not only typical variables such as images or weather parameters (Zalud, 2012; Anonymous, 2014; Yan et al., 2016; Kirkpatrick and Vacarelu, 2018; Bu and Gharajeh, 2019; Prall, 2019; Ritchey, 2019; Cui, 2020; Sharma et al., 2020b), but also more original inputs, such as social media traffic (Avgeris et al., 2019) and forest sounds (Zhang et al., 2019), whose frequency can provide indications on the type and extension of eventual forest fires.

Besides detecting the fire, it is also crucial to **extinguish** it quickly and effectively, thus properly training fire fighters. Only one paper (Moreno et al., 2014) discusses this action, proposing a simulation system based on virtual reality that reproduces a forest fire

**Table 3**
Overview of the papers' distribution and technologies' adoption.

| Needs | Actions | IoT | Big data | Cloud | Edge/fog computing | AI | AM | AR/ VR | CPS | Block-chain |
|---|---|---|---|---|---|---|---|---|---|---|
| Protect the forest (n = 30) | Forest fire prediction | 7 | | 6 | 4 | 10 | | | | |
| | Forest fire detection | 4 | 1 | 3 | 1 | 7 | | 1 | | |
| | Forest fire extinguishing | | | | | | | | | |
| | Insects/diseases detection | 1 | | 1 | | 1 | | | | |
| | Illegal logging detection | | 1 | | | 2 | | | | |
| Understand forest's characteristics and potential (n = 45) | Physical and biophysical attributes estimation | | | 1 | | 29 | | | | |
| | Forest analysis | | | 4 | | 12 | | | | |
| Optimize the harvesting process (n = 6) | Efficiency improvement | | | | | | | 2 | | |
| | Process performance prediction | | 1 | | | 4 | | | | |
| Avoid illegal timber trade (n = 4) | Product traceability | 2 | | | | | | | | 3 |
| | Wood species classification | | | | | 1 | | | | |
| Understand rough wood characteristics (n = 6) | Properties estimation | | | | | 6 | | | | |
| Optimize sawing and production processes (n = 11) | Health and safety improvement | | | | | 2 | | | | |
| | Efficiency improvement | | | | | 2 | | | | |
| | Cost and quality improvement | | | | | | 3 | | 1 | |
| | Production planning improvement | 1 | | 1 | | | | | | |
| | Monitoring improvement | | 1 | | | 2 | | | | |
| Manage finished products maintenance (n = 2) | Product deterioration prediction | | | | | 2 | | | | |
| Enhance customer service (n = 2) | Sales process improvement | | | | | | | 2 | | |
| | **Total** | **15** | **4** | **16** | **5** | **80** | **3** | **5** | **1** | **3** |

Note: The sum of technologies' applications is higher than the number of reviewed papers (n = 106) because many of them apply more than one technology in their studies.

and allows fire fighters to practice in an environment as close as possible to the natural one. Forest fire developments are also simulated in the system, considering contextual factors such as terrain slope and composition, wind direction and spotting fires.

A further action needed to protect the forest is the early **identification of insects and diseases**, which can cause irreversible damages to the trees and negatively affect their health and growth. Two papers address this issue. Potamitis et al. (2019) propose a methodology that uses a sensor to record the noises inside the tree and, through cloud computing and IoT technologies, stores and transfers the sound for a remote analysis process. The recorded vibrations allow indeed to identify eventual locomotion or feeding sounds that attest the presence of borers inside the tree, thus monitoring its health. Sandino et al. (2018) use instead an artificial intelligence algorithm that processes aerial images to map deteriorations by fungal pathogens in natural and plantation forests.

Finally, Clutton-Brock et al. (2019) and Shaw et al. (2020) highlight that a forest should be protected through **illegal logging detection** as well. According to the authors, artificial intelligence algorithms can support the implementation of this action through the processing of huge amounts of data coming from either forest acoustic sounds or satellite images.

### 4.2. Need 2 - understand forest's characteristics and potential

Understand forest's characteristics and potential is the second need emerging from the reviewed papers. Two actions are carried out to satisfy this need (see Table 5).

First, it is necessary to **estimate physical and biophysical attributes** of the forest. Different contributions address this action, which can be further specified into three sub-actions. A first group of authors focuses on the estimation of individual tree attributes, such

**Table 4**
Details on how to address the need 1 – protect the forest.

| Actions | Sub-actions | Industry 4.0 technologies | Involved variables/data | Supporting tools |
|---|---|---|---|---|
| Forest fire prediction (n = 14) | Fire occurrence and propagation analysis | AI | Images, weather and environmental data | Satellites, Geographic Information Systems, existing databases |
| | | Cloud | Fire indices, forecasted weather data | Geographic Information Systems, existing databases |
| | | IoT + edge computing | Weather and environmental data | Sensors |
| | | IoT + cloud | Weather and environmental data | Sensors |
| | | IoT + AI | Images, weather data | Cameras, sensors |
| | | IoT + fog computing + cloud + AI | Weather and environmental data | Sensors |
| Forest fire detection (n = 11) | Forest monitoring | AI | Images, real-time weather data | Sensors, unmanned aerial vehicles |
| | | Cloud | Images | Cameras |
| | | IoT | Sounds | Sensors |
| | | IoT + cloud | Images, real-time weather data | Cameras, sensors |
| | | IoT + AI | Images, videos, weather data | Cameras, sensors |
| | | IoT + edge computing + cloud | Images, real-time weather data, social media traffic | Cameras, sensors |
| | | Big data + AI | Images, weather data | Cameras, sensors |
| Forest fire extinguishing (n = 1) | Fire fighters training | Virtual reality | Weather and environmental data | Existing databases |
| Insects/diseases detection (n = 2) | | IoT + cloud | Sounds | Sensors |
| | | AI | Images | Unmanned aerial vehicles, cameras |
| Illegal logging detection (n = 2) | | AI | Images, sounds | Satellites, sensors |
| | | AI + big data | Images | Geographic Information Systems |

as height (Vieira et al., 2018; Bayat et al., 2020; Ercanli, 2020; Silva et al., 2020), tree or bark volume (Ashraf et al., 2013; da Silva et al., 2018; Diamantopoulou et al., 2018; Silva et al., 2019, 2020), biomass (Silva et al., 2019), wood density (Demertzis et al., 2017), diameter (Vieira et al., 2018) and basal area (Ashraf et al., 2013). In all these papers, artificial intelligence techniques are employed to improve the estimation results, with forest, environmental and other tree parameters used as independent variables. A second group of authors applies the same Industry 4.0 technology but estimates the attributes at the forest level, using information collected from aerial images as a further input for the algorithms. Except for Carrijo et al. (2020), who estimate the energy potential of a forest stand, all the other estimates concern mainly average volume and basal area of the forests (dos Reis et al., 2018; Sakici and Günlü, 2018; Sanquetta et al., 2018; Che et al., 2019; Varvia et al., 2019). The third group of authors deals instead with the estimation of precise forest attributes, namely aboveground biomass and carbon. The majority of these papers employs artificial intelligence algorithms to process and combine satellite imagery data and forest indexes. Ten papers (Dube et al., 2014; Wilhelm et al., 2014; Singh et al., 2015; Wu et al., 2016; Deb et al., 2017; Li et al., 2018; Vafaei et al., 2018; Debastiani et al., 2019; Yang et al., 2019; Ploton et al., 2020) focus on biomass estimation. Other authors (Suchenwirth et al., 2014; Safari et al., 2017; Vahedi, 2017; Sanderman et al., 2018) deal only with soil organic carbon measurements. Finally, Li et al. (2014) estimate both carbon and biomass values.

The second action needed to understand forest characteristics and potential is **forest analysis**. Five activities (i.e., sub-actions) can be identified in this group of papers, where artificial intelligence is again the most employed Industry 4.0 technology. These sub-actions include tree survival and mortality prediction (da Rocha et al., 2018; Reis et al., 2018), species classification (Franklin et al., 2017; Franklin and Ahmed, 2018; Guo et al., 2020), forest coverage mapping (Omer et al., 2015; Clark et al., 2018; Koskinen et al., 2019; Guirado et al., 2020), forest loss mapping or monitoring (Harris et al., 2017; Poortinga et al., 2018; Nicolau et al., 2019; Fromm et al., 2019; Hethcoat et al., 2019) and burned areas estimation (Mithal et al., 2018).

### *4.3. Need 3 - optimize the harvesting process*

Six papers focus on the need of optimizing the harvesting process (see Table 6). Two of them propose activities linked to **efficiency improvement** through harvester operators training and recruitment. Using virtual reality, the authors of these two papers recreate different forest environments and simulate the actuation of a forestry logging harvester: Zheng et al. (2018a) use this system to train the harvester operators, while Pagnussat et al. (2020) to evaluate and compare the performance of candidates for the position of harvester operators, thus improving the recruitment process.

The remaining four papers develop a **process performance prediction** model. Knowing times, costs and productivity of wood harvesting operations can help not only to manage the entire process, but also to identify the most appropriate harvesting method in different contexts. With this view, Rossit et al. (2019) combine big data and data mining technologies to understand how variables such as trees diameter, species, shift and operator affect the productivity of a forest harvester, whereas Çalişkan (2019) calculates the total extraction time by processing environmental and forest parameters with artificial intelligence algorithms. Proto et al. (2020) use instead artificial intelligence to predict times, costs and productivity of wood harvesting operations for different types of harvesting processes (e.g., full-tree, tree-length, cut-to-length). Finally, Hickey et al. (2015) employ non-parametric models and machine learning tools to estimate the proportions of planned end products (i.e., sawlog, pallet, stake and pulp) extractable from a forest compartment.

### *4.4. Need 4 - avoid illegal timber trade*

The fourth need of the wood sector is to avoid the illegal timber trade. Two activities are proposed to satisfy this need, as summarized in Table 7. The first, **product traceability**, is addressed by three papers, which leverage on the potential of blockchain technology to store secure and immutable transactions. In particular, Vilkov and Tian (2019) present a SWOT analysis to evaluate the blockchain use for addressing illegal logging between Russia and China, whereas Figorilli et al. (2018) and Ferguson et al. (2020) discuss the combination of blockchain with IoT devices to trace wood from forest to the final consumer. The second activity, **wood species classification**, is instead proposed by de Geus et al. (2020) through an automated image analysis with deep learning algorithms. The importance of such activity is linked to the illegal logging fight, as well as to correct taxing and timber certification.

### *4.5. Need 5 - understand rough wood characteristics*

Six papers focus on the need to understand the characteristics and quality of rough wood, which is important not only for the selection of raw materials (Iglesias et al., 2017), but also for pricing decisions (Daassi-Gnaba et al., 2017). In all the cases, the action carried out by the authors is **properties estimation**, which is always implemented with the support of artificial intelligence algorithms

**Table 5**
Details on how to address the need 2 – understand forest's characteristics and potential.

| Actions | Sub-actions | Industry 4.0 technologies | Involved variables/data | Supporting tools |
|---|---|---|---|---|
| Physical and biophysical attributes estimation (n = 30) | Individual tree attributes (e.g., height, volume) estimation | AI | Environmental data, tree and forest parameters | Direct measurements, existing database |
| | Forest attributes (e.g., average tree volume, total basal area) estimation | AI | Images, forest/vegetation indexes, tree parameters | Satellites, Unmanned aerial vehicles, cameras, direct measurements |
| | Aboveground biomass and carbon estimation | AI | Images, forest/vegetation indexes, tree parameters | Satellites, Laser sensors (LiDAR), Unmanned aerial vehicles, cameras, direct measurements |
| | | Cloud | Images | Laser sensors (LiDAR) |
| Forest analysis (n = 15) | Tree survival and mortality estimation | AI | Weather data and tree parameters | Direct measurements, existing database |
| | Species classification | AI | Images, tree parameters | Unmanned aerial vehicles, cameras, direct measurements |
| | Tree cover mapping | AI | Images | Satellites |
| | | Cloud + AI | Images | Satellites |
| | Tree cover monitoring | Cloud | Images, forest indexes | Satellites |
| | | AI | Images | Drones |
| | Burned areas mapping | AI | Images | Satellites |

**Table 6**
Details on how to address the need 3 – optimize the harvesting process.

| Actions | Sub-actions | Industry 4.0 technologies | Involved variables/data | Supporting tools |
|---|---|---|---|---|
| Efficiency improvement (n = 2) | Harvester operators training and recruitment | Virtual reality | – | – |
| Process performance (e.g., time, productivity) prediction (n = 4) | | AI | Environmental data, forest parameters, machine characteristics | Direct measurements, existing database |
| | | AI + big data | Machine characteristics, forest parameters | Direct measurements |

(see Table 8). The specific properties estimated by the authors include fire resistance (Naser, 2019a, 2019b), wood quality (Affonso et al., 2017), moisture content (Daassi-Gnaba et al., 2017), pulp properties (Iglesias et al., 2017) and mechanical properties under compressive stress (García et al., 2015).

### 4.6. Need 6 - optimize sawing and production processes

The optimization of sawing and production processes is a further relevant need of the wood sector. The eleven papers belonging to this category propose five actions and nine sub-actions to satisfy the aforementioned need, as reported in Table 9.

Two papers recommend activities linked to **health and safety improvement** through emissions monitoring and risk management. In particular, Nasir et al. (2019) propose the use of artificial intelligence to correlate acoustic emissions data in the sawing process with the cutting power and waviness; an appropriate sensor is used to collect data on blade vibration. Jocelyn et al. (2016) combine instead artificial intelligence and machine safety techniques to develop a dynamic tool for risk identification and accidents prevention. Other scholars aim at **efficiency improvement** through fault diagnosis in industrial chemical processes (Ragab et al., 2018) and automated feeding (Cunha et al., 2015). Three papers deal instead with additive manufacturing for **cost and quality improvement**. Some examples of additive manufacturing application are the production of molds for paper bottles (Saxena et al., 2020) and the design and production of a wood head golf club (Chang and Chen, 2017). The last paper belonging to this group, Murmura and Bravi (2018), does not propose a particular application of additive manufacturing but develops a survey-based questionnaire to understand whether Italian companies operating in the wood furniture industry are investing in such technology. The fourth action, proposed by Wang et al. (2020), can be defined as **production planning improvement**, since the authors develop a material management system for panelized construction that goes beyond traditional, and often manual, methods thanks to the introduction of IoT and cloud computing. Finally, the last three papers recommend actions linked to **monitoring improvement**. Vialetto and Noro (2019) use machine learning algorithms to predict the energy consumption of a company operating in the wood sector, Cheta et al. (2020) develop a system to monitor the production of wood products through the analysis of sounds with artificial intelligence algorithms, whereas Hämäläinen and Inkinen (2017) propose a reporting system on cost management, emission and economics based on big data.

### 4.7. Need 7 - manage finished products maintenance

A further important need concerns finished products maintenance and is addressed by two papers with **product deterioration prediction** activities (see Table 10). In both cases, the goal is to evaluate the health conditions of wood utility structures using artificial intelligence techniques. Srikanth and Arockiasamy (2020) focus on the timber superstructure of bridges and test some models to predict their remaining useful life. Dackermann et al. (2014) propose instead a non-invasive method called “guided waves propagation” to determine the health of the timber utility poles; this method consists in the propagation of acoustic waves along the timber structure that are collected through appropriate sensors and processed with machine learning algorithms.

### 4.8. Need 8 – enhance customer service

The last need is linked to the enhancement of customer service through **sales process improvement** (see Table 11). The two authors referring to this activity describe how virtual and augmented reality can be exploited in the context of wood home furnishing: in Bollinger’s (2019) case study, customers have the opportunity to see hardwood floors in their homes before their purchase, whereas in Burritt's (2018) solution, customers can also virtually explore entire furniture solutions (i.e., including doors, furnishings, etc.) for their rooms or homes.

## 5. Discussion and future research directions

From Fig. 4 and Table 3, it emerges that, while some Industry 4.0 technologies, such as artificial intelligence and cloud computing, have been widely applied to address the needs of the wood sector, some other technologies, such as blockchain, augmented reality and autonomous robots, were less studied or not considered at all by extant literature. By examining the potentialities of these under-

**Table 7**
Details on how to address the need 4 - avoid illegal timber trade.

| Actions | Industry 4.0 technologies | Involved variables/data | Supporting tools |
|---|---|---|---|
| Product traceability (n = 3) | Blockchain | – | – |
| | Blockchain + IoT | Information about logs' characteristics, location, movements, processing | RFID, QR codes |
| Wood species classification (n = 1) | AI | Images | Stereomicroscope |

**Table 8**
Details on how to address the need 5 - understand rough wood characteristics.

| Actions | Industry 4.0 technologies | Involved variables/data | Supporting tools |
|---|---|---|---|
| Properties (e.g., quality, mechanical properties, fire resistance) estimation (n = 6) | AI | Images, reflection coefficients, tree parameters, physical, thermal and mechanical characteristics | Cameras, antennas, direct measurements |

**Table 9**
Details on how to address the need 6 - optimize sawing and production processes.

| Actions | Sub-actions | Industry 4.0 technologies | Involved variables/data | Supporting tools |
|---|---|---|---|---|
| Health and safety improvement (n = 2) | Emissions monitoring | AI | Machinery and process parameters | Sensors |
| | Risk management | AI | Accident reports | Company's database |
| Efficiency improvement (n = 2) | Fault diagnosis | AI | Product and process parameters | Company's database |
| | Automated feeding | AI | Images | Cameras |
| Cost and quality improvement (n = 3) | Alternative production processes adoption | AM<br>AM + CPS | – | – |
| Production planning improvement (n = 1) | Materials management system automation | IoT + cloud | Supplier, production and inventory data | Barcodes |
| Monitoring improvement (n = 3) | Input resources forecasting | AI | Historical use of input resources | Company's database |
| | Production monitoring | AI | Sounds, acceleration values | Sensors, cameras |
| | Reporting system development | Big data | Sales, production, logistics and procurement data | Real time measurement systems |

investigated technologies, we identify and discuss future research opportunities, hoping that they will trigger researchers' ideas and creativity to develop future relevant contributions in this area. The suggestions for future research are summarized in Table 12 and discussed in detail in the following sections.

### 5.1. Blockchain technology to optimize the wood shipping process

The use of blockchain technology in the wood sector is clearly at first stages, since only three papers apply it for product traceability purposes. We propose here an alternative use of blockchain to optimize the wood shipping process, a wood sector need that was not addressed in the reviewed papers, through a better collaboration and information sharing between the involved parties. On the one hand, blockchain can be used to digitalize the shipping documents (e.g., charter party agreements, port document, certificates of origins, etc.), thus reducing the risk of delayed documents and speeding up customs transit (Gurtu and Johny, 2019). On the other, it can also automatize transactions thanks to the smart contract applications, which can result into reduced checks, manual processes and human errors (Wang et al., 2019). None of the reviewed studies considers the mentioned potentialities of the blockchain, but we believe that they may provide several benefits to the wood sector, given its global and international supply chains. As reported by Food and Agriculture Organization of the United Nations (2020), in 2018 the total value of forest products exports in the world was around $270 billion, indicating that the wood shipping process throughout different countries and continents can be long and complex. Researchers could perform some pilot projects and create a blockchain architecture including the most important wood shipping companies as well as the third parties involved in the process (e.g., port authorities, etc.). Such a project would allow to investigate not only the potentialities of blockchain, but also the drawbacks and costs of the proposed solution.

### 5.2. Augmented reality for operator assistance in the harvesting process

Forest harvesting is an important process performed in often complex and dynamic environments (Zheng et al., 2018a). We believe that visualization technologies, besides being useful to train harvester operators in a virtual forest environment, as already proposed in the literature, could also be used to assist the workers in the activities execution, when the operators have to deal with the actual conditions of the forest environment. For instance, augmented reality could be exploited to signal any obstacles or to rebuild the surrounding environment in case of poor visibility, thus improving process efficiency and enhancing the forestry production level. An analysis of such applications through specific pilot projects could offer original contributions, especially for complex environments that imply more dangerous tasks for the harvester.

### 5.3. Virtual and augmented reality for workers' training in the sawing and production processes

Besides the harvesting process, virtual and augmented reality could be used also in the sawing and production processes to train workers for both maintenance and process execution. An interesting application could be in the paper production, an extremely complicated process that involves several closely related phases (see Fleiter et al., 2012). An alternative candidate may be the assembly of wooden furniture or the production of semi-finished products. Future research could carry out some expert interviews, with system integrators or technological leading firms, to identify the process phases where these technologies offer the biggest contributions.

### 5.4. Autonomous and collaborative robots for production automation in the sawing and production processes

Other Industry 4.0 technologies not exploited in previous literature are autonomous and collaborative robots. Future studies could investigate their usage in the sawing and production processes and

**Table 10**
Details on how to address the need 7 - manage finished products maintenance.

| Actions | Industry 4.0 technologies | Involved variables/data | Supporting tools |
|---|---|---|---|
| Product deterioration prediction (n = 2) | AI | Product and environmental data, acoustic waves | Database, visual inspection, direct measurements |

**Table 11**
Details on how to address the need 8 – enhance customer service.

| Actions | Industry 4.0 technologies | Involved variables/data | Supporting tools |
|---|---|---|---|
| Sales process improvement (n = 2) | Virtual and augmented reality | Images | Smartphones, tablets |

**Table 12**
Future research directions on the adoption of Industry 4.0 technologies in the wood sector.

| Future research directions | Wood processes | Needs | Actions | Sub-actions | Industry 4.0 technologies |
|---|---|---|---|---|---|
| Use of blockchain to optimize the wood shipping process | Storage & transportation | Optimize the wood shipping process[a] | Global trade digitalization and automation | | Blockchain |
| Use of augmented reality for operator assistance in the harvesting process | Harvesting | Optimize the harvesting process | Efficiency improvement | Harvester operator assistance[b] | Augmented reality |
| Use of virtual and augmented reality for workers' training in the sawing and production processes | Processing & manufacturing | Optimize sawing and production processes | Worker's training[b] | | Virtual and augmented reality |
| Use of autonomous and collaborative robots for production automation in the sawing and production processes | Processing & manufacturing | Optimize sawing and production processes | Efficiency improvement | Production automation[b] | Autonomous and collaborative robots |
| Use of Industry 4.0 for environmental performance improvement in the sawing and production processes | Processing & manufacturing | Optimize sawing and production processes | Health and safety improvement | Environmental performance improvement[b] | To be defined |

[a] Additional need of the wood sector that may be addressed with Industry 4.0 technologies.
[b] Additional action/sub-action that may be useful to satisfy a need of the wood sector already discussed in the literature.

test their potentialities of increasing quality and safety described by Ghobakhloo (2018). The production process of wood furniture is indeed characterized by manual work and repetitive, physically stressful activities. The use of robots could help creating more ergonomic and safer work environments by relieving operators of many physically demanding tasks (e.g., wood panels loading and handling, pallet nailing, etc.). Alternatively, they could also substitute the workers in activities such as painting, polishing or smoothing. The use of robots in the production process has been already explored by extant research (e.g., Pérez et al., 2019). However, the wood industry represents a peculiar sector for this analysis because wood, compared to other materials such as plastic or metal, is characterized by knots, inconsistencies and other natural irregularities that pose special challenges to the manufacturing process. Failing to properly handle such aspects (e.g., through ad hoc vision systems) may result into the generation of excessive waste and, thus, into the loss of potential benefits of these technologies. Empirical research could thus be performed in companies that successfully implement such solutions to explore not only their practical feasibility, but also the benefits achieved, comparing them with those achieved in other sectors. Potential difficulties and barriers, as well as skills needed for the daily use of robots, could also be investigated to develop implementation roadmaps.

### *5.5. Industry 4.0 for environmental performance improvement in the sawing and production processes*

A further line of future research could aim to understand if and how Industry 4.0 technologies can improve the firm's environmental performance in the sawing and production processes. Identifying the effect of single Industry 4.0 technologies on specific environmental performances could not only help wood companies to direct Industry 4.0 investments, but also contribute to the overall debate concerning the relationship between Industry 4.0 and sustainability (see Ghobakhloo, 2020). In this context, quantitative research through survey and statistical analysis could be performed. Alternatively, future studies could explore, through qualitative research, if and how the new technologies may be useful to develop innovative and greener products (e.g., packaging solutions) that substitute the current plastic-based ones, in particular in the paper industry. The development of such high added value products, designed for intelligent recycling, would be a relevant achievement in a green economy perspective.

## 6. Conclusions

This study provides a SLR of the main applications of Industry 4.0 in the wood sector. 106 papers published between January 2011 and December 2020 are selected and analyzed. Overall, the review provides useful insights on the role played by Industry 4.0 technologies in the wood sector and allows to identify fruitful opportunities for future research studies on the topic.

### *6.1. Theoretical and managerial implications*

The SLR contributes to both theory and managerial practice. From a theoretical point of view, it offers a complete overview of previous research on the applications of Industry 4.0 in the wood sector. For each wood supply chain process, we identify which needs can be addressed with Industry 4.0 technologies and how this result can be reached, defining the specific actions to be implemented to satisfy each need, the Industry 4.0 technologies to be used, as well as other eventual supporting tools and input variables that may be required (Tables 4–11). Overall, it emerges that Industry 4.0 is manly used in the reviewed papers to collect, share and analyze data along the wood supply chain through technologies such as Internet of Things, cloud computing and artificial intelligence. Other technologies, such as blockchain, augmented reality and autonomous robots, are less investigated. Starting from these underexploited technologies, we discuss some suggestions for future research studies. For instance, we propose the investigation of blockchain in the wood shipping process, of augmented reality in the harvesting process and of autonomous and collaborative robots in the sawing and production processes. Different methodologies are proposed for the implementation of these lines of research. We highlight that our suggestions do not intend to be complete. Scholars can also use this SLR to develop additional ideas for future research, relying on the results presented in Tables 4–11.

From a practical viewpoint, the SLR has implications for several stakeholders, including forest managers, wood shipping managers, harvesters and manufacturing managers. First, we advise them that Industry 4.0 and, in particular, data processing technologies have several potentialities in the wood sector. Artificial intelligence, combined with network and interface technologies, can help to predict and detect forest fires, analyze forest and estimate its attributes, but also optimize the sawing and production processes in several ways. Practitioners can use this review to better understand the applications of Industry 4.0 and identify the technologies needed to satisfy their needs. Finally, they can also explore the list of references to deepen the topics of interest.

### 6.2. Limitations

The contributions of this study have to be viewed in light of some limitations. First, we analyze only papers written in English language and published in peer-reviewed and trade journals, thus excluding other publication forms such as conference proceedings and book chapters. Second, despite the efforts to be as much inclusive as possible, the keywords used for the selection may have left out some studies having slightly different inputs, thus influencing the SLR results and discussion. Finally, the categorization and summary of selected papers were performed in light of the three research questions steering this review. Alternative and additional insights may be provided by applying a different lens to explore previous research studies.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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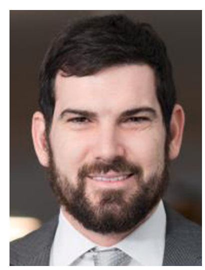

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