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Logistics Innovation and Social Sustainability: How to Prevent an Artificial Divide in Human–Computer Interaction

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Human–computer interaction (HCI) is a cornerstone for the success of technical innovation in the logistics and supply chain sector. As a major part of social sustainability, this interaction is changing as artificial intelligence applications (Internet of Things, autonomous transport, Physical Internet) are implemented, leading to larger machine autonomy, and hence the transition from a primary executive to a supervisory role of human operators. A fundamental question concerns the level of control transferred to machines, such as autonomous vehicles and automatic materials handling devices. Problems include a lack of human trust toward automatic decision making or an inclination to override the system in case automated decisions are misperceived. This paper outlines a theoretical framework, describing different levels of acceptance and trust as a key HCI element of technology innovation, and points to the possible danger of an artificial divide at both the individual and firm level. Based upon the findings of four benchmark cases, a classification of the roles of human employees in adopting innovations is developed. Measures at operational, tactical, and strategic level are discussed to improve HCI, more in particular the capacity of individuals and firms to apply state-of-the-art techniques and to prevent an artificial divide, thereby increasing social sustainability.

Keywords: artificial intelligence; social sustainability; logistics performance; human-computer interaction

INTRODUCTION

Logistics and supply chain management are subject to rapid changes as a result of technological, social, and market evolutions within the global economy, see, for example, Bloemhof et al. (2015), Hilger et al. (2016), Sternberg and Norrman (2017), Bertazzi and Mogre (2018), or Fors et al. (2015). In response to increasing customer demands (cost effectiveness, sustainability, speed, tailored problem solutions), automation in production and distribution has migrated from the execution of programmed tasks to a level, in which software agents and robots act (partly) autonomously using artificial intelligence (AI)-based algorithms (Gunsekaran and Ngai 2014; Lee et al. 2014; LeCun et al. 2015; Torabi et al. 2015; Kong et al. 2016; Castillo et al. 2017). A key question that comes along with these developments concerns the future form and performance of *human-computer interaction (HCI)*. In the past, working areas of robots and humans in production and transportation were largely separated and in case of cooperation, for example, in truck driving or CNC manufacturing, the roles were clear: Human workers performed control and decision tasks, machines and robots executed the mechanical tasks of production and transportation. That situation however is changing as automation enters a new stage of AI applications (Wong et al. 2012; Musa et al. 2014; Zhang et al. 2014; Knoll et al. 2016; Li et al. 2017; Deng 2018). Robots, machines, and devices such as containers or transportation equipment will be able to take informed and advanced decisions without manual intervention, while the human workforce takes a supervisory control and oversight role (Castelfranchi and Falcone 2000; Cantor 2016; Crainic and Montreuil 2016; Phan et al. 2017; Zhong et al. 2017). Consequently, the qualification requirements for humans will migrate toward cooperation with artificial intelligence applications within a "know-when"-domain: Humans have to recognize and decide, for example, *when* to override and stop automated applications in case of potential danger or unforeseen changing conditions (Fischhoff et al. 1978; Kim et al. 2011; Gurkaynak et al. 2016).

This development and the upcoming challenges embedded therein are relevant for a large number of employees. For example, in Germany, more than 2.9 million people are working in the logistics sector, of which 868,000 in the land transport sector. Although, for instance, automated truck driving technology is available and the number of tests is rapidly increasing, human drivers will still be needed for a long time. The further development of HCI performance in the light of upcoming AI applications is a highly relevant topic (Koo et al. 2015; Weyer et al. 2015). How logistics in particular will be influenced by AI applications and HCI—considering aging and demographic challenges in the transportation and logistics labor market—remains an intriguing question (Nuzzolo and Comi 2014; Hasanefendic et al. 2015; Königs and Gijselaers 2015).

Connecting these developments to sustainability and in particular to the triple bottom line approach (Schneider 2015; Brockhaus et al. 2016), it is clear that *social*, *environmental,* and *economic* sustainability are all affected by developments regarding AI applications in transportation and logistics. (1) So far, the social dimension has been largely neglected in research and practice as outlined already by Seuring et al. (2008, p. 1545). Further contributions include Ramos et al. (2014), Mani et al. (2016), and Sudarto et al. (2017). Work conditions, security, and safety connected with AI applications qualify as social dimension questions that require adequate training (Missimer et al. 2017a,b; Sodhi 2015). (2) The ecological dimension of sustainability is addressed as many AI

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applications include optimization procedures that have the potential to reduce required resources significantly (Sudarto et al. 2017). Whether this will be achieved indeed critically depends of the performance of HCI within AI applications in transportation and logistics. (3) Finally, most AI applications represent serious investments and therefore are also expected to yield a corresponding return on investment. This clearly affects the economic dimension of sustainability, not only in terms of profit and ROI but also in terms of long-term competitiveness of businesses (Hazen and Byrd 2012). And even legislative aspects may change severely: For example, European driving hour restrictions may change in case unmanned trucks are entering the roads, but the responsibility and accountability of human controllers for traffic safety and security are becoming a subject of intense debate. Therefore, again HCI performance will strongly influence the economic position and sustainability through AI applications. In summary, HCI performance will have a major impact on the overall sustainability performance of transportation and logistics, embedded in all three dimensions of people, planet, and profit. Or, expressed differently: Measures that enhance overall HCI performance within AI applications are a key factor in improving the sustainability position in all three dimensions throughout supply chains.

The *research question* of this paper therefore can be formulated as follows: How can social sustainability be expected to develop and be managed in the light of increasing automation and artificial intelligence applications in logistics with new challenges for HCI. This question becomes prominent given the rapid advance of Internet of Things technology (i.e., the autonomous decision making and actions of interacting devices) of which autonomous vehicles and intelligent material handling devices in transportation or warehousing are notable early examples. The contribution of this paper is threefold: (1) providing a literature overview and state-of-the-art description regarding the specific development of automation and artificial intelligence applications in business logistics, (2) outlining the potential risk to social sustainability of an artificial divide among employees and firms, and (3) providing benchmarking examples and management concept elements to mitigate this possible risk of social sustainability in logistics.

The paper is structured as follows. We start with an extensive literature review that posits recent and state-of-the-art trends in transport automation, especially in the road sector, and describe an overarching vision known as the Physical Internet (PI). As these concepts call for new roles of human employees, we develop a specific theoretical framework addressing developments in human–computer interaction in logistics and the risk of an artificial divide among workers as well as corporations. We furthermore provide four benchmarking cases to underline the viability of this problem and suggest ingredients of a managerial approach to mitigate this risk as a central pathway for social sustainability in logistics. Finally, we present conclusions and an outlook on future research questions.

LITERATURE REVIEW

Transport automation

Transport automation is a major technological development, which addresses all transport modes but also activities that link these modes, such as warehousing and transhipment operations. Examples are visible throughout the logistic world: from highly automated container terminals to driverless car and truck experiments, automated guided vehicles in production and automated storage and retrieval systems in warehousing, shuttle trains and ships and the development of unmanned cargo aircraft (including drones). Typically, these developments are driven by the need to increase speed and reduce operational costs but also by arguments related to environmental sustainability and social acceptability (e.g., unmanned night transport, cf. Bals and Tate 2018). In Table 1, these developments are detailed for external transportation.

Specifically, road transportation by truck is an important and insightful example: In business practice, truck driving does encompass a significant part of all logistics-related professions. In the United States, for example, there are more than 3 million truck drivers and within the European Union, this number reaches 3.5 million people. At the same time, aging becomes manifest also in this sector: 26.5% of all truck drivers in Germany, for example, is older than 55 years and therefore expected to retire in the next decade. Logistics companies take various measures to mitigate these aging effects through, for example, smart route planning and optimization (Verma and Verter 2010; Dondo and Cerdá 2015; Phan and Kim 2015; Gingerich et al. 2016) and automation, but also by offering incentives to existing and new, young truck driver personnel. Another motivation to introduce AI applications is safety: not only the safety of other road users, but also working conditions of drivers themselves (Khorashadi et al. 2005; Pattinson and Thompson 2014; Chen et al. 2015a, 2015b; Pahukula et al. 2015; Bedinger et al. 2016). The potential of support by AI applications in road transport is huge, with distance control and warning systems as obvious examples. Assisted and automated driving for cars and trucks is on the threshold of general application, due to the rapid increase in sensor technology in vehicles (infrared, radar, laser, lidar, visual cameras, etc.) (Bertoncello and Wee 2015). In addition, former independent systems are increasingly connected and able to cooperate in order to perform self-sufficiency in driving. For example, the cruise control system, initially meant to maintain a constant preset speed of trucks and cars, is currently coupled with further intelligent applications, for instance, GPS navigation and the automated gearbox, allowing vehicles to deploy dynamic cruise control. This does encompass three sublevel steps within the technology development, already implemented for trucks (cars following slightly behind, Bernhart et al. 2014): In the first generation of cruise control applications, the system steadily maintained a constant, predefined speed level. This was only steering the diesel input and propulsion system of the truck or car. Subsequently, the system was able to follow a preceding vehicle on a preset distance, therefore already combining the management of gas and brake in the vehicle. This is commercially applied in road transportation in modern-day platooning systems, where "virtual road trains" are formed by trucks following each other automatically at short distance. The next generation of cruise control systems is able to anticipate the route characteristics by GPS positioning in combination with map material. This allows the system, for instance, to decelerate before downhill passages or to accelerate and downshift before

Table 1: Status review transport automation

	Road	Rail	Air	Water
Status description	Platooning Adaptive cruise control Autonomous trucking	Automation Connectivity New rail infrastructure	Drone/UCA technology Zeppelin	Remote control technology Focus short-sea shipping/ costal lines
Specific focus	Efficiency Sustainability Drivers tasks/work	Intermodal transport and cooperation	Small package transportation Remote area access	Cost efficiency Safety HR/work situation
Examples				

Table 2: Automated driving levels

SAE level	Name	Narrative Definition	Execution of Steering and Acceleration/ Deceleration	*Monitoring* of Driving Environment	Fallback Performance of *Dynamic Driving Task*	System Capability *(Driving Modes)*
***Human driver* monitors the driving environment**						
0	No Automation	the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a
1	Driver Assistance	the *driving mode*-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	Human driver and system	Human driver	Human driver	Some driving modes
2	Partial Automation	the *driving mode*-specific execution by one or more driver assistance systems of both steering and acceleration/ deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	**System**	Human driver	Human driver	Some driving modes
***Automated driving system* ("system") monitors the driving environment**						
3	Conditional Automation	the *driving mode*-specific performance by an *automated driving system* of all aspects of the dynamic driving task with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	**System**	Human driver	Some driving modes
4	High Automation	the *driving mode*-specific performance by an automated driving system of all aspects of the *dynamic driving task*, even if a *human driver* does not respond appropriately to a *request to intervene*	System	System	**System**	Some driving modes
5	Full Automation	the full-time performance by an *automated driving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver*	System	System	System	**All driving modes**

Source: SAE International 2017, Standard J3016.

uphill road segments. This combines basic driver functions (gas pedal, brake, gear) with GPS and navigation systems to achieve optimal motor management. The driver is only steering and supervising the system in total.

This is a small but significant development on the road toward automated vehicle and truck driving (Jamson et al. 2013; Hengstler et al. 2016). Ultimately, this will lead to automated road transportation with the existing truck driver having at best a supervisory role. Note that, following legal regulations, a human will be on board at least in public traffic systems in the foreseeable future, but no longer employed for their "know-how" but rather their "know-why." The competence to actively gear and steer a truck will be implemented by a technology application—while the driver is supposed to understand the know-why of all systems and especially when to overrule the automated system (therefore also: "know-when"). To that end, the human has to understand largely the functions and applications as well as the capabilities and restrictions of automated systems—in the future, truck drivers will more resemble software experts (Warnquist 2016). This vision of the role of automation or even fully autonomous equipment has been detailed for cargo trucks (Tylor 2016), being the sector most heavily confronted with the consequences of aging, but it is easily extended to other logistics sectors (warehousing, port terminals, unmanned train shuttles), some of which already being well on their way toward full autonomy. It is important to describe autonomous driving as a continuum of different levels of autonomy and not a dichotomous question, as exemplified by the six levels of automated driving defined by the Society of Automotive Engineers (SAE International 2017) and outlined in Table 2.

In the next section, we complement this discussion with an overarching vision of a comprehensively automated supply chain, known as the Physical Internet.

The physical internet vision

The Physical Internet (PI) was initially defined by Montreuil (2011) as a visionary logistics system in which modular packages are automatically routed from source to destination through a network of hubs and spokes, see Ballot et al. (2014) for a more elaborate treatment. This long-term vision for efficient and sustainable logistics can only be successfully implemented if the HCI aspects discussed in this paper with the provided theoretical framework are carefully addressed by individuals and firms alike. (Phan et al. 2017) Basic PI elements of such a system are parcels, pallets, containers, and "swap bodies," all equipped with intelligence that allow them to connect with handling and transport devices on route toward their destination. Carriers of these types of loading units do optimize between various alternative routes in their networks, for example, by bypassing hubs, either in advance through offering more time definite services or in real time during the actual transport. A full-blown PI may be built upon all these elements with the holistic integration of existing elements and concepts as the main challenge, see Figure 1.

The PI should not be confused with the Internet of Things (IoT); the latter refers to the possibility of communicating devices, often followed by local actions initiated by software agents or even fully autonomously (see examples in the previous section). Internet of Things technology may be an important building block of the PI, for example, in determining alternative routes in case of congestion on the preferred route, or in signaling a potential quality loss in case of delays (e.g., in food and flower transport). The PI however is a full-fledged alternative to a classical, manually operated logistics network, with important consequences for all stakeholders involved but primarily transport companies and logistics service providers. It is perceived as a radical attempt to overcome the drawbacks of the classical decentralized market economy mechanisms that prevent holistic optimization as many providers of transport and logistics services are "locked-in" in their current ways of working and acting.

The PI is best viewed as an autonomous system, similar to the digital Internet, governed by protocols and traffic control systems, to which access is given by 4PL service providers that are capable to combine and synchronize freight flows, supported by a superb ICT and physical infrastructure. High levels of transport automation are an important condition in realizing such a PI vision. However, different from the digital Internet, the level of human interaction will remain significant as in the end we are dealing with physical transport of physical objects. There is no doubt that major hurdles have to be overcome, including the design of a multifaceted decision support system for the PI, with automated execution via intelligent agents wherever possible. But once sufficient scale is reached, the combination of standardized packages, automated transport and transshipment, and automated (re)routing offers an alternative that will be very hard to beat in terms of cost and speed, similar to the undeniable success of current container transport. The most radical change will be in the role of the many still existing transport companies, which either need to transfer to a 4PL service provider with initiating and supervisory skills or leave the business entirely. However, the current highly fragmented and scattered way of working is no

Figure 1: The physical internet vision (Montreuil 2012, p. 22).

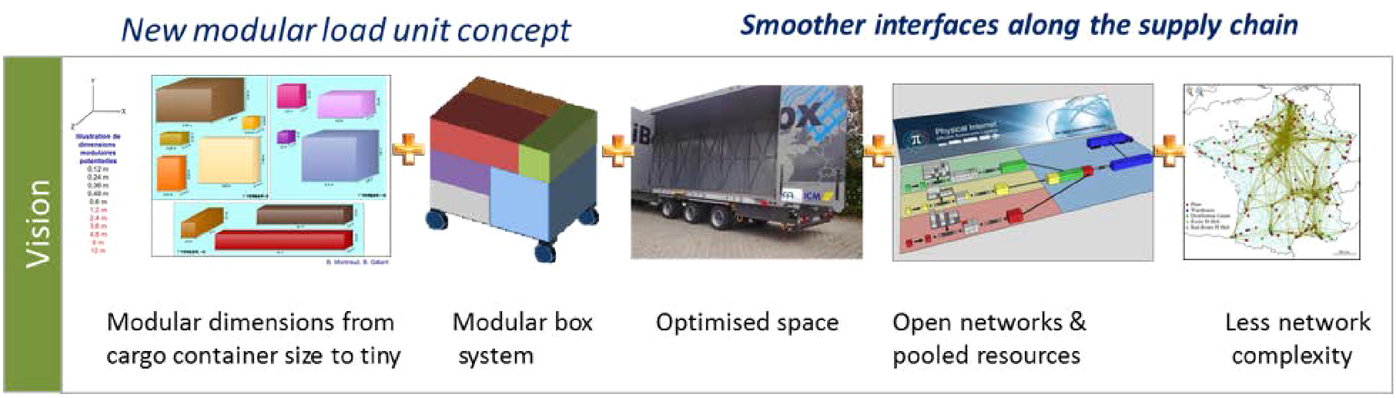
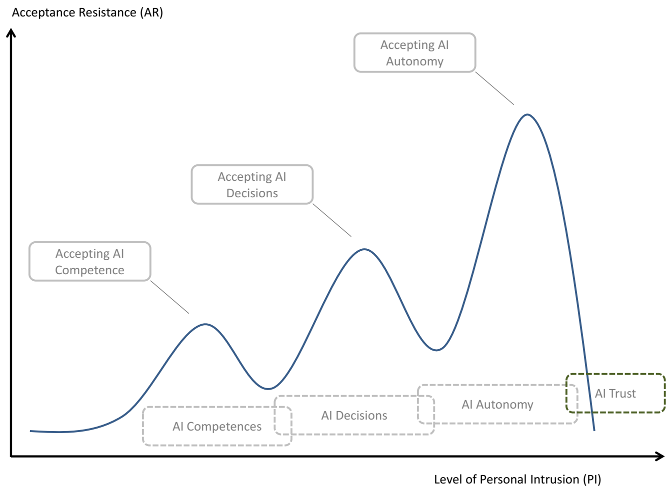


Figure 2: Human acceptance model for artificial intelligence applications (Klumpp 2017a).



longer sustainable, neither in an economic nor in an ecological and social way. At the same time, high-level supervisory and correcting mechanisms should be in place, for example, to overcome incidental infrastructural problems, to provide safe pathways for vulnerable freight, or to take counteracting measures in case of illegal intrusion.

Autonomous systems such as the PI are enabled by the latest technology developments in *sensor applications* as well as *machine learning*, which in combination allow machine systems to accomplish complex tasks as, for example, autonomous driving. Such applications are determined to be “weak AI” applications (Russell and Norvig 2010; Tsuji and Aburatani 2015; Hengstler et al. 2016) as they are restricted to and focused on specific applications—in contrast to “strong AI” which would be able to solve a multitude and increasing range of tasks like humans do, then becoming “super-human.” Machine learning is a cornerstone of AI applications as this concept allows a program to learn itself, leaving the former restrictions of coded actions behind, whereas formerly every machine action had to be programmed in one way or another, software and machines or robots are now able to learn from humans. For example, the robotics innovative corporations *Boston Dynamics* (www.bostondynamics.com) in the United States and *Magazino* in Germany (www.magazino.eu) have presented machines that are able to independently fulfill order picking tasks in intralogistics—and *learn* from humans regarding specific movements and hall layouts. In the *Magazino* case, this represents not only individual but also swarm intelligence learning as robots communicate among each other and each training effort is instantly shared with all machines within a group. For transportation and logistics, there are already a large number of theoretical concepts and applications, for example, in the fields of traffic flow prediction and management (Julio et al. 2015; Omrani 2015), transportation (Wojtusiak et al. 2012; Mrowczynska et al. 2017), production logistics (Schuhmacher and Hummel 2016; Wang and Tang 2017) or security and safety (Marucci-Wellman et al. 2017). In order to understand these changes better, an overarching vision of a theoretical framework is discussed in the following section.

THEORY FRAMEWORK DEVELOPMENT

Human–machine cooperation in logistics

Human interaction with artificial intelligence applications and automation (Lee et al. 2014; Bendoly 2016) can be characterized by three hurdles or areas of resistance, outlined below in Sections (1) to (3). Once an area is overcome, usually acceptance settles in (Rousseau et al. 1998; Martínez-Torres et al. 2015), see Figure 2.

The three depicted hurdles (“increased resistance areas” or “waves”) are connected to three AI functional areas and represent an increasing, but temporary, level of resistance throughout this development in line with an increasing level of personal intrusion (*x*-axis).

1. AI competence: Automation and AI applications are acquiring competences in specific fields, from playing chess to forecasting market demand. As separate competences, these are new for humans to get accustomed to but comparatively less frightening, and therefore, the resistance level toward them is relatively low. For logistics, this may include, for example, the automated gearbox in truck driving, automated routing and navigation systems as well as automated intralogistics applications in, for example, order retrieval and warehouse transportation systems. These systems have in common that usually any final decision, for example, regarding the travelled street, in reality is still taken by humans—and in many cases, AI suggestions from navigation systems are not implemented, an obvious sign of resistance (or of real or presumed “better knowledge”).
2. AI decisions: Here, AI applications suggest and implement single decisions, which usually rises greater anxiety and resistance levels with humans. This happens, for example, in cruise control applications in cars and trucks—where we distinguish three different phases: maintaining constant speed, maintaining constant distance to front vehicle, and finally variation of speed according to anticipated terrain features. In such cases, the automated device is taking a single or a sequence of decisions within a limited area of action (e.g., vehicle speed, vehicle gear). Such innovations already took place in the past, for example, in car and truck motor management (increasingly automated) or in the leisure area, for example, smartphone and social media applications. In these cases, humans are accepting automated applications without any security or fraud mistrust, at least not on a day-to-day basis (while trust may diminish incident-based, e.g., as a result of data fraud scandals or leaks). Understandably, this type of AI application is rising higher levels of rejection among humans, and therefore also requires a longer period of adaptation before, again, acceptance can settle in, see, for instance, Weyer et al. (2015).
3. AI autonomy: Finally, AI applications are taking a multitude of differentiated decisions, leading to autonomous behavior, for instance, when actively steering cars and trucks for longer periods and in interaction with other road users. In these cases, humans usually adopt a passive control role (supervision; Rauffet et al. 2015). These applications are at the

Figure 3: Artificial divide (Klumpp 2017b).

Divide 1 (Persons)

Divide 2 (Corporations)

	Persons well able to cooperate safely and innovatively with artificial intelligence applications in logistics	Persons **NOT** able to cooperate safely and innovatively with artificial intelligence applications in logistics
Corporations well able to implement and use artificial intelligence applications in logistics	○ „Winning teams“	○ „Perishing individuals“
Corporations **NOT** able to implement and use artificial intelligence applications in logistics	○ „Lost talent“	○ „Losing teams“

doorstep of industrial and real-world application, in production (autonomously moving robots with human interaction), traffic (autonomous cars and trucks) as well as health care (surgery as well as care robotics).

These levels or hurdles can be seen throughout a sequential level of personal intrusion (*x*-axis), arriving at a completely new situation after the three hurdle areas: the situation of trust with respect to an AI application, where humans are inclined to actively and trustfully cooperate with automated applications (Lahno 2001). This is closely related to the famous "Turing test": According to this concept, a human spectator is required to decide which part of an ongoing discussion between two parties (e.g., chatting via SMS or E-Mail) is performed by an artificial entity (computer) and which part is conducted by the human—if the spectator is not able to discern the right answer, e.g., accounting both parties for being humans, the artificial entity involved is said to have passed the test and possess artificial intelligence (Turing et al. 1952). This can be transferred to HCI when the human operator is not able to discern of the collaboration partner is human or artificial. The stage of AI trust is a special form of passing the Turing test as it is assumed that the human being in question may only be able to develop trust toward an AI application if a perceptive evaluation will judge the application to be, behave and communicate like a human being. This is in no way a sort of "blind trust," but actually the typical human fully aware of the realities in the world. This is a crucial and business-relevant form of trust between human beings and AI applications in logistics for a successful partnership. And this is also enlarging the predominant view of "technology acceptance" in the past (Venkatesh and Davis 2000; Nikou and Economides 2017), where generalized and also application-specific trust and acknowledgment of human workers and customers were tested and analyzed. Once we have reached this third level, the implementation of autonomous driving or autonomous materials handling in intralogistics in a safe and secure manner is built on full trust in AI applications in logistics.

Artificial divide

Next, we discuss the concept of a potential "artificial divide" and the possibility of feasible mitigation measures for individuals and corporations in logistics. This exceeds the question of steps and hurdles regarding human trust toward HCI from Figure 2 in the above section and connects this to the topic of positive conditions and requirements for automation and AI application in logistics on the individual worker and firm level (see Figure 3).The concept of an artificial divide with respect to human–machine cooperation in logistics refers to the difference between human workers that, depending on their acceptance and cooperation requirements, are or are not able to cooperate successfully with artificial intelligence applications in logistics. The same may hold for corporations as a whole. Therefore, the below described artificial "double divide" among persons and corporations with respect to their ability to cooperate with AI applications in logistics points to a serious risk that needs to be addressed in future logistics processes developments (see Figure 3):

Figure 3 actually describes conditions (i.e., personal or corporate situations) that may prevent or help to overcome the hurdles described in Figure 2 on the way to fully adopting AI solutions. For human workers, we distinguish between *persons* able to cooperate with AI applications, reaching a high-performance level, and persons that are not able to do so. For this definition, the outlined three levels of acceptance of AI competences, decisions, and autonomy may be used—but other measurement and definition schemes are also possible. The persons not able to cooperate with AI applications satisfactorily may therefore hamper the overall performance of the logistics processes within a company or supply chain. A truck driver, for example, may too often override the autonomous navigation, steering, and control system of a self-driving truck. This may lead to an increased number of travelled kilometers and a higher consumed fuel level and travel time for this specific truck—leaving the company or the supply chain in question with a long-term distinctive disadvantage compared to others. However, this incompetence to cooperate may also happen vice-versa: A truck driver option for no interruption of autonomous systems at all (therefore executing "automatic driving control") may also hurt the transport process as well as the involved company. When never interrupting the automated cruise control systems in an autonomous truck, accidents may happen (since risk and safety conditions were insufficiently included) or nonoptimal routes are taken (e.g., when not applying human knowledge about street conditions in winter, making certain routes inaccessible for particular trucks).

A similar distinction may be applied to corporations. Some logistics corporations are well able to implement AI application systems and profit from them. But others—due to various reasons such as neglect, lack of knowledge, low motivation, or even low investment capacity—may be in a position to deny or not fully apply AI applications in logistics. For example, if a company does not implement modern adaptive cruise control systems for the trucks used (which may also hold for rail, ship, and plane applications where possible, e.g., with drones), it may find itself at severe time and cost disadvantages (more diesel consumption) compared to competing corporations and supply chains. However, the same may happen with "overspending": Some corporations may spend a lot of money on AI applications, without paying sufficient attention to the human workforce that should be capable to handle these systems. In such overinvestment cases, mainly depreciation costs are incurred without obtaining cost reductions (or, even better, earnings increases) on the day-to-day business processes. This may put such corporations or supply chains at an economic disadvantage compared to competitors.

Based upon this definition of an "artificial double divide" in the future of logistics processes, four specific groups of persons or teams (understood as corporations or even complete supply chains) in logistics are distinguished (see Figure 3):

(a) In a "winning team" configuration, individuals and corporations able to cooperate with and to use AI applications in logistics are successfully combined. This combination will bring about the best possible effects and benefits of AI application in the specific logistics processes in practice.
(b) In the opposite case of "losing teams," individuals and corporations not able to cooperate with AI applications in logistics are working together. This may result in cases where a lot of potential is lost and the average process costs are significantly higher compared to competing teams (corporations or complete supply chains). In such cases, AI applications are installed but not used at all (corporate misjudgment or failing investment capacity) or continuously overridden by human operators, possibly because workers are not properly prepared and trained to work with the systems.
(c) Interestingly, there are also mixed combinations, for example, when persons very well able to cooperate with AI applications in logistics are working within corporations that are not (no investment, hesitation to invest, or even the overspending case). This can be termed "lost talent" as the persons encountered are well trained and motivated—but not efficiently used by their teams, leading to a loss of talent regarding logistics and management (cost) improvement.
(d) The fourth case comprises corporations very well able to use AI applications—and persons unable to do so within these teams. These people will be perishing one way or another, for example, by not participating fully in the corporate strategy with respect to such system implementations, by being forced to train and retrain until adaptation may set in or even by losing their employment. In such cases, it is generally irrelevant if this happens due to a lack of motivation (resistance as discussed above) or a lack of intellectual and even emotional capabilities. HR management in logistics has the responsibility to prevent such situations by early information, training, and adaptation (job change) management.

BENCHMARKING CASES

Method outline

Four cases are outlined and applied to the research question of this paper in order to shed light on the problem of how to cope with automation, digitalization, and human–computer interaction as the core social sustainability issue in the future of logistics operations. As Table 3 and the subsequent method descriptions outline, two secondary cases from public sources are combined with two primary analysis cases from new research in the field. At the same time, physical cases regarding transportation, materials handling, and robotics are combined with more managerial cases addressing decision making.

1. A secondary analysis describes the increasing use of cobots (cooperative robots) in a logistics and production context. Data are derived from the Internet describing current trends and application areas of these new generations of robots designed to work in tandem with human coworkers.
2. A further secondary analysis outlines the experiences and insights from the area of centaur chess, where chess tournaments are played by integrated human–computer teams against other centaur teams. Descriptions and experiences are based on Internet information and can be transferred to decision making in logistics management, for example, by human–computer teams in transportation routing and scheduling (Nagaraja and McElroy 2018).
3. Within the second largest food retailer in Germany, an expert workshop with 10 employees from different disciplines including logistics, work science, materials handling, and computer science was conducted during a full day in Cologne on November 30, 2017. The overarching topic of this expert

Table 3: Benchmarking cases overview

	Transportation and robotics	**Decision making**
Secondary analysis	(1) Cobots in production and logistics	(2) Centaur chess in human–computer teams
Primary empirical analysis	(3) Food distribution and picking case	(4) Logistics management cases

session was the implementation of digitalization in logistics processes and how to prepare employees for such developments by, for example, training, adaptation of technical solutions, or new process designs. The experts reported several implementation projects with specific problems, failures, and lessons learned, for example, in order picking or in transportation from warehouses to supermarkets (Fazili et al. 2017). The company representatives acknowledged the complexity of the topic and demanded more research as well as company experience, in particular in interdisciplinary teams as usually digital projects are implemented by computer experts, often without prior user feedback or process analysis from logistics experts. During the workshop, cases were reported in which digitalization steps had to be called back due to resistance of both blue-collar and white-collar workers in warehousing, order picking, and transportation.

4. Within November and December 2017, semistructured interviews were conducted with 12 logistics management experts from a master class cohort in Leverkusen, Germany (master program in logistics management as part-time study program for executives). Expert backgrounds ranged from small and medium-sized logistics service providers to large industrial firms. Further characteristics entail an age band of 22–35, a gender distribution of 6 female and 6 male experts as well as a qualification of academic education and work experience (all experts possessed a BA degree and had a business practice experience ranging from 1 to 11 years). All interviews were recorded and transcribed. The overarching topic was the digital transformation in logistics and how employees and managers cope with this development (De Santis et al. 2018).

Findings

From the four outlined cases, the following findings are derived that regard this paper's core research question on social sustainability in logistics in the light of automation and artificial intelligence applications:

1. Cobots are a "second wave" of robots, dedicated to teamwork with human employees as "collaborative robots." As such, they are demanding human coworkers to work more closely and in direct and everyday physical interaction with them. Security as well as ergonomic considerations are therefore in the center of cobot development. Reported problems include resistance based on data security as well as long-term medical reservations, for example, fear to lose one's physical strength due to the use of cobots (DGUV 2018).
2. In centaur chess, it is observed that usually winning teams in tournaments are not necessarily consisting of the "best" software or the "brightest" human minds but of well-functioning teams of quite normal people and average software applications. The specific USP and winning proposition of these teams are their ability to derive best chess moves from a rational–creative interaction of computer and human capabilities. This can be seen as a benchmark for AI applications in logistics and the related HCI.
3. The employees of the large food retailer reported major problems in integrating personnel in new digitalized logistics and transportation solutions. An example concerned a new transport management software solution, which had to be withdrawn from the operational processes again, as employees rejected to use it. It was observed that technical hindrances and technical competence gaps were responsible for these problems, but also a sincere resistance based on motivational, data security, or philosophical reasons on equal footing.
4. Among the interviewed experts, in general, enthusiasm and motivation for digitalization and AI applications in logistics were very high, especially among younger respondents. Motivational problems were reported in individual cases, for example, based on data protection and transparency or privacy issues with big data and AI applications. In smaller firms, digital processes and AI applications were reported to be less used, or to lower degrees, in comparison with larger firms. In addition, supervisor support was mentioned as one of the central factors in acceptance and performance of new digital and AI solutions in supply, production, and transportation processes.

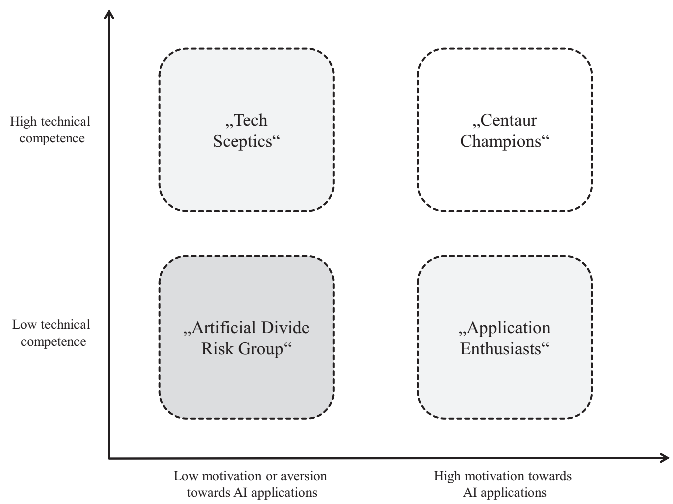
All insights from the four presented benchmarking case studies can be represented in a possible structural approach for employees in logistics regarding the social risk of an artificial divide. As outlined in Figure 4, personnel may be divided by their specific motivation (*x*-axis) and competence (*y*-axis) toward computer and AI applications.

The four identified personnel groups can be described as follows: "Centaur Champions" are employees with high competence levels regarding computers and HCI as well as high motivation levels regarding digitalization and innovation in logistics. These persons are usually the first users of new technologies and like to innovate, even to convince others of advantages for new applications.

"Application Enthusiasts" do not possess extensive technical knowledge but like to use new gadgets and technologies in order to help them in their work routines. This group of employees is important for application development and testing as they represent possibly the largest "silent majority" of end users in the final processes.

"Tech Sceptics" are typically providing high competence levels regarding computer and AI technologies and HCI but also entail an informed resistance toward AI usage, for example, due

Figure 4: Employee groups regarding artificial divide.



to data protection fears and general techno-scepticism. Such people have to be addressed in AI application implementation in order to lower the resistance as they usually have strong arguments on their side and are technically able to circumvent application enforcement.

The "Artificial Divide Risk Group" does feature low competence as well as motivation levels regarding computer and AI applications. Therefore, this group deserves the highest attention levels in any mitigation concept in order to foster social sustainability in logistics. Not uncommon, older age people might dominate this group.

These categories can be used to tailor the implementation of management elements in order to mitigate the associated risks of possible artificial divide developments for social sustainability in logistics as outlined in the following section.

SOCIAL SUSTAINABILITY AND IMPLICATIONS FOR LOGISTICS

In order to help analyze and mitigate the possible risk of an artificial divide, especially the corporate perspective is discussed in detail below.

- Analysis of AI implementation should predominantly include the feature of possibilities of *artificial divide elements*, such as rejection by individual employees and employee groups, qualification and training gaps with individuals and groups as well as historical experiences (failure of automation, rejection by employees).
- A second stream of analysis should be directed to the management and decision level within the corporation. For example, by using questionnaires and interviews, it should be clarified what attitude, experience, and development potential are present within the managerial workforce.
- Successful prevention of an artificial divide on the corporate level will then be possible if taking the analysis results into account and addressing them properly. This includes training and enhanced experience (life visit of other companies and systems) measures for workers *and* management; as outlined by Martínez-Torres et al. (2015), personal experience plays a major role in the question of acceptance and trust toward AI applications and technological systems. This can be connected to the use of serious gaming applications as a training tool, or even the use of flight simulators. In addition, a pilot implementation at a limited scale to gain experience is an option. Further, it might help to develop several alternatives and purposefully include the eventual users (workforce) in the final selection of one of these alternatives. All these measures are meant to enforce employee involvement at an early stage, which is crucial for acceptance.
- Further preparation and prevention measures may include the notion of a supervisory board and empowerment of employees (workers and managers). It is important to prevent individuals addressed to feel stripped of their professional powers and oversight. AI applications themselves as well as their providers are advised to cooperate with human partners on an equal level, to allow for oversight and corrections from humans as well as learning in both directions.

Corporations facing AI applications introductions may also benefit from communicating the *vision of a mutual acknowledgement and learning environment*. Humans should be trained and prepared to learn from the AI component while also claiming the oversight and control role for themselves. AI applications on the other hand should also be prepared and able to learn from humans (machine learning) and to express vividly their respect and acknowledgment toward the human partners. Adverse effects like AI applications learning the wrong and misdirected things from users have to be recognized and redirected.

These measures may help corporations to avoid the possible results of an artificial divide in the form of lower performance and higher cost levels for logistics and supply chain processes. This may lead to a special form of social sustainability helping also the economic performance, competitiveness, and sustainability of the company involved.

Combining the application of artificial intelligence (AI) and automation (LeCun et al. 2015; Schmidhuber 2015) with the reported characteristics of *human motivational structures*, implications may be discussed, for instance, in the case of truck drivers. The required productive human-artificial cooperation—facing demographic change—may be facilitated if AI applications learn to *appreciate and praise human co-workers* in any form for their input and cooperation. The conjecture is that a navigation system *thanking* the human driver for neglecting directions due to superior knowledge is desirable as this allows the system to improve suggestions and motivates the driver to still value automated directions in the future. This is enabled also by the fact that AI systems increasingly will be able to *recognize human emotions* via their voices and steer their reactions and answers accordingly as, for example, Harimi et al. (2015) or Abbasimehr and Tarokh (2015) report. This situation is exemplified with truck drivers but by no means limited to this group of logistics employees. Instead, all sorts of blue and white-collar workers in logistics, transportation and supply chain management will have to cope with the implications of AI applications within core processes.

Finally, we complement the discussion of a potential artificial divide with further implications for logistics processes and operations, considering the following items on an *operational* transport level:

1. Personal *attention and competences* of truck drivers will shift almost entirely from operational questions (steering, speed, gear, and route) toward supervision and also security and planning processes. This allows additional activities to be executed during driving and may even compete with office administration jobs. As a result, automated driving may significantly reduce the number of office clerks' jobs in logistics and forwarding companies, and to a lesser extent also drivers' jobs themselves.
2. Drivers' acceptance of such automated systems will therefore play an important role in the competition of road transportation companies from several perspectives. First, allowing the AI application to execute a job may be more efficient and

cost saving than when the human driver operates on its own (saving fuel, reducing travelled distance, and reducing truck wear). Second, as drivers may execute other company tasks and processes instead of driving while travelling, this may save costs at other places (e.g., administrative personnel). Third, driving personnel may also be more effective and efficient due to a motivation boost within an AI application scenario (being more the "tech guy" instead of the "working grunt guy"—perhaps even more applicable to female workers). This may also dramatically change the reflected perspective in the study results that drivers usually judge themselves as being at the "low end" of the working hierarchy in transportation and logistics; however, the demands in terms of an increase in competence and thinking levels are severe.

3. A third interesting research question concerns the introduction of new human-artificial cooperation systems in logistics ("revolution or evolution"). It can be expected that similar to the road vehicle fleet facing a multitude of propulsion systems ahead (diesel and CNG/LNG, hybrid, hydrogen, electric), the complexity of different systems in logistics operations existing in parallel may increase significantly. This will be a major challenge for strategic management of logistics operations, ensuring effective and efficient operations with a mixed landscape of more and less advanced AI application designs within road transportation. Besides the investment and maintenance question, this again is quite a change for driver motivation and training (McDonald et al. 2015), also closely related to overall supply chain resilience and risk strategies (Manuj and Sahin 2011).

Furthermore, on an elaborate *managerial tactical level*, also the use of automated systems in truck driving and especially *tour planning* can possibly be used to mitigate the other adverse effects for driver motivation: the question of *work planning and scheduling*, for example, for work breaks as well as holiday times and daily work extensions. By implementing advanced AI planning systems based on, for example, real-time traffic information, the day-to-day realization of necessary breaks and also manageable daily workloads for drivers can be achieved. This might also improve the overall security situation as outlined in the beginning—reducing the number of roadside deaths through truck accidents should be an important objective also for business improvements in logistics. Besides the work and social situation of drivers themselves, this could be a major contribution of logistics companies to *corporate social responsibility* for economies and societies in the future.

Finally, on a *strategic management level*, it has to be stressed that the process of AI application and increasing importance of human–machine cooperation is progressing in all logistics, production, and management areas. Therefore, also the potential danger of an artificial divide is at stake in all these areas, starting from the early experiences regarding MRP implementations in production—where planning decisions were often overridden by interventions of operators to account for changing circumstances, thereby ruining data integrity and in the end losing any trust in the system (the well-known spiral turning down). Strategic and management level decisions in logistics may also endanger executive tasks and positions in the financial sector and other service industries, which rely heavily on a large number of decisions. Such decisions may at least partly be automated in the future and an increased human–machine cooperation is required for a lower number of human workers and managers—stifling the potential danger of an artificial divide. This implies that individuals have to prepare (mainly through awareness and training), and the same holds for corporations, maybe harder to implement but also beginning with awareness at the management level.

CONCLUSIONS

In this paper, we (1) have presented a literature overview and state-of-the-art description regarding the specific development of automation and artificial intelligence applications in business logistics, (2) have outlined the potential risk to social sustainability of an artificial divide among both employees and firms, and (3) have provided benchmarking examples and management ingredients to mitigate this possible risk of social sustainability in logistics.

With rising automation levels in logistics, the problem of an artificial divide may represent a serious risk, and measures to close a possible business strategy gap are required: It is very important for logistics research institutes and logistics corporations to invest in further research and to test resources in the field of human–machine cooperation on their performance for logistics processes. The rise and success of the PI as a vision and symbol for fully automated transportation and supply chain systems may not be realized without sufficient attention for the human interaction factor. At least, the timeline and economic success of AI implementations in logistics will be severely distorted if such aspects are to be neglected. Therefore, attention has to be paid to real-life testing of AI applications in production and logistics (autonomous trucks etc.) with human workers—obviously before any long-term implementation on a larger scale. In addition, the explained stage of AI trust in human-artificial cooperation has to be further investigated as it is a crucial element in successful future logistics systems.

In outlining analytical approaches as well as trends in logistics employee motivation as major factors in enhancing the resilience and sustainability of global, national and local logistics systems, this paper addresses three major issues:

- Logistics employees—with the outlined example of truck drivers—are facing severe and adverse work conditions. Still, drivers will always be on the lookout for apprehension and acceptance by work as well as traffic partners (customers, managers, car drivers etc.), besides commonplace motivational factors such as wages and working times. This can be termed a "*social interaction trait*" of human motivation within the road transportation segment.
- The question of apprehension and appraisal can interestingly be connected to the oncoming field of artificial intelligence applications in road transportation. As, for example, automated driving will be a major challenge for corporations as well as human drivers in future road transportation, such changes may endanger all logistics and supply chain processes with a possible artificial divide in the successful cooperation of human employees with AI applications. Human motivation and behavior can be categorized

in at least four development and acceptance areas as outlined in this paper. This crucially influences the performance of human–machine cooperation at the workplace as was outlined for the example of automated truck driving, leading to adaptation as well as to persisting rejection patterns depending on the area of AI application. This again connects to recent developments in AI itself, allowing the AI application to actively recognize trust by the human cooperation partner and react to that analysis (Abbasimehr and Tarokh 2015).

- Furthermore, also with respect to the identified major motivation factors regarding work scheduling and working time (long-term/advance information, dynamic change), AI applications may bring some positive change about: Real-time advanced tour scheduling and planning systems will increasingly be able to (a) adapt to personal preferences, traffic situations as well as corporate objectives of time and cost optimization; (b) implement personal rest breaks and human daily workloads which will improve employee health and motivation; (c) therefore also advance the overall safety in road transportation, supporting an important CSR contribution of logistics. This, together with the feasibility to avoid an artificial divide, may enable the logistics industry to foster social sustainability in many dimensions.

In summary, the future competitiveness and logistics performance will significantly depend on the described factors regarding human work motivation as well as human–machine cooperation and acceptance. The challenge to overcome a potential artificial divide in the human workforce as well as among different companies is imminent and important. Therefore, a high level of interest—both in research and business practice—is required for this field, including interdisciplinary approaches from several science and application disciplines like human resource management, technology, and computer sciences as well as management science.

REFERENCES

Abbasimehr, H., and Tarokh, M.J. 2015. "Trust Prediction in Online Communities Employing Neurofuzzy Approach." *Applied Artificial Intelligence* 29(7):733–53.

Ballot, E., Montreuil, B., and Meller, R. 2014. *The Physical Internet - The Network of Logistics Networks*. Paris: Programme de recherche et d'innovation dans les transports terrestres (PREDIT), La Documentation française (ISBN 978-2-11-009865-8).

Bals, L., and Tate, W.L. 2018. "Sustainable Supply Chain Design in Social Businesses: Advancing the Theory of Supply Chain." *Journal of Business Logistics* 39(1):57–79.

Bedinger, M., Walker, G.H., Piecyk, M., and Greening, P. 2016. "21st Century Trucking: A Trajectory for Ergonomics and Road Freight." *Applied Ergonomics* 53 (B):343–56.

Bendoly, E. 2016. "'Fit, Bias, and Enacted Sensemaking in Data Visualization: Frameworks for Continuous Development in Operations and Supply Chain Management Analytics'." *Journal of Business Logistics* 37(1):6–17.

Bernhart, W., Winterhoff, M., Hoyes, C., Chivukuly, V., Garrelfs, J., Jung, S., and Galander, S. 2014. *Autonomous Driving*. Munich: Roland Berger.

Bertazzi, L., and Mogre, R. 2018. "Dynamic Expediting of an Urgent Order With Uncertain Progress." *European Journal of Operational Research* 267(1):78–85.

Bertoncello, M., and Wee, D. 2015. *Ten Ways Autonomous Driving Could Redefine the Automotive World*. New York: McKinsey & Company Online.

Bloemhof, J.M., van der Vorst, J.G., Bastl, M., and Allaoui, H. 2015. "'Sustainability Assessment of Food Chain Logistics'." *International Journal of Logistics Research and Applications* 18(2):101–17.

Brockhaus, S., Fawcett, S.E., Knemeyer, A.M., and Fawcett, A.M. 2016. "Motivations for Environmental and Social Consciousness: Reevaluating the Sustainability-Based View." *Journal of Cleaner Production* 143(1):933–947.

Cantor, D.E. 2016. "Maximizing the Potential of Contemporary Workplace Monitoring: Techno-Cultural Developments, Transactive Memory, and Management Planning." *Journal of Business Logistics* 37(1):18–25.

Castelfranchi, C., and Falcone, R. 2000. "Trust and Control: A Dialectic Link." *Applied Artificial Intelligence* 14(8):799–823.

Castillo, V.E., Bell, J.E., Rose, W.J., and Rodrigues, A.M. 2017. "Crowdsourcing Last Mile Delivery: Strategic Implications and Future Research Directions." *Journal of Business Logistics* 39 (1), 7–25.

Chen, H., Long, C., and Jiang, H.-B. 2015a. "Building a Belief-Desire-Intention Agent for Modeling Neural Networks." *Applied Artificial Intelligence* 29(8):753–65.

Chen, G.X., Sieber, W.K., Lincoln, J.E., Birdsey, J., Hitchcock, E.M., Nakata, A., Robinson, C.F., Collins, J.W., and Sweeney, M.H. 2015b. "NIOSH National Survey of Long-Haul Truck Drivers: Injury and Safety." *Accident Analysis and Prevention* 85:66–72.

Crainic, T.G., and Montreuil, B. 2016. "'Physical Internet Enabled Hyperconnected City Logistics'." *Transportation Research Procedia* 12:383–98.

De Santis, R., Montanari, R., Vignali, G., and Bottani, E. 2018. "An Adapted ant Colony Optimization Algorithm for the Minimization of the Travel Distance of Pickers in Manual Warehouses." *European Journal of Operational Research* 267 (1):120–37.

Deng, L. 2018. "Artificial Intelligence in the Rising Wave of Deep Learning: The Historical Path and Future Outlook." *IEEE Signal Processing Magazine* 35(1):177–180.

DGUV 2018. http://www.dguv.de/ifa/fachinfos/kollaborierende-roboter/index.jsp. Accessed January 30, 2018.

Dondo, R., and Cerdá, J. 2015. "The Heterogeneous Vehicle Routing and Truck Scheduling Problem in a Multi-Door Cross-Dock System." *Computers and Chemical Engineering* 76:42–62.

Fazili, M., Venkatadri, U., Cyrus, P., and Tajbaksh, M. 2017. "Physical Internet, Conventional and Hybrid Logistics Systems: A Routing Optimization-Based Comparison Using the Eastern Canada Road Network." *International Journal of Production Research* 55(9):2703–30.

Fischhoff, B., Slovic, P., Lichtenstein, S., Read, S., and Combs, B. 1978. "How Safe is Safe Enough? A Psychometric Study of Attitudes Towards Technological Risks and Benefits." *Policy Sciences* 9(2):127–52.

Fors, C., Kircher, K., and Ahlström, C. 2015. "Interface Design of eco-Driving Support Systems – Truck Drivers' Preferences and Behavioural Compliance." *Transportation Research Part C* 58:706–20.

Gingerich, K., Maoh, H., and Anderson, W. 2016. "Classifying the Purpose of Stopped Truck Events: An Application of Entropy to GPS Data." *Transportation Research Part C* 64:17–27.

Gunsekaran, A., and Ngai, E.W.T. 2014. "Expert Systems and Artificial Intelligence in the 21st Century Logistics and Supply Chain Management." *Expert Systems With Applications* 41:1–4.

Gurkaynak, G., Yilmaz, I., and Haksever, G. 2016. "'Stifling Artificial Intelligence: Human Perils'." *Computer Law & Security Review* 32:749–58.

Harimi, A., Fard, A.A., Shahzade, A., and Yaghmaie, K. 2015. "Anger or Joy? Emotion Recognition Using Nonlinear Dynamics of Speech." *Applied Artificial Intelligence* 29 (7):675–96.

Hasanefendic, S., Heitor, M., and Horta, H. 2015. "Training Students for new Jobs: The Role of Technical and Vocational Higher Education and Implications for Science Policy in Portugal." *Technological Forecasting & Social Change Journal* 113:328–40.

Hazen, B.T., and Byrd, T.A. 2012. "Toward Creating Competitive Advantage With Logistics Information Technology." *International Journal of Physical Distribution & Logistics Management* 42:8–35.

Hengstler, M., Enkel, E., and Duelli, S. 2016. "Applied Artificial Intelligence and Trust – The Case of Autonomous Vehicles and Medical Assistance Devices." *Technological Forecasting & Social Change* 105:105–20.

Hilger, T., Sahling, F., and Tempelmeier, H. 2016. "Capacitated Dynamic Production and Remanufacturing Planning Under Demand and Return Uncertainty." *OR Spectrum* 38:849–76.

Jamson, A.H., Merat, N., Carsten, O.M., and Lai, F.C. 2013. "Behavioural Changes in Drivers Experiencing Highly-Automated Vehicle Control in Varying Traffic Conditions." *Transportation Research Part C: Emerging Technologies* 30:116–25.

Julio, N., Giesen, R., and Lizana, P. 2015. "Real-Time Prediction of bus Travel Speeds Using Traffic Shockwaves and Machine Learning Algorithms." *Research in Transportation Economics* 59:250–7.

Khorashadi, A., Niemeier, D., Shankar, V., and Mannering, F. 2005. "Differences in Rural and Urban Driver-Injury Severities in Accidents Involving Large-Trucks: An Exploratory Analysis." *Accident Analysis and Prevention* 37:910–21.

Kim, T.G., Hornung, S., and Rousseau, D.M. 2011. "Change-Supportive Employee Behavior: Antecedents and the Moderating Role of Time." *Journal of Management* 37:1664–93.

Klumpp, M. 2017a. "Automation and Artificial Intelligence in Business Logistics Systems: Human Reactions and Collaboration Requirements." *Journal of Logistics Research and Applications* 21(3):224–42.

Klumpp, M. 2017b. "Artificial Divide: The New Challenge of Human-Artificial Performance in Logistics." In *Innovative Produkte und Dienstleistungen in der Mobilität*. edited by H. Proff and T. Fojcik, 583–593. Wiesbaden: Springer Gabler.

Knoll, D., Prüglmeier, M., and Reinhart, G. 2016. "'Predicting Future Inbound Logistics Processes Using Machine Learning'." *Procedia CIRP* 52:145–50.

Kong, T.R.K., Chen, J., Luo, H., and Huang, Q.G. 2016. "Scheduling at an Auction Logistics Centre With Physical Internet." *International Journal of Production Research* 54(9):2670–90.

Königs, K.D., and Gijselaers, W.H. 2015. "Bringing Learning to the Workplace: A Smartphone app for Reflection and Increased Authenticity of Learning." In *Transformative Perspectives and Processes in Higher Education, Series Advances in Business, Education and Training 6*, edited by A. Dailey-Heben, and K.S. Dennis, 117–35. Cham: Springer.

Koo, J., Kwac, J., Ju, W., Steinert, M., Leifer, L., and Nass, C. 2015. "Why did my car Just do That? Explaining Semi-Autonomous Driving Actions to Improve Driver Understanding, Trust, and Performance." *International Journal on Interactive Design and Manufacturing* 9(4):269–75.

Lahno, B. 2001. "On the Emotional Character of Trust." *Ethical Theory and Moral Practice* 4:171–89.

LeCun, Y., Bengio, Y., and Hinton, G. 2015. "'Deep Learning'." *Nature* 521:436–44.

Lee, H.-D., Lee, B.-K., Kim, W.-S., Han, J.-S., Shin, K.-S., and Han, C.-S. 2014. "Human–Robot Cooperation Control Based on a Dynamic Model of an Upper Limb Exoskeleton for Human Power Amplification." *Mechatronics* 24:168–76.

Li, B.-H., Hou, B.-C., Yu, W.-T., Lu, X.-B., and Yang, C.-W. 2017. "Applications of Artificial Intelligence in Intelligent Manufacturing: A Review." *Frontiers of Information Technology & Electronic Engineering* 18(1):86–96.

Mani, V., Gunasekaran, A., Papadopoulos, T., and Hazen, B. 2016. "Supply Chain Social Sustainability for Developing Nations: Evidence From India." *Resources, Conservation and Recycling* 111:42–52.

Manuj, I., and Sahin, F. 2011. "A Model of Supply Chain and Supply Chain Decision-Making Complexity." *International Journal of Physical Distribution & Logistics Management* 41(5):511–49.

Martínez-Torres, M., Díaz-Fernández, M., Toral, S., and Barrero, F. 2015. "The Moderating Role of Prior Experience in Technological Acceptance Models for Ubiquitous Computing Services in Urban Environments." *Technological Forecasting & Social Change* 91:146–60.

Marucci-Wellman, H.R., Corns, H.L., and Lehto, M.R. 2017. "Classifying Injury Narratives of Large Administrative Databases for Surveillance — A Practical Approach Combining Machine Learning Ensembles and Human Review." *Accident Analysis and Prevention* 98:359–71.

McDonald, C.C., Goodwin, A.H., Pradhan, A.K., Romoser, M.R.E., and Williams, A.F. 2015. "A Review of Hazard Anticipation Training Programs for Young Drivers." *Journal of Adolescent Health* 57:S15–23.

Missimer, M., Robèrt, K.-H., and Broman, G. 2017a. "A Strategic Approach to Social Sustainability - Part 1: Exploring the Social System." *Journal of Cleaner Production* 140:32–41.

Missimer, M., Robèrt, K.-H., and Broman, G. 2017b. "A Strategic Approach to Social Sustainability - Part 2: A

Principle-Based Definition." *Journal of Cleaner Production* 140:42–52.

Montreuil, B. 2011. "Towards a Physical Internet: Meeting the Global Logistics Sustainability Grand Challenge." *Logistics Research* 3(2–3):71–87.

Montreuil, B. 2012. "Physical Internet Manifesto." Presentation on 28.11.2012. Available at: https://de.slideshare.net/physical_internet/physical-internet-manifesto-eng-version-1111-20121119-15252441, accessed September 11, 2018.

Mrowczynska, B., Ciesly, M., Krol, A., and Sladkowski, A. 2017. "Application of Artificial Intelligence in Prediction of Road Freight Transportation." *Traffic & Transportation* 29 (4):363–70.

Musa, A., Gunasekaran, A., Yusuf, Y., and Abdelazim, A. 2014. "Embedded Devices for Supply Chain Applications: Towards Hardware Integration of Disparate Technologies." *Expert Systems With Applications* 41:137–55.

Nagaraja, C.H., and McElroy, T. 2018. "The Multivariate Bullwhip Effect." *European Journal of Operational Research* 267(1):96–106.

Nikou, S.A., and Economides, A.A. 2017. "Mobile-Based Assessment: Integrating Acceptance and Motivational Factors Into a Combined Model of Self-Determination Theory and Technology Acceptance." *Computers in Human Behavior* 68:83–95.

Nuzzolo, A., and Comi, A. 2014. "A System of Models to Forecast the Effects of Demographic Changes on Urban Shop Restocking." *Research in Transportation Business & Management* 11:142–51.

Omrani, H. 2015. "Predicting Travel Mode of Individuals by Machine Learning." *Transportation Research Procedia* 10:840–9.

Pahukula, J., Hernandez, S., and Unnikrishnan, A. 2015. "A Time of day Analysis of Crashes Involving Large Trucks in Urban Areas." *Accident Analysis and Prevention* 75:155–63.

Pattinson, W., and Thompson, R.G. 2014. "Trucks and Bikes: Sharing the Roads." *Procedia - Social and Behavioral Sciences* 125:251–61.

Phan, S., Ballot, E., Huang, G.Q., and Montreuil, B. 2017. "Physical Internet and Interconnected Logistics Services: Research and Applications." *International Journal of Production Research* 55(9):2603–9.

Phan, M.-H., and Kim, K.H. 2015. "Negotiating Truck Arrival Times Among Trucking Companies and a Container Terminal." *Transportation Research Part E: Logistics and Transportation Review* 75:132–44.

Ramos, T.R.P., Gomes, M.I., and Barbosa-Póvoa, A.P. 2014. "Planning a Sustainable Reverse Logistics System: Balancing Costs With Environmental and Social Concerns." *Omega* 48:60–74.

Rauffet, P., Lassalle, J., Leroy, B., Coppin, G., and Chauvina, C. 2015. "The TAPAS Project: Facilitating Cooperation in Hybrid Combat air Patrols Including Autonomous UCAVs." *Procedia Manufacturing* 3:974–81.

Rousseau, D.M., Sitkin, S.B., Burt, R.S., and Camerer, C. 1998. "Not so Different After all: A Cross Discipline View of Trust." *Academy of Management Review* 23(3):393–404.

Russell, S.J., and Norvig, P. 2010. *Artificial Intelligence: A Modern Approach*, 3rd ed. Englewood Cliffs, NJ: Prentice Hall.

SAE International. 2017. *Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles (J3016)*. Warrendale, PA: SAE International.

Schmidhuber, J. 2015. "Deep Learning in Neural Networks: An Overview." *Neural Networks* 61:85–117.

Schneider, A. 2015. "Reflexivity in Sustainability Accounting and Management: Transcending the Economic Focus of Corporate Sustainability." *Journal of Business Ethics* 127(3):525–36.

Schuhmacher, J., and Hummel, V. 2016. "Decentralized Control of Logistic Processes in Cyber-Physical Production Systems at the Example of ESB Logistics Learning Factory." *Procedia CIRP* 54:19–24.

Seuring, S., Sarkis, J., Müller, M., and Rao, P. 2008. "Sustainability and Supply Chain Management – An Introduction to the Special Issue." *Journal of Cleaner Production* 16:1545–51.

Sodhi, M.S. 2015. "Conceptualizing Social Responsibility in Operations Via Stakeholder Resource-Based View." *Production and Operations Management* 24(9):1375–89.

Sternberg, H., and Norrman, A. 2017. "The Physical Internet – Review, Analysis and Future Research Agenda." *International Journal of Physical Distribution & Logistics Management* 47 (8):736–62.

Sudarto, S., Takahashi, K., and Morikawa, K. 2017. "Efficient Flexible Long-Term Capacity Planning for Optimal Sustainability Dimensions Performance of Reverse Logistics Social Responsibility: A System Dynamics Approach." *International Journal of Production Economics* 184:179–92.

Torabi, S.A., Hassini, E., and Jeihoonian, M. 2015. "Fulfillment Source Allocation, Inventory Transshipment, and Customer Order Transfer in e-Tailing." *Transportation Research Part E: Logistics and Transportation Review* 79:128–44.

Tsuji, S., and Aburatani, H. 2015. "Deep Learning for the Large-Scale Cancer Data Analysis." *Cancer Research* 75(22 Suppl 2):B1-08.

Turing, A., Braithwaite, R., Jefferson, G., and Newman, M. 1952. "Can Automatic Calculation Machines be Said to Think?" In *The Essential Turing – Seminal Writings in Computing, Logic, Philosophy, Artificial Intelligence and Artificial Life*, edited by B.J. Copeland, 487–505. Oxford: Oxford University Press.

Tylor, P. 2016. "Data Mining for Vehicle Telemetry." *Applied Artificial Intelligence* 30(3):233–56.

Venkatesh, V., and Davis, F.D. 2000. "A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies." *Management Science* 46(2):186–204.

Verma, M., and Verter, V. 2010. "A Lead-Time Based Approach for Planning Rail–Truck Intermodal Transportation of Dangerous Goods." *European Journal of Operational Research* 202:696–706.

Wang, X., and Tang, L. 2017. "A Machine-Learning Based Memetic Algorithm for the Multi-Objective Permutation Flowshop Scheduling Problem." *Computers & Operations Research* 79:60–77.

Warnquist, H. 2016. “A Modeling Framework for Troubleshooting Automotive Systems.” *Applied Artificial Intelligence* 30(3):257–96.

Weyer, J., Fink, R.D., and Adelt, F. 2015. “Human-Machine Cooperation in Smart Cars: An Empirical Investigation of the Loss-of-Control Thesis.” *Safety Science* 72:199–208.

Wojtusiak, J., Warden, T., and Herzog, O. 2012. “Machine Learning in Agent-Based Stochastic Simulation: Inferential Theory and Evaluation in Transportation Logistics.” *Computers and Mathematics With Applications* 64:3658–65.

Wong, W.K., Leung, S.Y.S., Guo, Z.X., Zeng, X.H., and Mok, P.Y. 2012. “Intelligent Product Cross-Selling System With Radio Frequency Identification Technology for Retailing.” *International Journal of Production Economics* 135:308–19.

Zhang, S., Lee, C.K.M., Chan, H.K., Choy, K.L., and Zhang, W. 2014. “Swarm Intelligence Applied in Green Logistics: A Literature Review.” *Engineering Applications of Artificial Intelligence* 37:154–69.

Zhong, R.Y., Xu, C., Chen, C., and Huang, G.Q. 2017. “Big Data Analytics for Physical Internat-Based Intelligent Manufacturing Shop Floors.” *International Journal of Production Research* 55(9):2610–21.

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