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Automation and artificial intelligence in business logistics systems: human reactions and collaboration requirements

Matthias Klumpp [a,b]

[a]Department of Industrial Engineering and Business Information Systems (IEBIS), University of Twente, Enschede, The Netherlands; [b]Institute for Logistics and Service Management (ild), FOM University of Applied Sciences, Essen, Germany

ABSTRACT

Increasing application areas and depths of autonomous systems in logistics provide a new level of challenge for the analysis and design of human–machine interaction concepts. Due to scarce high-skilled personnel in several regions and the objectives of efficiency and sustainability improvement, logistics operators have to pursue technological progress like automation with all means. In order to distinguish between more or less performing human–artificial collaboration systems in logistics ex ante for investment decision purposes, a multi-dimensional conceptual framework is developed. A comprehensive case study regarding automated truck driving in logistics is provided in order to test the concept concerning practical implications. Results include the notion of four distinctive and increasing resistance levels before finally an efficient 'trusted' collaboration between human operators and artificial intelligence systems can be achieved. This is important for the design of many automated systems in logistics, among others for driving and piloting professions regarding autonomous driving supervision.

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Automation in logistics; trusted collaboration human–artificial performance analysis; acceptance model; autonomous driving; human–machine interaction

1. Introduction

In the past, design and implementation of logistics systems followed a *sequential model* regarding education and training: First, requirements were defined for example due to the implementation of new technology. Second, human capabilities and required competences were derived and trained if necessary (Chistopher, Peck, and Towill 2006; Cruijssen, Cools, and Dullaert 2007; Huang, Sheroan, and Keskar 2005; Zijm and Klumpp 2016). Therefore, education and training in logistics was discussed in many contexts as a crucial element but *without* a strategic veto role: Whether it be the evaluation of logistics partners (Aguezzoul 2014; Grimm, Hofstetter, and Sarkis 2014; Prakash and Barua 2015; Tavana et al. 2016), new technologies in logistics qualification (Liu and Wang 2015; Wu and Huang 2013) or the important role in such specific fields as e.g. humanitarian and disaster logistics (Bölsche, Klumpp, and Abidi 2013; Lijo, Ramesh, and Sridharan 2012; Santarelli et al. 2015; Sheu 2014; Van Wassenhove 2006). Several levels of education and training (vocational, academic, and continuing) usually are addressed matching a comprehensive supply chain (Hasanefendic, Heitor, and Horta 2015; Liu 2009; McDonald et al. 2015). In all these cases, it is stressed that education and training is an essential part – but as an element to be adjusted in a second step after a change of requirements e.g. due to new technologies, methods or processes.

CONTACT Matthias Klumpp matthias.klumpp@fom.de

However, in the future two major changes are prohibiting the continuation of this approach: (i) Due to rising competence requirements and shortage of highly skilled workforce personnel at least in some world regions and countries, easy availability of labour is not a given. Therefore, competition for talent also in the logistics sector is increasing, putting pressure on operational ('blue-collar') as well as management ('white-collar') occupations within global value chains (Gammelgaard and Larson 2001; Liu and Hu 2013; Nuzzolo and Comi 2014; Shi and Handfield 2012). (ii) Second, technology trends in logistics are important and aim for further automatisation on a new level (Craighead et al. 2007; Galceran et al. 2017; Meech and Parreira 2011; Ni and Hu 2017; Ohlson and Osvalder 2015; Pham and Jeon 2017) – usually requiring an increasing interaction with artificial intelligence applications (Manuj and Sahin 2011). One concept is the proposed 'Physical Internet' as depicted in Figure 1 as a vision for an integrated automated physical transportation network, including an indicative implementation timeline until 2050.

This implies that the question of successful human–artificial interaction has to be evaluated and tested ex ante, before logistics systems are implemented. Otherwise, the risk of huge failing investments is imminent as the human workforce cannot be educated and aligned *after the fact* of technology implementation anymore: Due to increasing investment volumes, implementation complexity and higher levels of competences required, training personnel after investing in e.g.

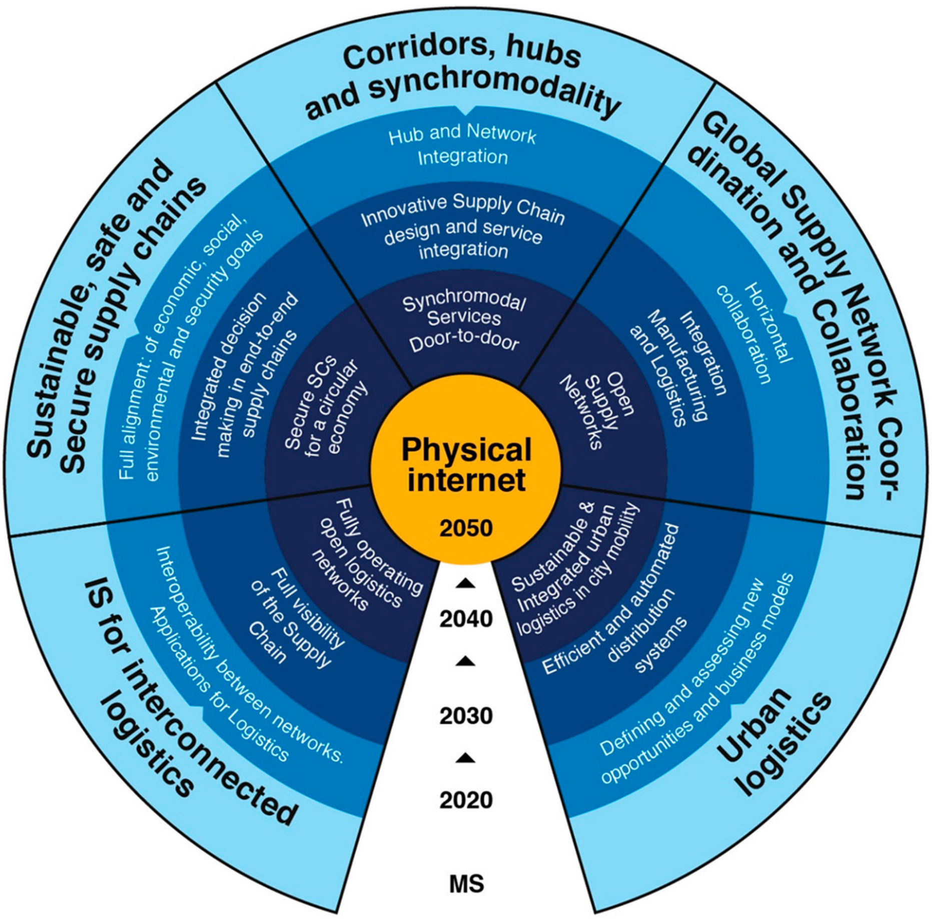

Figure 1. Physical Internet according to the European Technology Platform ALICE (ETP-ALICE 2017).

automated logistics systems will impose prohibitively long lead times onto the realisation process. The research question is therefore:

> RQ: What sort of framework concept can allow for an ex ante analysis of human–artificial collaboration in logistics in order to prevent investment failure e.g. by education and training measures?

The contribution is structured as follows: Section 2 provides a timeline for the development of logistics automation, intertwined with education and competence requirements and concepts in supply chain systems and functions. Section 3 describes an analytical approach regarding the performance of human–artificial collaboration in logistics systems, whereas Section 4 offers a case study for the field of truck driving, supplementing a proof of concept for the theory concept from Section 3 as well as an extensive discussion regarding implications for business logistics. Section 5 finally outlines some conclusions and interesting future research questions.

2. Logistics automation trends and training requirements

Three major trends with important impacts towards education and training have dominated logistics and supply chain management in the last three decades:

(i) First, the overall integration and optimization of increasingly global supply chains has occupied logistics research (Bernal, Burr, and Johnsen 2002; Bolumole 2001; Chae 2009; Dong and Chen 2005; Forslund and Jonsson 2007; Lee and Cavusgil 2006; Simatupang and Sridharan 2005; Soosay, Hyland, and Ferrer 2008; Stevens 1989; Verstrepen et al. 2009; Yao and Chu 2008).

(ii) Second, the struggle for agile, flexible, and resilient supply chains was experienced in research and business practice in order to mitigate risk and volatility of global market impacts and increasingly demanding customers, e.g. with e-commerce (Canbolat et al. 2008; Glickman and White 2006; Hendricks and Singhal 2005; Manuj and Mentzer 2008; Torabi, Hassini, and Jeihoonian 2015).

(iii) And third, the requirement of sustainable logistics and supply chain operations took hold (Asgari et al. 2015; Bloemhof et al. 2015; Carter and Rogers 2008; Quak and De Koster 2007; Sharma et al. 2010; Walker and Brammer 2009).

Altogether, these trends led to an increase in complexity and competence requirements (Fawcett, Vellenga, and Truitt 1995; McKinnon 2013). This is due to the fact that higher complexities, international connections (cultural and language competencies) and technology applications require in general higher levels of competencies with the human workforce. At the same time, the requirements rise faster than humans can be trained in each generation of workers. This constitutes a *knowledge accumulation gap* as explained in Figure 2.

When considering a timescale (x-axis), starting at the time of the industrial revolution (point A) the *expected and required workforce competence level* started to increase on average due to increased technology development and implementation (line in black). For logistics processes, it can be argued that this ongoing process has at least two dimensions: First, existing activities such as truck driving, warehouse processes or production processes demand increasing competence levels. This is for example demonstrated by new legal regulations for mandatory further training of truck drivers regarding safety, sustainability, hazardous goods, and technology usage. This dimension can be labelled a competence *enrichment* of existing processes. Second, competence *enlargement* happens as new activities arise in logistics and global supply chains: These are typically requiring a high competence level such as IT systems management, logistics consulting, logistics and supply chain finance, logistics tender management or logistics controlling.

Between ever-increasing expectations and requirements and real human competence levels a ‘gap’ is developing as required training for humans has for each and every person to start anew – learning cannot be automated for human workers: Longer education and training programmes are needed in

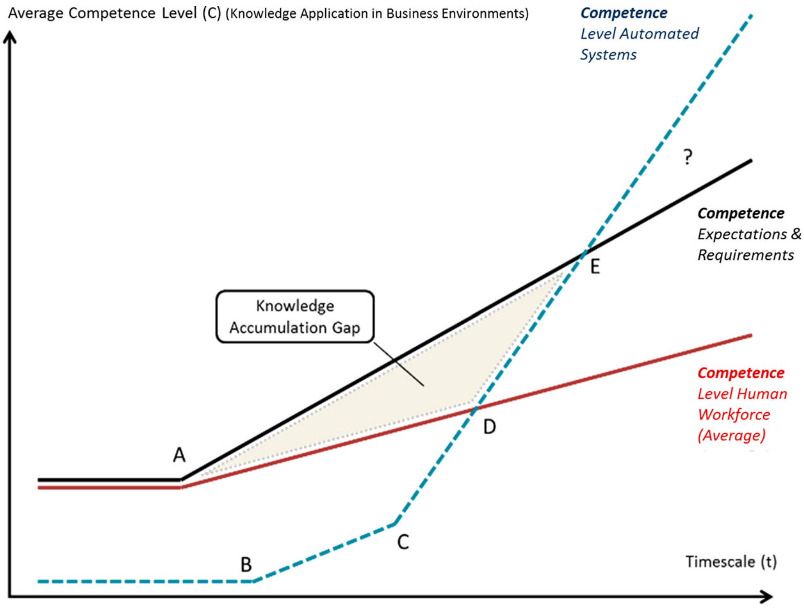

Figure 2. Competence requirements and provisions in logistics (Zijm and Klumpp 2016, 15).

order to arrive at required higher competence levels for a modern-day logistics and business environment. This constitutes a *knowledge accumulation gap* (grey field in Figure 2) that arises due to the fact that humans are *not* able to accumulate knowledge over generations – as opposed to machines and computers which are able to do so.

In addition to human competence levels, automated or machine (non-human) competence levels (dotted line) have an important impact on technology and business development. Though artificial intelligence (AI) in the beginning possessed only simple competences starting in the sixties, seventies and eighties of the twentieth century, development has nowadays significantly accelerated in solution contribution width and depth (Hassabis 2017), e.g. detecting cancer in medicine (Leachman and Merlino 2017; Van der Waal 2017) or enabling autonomous flight (Huang et al. 2016). This is connected to the trend of *deep learning*, allowing computers autonomously to acquire new knowledge and to find directions of further learning themselves (LeCun, Bengio, and Hinton 2015; Schmidhuber 2015; Tsuji and Aburatani 2015). As depicted by point B in Figure 2, automated systems were initially very slowly adopted. Examples in logistics include the automated gearbox for trucks, partly automated cranes and warehouse equipment as well as automated communication and transmission devices in logistics management (EDI systems, automated decision protocols). These limited systems never really matched human competence levels as these systems were isolated – which is why the dotted line traverses significantly below average human competence levels between the points B and C. In recent years however – symbolised by point C – automated systems have undergone a major change, characterised by a *merging* of separate systems. Such systems are now increasingly coupled and begin to interact (Barrat 2013), especially by being linked to the internet and joint information and learning resources or GPS systems for navigation in transportation applications (Bravo, Parra, and Pereira 2017; Dalumpines and Scott 2017). For example, state-of-the-art *automated warehouses* are integrated systems of software (warehouse management systems), hardware (moving goods) and even optimization (error analysis, automated storage optimization, learning and prognosis with e.g. predictive analytics). This integration increases the capability of such systems and allows also for self-steered innovation and learning.

In some cases, artificial intelligence and automated systems are already *overtaking* human competence levels (point D): Regarding truck driving for example, the combination of the old automated gearbox with GPS-based navigation systems allows trucks to actually efficiently downshift before a steep slope of an oncoming mountain street is even visible to the human driver (Hoijati-Emami, Dhillon, and Jenab 2012; Yoshida, Sugimachi, and Fukai 2011). This form of foresight and decision as well as action is a new capability of automated systems which has reached new levels in automated passenger car driving experiments (Koo et al. 2015).

Implication areas traversing point D can only be hypothesised: It could be imagined that a future point E lies ahead where automated systems even *exceed expectations* of society and business as defined by humans. This may entail risks, as unforeseen behaviour of automated systems may worry humans. However, risks and opportunities are usually embedded in any development, the core question is how they are used and which rules and limitations apply. Just for a hypothetical example outline, some applications and developments are listed for the area beyond point E, indicated with a question mark in Figure 2:

- Automated trucks may communicate with other trucks on the road in order to allow priority passage for cargo trucks behind their time and delivery schedule. This especially may not be understood by individual drivers lacking the 'overall picture' of a larger number of vehicles, positions and supply chain demands.
- AI applications in supply management may re-schedule the production sequence as specific supply items are running late for inbound arrival at production sites, e.g. due to distant traffic jams or other operational transportation hurdles.
- Automated manufacturing systems could suggest improved working rhythms or movements to their human co-workers as they have access to databases of benchmarking pictures or communications with other production support applications ('real-time benchmarking and ubiquitous learning').
- With automated warehouse systems, specific products may be released from stock as information from distant places with other supply chain partners regarding e.g. increasing end-customer sales or production demands are received real-time. This would also incorporate an advanced level of bullwhip effect mitigation in supply chains.

In the light of such developments in logistics, there will be huge changes necessary and qualification and training schemes in technology implementation have to be evaluated anew: In the past, often a *sequential model* was implemented. This model of technology development first, then followed by implementation and finally training of human workers has a clear structure and also a successful risk avoidance mechanism – workers were only trained for technologies already developed and implemented. However, current models use a *parallel approach* for at least part of the timeline, regarding implementation and training experiences as essential input for further technology development (user involvement in research and development). In the future, it can be surmised that in an environment of automated blue- and white-collar work in logistics, the innovation process may even take place *without* any large-scale human training. In such systems, human roles may be limited to technology development and general oversight. Artificial intelligence and robotics appliances may take over the innovation process completely by introducing new manufacturing, transportation and management decision concepts without detailed human training. Such a scenario implicates that technology development and implementation are two *intertwined and parallel* processes – as already applied to smartphone applications (Königs and Gijselaers 2015; Neubeck et al. 2015; Zia et al. 2016). This leads to the core question of how human workers and artificial intelligence applications collaborate in such new environments, addressed in the following section.

3. Analytical model for human–artificial collaboration

3.1. Acceptance and resistance

Human interaction towards artificial intelligence applications and automation (Kolbjørnsrud, Amico, and Thomas 2017; Lee et al. 2014; Nicolescu 2017) can be characterised by three hurdles or areas of resistance. Once an area is overcome, usually acceptance settles in. This can be outlined as described in Figure 3.

The three identifiable hurdles are connected to three increasing AI functional areas and develop an increasing level of resistance throughout this development in line with an increasing level of personal intrusion (x axis):

- AI *Competences*: 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 are comparatively less frightening and therefore the resistance level towards 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 intra-logistics applications systems like picking and warehouse transportation systems. These systems have in common that usually any final decision, e.g. regarding the travelled street in reality is still taken by humans. In many cases, AI suggestions for example from navigation systems are not followed through by humans, an obvious sign of resistance (or real and assumed 'better knowledge').
- AI *Decisions*: Furthermore, AI applications are suggesting and applying single decisions, which usually rises greater anxiety and resistance levels with humans. This happens for example in *cruise control* applications in cars and trucks, maintaining constant speed or constant distance to a leading vehicle (Alam et al. 2015). In such cases, the automated device is taking a row of decisions within a limited area of action (e.g. vehicle speed, vehicle gear). Such developments have already happened in the past for example for car and truck motor management (increasingly automated) or in the leisure area for smartphone and social media applications. In these cases, humans are accepting automated applications without major security or fraud mistrust, at least not on a day-to-day basis (only incident-based e.g. with data fraud scandals or leaks). Understandably,

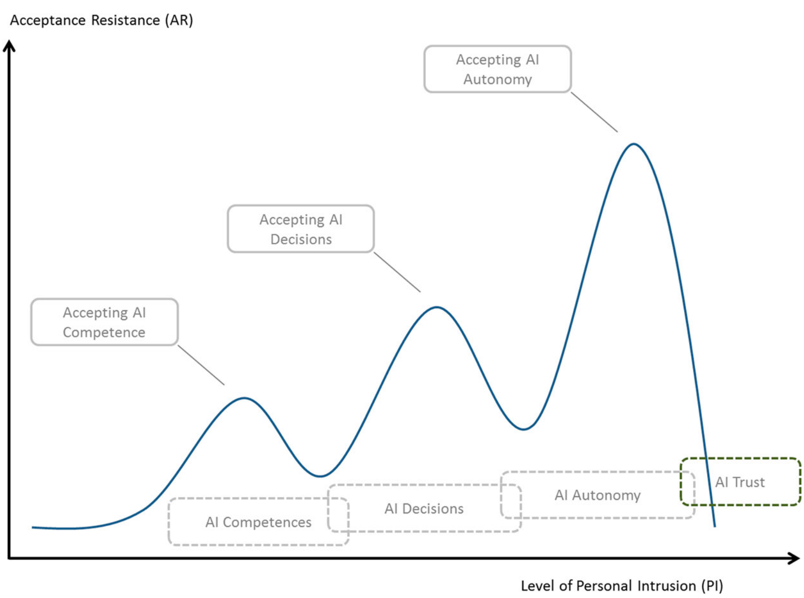

Figure 3. Human acceptance resistance model for AI applications (author's creation).

this sort of AI application is rising higher levels of rejection among humans, usually also requiring a longer period of adaption before acceptance can settle in (Weyer, Fink, and Adelt 2015).

- AI *Autonomy*: Finally, AI applications are taking a *multitude of different decisions*, leading to autonomous behaviour as for example in actively steering cars and trucks for longer periods and with interaction towards other participants in road traffic. In these cases, humans usually take over a passive supervising role (Rauffet et al. 2015). These applications are at the doorstep to industrial and real-world applications, in production (autonomously moving robots with human interaction), traffic (autonomous cars and trucks) and health care (surgery, robotics).

These levels or hurdles can be seen as a sequentially increasing level of *personal intrusion* (*x*-axis), arriving at a completely new situation *after* the three hurdle areas: The situation of *trust towards an AI application*, where humans are inclined to actively and trustfully collaborate with automated applications. This is linked to the famous 'Turing test', where in the positive case humans are not able to distinguish between human or artificial counterparts for their communication (Harnad 1992; Saygin, Cicekli, and Akman 2000; Turing et al. 1952). In the original BBC interview from 1952 Turing formulated as follows:

> In about fifty years' time it will be possible to programme computers … to make them play the imitation game so well that an average interrogator will not have more than 70% chance of making the right identification after five minutes of questioning. (Turing et al. 1952, 489)

The proposed 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 towards an AI application if perceptive evaluation will judge the application to behave and communicate like a human being.

3.2. Analysis application matrix

The resulting four areas of AI application development can be combined with four areas of human *impact*, arriving at an analytical four-by-four-matrix determining *ex ante* possible human rejection levels towards AI applications. This stems from the fact that not all areas of AI applications are evaluated the same by human beings (see Figure 4).

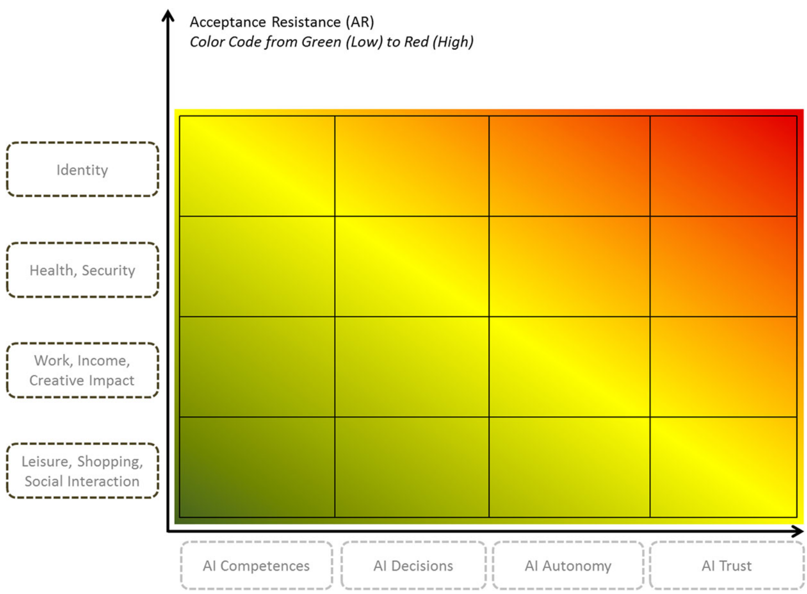

Figure 4. Human acceptance resistance matrix (author's creation).

On the horizontal *x*-axis, Figure 4 presents the aforementioned four development areas for AI applications. Additionally, the perceived level of human acceptance resistance on the vertical *y*-axis is based on the human self-concept regarding self-maintenance, self-autonomy and self-identity:

- On a low level of impact and possible rejection, all leisure, shopping and social interaction applications can be placed. This is a 'trial-and-care-free' arena in the human self-perception (as also socially accepted loss of self-control with e.g. alcohol, sports games and other areas). Therefore, AI applications are understood to be enlarging the human experience, e.g. by using automated social media and shopping proposals. In these areas, humans are actively accepting AI applications without larger resistance attempts, as this does not pierce their self-evaluated personal core (Hoff and Bashir 2015).
- Second, AI applications in the field of work and income are slightly more concerning for humans. Whereas AI competences as support and case-to-case help may be accepted easily, AI decision and autonomy applications are seen more critically. This mainly comes with the much-discussed notion of AI applications 'putting jobs at risk': Since the 200-year-old Luddite movement, critical positions towards technology applications are potentially work- and job-replacing for humans have been voiced and discussed (Autor, Levy, and Murnane 2003; Fox 2002; Jones 2006). Therefore, this can be evaluated as a deep and emotional resistance towards AI applications addressing human work tasks and income potentials.
- Third, AI applications in the area of human health and security are seen even more sceptical. This relates to applications regarding surgery and personal security systems and features, e.g. access control and denial (Nicolescou 2017).
- Finally, a virtual 'no go area' exists in the field of AI applications entering the self-identity of humans. This concerns actions and decisions attached to the very self-concept of humans, e.g. from the actual dressing (clothes) to the choice of education and profession or children and leisure activities. If such actions and decisions may be taken by AI applications (hard to imagine but already described in Huxley's *Brave New World* with automated reproduction decisions), the expected reactions by humans may be very hostile and rejecting.

The outlined matrix provides a very general but also instructive evaluation scheme for AI applications. This is further elaborated with the subsequent case study addressing the logistics application of automated truck driving in order to outline a 'proof of concept'.

4. Case study truck driving

4.1. Background and data

Road transportation is the backbone of modern logistics, providing an unrivalled level of flexibility, efficiency and door-to-door-access. This is reflected in the large shares of modal split in cargo transportation for the road sector: Depending on country characteristics, large shares of cargo transportation are implemented by trucks – for example 50.0% in Switzerland, 64.7% in Germany and 95.0% in Spain (2015 in inland freight tonne-km shares, Eurostat 2017). Moreover, usually multi-modal transport chains rely on the road sector for first- or last-mile delivery, e.g. combined with rail, ship or plane transportation on the main haul section of transportation.

Academic research has also contributed hugely to this important part of transportation and logistics: Dedicated topics are for example optimization (Dondo and Cerdá 2015; Gingerich, Maoh, and Anderson 2016; Phan and Kim 2015), inter-modal cooperation (Nossack and Pesch 2013; Verma and Verter 2010), safety and security (Chen et al. 2015; Pahukula, Hernandez, and Unnikrishnan 2015; Pattinson and Thompson 2014) as well as sustainability and alternative propulsion systems (Fors, Kircher, and Ahlström 2015; Zhu et al. 2014) of truck transportation. Truck driving also is a large section of logistics-related professions: for example, in the US there were 3,105,980 truck drivers as of May 2016 (Bureau of Labor Statistics 2017) and within Europe, e.g. in Germany more than 800,000 people are working in this field. Therein a demographic challenge is increasingly obvious: 26.5% of all truck drivers in Germany are more than 55 years old and are therefore expected to retire in the next decade (Statista 2017). This implies that there is pressure for logistics companies to deal with automatisation and increased incentives for young personnel for example via technology implementation (Shankwitz 2017; Sullman, Stephens, and Pajo 2017). This leads to the question addressed in the following section regarding the motivation circumstances of drivers.

4.2. Motivation modelling for truck driving

In order to provide an insight into the motivational structure of truck drivers, data from Germany is presented: From a 2014/2015, empirical survey among 469 truck drivers a factor analysis model regarding motivation factors is developed. This is connected for example to these existing studies: Nowakowski, Shladover, and Tan (2015) from the USA find that during a long historic development of automation features in heavy/commercial truck fleets and available training facilities to professional truck drivers, application areas as well as design concepts for automated driving application for trucks may differ significantly from car passenger applications (e.g. 2951). Kalra and Paddock (2016) document that extensive reliability testing is required in order to establish human trust towards automated driving applications in cars as well as trucks (189). Finally, Bazilinskyy and de Winter (2017) posit that even a situation-by-situation decision background has to be taken into account for automated driving: Drivers may be inclined to use automated steering support in some situations – but not in others e.g. with very heavy traffic (62).

For this survey, two data requisition approaches were implemented: for half of the respondents, a random sample of truck transportation companies from the largest German state of Northrhine-Westfalia was drawn and invited to the survey by surface mail letter and subsequent visits from interviewers with written questionnaires. For the other half of the sample, also within the German state of Northrhine-Westfalia, all vocational training schools for truck drivers were invited by telephone to take part in the survey. If willing, interviewers visited the schools and their classes on site and distributed written questionnaires. Altogether the representative characteristics of the 469 respondents (age, gender) provide a good match with the overall truck driver population in Germany.

Based on the empirical findings in the survey (Klumpp et al. 2014), two new regression models for dependent variables were developed: one regarding the dependent factor of recommendation for the truck drivers job towards others (Figure 5); and another regarding the dependent factor if drivers assume that they will be able to continue their job until retirement under the current working conditions (Figure 6). Both dependent factors are a representation of the truck drivers work motivation – and in each case, three statistically significant independent and influencing factors were identified from all variables within the survey. For example, motivational connections between the dependent factors and the survey item 'pay increase' were not detected, though ceteris paribus usually pay questions are of importance to truck drivers (Belman and Monaco 2001; Lamere et al. 1996; Min and Emam 2003).

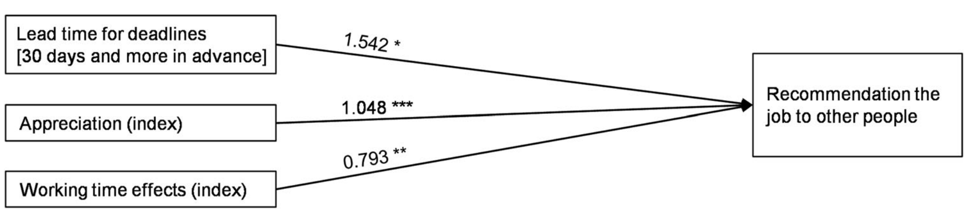

Figure 5. Regression factor model for truck driver motivation/recommendation.

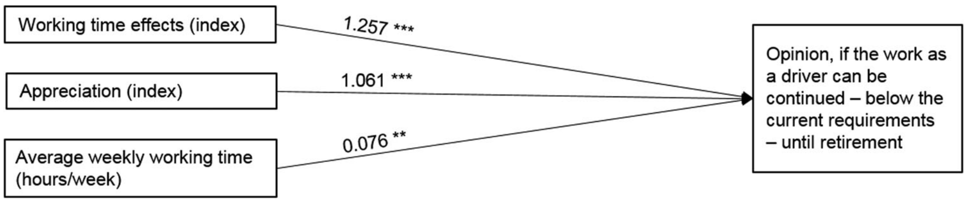

Figure 6. Regression factor model for truck driver motivation/working until retirement.

For the dependent variable recommendation of their job, the three input variables 'lead time for deadlines', 'appreciation' and 'working time effects' were identified, the latter two being index variables from a group of related cluster variables in the questionnaire (e.g. requesting appreciation evaluations separately from customers, fellow workers and traffic participants). Especially, the factor of *appreciation* highlights the specific motivation, interaction and collaboration role in the truck driver domain.

For the dependent variable continuation of the driver's job until retirement, the three input variables 'working time effects', 'appreciation' and 'average working time' were identified by the regression model. Again, workload and conditions (time schedule) as well as appreciations from managers, customers, fellow workers, and traffic participants are important for drivers. This could lead to the proposition that positive human–artificial collaboration may even be easier if AI application learn to *accolade and praise human co-workers* in any form in order to show some appreciation for their input. This could be implemented for example within voice communication between drivers and Ai applications (Baldwin 2011; He et al. 2017; Nasirian, Ahmadian, and Lee 2017; Parasuraman, Sheridan, and Wickens 2000).

4.3. Technology developments and applications in truck driving

Automated driving for cars and trucks is on the threshold of general application. This is because on the one hand an increased number of sensors is employed in vehicles (infrared, radar, laser, lidar, visual cameras, etc., Cheng 2011; Naranjo et al. 2007). On the other hand, increasingly former independent systems are connected and cooperating in order to perform self-sufficiency in driving. For example, the cruise control system was known for many years in trucks and cars, maintaining a constant pre-set speed for the vehicle. This is now coupled with further intelligent applications, e.g. with GPS navigation and the automated gearbox, allowing vehicles to deploy dynamic cruise control.

This has three sub-level steps, already implemented in the truck business (Schakel, van Arem, and Netten 2010):

- In the first generation of cruise control applications, the system steadily maintained a constant, pre-set speed level. This was only managing the gas/propulsion system of the truck or car.
- Second, the system was able to follow a preceding vehicle with a pre-set distance length, therefore already combining the management of gas and brake in the vehicle.
- Third and available today is a cruise control systems to anticipate the route characteristics by GPS positioning in combination with map material. This allows the system e.g. to decelerate before downhill passages or accelerate and downshift before uphill road segments. This combines gas, brake, gear and GPS navigation capabilities of the system. The driver is furthermore only steering the truck direction along the road and supervising the system in total (Marsden, McDonald, and Brackstone 2001).

Currently, this leads to the further step of 'platooning' where trucks form automated chains or trains out of several independent vehicles in order to travel long distances in an efficient mode (e.g. saving fuel and also allowing following drivers to take rest with auto-pilots engaged, Alam et al. 2015; Bergenheim, Shladover, and Coelingh 2012).

This is a significant development on the pathway towards automated vehicle driving as described also for cars. Finally, this will lead to automated road transportation with the existing truck driver playing only a supervisory role – though according to many regulatory demands and authorities, a human person will be on board at least in public traffic environments (first and last mile) for the foreseeable future. This allows the observation that in the future humans will not be employed for their 'know-how' but their 'know-why'. The competence to actively gear and steer, e.g. the truck will be implemented by a technology application – whereas the driver is supposed to understand the *know-why* of all systems and especially *when* to interrupt the automated system (therefore also: 'know-when').

4.4. Model analysis regarding human–artificial performance

In order to develop *operational strategies* coping with AI applications in logistics (Bostrom 2014), the proposed analytical matrix is applied to this specific question of truck driving. The following deductions are feasible as described in Figure 7:

- Known applications in the fields of leisure and social interaction as e.g. web 2.0 applications (social media) in general and especially logistics applications as for example automated picking systems and the automated gearbox in trucks are met with very low resistance or even enthusiasm as humans are deeming the isolated AI competence as not very much frightening.
- But in the second area of cruise control applications in truck driving as described above, the resistance level may rise to a higher, medium level. It will also be necessary to train drivers using such cruise control systems (level 3 with GPS application) in order for them to be able to understand the system. This is mainly directed at their necessary competence to recognise failures in the system and possible dangers from the AI application. This could for example be the fact that lower gears are used for braking effects on downhill sections: an AI application may shift up in order to save fuel but endanger the truck in terms of insufficient braking power downhill.

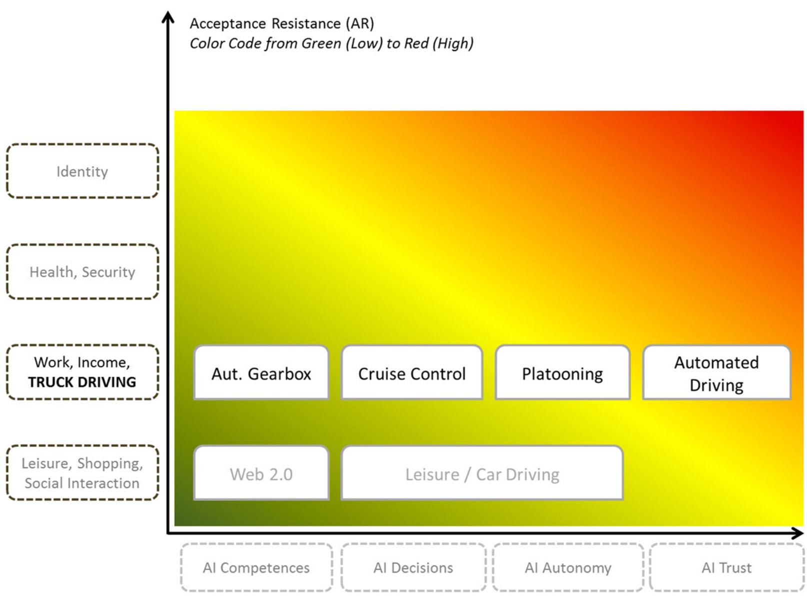

Figure 7. Human acceptance resistance matrix for truck driving (author's creation).

- Third, platooning systems as described will require even more education and training as drivers will have to 'fight' their emotional responses and 'gut feelings' regarding leaving control of the truck to an AI application for long distances. Therefore, such systems will not be available and usable to inexperienced and untrained drivers, for their own as well as other traffic participants' safety.
- Fourth, fully automated driving systems in trucks in the future may be met with an even higher level of resistance. And the training and competence level of truck drivers for such systems will have to be enhanced significantly in order to overcome this resistance and use the drivers' time efficiently during supervising the automated steering sections (e.g. on motorways). A comparison with plane pilots may be adequate as with introducing automated flight systems in the past it was not the case that pilots were abolished, but their time was necessarily used more efficiently (e.g. for planning and administrative tasks). And their training had to increase, not decrease. Therefore, though resistance may occur, the already aired fears for huge job losses may not be that imminent. But qualification and training will be an important issue in the future for truck drivers than today.

4.5. Implications for logistics

The outlined acceptance model in the case of automated truck driving could be continued towards further implications for logistics processes and operations, e.g. with the following items:

- With automated trucks, personal attention and competencies of truck drivers will shift from operational questions (steering, speed, gear and route) towards *supervision* and also security and planning processes. This will allow for additional activities to be carried out during driving and may even compete with office administration jobs. This is of major importance as currently especially consultant studies and prognoses (e.g. Balakrishnan 2017; Center for Global Policy Solutions 2017, 32; Hook 2017) mainly talk about driver jobs to be lost – but in the opposite, possibly a *loss of administration jobs* will occur as drivers will always be required in the driver's seat for safety supervision reasons (Kianfar, Falcone, and Fredriksson 2013; Kritayakirana and Gerdes 2012; Rodriguez-Castano, Heredia, and Ollero 2016; Urciuoli and Hintsa 2017) and will take over administration tasks en route in their vehicles. This might lead to an evolution in the driver job market, leading to a situation where 'piloting trucks (…) might eventually evolve into a white-collar profession actively sought after by college graduates' (Ford 2017). A downside may be that sleepiness risks may increase due to 'dull' supervision similarly to the situation of aeroplane pilots – as well as the adverse effect of long-term competence loss (Anund, Fors, and Ahlstrom 2017; Bainbridge 1983; Brown et al. 2017; Childress et al. 2015; Dawson, Searle, and Paterson 2014).
- Acceptance of drivers towards automated systems will therefore play an important role for the competitiveness of road transportation companies from several perspectives: First, if the driver allows the AI application to do its job based on a *trusted collaboration* (see Hoff and Bashir 2015; Muir 1987; Rezvani et al. 2016; Verberne, Ham, and Midden 2012), this will be more efficient and cost-saving than the human driver alone (saving fuel, reducing travelled distance and reducing truck wear). Second, as drivers may assume administrative tasks and processes instead of driving while travelling, this may save costs at other places (e.g. administrative processes) or even enhance customer-perceived quality and service: this could encompass the driver calling ahead and communicating with addressees of shipments as well as exploring future tasks with those customers. Third, driving personnel may also be more effective and efficient due to a motivation boost within an AI application scenario: truck driving may be seen in the future as a 'technology job' (Ford 2017).
- The third important item is the question of how to introduce new human–artificial collaboration systems in logistics ('revolution or evolution'). It can be expected that similarly to the road vehicle

fleet with an oncoming multitude of propulsion systems ahead (diesel and CNG/LNG, hybrid, hydrogen, electric – see Gao et al. 2015; Shahraeeni et al. 2015), the *complexity* of different systems in logistics operations existing in parallel will 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 a truck fleet for example. This case is concurrently largely neglected by research; instead the analysis focus is on 'on-road interaction' between autonomous and human drivers. But this is also important within corporations, truck fleets and supply chains, e.g. in cases where due to technical failures, human drivers with their 'old-fashioned' trucks have to replace trips scheduled originally for autonomous trucks. This will be a new challenge for routing and fleet management in logistics operations.
- And finally there is also a general preparation and communication task ahead for the logistics industry: In line with an implementation of automated trucks, many *interaction and acceptance questions* within the traffic system (towards car drivers, see Levin and Boyles 2016; Talebpour and Mahmassani 2016; Wietholt and Harding 2016), the economic system and the legal system (responsibility and damage claim questions, see Rao 2016, 20) will be encountered. Therefore, logistics research and business practice has to prepare for such comprehensive implementation and communication strategies in order to earn the full advantages possible with automated truck driving (Fagnant and Kockelman 2015).

Further inquiries into human–artificial collaboration will be necessary for business applications at large as a large amount of investments in AI applications in logistics and operations management can be expected.

5. Conclusions

By outlining analytical approaches and trends in human–artificial collaboration in logistics systems, this contribution has identified three major issues: (a) The apprehension and resistance of humans towards artificial intelligence applications – e.g. in logistics – has many sources (Armstrong 2014) and can be categorised in at least four development areas. (b) This is largely influencing the performance of human–artificial corporation at the workplace as was outlined with the case study example regarding automated truck driving, leading to adaption as well as to persisting rejection patterns depending on the area of AI application. (c) In order to cope with human–artificial collaboration in logistics in general and *ex ante* investment decisions specifically, a structuring and evaluation matrix was proposed and tested based on the four levels of acceptance, resistance and impact areas for the human workforce. This helps to evaluate human–artificial collaboration in logistics systems *in advance* and therefore support decisions avoiding lost investments for example by increasing information, testing and training for human workers when a rejection hurdle is identified (Koo et al. 2015).

Further research is necessary and interesting along the lines of the following possible research questions: (i) How can the outlined acceptance and resistance hurdles possibly be lowered by information and training or experience on the side of the human collaboration partners? (ii) Are there distinctive communication and presentation variables on the artificial side of the collaboration which can be used to lower resistance (e.g. design and speech variation of automated applications as female navigation system voice tones, comparable insights, see Bazilinskyy and de Winter 2015; Baldwin 2011; Parasuraman, Sheridan, and Wickens 2000)? (iii) How can a break-even analysis for logistics systems investments be designed based on the outlined findings in order to distinguish operational areas with a potentially higher business value in logistics compared to others (e.g. driving or picking; planning or deviation management)?

Further research questions will also arise from further technological development such as in deep learning (Graf et al. 2014; Kuhnt et al. 2016) or in further integrating the human–artificial collaboration (e.g. by thought connection and control, Zander et al. 2017). Altogether, the future competitiveness of logistics systems will largely depend on the described factors regarding human–artificial collaboration and acceptance. Therefore, a high level of interest in both research and business practice is necessary and legitimate for this field, including interdisciplinary approaches from several science and application disciplines.

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ORCID

Matthias Klumpp http://orcid.org/0000-0002-7543-2751

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