

Relative Strengths of Teachers and Smart Machines: Towards an Augmented Task Sharing

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Abstract: In education, smart machines (e.g., chatbots or social robots) have the potential to support teachers in the classroom in order to improve the quality of teaching. From a teacher's point of view, smart machines also pose a challenge because the presence of smart machines in the classroom questions traditional teacher and student roles. This paper presents a theoretical basis for the use of smart machines in education. It describes the relative strengths of teachers and smart machines and presents them in a framework, which makes a proposal for an augmented task sharing. In light of human augmentation, the framework proposes ways in which teachers can position themselves with regard to smart machines in a complementary and mutually reinforcing way. It also has implications for knowledge that is necessary for teachers to play an active role in the digital transformation.

1 INTRODUCTION

The society, economy, and the labor market are on the threshold of a major transition phase. Widely used labels for this phase are: The fourth industrial revolution (Braga et al., 2019), the second machine age (Brynjolfsson & McAfee, 2014), the second wave of digitalization (Wahlster, 2017), artificial intelligence (AI) revolution (Makridakis, 2017), and globotics (globalization and robotics) (Baldwin, 2020). Technological developments in robotics combined with machine learning and AI underscore the importance of a better understanding of the human-machine relationship, as humans and machines may become partners in learning and problem solving (Brynjolfsson & McAfee, 2014; Jarrahi, 2018). Humans and smart machines engage in task sharing and combine their individual strengths.

These technological developments also have an influence on classrooms. Teachers become increasingly part of a digital classroom ecosystem. Such smart classrooms are equipped with tools that facilitate the transfer of knowledge (e.g., by means of more efficient communication or automated assessment/feedback), with the goal to enhance the teaching and learning experience (Saini & Goel, 2019, pp. 1-2).

As part of a digital classroom ecosystem, a *smart machine* can be defined as a cognitive computer system that can, to a certain extent, make decisions and solve problems without the help of a human being (Pereira, 2019). This is achieved by advanced technology (e.g., AI, machine learning), which enables the machine to process a large amount of data and make decisions based on these data.

Chatbots (e.g., Apple's Siri) or social robots can be regarded as important manifestation of smart machines, provided that these smart machines are capable of learning from the environment and build on capabilities based on that knowledge (Pereira, 2019).

Smart machines are increasingly used in everyday life due to advances in sensor and actuator technology. During the last ten years, the use of smart machines has been increasingly extended to the field of education, starting with the use as an aid in STEM education (Belpaeme et al., 2018). "Socially conscious" robots interact for example with children in language learning classes (Van den Berghe, Verhagen, Oudgenoeg-Paz, van der Ven & Leseman, 2019). According to Reich-Stiebert, Eyssel and Hohnemann (2019, p. 5) such robots can be used as assistants to teachers or personal tutors for students: "provide information on specific topics, query

learned lessons, give advice to the learning process, correct errors, or provide feedback on students' progress" (Reich-Stiebert et al., 2019, p.5).

Unlike the digital classroom ecosystem (e.g., projectors, cameras, interactive white boards), smart machines are perceived as more than just a tool. Due to their nature, they act as *someone* (personality) and not as *something* (tool).

A teacher has many different tasks to perform. These are for example to plan lessons, to teach, to coach, to create assignment and homeworks, to conduct and correct exams, to manage the classroom, and to activate students.

From a teacher's point of view, the additional presence of a smart machine could be beneficial as the smart machine can engage in task sharing and take over selected duties of the teacher. However, smart machines (respectively the inherent technology of AI) have also the potential to replace white-collar jobs (see e.g. Baldwin 2020, p. 9). Hence, the smart machine could also be perceived as a threat, because the presence of the smart machine in the classroom challenges the traditional role of teachers and students.

At the moment, there is a gap between the available technological capabilities and their utilization for educational purposes (Luan et. al., 2020, p. 3). Even though the education industry has developed various AI applications, they may not be guided by theoretical frameworks and research findings from psychology of learning and teaching (Luan et. al., 2020, p. 3). There seems to be a disparity between the technology readiness and its application in education (Macfadyen, 2017).

To tackle this issue, it might be important to gain a better understanding of the relative strengths of teachers and smart machines. Afterwards, based on the theory of comparative advantages (Ricardo, 1891; Ruffin, 2002; Landsburg, n.d.), ways could be pointed out in which teachers can position themselves in relation to smart machines in a complementary and mutually reinforcing way.

In light of the identified research desideratum, the following research questions should be addressed:

- *What are the relative strengths of teachers and smart machines within the classroom?*
- *How can both parties engage in an augmented, mutually reinforcing way of task sharing?*

The objectives of the paper at hand are therefore twofold:

- Elaboration of the theoretical foundations for the use of smart machines in education, in order to investigate underlying assumptions, goals,

methods, and empirical results for the design and evaluation of teaching;

- Development of a conceptual framework from the teacher's perspective on augmentation strategies of teachers in relation to smart machines.

From a theoretical point of view, our conceptual framework can serve as starting point for future empirical research, as it highlights important concepts and variables related to the relative strengths of teachers and smart machines.

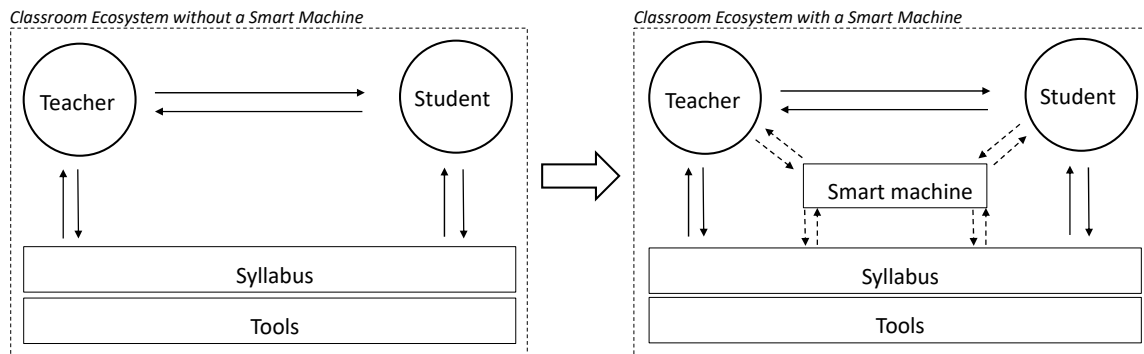
From a practical standpoint, our conceptual framework might be useful for designing use cases; it could serve as a guideline in the implementation process of new technologies. Overall, the conceptual framework at hand might act as a stepping stone for coming researchers who might uncover further potential of the technology in more detail, e.g., how to ensure a smooth adoption of social robots, as a concrete manifestation of smart machines, in education.

To this end, we lay the foundation for our framework in section 2 and 3. Since comparative advantages of smart machines may depend on the environment and context of use, we will point out the relationship of smart machine and the digital classroom ecosystem in section 2. Section 3 discusses relative-strength profiles of teachers and smart machines based on the theory of comparative advantages and evaluates them with regard to specific teaching tasks. Section 4 lays out our own extended framework, and section 5 concludes with some final remarks.

2 SMART MACHINES AS PART OF A CLASSROOM ECOSYSTEM

According to Floridi (2016), we are in transition to a new era in which we will become increasingly dependent from our own technical achievements. ICT is not only used to record and transmit data, but also to process it more and more autonomously.

Floridi (2013, pp. 6-7) coined the term "infosphere", i.e., an information environment comparable to, but different from, cyber space, which is becoming increasingly blurred with our everyday life. The infosphere is constituted by all informational entities (biological as well as digital agents/smart artifacts). A digital classroom ecosystem can also be seen as such a form of an infosphere and is often referred to as smart classroom (see e.g., Saini & Goel, 2019).



Source: Based on Lehmann & Rossi (2019, p. 36) and own contributions.

Figure 1: Changes in interaction due to smart machines.

Biological agents (teachers and students) as well as digital artefacts (e.g., tools such as interactive whiteboards, laptops, smartphones) interact in an ecosystem according to a syllabus.

Digital classroom ecosystems have the potential to facilitate the transfer of knowledge from teacher to students in various ways (Saini & Goel, 2019). It can support the teacher in content creation, content presentation, and content distribution (Saini & Goel, 2019, pp. 6-12) promote interaction between different biological agents (Saini & Goel, 2019, pp. 12-14) and provide automated assessment and feedback as well as some background functions (e.g., temperature control inside the classroom) (Saini & Goel, 2019, pp. 15-20). Due to the nature of an infosphere, the digital classroom ecosystem can be seen as an advanced tool (like a car) that helps the teachers to better achieve their goals. It supports teachers to get from A to B more quickly, but teachers still have to steer and to drive.

In contrast, smart machines rather play a collaborative role because they are perceived as a form of digital personality and to a certain extent can make decisions and solve problems without the help of the teacher. Smart machines are not just a tool (something), but *someone*, who in certain cases could also be sitting in the driver's seat. This leads to changes in the classroom interaction as Figure 1 illustrates.

In the context of smart machines, Lehmann and Rossi (2019) propose an enactive robot assisted didactics (ERAD) approach, where robots act as intermediaries and catalysts between teacher, students, and context (see Figure 1). Smart machines can perform such a role because they generate attention and expectations in both teachers and students, which enables them to influence and adapt the behaviour of their human counterpart.

The presence of the smart machine in the classroom changes the situation in teaching. From the teacher's point of view, new questions arise. Some of these questions could be: What role does the smart

machine play in relation to the learners? For which parts of the curriculum is the smart machine suitable to provide support? What role do I play as a teacher when the smart machine is suddenly present? These questions can cause stress or even lead to anxiety about being replaced by the robot.

Since the smart machine is perceived as a form of digital personality, possible roles that the smart machine can play are important. In education, according to Sharkey (2016) four main roles exist:

1. Smart machines as teachers (e.g., to take over selected teacher duties in the classroom);
2. Smart machines as companions and peers (e.g., to work collaboratively with students);
3. Smart machines as care-eliciting companions (e.g., supporting students with disabilities); and
4. Smart machines as telepresence teachers (e.g., online teaching through digital technologies along the lines of teachers in distance education).

On the one hand, these different role models show that smart machines (respectively the inherent technology of AI) tend to contain a disruptive potential, because the machine is perceived on a par with the teacher. Unlike digital classroom ecosystems in general, the inherent role of the smart machine confers a certain authority that could challenge the authority and competence of the human teacher. Table 1 compares smart machines and the digital classroom ecosystem to clearly point out the differences.

Smart machines could offer a learning experience tailored to the learner, support and challenge students, and free up precious time for human teachers through ways currently unavailable in our educational environments (Belpaeme et. al, 2018, p. 7). In addition, as an adapter between the digital and analogue world, smart machines would be ideally suited to manage the digital classroom ecosystem according to teachers' needs.

Table 1: Comparison between a smart machine and a digital classroom ecosystem.

Factors	Characteristics of a smart machine	Characteristics of a digital classroom ecosystem
<i>Perception</i>	Digital personality, digital agent	Tool, digital environment, artefact
<i>Role</i>	Someone (can also be in co-role or lead)	Something (an advanced tool)
<i>Representation</i>	Generic chatbots, social robots	The connected eco-system of technology inside the classroom (e.g. interactive whiteboards, projectors, cameras, printers, smart-phones)
<i>Underlying technology</i>	AI, machine learning, ICT	Information and communication technology (ICT)
<i>Nature of work</i>	Make decisions and solve problems without the help of a human being	Data collection- and decision-support-system
<i>Disruptive potential</i>	Disruptive (potential to substitute the teacher)	Incremental (human teacher required)

Both chatbots and social robots are manifestations of smart machines. In addition to chatbots, social robots also have a physical presence. A new field of research is currently emerging: Human-Robot-Interactions or social robots in education (Belpaeme et al., 2018; Byrne, Rossi & Doolan, 2017; Chua & Chew, 2015; Flynn, 2017). The emerging use of robots is changing human augmentation, as these smart machines have a physical presence. In the field of human-computer interactions, a robot is not only a computer-based machine, but also a physical and autonomous agent, whose physical form and degree of autonomy influences the relationship to humans (Thimm et al., 2019).

In the field of education, there are several studies where robots have been used to teach groups of substantial size (e.g., Abildgaard & Scharfe, 2012; Cooney & Leister, 2019; Guggemos, Seufert & Sonderegger, 2020; Masuta et al., 2018) but also to teach smaller workshop-like (e.g., Bolea, Grau, & Sanfeliu, 2016) or even one-on-one interactions (e.g., Gao, Barendregt, Obaid, & Castellano, 2018).

According to Belpaeme et al. (2018, p. 7), smart machines such as social robots have the potential to become part of the educational infrastructure, just as paper, white boards or computer tablets. In their meta-analysis they gathered results from a wide range of countries and took different robot types and approaches into account. They conclude that robots show great promise when teaching restricted topics, with effect sizes on cognitive outcomes almost matching those of human tutoring (Belpaeme et al., 2018, p. 7).

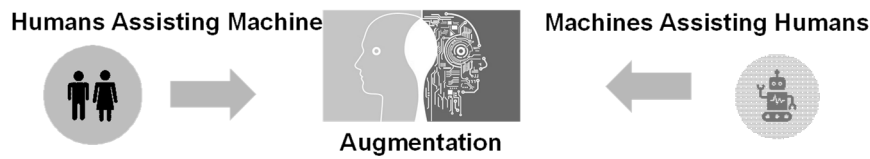
If smart machines may become part of the educational infrastructure in the future, ways must be found to enable smart machines and teachers to collaborate in the classroom for mutual benefit. With the goal of creating a meaningful task sharing in the classroom, we will therefore take a closer look at the relative strengths of teacher and smart machine in the next section.

3 COMPARATIVE STRENGTHS OF TEACHERS AND SMART MACHINES

Among the many effects, digitalization will have on our way of working and living, the augmentation of human skills is the most central (Davenport & Kirby, 2016). Davenport and Kirby (2016) draw attention to the mutual complementation and task sharing that they call “augmentation: People and computers supported each other in the fulfilment of tasks” (p. 2). According to Jarrahi (2018) augmentation can be understood as a “Human-AI symbiosis” meaning that interactions between humans and AI can make both parties smarter over time (p. 583).

Figure 2 illustrates this relationship. On the one hand, people have to train machines to perform certain tasks. They have to explain the results of those tasks to other stakeholders and ensure the responsible use of machines. On the other hand, smart machines help people by enhancing their cognitive strengths, relieving them from repetitive tasks, and expanding their physical abilities.

To investigate the relative strengths of the teacher and the smart machine, we use as a foundation the theory of comparative advantage, which originates from the field of economics (Ruffin, 2002; Landsburg, n.d.). Ricardo (1891) was first able to show with his theory, why two countries A and B engage in trade, even if one country is *in absolute terms* superior to the other regarding the production of all goods in the economy. He was able to explain, why countries specialize on the production of certain goods and trade them. He showed that not *the absolute advantage* matters (being better at producing all goods), but *the relative advantage* instead (having lower opportunity costs).



Humans need to perform three crucial roles.

1. They must *train* machines to perform certain tasks;
2. *explain* the outcomes of those tasks, especially when the results are counterintuitive or controversial
3. *sustain* the responsible use of machines (by, for example, preventing robots from harming humans)

Smart machines are helping humans expand their abilities in three ways:

1. They can *amplify* our cognitive strengths (in particular with analytic decision support);
2. *interact* with other humans (learners, customers, employees) to free us for higher-level tasks; and
3. *embody* human skills to extend our physical capabilities

Source: Own representation based on Wilson & Daugherty (2018).

Figure 2: Human Augmentation.

When we apply the concept of comparative advantages to the classroom, teacher and smart machine can be seen as countries A and B. In the classroom different tasks have to be carried out (production of goods). For example, two of these tasks could be to provide feedback to homework or to individually support students. To illustrate the comparative advantage, we assume the task times of teacher and smart machine depicted in Table 2. Differences in task quality are implicitly reflected in longer task times.

Table 2: Comparison of the task time (absolute).

Task-time needed	Teacher	Smart machine
Individual Coaching	10 min	15 min
Provide Feedback	5 min	15 min

As it can be seen in Table 2, in absolute terms, the teacher is better in both tasks *coaching* and *feedback* (lower task times). The question is: Can it be beneficial for the teacher to shift tasks to the smart machine?

According to the theory of comparative advantages it can, because not the absolute but the relative advantages matter. Table 3 shows the opportunity costs for our scenario.

Table 3: Comparison of the opportunity costs (relative).

Opportunity costs	Teacher	Smart machine
Individual Coaching	10/5 = 2	15/15 = 1
Feedback	Feedback	Feedback
Provide Feedback	5/10 = 0.5	15/15 = 1
	Coaching	Coaching

As the smart machine is equally fast in both tasks, for every unit of *coaching*, the smart machine cannot

produce a unit of *feedback*. Hence their opportunity costs are 1 for both *coaching* and *feedback*.

However, as the teacher is much faster providing *feedback* than *coaching*, the opportunity costs for *coaching* are very high, as for each *coaching* he or she cannot give two units of *feedback*.

Each party (teacher and smart machine) should do the tasks where they have lower opportunity costs compared to their counterpart. In the example at hand, the teacher will specialize on providing *feedback* ($0.5 < 1$) and the smart machine will do *coaching* ($1 < 2$).

Our example shows, that smart machines can be useful even if they are inferior to humans in absolute terms. On a more general level, smart machines have comparative advantages over the teacher in certain fields. Hence, it is beneficial that they take over specific tasks for the teacher. This means that a given set of tasks can be carried out in less time (costs) or within a given time (costs), the number of carried tasks (quality) can be increased.

As it has been shown, the crucial point is the relative strengths of teachers and smart machines. Jarrahi (2018) created relative strength-profiles of humans and AI regarding their core skill set along three dimensions: *uncertainty*, *complexity* and *equivocality* (Jarrahi, 2018, p. 583), see Figure 3.

When assessing the threat posed by technology to a particular profession, Latham and Humbert (2018, p. 12) point out that it is important to look at the core skill set, but also at how the value of the core skill set is delivered (value form). Latham and Humbert (2018, p. 13) grounded the value form in consumer preferences, task diversity and wage differences, on the basis of which we created the three dimensions

preferences, variety and attractivity. Figure 3 summarizes the created relative strength-profile of teachers and smart machines along the two categories *core skill set* and *value form* as well as the six dimensions *uncertainty*, *complexity*, *equivocality*, *preferences*, *variety* and *attractivity*.

Jarrahi (2018, pp. 580-581) characterizes *uncertainty* as a lack of information about all alternatives or their consequences, which makes interpreting a situation and making a decision more difficult. He argues that for situations, which there is no precedent, an intuitive style of decision making may be more helpful. According to Jarrahi (2018, pp. 580-581) in the dimension of *uncertainty*, humans have a relative advantage over AI due to their ability of intuitive decision making (e.g., Harteis & Billett, 2013). Smart machines can still help to reduce *uncertainty* by providing access to real time information, but as machines are mostly incapable of capturing the inner logic and subconscious patterns of human intuition, humans tend to keep their comparative advantage in situations that require holistic and visionary thinking (Jarrahi, 2018, p. 581).

In the classroom, *uncertainty* may occur through different channels. On the one hand, students may ask surprising questions or give inputs, that require some forms of intuitive thinking or creativity in order to answer the question. On the other hand, classroom dynamics itself are to a certain degree unpredictable and uncertain as students are individuals with their own needs. Students do not behave the same way every day, and sometimes they may not even show up. How to react to these situations requires intuition and cannot be solved by a fixed rule alone.

Complexity is characterized by an abundance of elements or variables, that demand the processing of masses of information. AI has a comparative advantage in handling *complexity* due to their ability of collecting, curating, processing, and analyzing large amounts of data (Jarrahi, 2018, p. 581).

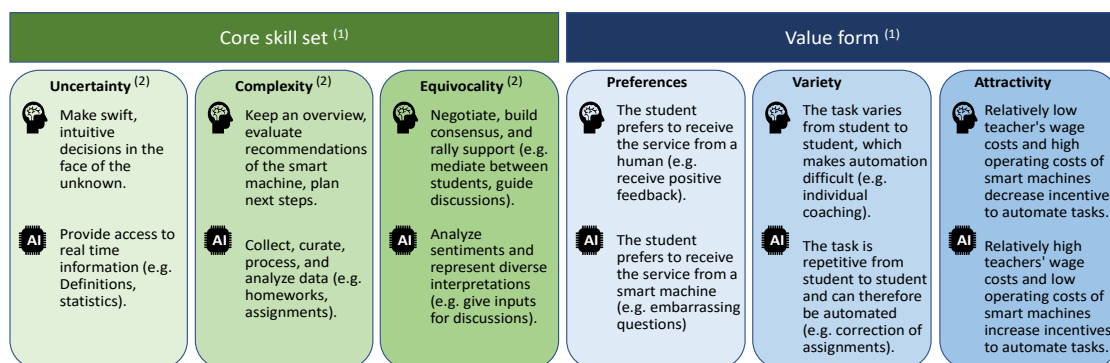
In the classroom, *complexity* increases with the number of students as the same assignments, exercises and exams are conducted for more people. With more students, it gets more difficult to keep an overview over the learning success of each student. Especially in large classes, smart machines can be a valuable research if they support the teacher in providing automated feedback for homework and exams.

Equivocality is characterized by the presence of several simultaneous but divergent interpretations of a decision domain and often occurs due to the conflicting interests of stakeholders, customers, and policy makers (Jarrahi, 2018, p. 581). It means, that there is not always one objective solution to a problem, but multiple different and subjective views about an issue. Even though smart machines may be able to analyse sentiments and represent diverse interpretations, humans have a comparative advantage, when it comes to handling equivocality as they are better in negotiating and coalition building (Jarrahi, 2018, p. 582).

In the classroom, *equivocality* may occur due to different circumstances. On the one hand, the syllabuses of certain school subjects may be more subjective than others. While subjects like accounting or mathematics provide clear guidance on “true” and “false”, this line is more difficult to draw in subjects such as history or literature. On the other hand, students often also have different opinions and there is a need for a teacher who can work out a common consent during discussions.

A smart machine and a human teacher are very different by nature. Hence, for certain tasks it will depend simply on the *preferences* of the students, who they address with their problems.

In the classroom, *preferences* depend primarily on social norms and informal social rules between humans. In human conversation, there are informal rules that have to be followed (e.g., be friendly), which are time consuming and can make communication



Source: (1) Latham & Humberd (2018), (2) Jarrahi (2018) and own contributions.

Figure 3: Relative strength-profiles of teachers and smart machines.

Table 4: Augmentation strategies of teachers in relation to smart machines.

Augmentation strategy	Added value to the smart machine	Relative strength of the teacher	Example
<i>Step In</i>	To train the smart machine and shift tasks to it.	Uncertainty, Equivocality	To automate correction of assignments. To decide on the appropriate content and supervise training.
<i>Step Up</i>	To manage the classroom and its players, keep an overview, evaluate, decide on the ethical use of a smart machine.	Uncertainty, Complexity, Equivocality	To decide on how to proceed if homework has not been done. To decide on appropriate tasks for the smart machine.
<i>Step Forward</i>	To participate in the content development and data analysis of the smart machine.	Uncertainty, Equivocality	To develop new teaching content for a smart machine, to check and correct for data biases.
<i>Step Aside</i>	To take on tasks that go beyond information processing or require tacit knowledge.	Equivocality, Preferences	To coach the students, engage with them in creative problem solving, to motivate and consult.
<i>Step Narrowly</i>	To perform tasks that cannot be performed well by smart machines (e.g. non-repetitive tasks).	Variety	To maintain the smart machine.

inefficient. Since those rules do not apply to smart machines, students can ask any question and they do not have to be afraid of asking a “stupid” question or acting socially inappropriately. Smart machines can also repeat answers as often as needed (e.g., in language learning) without getting tired, which makes them a cooperative learning partner. Teachers may be reluctant to answer the same question several times.

For other tasks, the *variety* is decisive. If a task varies from student to student, it will be more difficult to automate and harder to solve by a smart machine. However, if a task is repetitive, it can be more easily automated as the smart machine can be better trained on it.

In the classroom, *variety* is task dependent. Especially the correction of written assignments is repetitive, because the same work steps have to be carried out for each student. Other tasks like an individual discussion with a student about his or her research project differ from student to student and from project and cannot simply be taken over by a smart machine.

Last but not least, the *attractivity* to automate tasks also has an influence if a certain task is shifted from a human teacher to a smart machine. The *attractivity* depends largely on the wage costs of the human teacher in relation to the operating costs of the smart machine.

The *attractivity* depends also on the type of smart machine. As chatbots have lower operating costs than social robots, it may be more attractive to offer human teachers chatbots as a companion rather than social robots, unless the physical presence is a critical element.

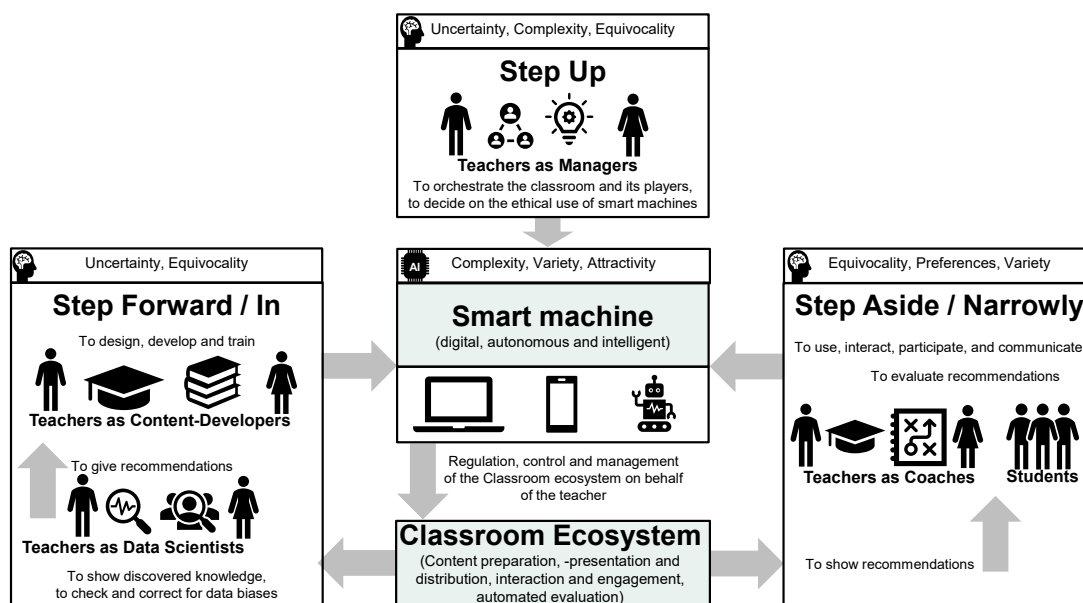
4 TOWARDS AN AUGMENTED TASK SHARING

In summary, smart machines may have three comparative advantages compared to teachers.

First, smart machines can handle *complexity* very well due to their ability to collect, curate, process and analyse large amounts of data. No matter how many students or simultaneous inputs, the smart machine does not forget and can serve the teacher by providing analytical decision support. In addition, smart machines are, due to their nature, ideally suited to regulate, control, and manage the digital classroom ecosystem on behalf of the teacher.

Second, smart machines are good at tasks with a low *variety*, because it is easier to train smart machines on tasks which are repetitive. In the classroom, such repetitive tasks could be for example the correction of assignments or exams. For human teachers those tasks are often boring and they may make mistakes over time. A smart machine does not get bored and can correct all exam questions which are not characterized by uncertainty or equivocality.

Third, smart machines have a high *attractivity* to take over selected classroom tasks, because the wage costs of human teachers in industrialized countries are high compared to the operating costs of smart machines. In particular, chatbots as representatives of smart machines are attractive, as they are cheaper than social robots due to their lack of a physical presence. To put it another way: For a given budget, the quality of teaching can be improved by realising comparative advantages.



Source: Based on Davenport & Kirby (2016); Daud et. al. (2017) and own contributions.

Figure 4: Augmentation strategies of teachers in relation to smart machines.

Against this backdrop, the question is: How should teachers position themselves in relation to smart machines to be able to engage in an augmented, mutually reinforcing way of task sharing?

According to Davenport and Kirby (2016), five augmentation strategies are possible, which are pertinent to different occupational groups, but especially to knowledge workers. Table 4 shows an adaptation of the five augmentation strategies to the teaching profession and indicates how teachers could position themselves in relation to smart machines; teachers have various options to engage with smart machines in an augmented task sharing.

According to the *Step In* strategy, teachers could train the smart machine and shift tasks to it. This creates added value because the smart machine can relieve the teacher of work. The human teacher is needed for this training process as it involves to some degree uncertainty and equivocality. Only the teacher can decide on the appropriate training tasks and measures to be applied.

The *Step Up* strategy is similar to the concept of Dillenbourg (2013), who introduced the concept of “orchestration” of learning activities as real time management for distributed activities over the classroom ecosystem. In the *Step Up* strategy, the teacher could concentrate on higher level tasks inside the classroom. Similar to a conductor of a concert (Shahmoradi et al., 2020), the teacher orchestrates and manages the classroom and its players. He or she keeps an overview, evaluates and decides on the ethical use of

a smart machine. As these tasks involve a high degree of uncertainty, complexity and equivocality, a human teacher is needed. The smart machine can support the teacher in this process, by serving as an interface to the functions of the classroom ecosystem. The smart machine further amplifies the cognitive strengths of the human teacher by making recommendations and providing decision support.

Human teachers could also *Step Forward* and participate in the content development and the data analysis of the smart machine. They could control for data biases of the smart machine and share content with other teachers. Through this, they could contribute to a long-term improvement of the smart machine and its applications. In this process, positive and negative aspects have to be weighed against each other, which is why the process is characterized by *uncertainty* and *equivocality*.

According to the *Step Aside* strategy, teachers could take on tasks that go beyond information processing (*complexity*) or require tacit knowledge. Teachers could increasingly take on the role of a coach, who communicates the learning content provided by the smart machine in a didactically appealing way and assists the learners in an advisory role. The teacher is supported in this process by the smart machine, for example through the means of learning analytics. From the smart machine, students could also receive additional prompts to plan their own learning processes more effectively and improve their metacognitive learning strategies (Bräuer, 2003). The

Step Aside approach is characterized by equivocality (e.g., discussing), but also by preferences (e.g., motivating), which is why a human teacher is needed.

Finally, in the *Step Narrowly* strategy, the teacher could perform tasks that cannot be performed well by smart machines (*variety*). This could include non-repetitive tasks as the individual coaching of students with different needs or the maintenance of the smart machine.

Figure 4 summarizes the conceptual framework with the different augmentation strategies of teachers in relation to smart machines. It is important to point out, that teachers can follow multiple strategies and do not have to choose just one. For example, during the lecture, teachers could use the *Step Up* and *Step Aside* strategy and switch between their roles as managers and coaches.

With our framework, we provide a guideline for an augmented task sharing based on the relative strengths of teachers and smart machines. We highlight ways how teachers could collaborate with smart machines, and how they may leverage their capabilities through smart machines.

5 SUMMARY AND OUTLOOK

Our conceptual framework is based on the theory of comparative advantage. Drawing from this, we have shown ways how an augmented task sharing based on relative strengths of teachers and smart machines could look like.

How the task sharing in the classroom will look like in the future is ultimately an empirical question; relative strengths heavily depend on student perceptions that could be empirically investigated. With our framework, we want to contribute to a better understanding of the concepts and variables that should be considered when investigating task sharing of teachers and smart machines. In a next step, empirical research could further investigate the relative strength dimensions to get a better understanding of which tasks could be assigned to smart machines.

AI has currently triggered a second wave of digitalization, in which data is not only stored and processed digitally (first wave) but also automatically interpreted and actively used by intelligent algorithms (Wahlster, 2017). While schools and teachers are still absorbing and integrating the first wave of digitalization (Wahlster, 2017) into their curriculum, another wave of digitalization is already rolling in. Due to the novelty and complexity of the topic, there is a risk that teachers will be overwhelmed by smart machines and

will not know how to use them in teaching. To prevent this, prospective teachers should be equipped with the necessary knowledge, skills, and attitudes to see the opportunities in the use of smart machines rather than dangers. Teachers should be enabled and supported to sit in the driver seat for shaping their school in the current major transition phase.

AI transformation does not mean that less teachers are needed (Dillenbourg, 2016). However, the role of the teacher may change. Just as paper, white boards or computer tablets – smart machines have the potential to become part of the educational infrastructure, delivering a learning experience tailored to the learner and relieving the burden on teachers where necessary (Belpaeme et al, 2018, p. 7). Such individual support could particularly be beneficial for disadvantaged learners. Currently, the use of smart machines in educational institutions may be limited due to technical and logistical challenges (Belpaeme et al., 2018, p. 7), but as technology becomes cheaper and better, the use of smart machines in education is likely to increase.

Through our conceptual framework, we aim at a better understanding of the digital transformation from a teacher perspective. However, as many pre-service and in-service teachers are not ready to support and adopt new technologies related to AI, effective teacher education and continuing education programs have to be designed and offered to support the adoption of these new technologies (Luan et. al., 2020, p. 7). There is a need for more robot-proof skills and strategies, that make it possible to cooperate successfully with smart machines without being replaced by them in the long term (Aoun, 2017).

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