http://pubsonline.informs.org/journal/serv

SERVICE SCIENCE
Vol. 14, No. 2, June 2022, pp. 77–89
ISSN 2164-3962 (print), ISSN 2164-3970 (online)

How Artificial Intelligence Enhances Human Learning Abilities: Opportunities in the Fight Against COVID-19

Cristina Mele,[a] Marialuisa Marzullo,[a] Swapnil Morande,[a] Tiziana Russo Spena[a]

[a] Department of Economics, Management, Institutions, University of Naples Federico II, Naples 80126, Italy

Contact: cristina.mele@unina.it, https://orcid.org/0000-0002-8353-8150 (CM); marialuisa.marzullo@unina.it, https://orcid.org/0000-0001-8735-612X (MM); swapnil.morande@unina.it, https://orcid.org/0000-0003-4720-2980 (SM); russospe@unina.it, https://orcid.org/0000-0002-1732-6029 (TRS)

Received: November 30, 2020
Revised: August 16, 2021
Accepted: October 1, 2021
Published Online in Articles in Advance: February 7, 2022

https://doi.org/10.1287/serv.2021.0289

Abstract. This paper widens the focus on how artificial intelligence (AI) can foster the learning abilities of human actors, adopting a wider view with respect to a strict focus on tasks and activities. The interaction between AI and human learning has not been investigated in service research. Placing its theoretical roots in work by Huang and Rust [Huang MH, Rust RT (2021) Engaged to a robot? The role of AI in service. *J. Service Res.* 24(1):30–41.] in service research and on Bloom's revised taxonomy in education studies [Anderson LW, Krathwohl DR, Airasian PW, Cruikshank KA, Mayer RE, Pintrich PR, Raths J, Wittrock MC (2001) *A Taxonomy for Learning, Teaching, and Assessing: A Revision of Bloom's Taxonomy of Educational Objectives* (Longman, London).], this study offers an integrative framework for the ways AI enhances human learning abilities. Some cases in the context of COVID-19 offer insightful illustrations of the framework.

History: This paper has been accepted for the *Service Science* Special Issue on Reimagining the Science of Service in a Post-Pandemic World (Part 2 of 2).

Keywords: artificial intelligence • human learning abilities • Bloom's revised taxonomy • COVID-19

1. Introduction

A cough on the phone: it is enough for artificial intelligence (AI) to recognise asymptomatic people carrying the SarsCoV2 virus. In fact, a characteristic sound comes out of their mouths that, although it is indistinguishable by the human ear, does not escape the algorithm developed by researchers. Its success rate is close to 100% for asymptomatic patients (Massachusetts Institute of Technology 2020). By analysing an audio stream containing a short conversation, processing it through personal devices (smartphones, tablets, and computers), Neosperience Cloud Health can identify people who present the characteristic sounds of the coronavirus infection (Neosperience 2020).

During the COVID-19 pandemic, other AI-based solutions have been developed (Budd et al. 2020, Bullock et al. 2020) to support human actors in healthcare, such as the elaboration of images and proposals for preventive and predictive care (Rahman et al. 2020, Ting et al. 2020). There has been an increase in the implementation of the different forms of AI equal to a 35% increase compared with 2019 (McKinsey and Company 2020). AI-based solutions can be briefly described as the capability of machines to act as intelligently as humans (McCarthy et al. 2006). These machines can acquire, interpret, and learn from data to accomplish tasks, emulating human cognition and behaviour (Jarrahi 2018, Kaplan and Haenlein 2019).

For the purpose of this paper, we use the terms intelligent machines and AI-based solutions (or devices) to describe networked technology interfaces that can learn from data, information, and experiences (Meuter et al. 2003, Porter and Heppelmann 2014) for the elaboration and identification of probable solutions.

In service research, scholars have begun to question how AI-driven solutions could affect services (Huang and Rust 2017), igniting a debate about AI's contribution to human activities (Brynjolfsson and Mcafee 2017, Von Krogh 2018). Studies have analysed the learning abilities of AI, facilitating the process of resource integration (Mele et al. 2021) or customer engagement (Huang and Rust 2021). The increasing interest lies in analysing effects on service provision or experience thanks to automation or augmentation provided by smart solutions (Wirtz 2020, Heller et al. 2021, Mele et al. 2021). A major part of the analysis focuses on how AI technologies "learn to learn" and provide support to humans in their daily activities (Yang et al. 2019)—although a negative view reports that AI can also threaten human jobs (Huang and Rust 2018).

This paper widens the focus on the learning abilities of AI and moves to understanding how AI can foster the learning abilities of human actors (Nguyen et al. 2020), adopting a wider view to a previously strict focus on tasks and activities. The interaction between AI and human learning has not been investigated in service research. Placing its theoretical roots in the work by Huang and Rust (2021) in service research and on Bloom's revised taxonomy in education studies (Anderson et al. 2001), this study offers an integrative framework into the ways AI enhances human learning abilities. Some cases in the context of COVID-19 offer insightful illustrations of the framework.

The remainder of the article proceeds as follows. First, we present the methodology. Second, we review the literature on AI in service science and human learning abilities. Third, we present the integrative framework; finally, we discuss our main contributions, present implications, and offer avenues for further research.

2. Methodology

To investigate a novel phenomenon, we chose to develop a conceptual paper, as this type of research enables theory-building unrestricted by the demands of empirical generalisation (Jaakkola et al. 2020). A conceptual paper does not propose a new theory (Gilson and Goldberg 2015). However, it may bridge existing theories, working across disciplines and providing multilevel insights to broaden the scope of thinking.

Our argument involved the assimilation and combination of evidence in the form of previously developed concepts and theories. We follow an adaptation approach (MacInnis 2011) consisting of developing contributions on AI-based learning processes by introducing alternative frames of reference. We initially drew on AI in service literature (Huang and Rust 2018, 2021; Perez-Vega et al. 2021; Stahl et al. 2021) and complemented that with insights from the human learning approach (Bloom 1956, Anderson and Krathwohl 2001, Crowe et al. 2008).

The focus was on connecting previously differentiated categories to expand the multifaceted issue of AI learning. The work is in line with MacInnis's (2011, p. 24) integration process that involves synthesis—"the way to find an overarching idea that can accommodate previous findings, resolve contradictions or puzzles, and produce novel perspectives that accommodate complexity" (MacInnis 2011, p. 24). This process also highlights directions for future inquiry beyond summarising recent research (Gilson and Goldberg 2015).

To make our framework more robust, we use illustrations involving actors using AI-based solutions to tackle COVID-19.

Illustrations come from cases used to illuminate the core categories of the developed framework (Gummesson 2005). Scholars consider that case studies can be adopted as illustrations of conceptual contributions (MacInnis 2011, Taillard et al. 2016), in which their role is to help readers to see "how the conceptual argument might actually be applied to one or more empirical settings" (Siggelkow 2007, p. 22).

We developed a two-step process to acquire appropriate illustrations. A first step involved direct encounters with 15 members of top management in technology firms and 7 digital transformation specialists. They provided us with preliminary insights into the way AI learns (or acts as a learner). The interviews, conducted through Webex or Skype, had a range of 45–60 minutes. The second step involved 52 users of AI-based solutions who were interviewed to gain an understanding of people's thoughts and behaviours concerning whether, and if so how, AI supports human learning abilities.

3. Literature Review

3.1. AI in Service Science

A seminal work on AI addresses the proposition that "every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it" (McCarthy et al. 2006, p. 1). This includes language, forming abstractions and concepts, problem-solving, pattern recognition, and adapting to changing circumstances (Russo Spena et al. 2019). Following this perspective, service scholars define intelligent machines as capable of learning (Huang and Rust 2018, Perez-Vega et al. 2021, Stahl et al. 2021). The debate as to how AI and its learning abilities affect the service context is rapidly emerging (Meyer et al. 2020, Allal- Chérif et al. 2021, Rodgers et. al. 2021).

Huang and Rust (2018) developed a first framework depicting "four intelligences" required for service tasks—mechanical, analytical, intuitive, and empathetic—and asserting "that AI job replacement occurs fundamentally at the task level, rather than the job level, and for "lower" (easier for AI) intelligence tasks first" (p. 155). Subsequently, these authors upgrade the framework into three main categories to address how to engage customers for different service benefits (Huang and Rust 2021): mechanical, thinking, and feeling. Each intelligence is characterised by its specific nature and supports different tasks (see Table 1). We use this categorisation to offer a review of AI in service research (LeCun et al. 2015, Garry and Harwood 2019, Langley et al. 2020).

3.1.1. Mechanical Intelligence. Intelligent machines can perform mechanical and repetitive tasks with relatively limited amounts of learning or adaptation (Dawar and Bendle 2018). Advances in deep learning have improved data processing capacity (LeCun et al. 2015); enabling mechanical intelligence to operate through silos of data automatically extracted from text, voice, and images to generate models and refine functions based on real-world optimisation. Other

Table 1. Intelligences, Nature of Tasks and AI Applications

Intelligences	Nature of tasks	AI applications
A. Mechanical		
Minimal degree of learning or adaptation Precise, consistent and efficient Rely on observations to act and react repetitively	Simple, standardised, repetitive, routine, and transactional tasks Tasks require consistency Commodity service	McDonald's "Create Your Taste" touch screen kiosks Robot Pepper takes on frontline greeting tasks Virtual bots turn customer service into self-service
B. Thinking		
Learns and adapts systematically based on data Logical, analytical, and rule-based learning Rational decision making Learns and adapts intuitively based on understanding Artificial neural networks-based or statistics-based deep learning Boundedly rational decision making	Analytical, rule-based, systematic complex tasks Tasks require logical thinking in decision making Data, information, and knowledge-based service Complex, chaotic, and idiosyncratic tasks Tasks require intuitive, holistic, experiential, and contextual interaction and thinking Personalised, idiosyncratic, experience- and context-based service	Toyota's in-car intelligent systems replace problem diagnosis tasks for technicians IBM's Watson helps H&R Block with tax preparation Penske's onboard technology takes over navigation tasks Associated Press's robot reporters take on the reporting task for minor league baseball games Artificial intuition takes on the data interpretation task in gestalt psychology Narrative Science's AI Quill writes as if human authors
C. Feeling		
Learn and adapt empathetically based on experience Emotion recognition, affective computing, and communication- style learning Decision making incorporates emotions	Social, emotional, communicative, and highly interactive service Tasks that require empathy, emotional labour, or emotional analytics High-touch service	Chatbots communicate with customers and learn from it Replika replaces psychiatrists for psychological comfort Sophia robots interact with customers as if employees

Source. Synthesis drawn from Huang and Rust (2018, 2021).

examples are effective automation of services (Garry and Harwood 2019) and their standardisation (Huang and Rust 2021) with positive outcomes for users, such as improving user comfort, actor experience, or other human-defined goals (Langley et al. 2020). AI-based solutions rely on observations to act and react repetitively (Huang and Rust 2018). The tasks to be performed are simple, standardised, repetitive, routine, and transactional.

3.1.2. Thinking Intelligence. More advanced learning skills enable machines to analyse ever-growing volumes of data and use it to provide strategic decision making, forecasting, and modified processes (Buhalis et al. 2019, Stahl et al. 2021, Zhu et al. 2021). Scholars label it as "thinking intelligence" (Schuller 2018, Huang and Rust 2018), including in this categorisation all of the intelligent machines that can analyse and make decisions rationally and that involve learning and adapting systematically (Chung et al. 2009, 2016). It churns through vast amounts of data, searches for dependencies in it, and takes action (Heinonen and Strandvik 2020). This type of intelligence enables complex, strategic decision making in an unpredictable environment (Wedel and Kannan 2016) and could be capable of helping to resolve complex problems to facilitate decision making (Albrecht et al. 2021). Thinking intelligence can address the situation that was previously unsolvable or establish scenarios and suggest the best performance and the lowest risks (Allal-Chérif et al. 2021). Thinking intelligence connects people and organisations, and smart devices offer opportunities for augmentation (Mele et al. 2021) and greater productivity (Paschen et al. 2020). Such a level of AI prompts new service provision and the emergence of well-informed interactions between humans and nonhumans thanks to the enhanced state of problem-solving abilities (Huang and Rust 2018).

3.1.3. Feeling Intelligence. The ability to support the development of emotion-based interactions between humans and nonhumans is defined as "feeling intelligence"; and it refers to all machines with the potential to recognise, emulate, and respond appropriately to human emotions (Schuller 2018). The ability to mimic empathy and offer emotional support—defined as a personalized relationship—makes it ideal for service relation (Bolton et al. 2018, Huang and Rust 2018). Feeling intelligence not only invokes judgements or regulates emotions (Drigas and Papoutsi 2018) but also learns and adapts from associated experiences. It can be inspired by intuition and reflective practice among its users, requiring recognition of a complex system between culture and human responsiveness (Taylor and Taylor 2021). For example, social robots seem to improve both the physical and psychosocial well-being of people interacting with them, when they learn and manage to master empathy and social sensitivity (Odekerken-Schröder et al. 2020). The focus on social robots in elder care services shows ways in which their humanlike affect and cognition influence users' social perceptions and lead to anticipation of their potential—both negative and positive—for value cocreation (Čaić et al. 2019).

In sum, the technological developments described above gave rise to the need to understand not simply how AI learns but how it can support humans in their learning abilities (Nguyen et al. 2020). To accomplish this aim, we move to the literature on human learning abilities (Anderson et al. 2001).

3.2. Human Learning Abilities

Learning is the process through which humans acquire knowledge and develop skills or abilities (Zhou et al. 2019). Research into the learning process and human abilities is wide and integrates insights across multiple fields, from the biological and neurosciences to psychology, sociology, and developmental and learning sciences.

In educational studies, consensus about the science of learning and development has increased since the publication of Bloom's research in 1956 concerning the learning ability and motivation for further learning. Based on their understanding of conditions under which the learning process is favoured, Bloom et al. (1956) recognise the existence of three *domains* of learning: cognitive (*knowledge*), affective (*attitude or self*), psychomotor (*skills*). They also develop a taxonomy for the cognitive domain as it involves knowledge; this includes the recall or recognition of specific facts, procedural patterns, and concepts that serve in the development of intellectual abilities and skills (Bloom et al. 1956). The other two domains were developed by Bloom and coauthors later (Bloom et al. 1956, Simpson 1972, Krathwohl et al. 1973), although scholars recognise that it does not seem possible to artificially separate the cognitive and affective aspects of learning.

There are six classes relating to the cognitive domain: knowledge, comprehension, application, analysis, synthesis, and evaluation. Since the publication of the Bloom et al. work in 1956, several weaknesses have been identified, particularly that each level was a prerequisite for the next and that the higher levels contain all of the cognitive abilities of the lower ones (Krathwohl 2002). Also identified was the lack of constructivist integration (Granello 2001). In response, Anderson et al. (2001) have proposed a revised version composed of six cognitive action-verbs, rather than concept-based nouns, pointing to a more dynamic classification and reflecting a more active form of thinking. Each level includes different human skills to be engaged in active cognitive processing: "a meaningful learning is consistent with the view of learning as knowledge construction, in which (actors) seek to make sense of their experiences" (Anderson et al. 2001, p. 65).

The action-verb "remember" represents the simplest cognitive activities, and it is referred to as retrieving related knowledge from long-term memory. The remembering action implies the recall or recognition of information based on the memorising capability of human actors (Anderson et al. 2001). Through it, human actors are able to recollect concepts as presented and can develop knowledge with the help of relevant data (Crowe et al. 2008).

"Understanding" is the ability to extract meaning from the data (Poluakan et al. 2019). According to Pepin et al. (2021), the understanding action implies the construction of meaning from the information that human actors have at their disposal. This ability also includes building connections between newly introduced and prior knowledge. Through it, human actors can interpret, classify, summarise, and compare information (Ulmeanu et al. 2019).

"Apply" refers to using a learned procedure in new conditions (Anderson et al. 2001). Abilities involve transferring knowledge or understanding to another task, be it familiar or not (Ben-Zvi 2004). Through the application of relevant information, human actors are enabled to integrate information, make it more complete, and to develop ideas (Ben-Zvi 2004).

"Analyse" is the ability to make connections between data, information, and ideas (Wang et al. 2021). The analysing ability consists of breaking down a concept into its constituent parts and determining the relation between them and an overall structure (Wang et al. 2021). Through it, human actors can determine the significant elements of information and concept (differentiating), determining how these elements are organised (organising) and determining their reason and significance (interpreting) (Canziani and Welsh 2019).

The evaluation of the results enables human actors to make judgements based on criteria or standards, through a continuous process of reviewing and critiquing (Zhang et al. 2019). The "evaluate" involves exercising judgement, spotting inappropriate or missing elements, and demonstrating critical thinking. This taxonomic level involves the cognitive processes of checking (making judgements about internal consistency) and critiquing (making judgements based on external criteria) (Thote and Gowri 2020).

Finally, to put all the elements together to form a new context is possible using the highest form of learning known as "creating" (Gelmez and Bagli 2018). The ability to generate, plan, and process data and information enables human actors to create information, to investigate other processes, and to explore new solutions (Thote and Gowri 2020, Waite et al. 2020).

Bloom's revised taxonomy is one of the most widely used methods to analyse the human learning process (Lahuerta-Otero and González-Bravo 2017). It has been used in a wide range of applications with simplified contextualisation (Crowe et al. 2008) ranging from linguistics (Kozikoğlu 2018), business (Tran and Anvari 2013, Ulmeanu et al. 2019, Pepin et al. 2021), medicine (Roca et al. 2016), computer science (Wang et al. 2021), and entrepreneurship (Aranha et al. 2018, Canziani and Welsh 2019, Clement and Silvernagel 2019). It has also been applied to various situations describing everything from analysing games (Haring et al. 2018) to designing learning for mobile applications (Ekren and Keskin 2017).

In this study, Bloom's revised taxonomy is used to understand key aspects of human learning abilities as enhanced by AI.

4. An Integrative Framework

Our literature review highlights the ever-growing scholarly interest in the idea that artificial intelligence can take over human roles (Brynjolfsson and Mcafee 2017, Von Krogh 2018). Recent advances in AI enable the processing of a vast amount of data and translation of useful information into specified actions. "Feature extraction" carried out by AI has made it possible to pinpoint significant facts that would otherwise have been missed from silos of data (Arel et al. 2010). At the same time, using data-driven insights, AI can act rationally. Such action resembles the characteristic reasoning and thinking patterns of humans (Pedersen et al. 2018).

However, the objective is not to substitute intelligent machines for human actors but to consider how AI can offer assistance to human cognition and behaviour. Humans receive data every day and capture a critical aspect of them based on experiences. However, such data become difficult to process as learning complexity grows exponentially with an increase in number, dimension, and typology (Holzinger 2016). There is a need to move from AI learning to AI-based human learning.

By integrating the model by Huang and Rust (2021) and Bloom's revised taxonomy (Anderson et al. 2001), we offer a more comprehensive framework to depict how AI can enhance human learning abilities (the Artificial Intelligence-Human Learning Aabilities (AIH-LA) Framework).

Our framework moves from the three types of AI categories summarised by Huang and Rust (2018)—(AI as a learner)—and proposes that AI intelligence can enhance human learning abilities—(AI as a human learning enhancer). By integrating the model by Huang and Rust (2021) and Bloom's revised taxonomy (Anderson et al. 2001), we offer a more comprehensive framework to depict how human actors can exploit mechanical, thinking, and feeling to boost their learning abilities (see Table 3) .

4.1. Human Learning Abilities Enhanced by Mechanical Intelligence

Mechanical intelligence enables automatic extraction of information from data and performance of repetitive tasks thanks to observation and standardisation (Huang and Rust 2018, 2021). AI's ability to carry out repetitive functions and routine tasks supports human actors' ability to manage data in real time by recalling relevant information from memory and enabling rapid recognition (e.g., retrieving data about the temperature of an individual that means that an alarm must be raised; recognising the critical nature of the data instantaneously to raise the alarm). Further, mechanical intelligence, relying on observations and repetitive actions, enables the human actor to understand across the data by comparing and classifying these data, resulting in a dramatic reduction in error (e.g., recognising observed temperature as either critical or normal). The use of machine intelligence promotes higher learning abilities for human actors who can have access to more data and who can detect correspondences between data and information in a short time. The automatic mechanical observation facilitates a wider understanding that can offer the opportunity to see the cause and effect of a phenomenon. In sum, AI-based devices can be tools for remembering and managing a greater amount of data in real time more easily and for enabling a wider understanding across data.

4.2. Human Learning Abilities Enhanced by Thinking Intelligence

Thinking intelligence can analyse and make decisions rationally and involves adapting systematically to data (Chung et al. 2009, 2016). It can be useful for real-time detection, clustering, and forecasting (Rust and Huang 2012). Thanks to its ability to discover relevant data and information, thinking intelligence can support human actors to obtain information and check their decisions. Furthermore, supported by systematic learning based on the data, people carry out data analysis and determine how to implement the best solutions in a limited time. The analytical and forecasting skills of device-based thinking intelligence supports human actors in the detection of inconsistencies, errors, or anomalies, letting them identify the effectiveness of a solution—that is being implemented—in novel contexts. Human actors can apply a contextual procedure to a task and provide a logical perspective (see Table 2). In sum, AI-based devices can be a tool

Table 2. Bloom's Revised Cognitive Taxonomy

Categories & cognitive process	Definitions & examples
1. REMEMBER: Retrieve relevant knowledge from long term memory	
1.1 Recognizing	Locating knowledge in long-term memory that is consistent with presented material (e.g., recognize the dates of important events in U.S. history)
1.2 Recalling	Retrieving relevant knowledge from long-term memory (e.g., recall the dates of important events in U.S. history)
2. UNDERSTAND: Construct meaning from instructional messages, including oral, written, and graphic communication	
2.1 Interpreting	Changing from one form of representation (e.g., numerical) to another (e.g., verbal) (e.g., paraphrase important speeches and documents)
2.2 Exemplifying	Finding a specific example or illustration of a concept or principle (e.g., give examples of various artistic painting styles)
2.3 Classifying	Determining that something belongs to a category (e.g., classify observed or described cases of mental disorders)
2.4 Summarizing	Abstracting a general theme or major point(s) (e.g., write a short summary of the event portrayed on a videotape)
2.5 Inferring	Drawing a logical conclusion from presented information (e.g., in learning a foreign language, infer grammatical principles from examples)
2.6 Comparing	Detecting correspondences between two ideas, objects, and the like (e.g., compare historical events to contemporary situations)
2.7 Explaining	Constructing a cause-and-effect model of a system (e.g., explain the causes of important 18th century events in France)
3. APPLY: Carry out or use a procedure in a given situation	
3.1 Executing	Applying a procedure to a familiar task (e.g., divide one whole number by another whole number, both with multiple digits)
3.2 Implementing	Applying a procedure to an unfamiliar task (e.g., use Newton's Second Law in situations in which it is appropriate)
4. ANALYZE: Break material into its constituent parts and determine how the parts are related to one another as well as to an overall structure or purpose.	
4.1 Differentiating	Distinguishing relevant from irrelevant parts or important from unimportant parts of presented material (e.g., distinguish between relevant and irrelevant numbers in a mathematical word problem)
4.2 Organizing	Determining how elements fit or function within a structure (e.g., structure evidence in a historical description into evidence for and against a particular historical explanation)
4.3 Attributing	Determining a point of view, bias, values, or intent underlying presented material (e.g., determine the point of view of the author of an essay in terms of his or her political perspective)
5. EVALUATE: make judgements based on criteria and/ or standards	
5.1 Checking	Detecting inconsistencies or fallacies within a process or product; determining whether a process or product has internal consistency; detecting the effectiveness of a procedure as it is being implemented (e.g., determine if a scientist's conclusions follow from observed data)
5.2 Critiquing	Detecting inconsistencies between a product and external criteria, determining whether a product has external consistency; detecting the appropriateness of a procedure for a given problem (e.g., judge which of two methods is the best way to solve a given problem)
6. CREATE: put elements together to form a novel, coherent whole or to make an original product	
6.1 Generating	Coming up with alternative hypotheses based on criteria (e.g., generate hypotheses to account for an observed phenomenon)
6.2 Planning	Devising a procedure for accomplishing some task (e.g., plan a research paper on a given historical topic)
6.3 Producing	Inventing a product (e.g., build habitats for a specific purpose)

Source. Synthesis drawn from Anderson et al. (2001).

Table 3. The AIHLA Framework

AI as a learner	AI skills	AI as a learning enhancer	Enhanced human learning abilities	
Mechanical	Observe automate standardise	Easier	Remember a greater amount of data in real time	Recognising/recalling
		Wider	Understanding across data	Classifying/comparing
Thinking	Analyse augment decide	More efficient	Analysing choices	Differentiating/organising/attributing
		More accurate	Applying well-informed decision	Executing/implementing
Feeling	Acknowledge excite adapt empathetically	More effective	Evaluating and making judgement based on empathy and experience	Checking/critiquing
		Highly interactive	Creating new patterns	Generating/planning/producing

for more accurate analysis of choices in order to reach well-informed decisions.

4.3. Human Learning Abilities Enhanced by Feeling Intelligence

Feeling intelligence focuses on the potential of AI to acknowledge and respond appropriately to human emotions (Schuller 2018). Such an approach is ideal for a personalised relationship and customer satisfaction and retention (Huang and Rust 2017, 2018). Thanks to the ability to acknowledge human emotions, AI-based solutions supports human actors to respond to human emotional needs in an empathetic manner based on prior experiences (e.g., *generate solutions for the human actors based on observed emotions-based information*). Further, it helps people create personalised relationships for accomplishing experiential tasks (e.g., *plan a daily health-related goal based on the investigation of emotion*). In this way, decision making is incorporated with emotions and the machine helps to make intuitive judgements. In sum, this type of intelligence enhances social skills in the direction of greater empathy, taking into account new forms of human-robot interactions.

5. An illustration: AI and Human Actors Against COVID-19

We will illustrate our framework in terms of how AI enhances human learning abilities in the healthcare context in the fight against COVID-19 (see the appendix).

5.1. Mechanical Intelligence and the Human Learning Abilities of Remembering and Understanding

During the COVID-19 pandemic, *mechanical intelligence* has been used to emulate human repetitive tasks and human behaviour in an automatic way and following predefined protocols. In this process, intelligent machines have carried out ”COVID-19 data extraction activities” thanks to their skills in capturing a large amount of data about COVID-19 infection and processing a rapid automatic combination of them. The use of mechanical intelligence to observe a large amount of data fosters the skills of human actors (e.g., doctors, researchers, nurses, and police) in their collection and comparison of different types of data, thus enabling learning abilities of understanding and remembering COVID-19 data and information. This standardisation and automation of activities supports doctors and other human actors in recalling and recognising significant data and facts.

An example is the AI thermometer, by OpenPose technology, a thermal imaging camera. AI thermometer is able to extract data from images in an automatic manner and enables detection of the position and posture of individuals in the frame. This device can identify people through a standard detector that reads the body shape of the subjects and then locates a point on the face at which to measure the temperature. The software is rule based and relies on a priori knowledge and its continuous sensor-based perception to observe and react to physical and temporal variability. Real-time data are registered, categorised, and sent to the app through Bluetooth with sound notice in the case of difficult situations. The AI thermometer does not understand any change in environment but uses algorithms to identify the meaning of data, observe data, and return the appropriate results. Thus, it helps human actors to remember and understand healthcare data. For humans, the mechanical process of measuring the temperature of skin does not require much creativity, advanced training, or education but requires mostly automatic skills of considerable importance to combatting the COVID-19 infection. The intelligent device supports human actors, sending them a notification if a higher temperature range is identified and a daily list of health data about the users' body temperature to support human actors in their categorisation. It is free from human fatigue and observes the environment in a very reliable manner, mapping many people simultaneously. The nature of the task—repetitive and with little variation—renders learning over time to be of limited value—nothing new to learn over the course of service transactions. However, the automated process enables human learning by facilitating the recall and recognition of trends in healthcare data. The human actors, thanks to the AI thermometer's data integration, can compare and classify large volumes of healthcare data faster than ever before.

5.2. Thinking Intelligence and the Human Learning Abilities of Analysing and Applying

Thinking intelligence has been used to emulate human thinking tasks and behaviour, analysing a large amount of data in a limited time and following algorithm-based machine learning and deep learning to implement decision-making processes. Through this process, AI-based devices forecast options, identify a large number of possible solutions to a problem (decision making), and analyse them to refine them for different contexts. Thanks to its ability to learn from experience, the intelligent machine has educated itself to learn about COVID-19 infection without repeating the same mistakes twice. Such features of thinking intelligence enable human actors to organise and identify data correctly and to check and apply solutions in a more effective way. During the COVID-19 pandemic, thinking intelligence has been used for anomaly detection, clustering, and association modelling.

An example is IBM Summit, characterised by creative and problem-solving abilities. In the exploratory phases of medical and pharmaceutical research, it has been particularly useful for accelerating the research phase for the development of COVID-19–related drugs. The possibility of analysing a multiplicity of data from different sources (drug monographs, reports based on therapeutic evidence, disease monographs, scientific articles, etc.) allowed increasing data-learning relating to the phenomenon observed, and its evolutions also in different contexts, highlighting effective proposals for the treatment and care of patients. This AI-based solution has performed a range of tasks and leverages its logical reasoning to discover facts and interpret data for effective decision making in the fight against COVID-19. Thanks its abilities to observe big data, and analyse them for problem-solving, IBM Summit helps human actors to apply and analyse possible drug solutions: its automated process identified 77 potential solutions in a much wider range within a few days, performing a range of analytics tasks requested by humans and leveraging their logical reasoning to refine these for different contexts. IBM Summit enhances the human learning ability to organize data: humans can then consider the best solutions among those identified, with forecasts about their implications, by the automated analysis.

5.3. Feeling Intelligence and the Human Learning Abilities of Evaluating and Creating

During COVID-19, *feeling intelligence* has been used to acknowledge actors' emotions, respond appropriately emotionally, influence others' emotions, and support the creation of new patterns of interactions and relationships. Characterised by affective computing, these devices can learn the communication style of an individual and adapt empathetically based on prior experiences. They also offer decision making that incorporates emotions and facilitate relationship building during their interactions. They offer interactive support using the interpersonal and social features of humans for the enhancement of their well-being. Feeling intelligence has helped human actors to formulate and detect the emotions-related details of an individual in a deeper way to offer support and to respond in time. In the creation of possible supports against COVID-19, the focus stays on the empathetic and emotional dimensions of the person.

Laila is a chatbot that includes interpersonal and social skills that can support humans in stressful situations during the pandemic. Laila can learn from experience, recognise and acknowledge other actors' emotions, respond appropriately emotionally, influence others' emotions, and extract new information based on the analysis of data. This social robot shows that the capacity to assemble data can lead to the generation of new information in a complex context where it can produce and plan the interpersonal and social features of human actors, supporting and enhancing their ability to create and to process emotional details. This intelligent application can act as though it has feelings. Its dynamic character allows the device to try to experiment with the solution it has created, improving the human's ability to make decisions.

6. Conclusion

This paper focuses on how AI enhances human learning abilities. Moving from different types of intelligent machines as detected in service research and using Bloom's revised taxonomy, we offer a more comprehensive framework, with illustrations taken from AI-based solutions developed in the fight against COVID-19. Our work makes two contributions. First, we argue that scholars need to understand not simply how AI learns but how it can support humans in their learning abilities. To be specific, the mechanical intelligence carries out automatic COVID-19 data extraction using its AI skills to observe data and standardize the activities. These features enable AI to enhance human learning abilities to recall and recognise information but also to compare and classify important data. In summary, AI fosters human actors' ability to remember and understand information promptly. The thinking intelligence carried out data processing activities thanks to the AI skills of data analysis, forecasting information, and developing decision-making processes. Such processes enable AI to enhance the human learning capability to conduct detailed analysis and further select the best possible solution for the contextual application of data. They can implement solutions in different contexts, check the best solutions, and organise information to support the evaluation activities that humans will conduct. Finally, the feeling intelligence carried out features extraction activities that use its learning skills to acknowledge and emulate emotions. AI can enhance human learning by assisting empathic decision making, planning goals, and the creation of emotionally driven solutions. As a result, intelligent machines not only provide access to resources allowing the human actor to have relevant information at their fingertips but also supports the decision-making processes.

Second, in line with Nguyen et al. (2020), our study addresses the potential of AI to utilise learning abilities to drive mechanical, thinking, and feeling intelligence to manage the COVID-19 outbreak. Rather than understanding situations in which mechanical intelligence is used for effective automation of services (Garry and Harwood 2019) and their standardisation (Huang and Rust 2018, 2021) with complete substitution of human actors, this study offers an understanding of how the mechanical intelligence collaborates with human actors in healthcare where there is a need to understand and remember data and information in a more profound manner. This combination allows for the identification of significant facts that would otherwise have been lost.

In a similar way, thinking intelligence allows meeting the need to analyse how the machines help human actors to resolve complex problems, facilitating decision making in the healthcare context (Albrecht et al. 2021). Broadening the understanding of Huang and Rust (2018, 2021) who showed that thinking intelligence enables service personalisation, this study offers an understanding of how thinking intelligence collaborates with human actors in healthcare emergency situations where there is a need to elaborate a more detailed analysis to evaluate and create the best solution to the problem, in a contextual manner. This combination allows for a more efficient decision-making process.

Our study of machines with feeling intelligence allowed us to analyse how these AI-based devices help human actors to develop service interaction based on emotion (Schuller 2018). It has shown that the ability of the feeling intelligence to learn from emotional data and emotional experience has helped human actors to offer support and react in time. This combination allows for the improvement of the human actors' abilities to make decisions about emotional service interactions.

In sum, the framework satisfies the need to understand how AI influences the activities that make up the learning process, as listed by Bloom's revised taxonomy (Greiner et al. 2021). In line with Perez-Vega et al. (2021), the use of richer theories that aim to explain human behaviour can be appropriate to guide the development of applications for new technologies, especially because these technologies are designed to emulate humanlike responses.

7. Implications for Practitioners

This study contributes to the understanding of how to improve human learning abilities thanks to AI-based technology. Important implications arise.

First, professionals should foster the combination of the AI and human actors' learning abilities, designing services that promote the integration of intelligent machines as a learning enhancer. To do this, they must have a strong understanding of the context, and of the features of intelligent machines, to ensure their effective use and integration into the human actor's learning process.

Second, the COVID healthcare emergency requires a shift toward participatory and predictive care, including a more feeling-centred approach that is personalised, contextualised, connected, and data and information driven. Practitioners should recognise the importance of acting promptly after receiving the emotional information to implement effective predictive solutions. In other words, the insights offered by this study could further help practitioners allocate required resources and workforce as required by the different types of tasks. Practitioners would be able to harness the power of AI to improve the accuracy of mechanical tasks, make robust predictions with thinking tasks, and enable empathic responses for feeling tasks in services.

Third, considering how COVID-19 has exhausted healthcare resources and outpaced medical facilities, practitioners should foster the application of AI while dealing with this pandemic (Abd-Alrazaq et al. 2020). The same stands true for the people who have had considerably restricted access to healthcare facilities because of the emergence of the coronavirus. Considering the constraints on the resources and accessibility of healthcare (caused by COVID-19), AI can identify anomalies, analyse the data, and support people during the pandemic to have a better understanding of the virus.

Finally, with its success in areas like disease diagnosis, treatment, patient monitoring, drug discovery, epidemiology, and more, AI is expected to be an indispensable and pervasive tool in the post-pandemic world (Khosla 2020, Hanaba et al. 2021). The application of AI manifests patient-centric preventive healthcare. It can act as a tool to support public health experts worldwide in their efforts to keep people safe and informed amid the coronavirus pandemic. It further enables scientists, policymakers, and healthcare professionals to find the most relevant information tailored to their questions of interest in real time (Haas et al. 2021).

8. Limitation and Further Research

The present study has limitations that can be addressed in future research. First, the research elaborates on the specific features of intelligent machines, based on the categorisation made by Huang and Rust (2021); but their applications can potentially combine different types of AI. Future research could explore the evolution of AI features emerging through the combination of intelligent machines.

Second, the study does not report challenges and constraints in the learning process enabled by AI. Other studies could benefit from observing individuals as they proceed through the learning phases. This could yield more profound insights into the magnitude of the efforts required to overcome barriers as the learning process unfolds and make advances in other fields.

Third, the AIHLA could be implemented in other fields beyond healthcare. It would create several opportunities for researchers to explore the "AI as a learner" and "AI as a learning enhancer" also in other sectors.

Finally, it is also possible to extend the research in the other two domains introduced by Bloom (1956), besides the cognitive one, namely, the affective domain and the psychomotor domain. First, the affective domain (Krathwohl et al. 1973) includes the way we deal with things emotionally, such as feelings, values, appreciation, enthusiasms, motivations, and attitudes. Second, the psychomotor domain (Simpson 1972) includes physical movement, coordination, and use of the motor-skill areas. Development of these skills requires practice and is measured in terms of speed, precision, distance, procedures, or techniques in execution.

Appendix

AI-Based Solutions Illustrations About the Role of AI as a Learner and a Learning Enhancer

AI types	Cases	Function	AI skills	AI as a human learning enhancer
A. Mechanical intelligence	AI Thermometer	Thermal imaging	Observe temperature data of a large number of people in a short time	Enabling the human actor to classify extended or unusual temperature
	Immuni App	Contact tracing	Standardise the data tracing about people that were in close contact	Foster the recognition of data about infected people
	Little Peanut	Remote assistance	Automatise the mapped area and people position to deliver content	Support people to recall activities about isolated people's needs
	EngDE4Bio	Bio surveillance	Observe data about the geolocation of infected subjects and those who came into contact with them.	Enable a fast classification of information related to possible dangers to society
	Memora Health	Diagnostic chatbot	Automatise the conduction of a risk assessment based on symptoms and exposure profile.	Facilitate doctors' ability to compare information, and data flow bigger and faster between patients and doctors.
B. Thinking intelligence	Qure.ai	Rapid diagnostics	Analyse data about COVID-19 diagnosis achieved by real-time processing activities.	Enable doctors to organise information based on detailed analysis of x-rays and CT scans.

Appendix. (Continued)

AI types	Cases	Function	AI skills	AI as a human learning enhancer
	DynaMed	Treatment discovery	Augment solutions and implement decision-making process to support COVID-19 scientific research	Help researchers to differentiate and organise specific and contextual information about treatments for varied symptoms
	IBM Summit	Dimension reduction	Analyse COVID-19 information and solutions with exceptional processing speed	Support researchers to implement a deep analysis and research activities based on evaluated COVID-19 data
	Benevolent AI	Information archive	Assist with decisions about implementing information archiving procedures and with the identification of potentially effective solutions.	Support researchers to execute analysis about different types of data and information, augmenting identification of potentially effective solutions.
	Simulgens	Simulation of contagion	Augment data-driven models to detect the behaviour of people.	Enable people to implement possible preventive solutions through the identification of high risk of contagion in a virtual environment.
C. Feeling intelligence	Laila	Support feeling Interaction	Acknowledge emotions facilitating feeling communication and supporting interaction	Help doctor, caregivers and other actors to evaluate patient's emotion during stressful situations via interaction
	Paro	Emotional support	Acknowledge and emulate activities of elderly emotion and feeling adapting emphatically and influencing others' emotions	Help caregivers to check and process the emotions-related details of elderly people to be able to create/produce emotional support and react in time

References

Abd-Alrazaq A, Alajlani M, Alhuwail D, Schneider J, Al-Kuwari S, Shah Z, Hamdi M, Househ M (2020) Artificial intelligence in the fight against COVID-19: Scoping review. *J. Medical Internet Res.* 22(12):e20756.

Albrecht T, Rausch TM, Derra ND (2021) Call me maybe: Methods and practical implementation of artificial intelligence in call center arrivals' forecasting. *J. Bus. Res.* 123(September 2020):267–278.

Allal-Chérif O, Simón-Moya V, Ballester ACC (2021) Intelligent purchasing: How artificial intelligence can redefine the purchasing function. *J. Bus. Res.* 124(November 2020):69–76.

Anderson LW, Krathwohl DR, Airasian PW, Cruikshank KA, Mayer RE, Pintrich PR, Raths J, Wittrock MC (2001) *A Taxonomy for Learning, Teaching, and Assessing: A Revision of Bloom's Taxonomy of Educational Objectives* (Longman, London). https://www.uky.edu/~rsand1/china2018/texts/Anderson-Krathwohl - A taxonomy for learning teaching and assessing.pdf.

Aranha EA, dos Santos PH, Garcia NAP (2018) EDLE: An integrated tool to foster entrepreneurial skills development in engineering education. *Ed. Tech. Res. Development* 66(6):1571–1599.

Arel I, Rose DC, Karnowski TP (2010) Deep machine learning: A new frontier in artificial intelligence research. [research frontier] *IEEE Comput. Intelligence Magazine* 5(4):13–18.

Ben-Zvi D (2004) Reasoning about variability in comparing distributions. *Statist. Ed. Res. J.* 3(2):42–63.

Bloom BS (1956) *Taxonomy of Educational Objectives: The Classification of Educational Goals, Handbook I, Cognitive Domain* (McKay, New York).

Bloom BS, Engelhart MD, Furst EJ, Hill WH, Krathwohl DR (1956) *Handbook I: Cognitive Domain* (McKay, New York).

Bolton RN, McColl-Kennedy JR, Cheung L, Gallan A, Orsingher C, Witell L, Zaki M (2018) Customer experience challenges: Bringing together digital, physical and social realms. *J. Service Management* 29(5):776–808.

Brynjolfsson E, Mcafee A (2017) Artificial intelligence, for real. *Harvard Bus. Rev.* Accessed May 3, 2021, https://hbr.org/2017/07/the-business-of-artificial-intelligence.

Budd J, Miller BS, Manning EM, Lampos V, Zhuang M, Edelstein M, Rees G, et al. (2020) Digital technologies in the public-health response to COVID-19. *Nature Medicine* 26(8):1183–1192.

Buhalis D, Harwood T, Bogicevic V, Viglia G, Beldona S, Hofacker C (2019) Technological disruptions in services: Lessons from tourism and hospitality. *J. Service Management* 3(2):33–56.

Bullock J, Luccioni A, Pham KH, Lam CSN, Luengo-Oroz M (2020) Mapping the landscape of artificial intelligence applications against COVID-19. *J. Artificial Intelligence Res.* 69:807–845.

Čaić M, Mahr D, Oderkerken-Schröder G (2019) Value of social robots in services: Social cognition perspective. *J. Services Marketing* 33(4):463–478.

Canziani BF, Welsh DHB (2019) How entrepreneurship influences other disciplines: An examination of learning goals. *Internat. J. Management Ed.* 19(1):100278.

Chung TS, Rust RT, Wedel M (2009) My mobile music: An adaptive personalization system for digital audio players. *Marketing Sci.* 28(1):52–68.

Chung TS, Wedel M, Rust RT (2016) Adaptive personalization using social networks. *J. Acad. Marketing Sci.* 44(1):66–87.

Clement T, Silvernagel C (2019) A conceptual framework of entrepreneurial finance. *Entrepreneurship Ed. Pedagogy* 2(4):308–332.

Crowe A, Dirks C, Wenderoth MP (2008) Biology in bloom: Implementing Bloom's taxonomy to enhance student learning in biology. *CBE Life Sci. Ed.* 7(4):368–381.

Dawar N, Bendle N (2018) Marketing in the age of Alexa. *Harvard Bus. Rev.* 96(3):80–86.

Drigas AS, Papoutsi C (2018) A new layered model on emotional intelligence. *Behav. Sci. (Basel)* 8(5):1–17.

Ekren G, Keskin NÖ (2017) Using the revised bloom taxonomy in designing learning with mobile apps. *GLOKALde* 3(1):33–48. http://www.glokalde.com/pdf/issues/11/Article2.pdf.

Garry T, Harwood T (2019) Cyborgs as frontline service employees: A research agenda. *J. Service Theory Practice* 29(4):415–437.

Gelmez K, Bagli H (2018) Exploring the functions of reflective writing in the design studio: A study from the point of view of students. *Art Design Comm. Higher Ed.* 17(2):177–197.

Gilson LL, Goldberg CB (2015) Editors' comment: So, what is a conceptual paper? *Group Organ. Management* 40(2):127–130.

Greiner C, Jovy-Klein F, Peisl T (2021) AI as co-workers: An explorative research on technology acceptance based on the revised Bloom taxonomy. Arai K, Kapoor S, Bhatia R, eds. *Proc. Future Tech. Conf., Advances in Intelligent Systems and Computing*, vol. 1288 (Springer, Cham), 27–35.

Granello DH (2001) Promoting cognitive complexity in graduate written work: Using Bloom's taxonomy as a pedagogical tool to improve literature reviews. *Counselor Ed. Supervision* 40(4):292–307.

Gummesson E (2005) Qualitative research in marketing: Road-map for a wilderness of complexity and unpredictability. *Eur. J. Marketing* 39(3–4):309–327.

Haas Q, Alvarez DV, Borissov N, Ferdowsi S, von Meyenn L, Trelle S, Teodoro D, Amini P (2021) Utilizing artificial intelligence to manage COVID-19 scientific evidence torrent with Risklick AI: A critical tool for pharmacology and therapy development. *Pharmacology* 106(5–6):244–253.

Hanaba S, Mysechko O, Bloshchynskyi I (2021) Changing the educational paradigm in post-pandemic world: Possibilities and risks of artificial intelligence using. *BRAIN. Broad Res. Artificial Intelligence Neuroscience* 11(2Sup1):48–55.

Haring P, Warmelink H, Valente M, Roth C (2018) Using the revised Bloom taxonomy to analyze psychotherapeutic games. *Internat. J. Comput. Games Tech.* 1(1):1–9.

Heinonen K, Strandvik T (2020) Reframing service innovation: COVID-19 as a catalyst for imposed service innovation. *J. Service Management* 32(1):101–112.

Heller RA, Sun Q, Hackler J, Seelig J, Seibert L, Cherkezov A, Minich WB, Seemann P, Diegmann J, Pilz M (2021) Prediction of survival odds in COVID-19 by zinc, age and selenoprotein P as composite biomarker. *Redox Biol.* 38:101764.

Holzinger A (2016) Interactive machine learning for health informatics: When do we need the human-in-the-loop? *Brain Inform.* 3(2):119–131.

Huang M-H, Rust RT (2017) Technology-driven service strategy. *J. Acad. Marketing Sci.* 45(6):906–924.

Huang MH, Rust RT (2018) Artificial intelligence in service. *J. Service Res.* 21(2):155–172.

Huang MH, Rust RT (2021) Engaged to a robot? The role of AI in service. *J. Service Res.* 24(1):30–41.

Jaakkola E (2020) Designing conceptual articles: Four approaches. *AMS Rev.* 10(1):18–26.

Jarrahi MH (2018) Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Bus. Horizons* 61(4):577–586.

Kaplan A, Haenlein M (2019) Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Bus. Horizons* 62(1):15–25.

Khosla R (2020) Technology, health, and human rights: A cautionary tale for the post-pandemic world. *Health Human Rights* 22(2):63.

Kozikoğlu İ (2018) The examination of alignment between national assessment and English curriculum objectives using revised Bloom's taxonomy. *Ed. Res. Quart.* 41(4):50–77.

Krathwohl DR (2002) A revision of Bloom's taxonomy: An overview. *Theory Pract.* 41(4):212–218.

Krathwohl DR, Bloom BS, Bertram BM (1973) Taxonomy of educational objectives, the classification of educational goals. Krathwohl DR, Bloom BS, Masia B, eds. *Handbook II: Affective Domain* (David McKay Co. Inc, New York), 1–196.

Lahuerta-Otero E, González-Bravo MI (2017) How to teach business subjects to foreign students without previous experience: The success of participative and active learning strategies. *J. Econom. Econom. Ed. Res.* 18(1):1–19.

Langley DJ, van Doorn J, Ng ICL, Stieglitz S, Lazovik A, Boonstra A (2020) The internet of everything: Smart things and their impact on business models. *J. Bus. Res.* 122:853–863.

LeCun Y, Bengio Y, Hinton G (2015) Deep learning. *Nature* 521(7553):436–444.

MacInnis DJ (2011) A framework for conceptual contributions in marketing. *J. Marketing* 75(4):136–154.

Massachusetts Institute of Technology (2020) Artificial intelligence model detects asymptomatic Covid-19 infections through cell phone-recorded coughs. Accessed October 29, 2020, https://news.mit.edu/2020/covid-19-cough-cellphone-detection-1029.

McCarthy J, Minsky ML, Rochester N, Shannon CE (2006) A proposal for the Dartmouth summer research project on artificial intelligence. *AI Magazine* 27(4):12.

McKinsey & Company (2020) The state of AI in 2020. Accessed October 29, 2020, https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/global-survey-the-state-of-ai-in-2020.

Mele C, Spena TR, Kaartemo V, Marzullo ML (2021) Smart nudging: How cognitive technologies enable choice architectures for value co-creation. *J. Bus. Res.* 129:949–960.

Meuter ML, Ostrom AL, Bitner MJ, Roundtree R (2003) The influence of technology anxiety on consumer use and experiences with self-service technologies. *J. Bus. Res.* 56(11):899–906.

Meyer C, Cohen D, Nair S (2020) From automats to algorithms: The automation of services using artificial intelligence. *J. Service Management* 31(2):145–161.

Neosperience (2020) AI e orecchio per riconoscere il Covid. Accessed October 29, 2020, https://www.neosperience.com/it/neosperience-cloud/.

Nguyen TT, Nguyen QVH, Nguyen DT, Hsu EB, Yang S, Eklund P (2020) Artificial Intelligence in the battle against coronavirus (COVID-19): A survey and future research directions. Preprint, submitted July 30, http://arxiv.org/abs/2008.07343.

Odekerken-Schröder G, Mele C, Russo-Spena T, Mahr D, Ruggiero A (2020) Mitigating loneliness with companion robots in the COVID-19 pandemic and beyond: An integrative framework and research agenda. *J. Service Management* 31(6):1149–1162.

Paschen U, Pitt C, Kietzmann J (2020) Artificial intelligence: Building blocks and an innovation typology. *Bus. Horizons* 63(2):147–155.

Pedersen T, Johansen C, Jøsang A (2018) Behavioural computer science: An agenda for combining modelling of human and system behaviours. *Human-Centric Comput. Inform. Sci.* 8(7):1–20.

Pepin M, Audebrand LK, Tremblay M, Keita NB (2021) Evolving students' conceptions about responsible entrepreneurship: A classroom experiment. *J. Small Bus. Enterprise Dev.* 28(4):570–585.

Perez-Vega R, Kaartemo V, Lages CR, Borghei Razavi N, Männistö J (2021) Reshaping the contexts of online customer engagement behavior via artificial intelligence: A conceptual framework. *J. Bus. Res.* 129(November 2020):902–910.

Poluakan C, Tilaar AF, Tuerah P, Mondolang A (2019) Implementation of the revised Bloom taxonomy in assessment of physics learning. *Proc. 1st Internat. Conf. Ed. Sci. Tech. (ICESTech), Gorontalo, Indonesia.*

Porter ME, Heppelmann JE (2014) How smart, connected products are transforming competition. *Harvard Bus. Rev.* 92(11):64–88.

Rahman MA, Zaman N, Asyhari AT, Al-Turjman F, Bhuiyan MZA, Zolkipli MF (2020) Data-driven dynamic clustering framework for mitigating the adverse economic impact of Covid-19 lockdown practices. *Sustain Cities Soc.* 62:102372.

Roca J, Cano I, Gomez-Cabrero D, Tegnér J (2016) From systems understanding to personalized medicine: Lessons and recommendations based on a multidisciplinary and translational analysis of COPD. Schmitz U, Wolkenhauer O, eds. *Systems Medicine, Methods in Molecular Biology*, vol. 1386 (Humana Press, New York), 283–303.

Rodgers W, Yeung F, Odindo C, Degbey WY (2021) Artificial intelligence-driven music biometrics influencing customers' retail buying behavior. *J. Bus. Res.* 126:401–414.

Russo-Spena T, Mele C, Marzullo M (2019) Practising value innovation through artificial intelligence: The IBM Watson case. *J. Creating Value* 5(1):11–24.

Rust RT, Huang M-H (2012) Optimizing service productivity. *J. Marketing* 76(2):47–66.

Schuller BW (2018) Speech emotion recognition: Two decades in a nutshell, benchmarks, and ongoing trends. *Commun. ACM* 61(5): 90–99.

Siggelkow N (2007) Persuasion with case studies *Acad. Management J.* 50(1):20–24.

Simpson E (1972) *The Classification of Educational Objectives in the Psycho Motor Domain*, vol. 3 (Gryphon House, Washington, DC).

Stahl BC, Andreou A, Brey P, Hatzakis T, Kirichenko A, Macnish K, Laulhé Shaelou S, Patel A, Ryan M, Wright D (2021) Artificial intelligence for human flourishing–Beyond principles for machine learning. *J. Bus. Res.* 124(January):374–388.

Taillard M, Peters LD, Pels J, Mele C (2016) The role of shared intentions in the emergence of service ecosystems. *J. Bus. Res.* 69(8):2972–2980.

Taylor JET, Taylor GW (2021) Artificial cognition: How experimental psychology can help generate explainable artificial intelligence. *Psychonomic Bull. Rev.* 28(2):454–475.

Thote P, Gowri S (2020) Analysis of senior secondary examination questions according to revised Blooms taxonomy complexity. *Internat. J. Res.-GRANTHAALAYAH* 8(3):119–127.

Ting DSW, Carin L, Dzau V, Wong TY (2020) Digital technology and COVID-19. *Nature Medicine* 26(4):459–461.

Tran HMT, Anvari F (2013) The five-dimensional reflective cycle framework for designing financial information management systems courses. *Electronic J. Inform. Systems Evaluation* 16(3): 241–254.

Ulmeanu ME, Doicin C, Rosca L, Rennie AEW, Abram T, Bajdor P (2019) TecHUB 4.0-Technology and entrepreneurship education for bridging the gap in smart product development. *9th Internat. Conf. Manufacturing Sci. Ed. – MSE 2019. Trends New Indust. Revolution, MATEC Web Conf.*, vol. 290, 32–78.

Von Krogh G (2018) Artificial intelligence in organizations: New opportunities for phenomenon-based theorizing. *Acad. Management Discoveries* 16(3):141–200.

Waite J, Curzon P, Marsh W, Sentance S (2020) Difficulties with design: The challenges of teaching design in K-5 programming. *Comput. Ed.* 150:103838.

Wang Z, Manning K, Mallick DB, Baraniuk RG (2021) Toward Blooms taxonomy classification without labels. Roll I, McNamara D, Sosnovsky S, Luckin R, Dimitrova V, eds. *Artificial Intelligence in Education, Lecture Notes in Artificial Intelligence* (Springer, Cham), 433–445.

Wedel M, Kannan PK (2016) Marketing analytics for data-rich environments. *J. Marketing* 80(6):97–121.

Wirtz J (2020) Service products, development of service knowledge and our community's target audience. *J. Services Marketing* 42(7):596–615.

Yang H, Lou C, Sun L, Li J, Cai Y, Wang Z, Li W, Liu G, Tang Y (2019) AdmetSAR 2.0: Web-service for prediction and optimization of chemical ADMET properties. *Bioinformatics* 35(6): 1067–1069.

Zhang S, Yao L, Sun A, Tay Y (2019) Deep learning based recommender system: A survey and new perspectives. *ACM Comput. Surveys* 52(1):1–38 (CSUR).

Zhou Z, Xu R, Blanchet J (2019) Learning in generalized linear contextual bandits with stochastic delays. *Adv. Neural Inform. Processing Systems* 32:5197–5208.

Zhu JJ, Chang YC, Ku CH, Li SY, Chen CJ (2021) Online critical review classification in response strategy and service provider rating: Algorithms from heuristic processing, sentiment analysis to deep learning. *J. Bus. Res.* 129(May):860–877.