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Artificial Intelligence in Service

Ming-Hui Huang[1] and Roland T. Rust[2]

Abstract

Artificial intelligence (AI) is increasingly reshaping service by performing various tasks, constituting a major source of innovation, yet threatening human jobs. We develop a theory of AI job replacement to address this double-edged impact. The theory specifies four intelligences required for service tasks—mechanical, analytical, intuitive, and empathetic—and lays out the way firms should decide between humans and machines for accomplishing those tasks. AI is developing in a predictable order, with mechanical mostly preceding analytical, analytical mostly preceding intuitive, and intuitive mostly preceding empathetic intelligence. The theory asserts that AI job replacement occurs fundamentally at the task level, rather than the job level, and for "lower" (easier for AI) intelligence tasks first. AI first replaces some of a service job's tasks, a transition stage seen as augmentation, and then progresses to replace human labor entirely when it has the ability to take over all of a job's tasks. The progression of AI task replacement from lower to higher intelligences results in predictable shifts over time in the relative importance of the intelligences for service employees. An important implication from our theory is that analytical skills will become less important, as AI takes over more analytical tasks, giving the "softer" intuitive and empathetic skills even more importance for service employees. Eventually, AI will be capable of performing even the intuitive and empathetic tasks, which enables innovative ways of human–machine integration for providing service but also results in a fundamental threat for human employment.

Keywords

artificial intelligence, human intelligence, machine learning, replacement, service strategy, robots, automation, singularity, mechanical intelligence, analytical intelligence, intuitive intelligence, empathetic intelligence, economics, human resources

Artificial intelligence (AI), manifested by machines that exhibit aspects of human intelligence (HI), is increasingly utilized in service and today is a major source of innovation (Rust and Huang 2014). For example, robots for homes, health care, hotels, and restaurants have automated many parts of our lives, virtual bots turn customer service into self-service (Fluss 2017), big data AI applications are used to replace portfolio managers (Javelosa 2017), and social robots such as Pepper are used to replace human greeters to welcome customers in customer-facing services (Choudhury 2016). These developments have made some people declare that we are in the fourth industrial revolution in which technology is blurring the boundary between the physical, digital, and biological spheres (Schwab 2017).

Despite being a major source of innovation, AI also threatens human service jobs. We have already seen severe job displacement in manufacturing, resulting in a shift from manufacturing to the service industries (Buera and Kaboski 2012). Are service jobs immune from this replacement? Traditionally, it has been considered that service jobs, even low-skilled ones, are more difficult to automate due to their relying more heavily on contextual understanding and spontaneous interactive communication than manufacturing jobs (Autor and Dorn 2013). However, this may soon no longer be the case. For example, Young and Cormier (2014) investigate the idea of whether robots can be managers, and the results show that although a human experiment controller has more perceived authority, nearly 46% of the participants obey the robots. Chui, Manyika, and Miremadi (2015) find that a significant percentage of the tasks performed by those in high-paying jobs, such as portfolio managers, physicians, and senior managers, can be automated by using current technology.

This AI revolution and threat have sparked multidisciplinary research attention. There are two major research streams related to the progress of AI. The service and technology literatures tend to focus on the positives of AI technology usage, while the economic literature tends to focus on the effect of AI on jobs. The service literature tends to focus on applications of intelligent technology (Colby, Mithas, and Parasuraman 2016; Marinova et al. 2017; Rafaeli et al. 2017), service enabled by various technologies (Huang and Rust 2013), and service technologies (Kunz et al. 2018). Research has shown that the advance of technology should lead to predictable consequences

[1] Department of Information Management, College of Management, National Taiwan University, Taipei, Taiwan
[2] University of Maryland, College Park, MD, USA

Corresponding Author:
Roland T. Rust, University of Maryland, 3451 Van Munching Hall, College Park, MD 20742, USA.
Email: rrust@rhsmith.umd.edu

including increasing adoption of self-service technologies (Meuter et al. 2000), higher optimal productivity (Rust and Huang 2012), and a larger service sector (Rust and Huang 2014).

The strategic management, economic, scientific, and practitioner literatures focus more on the impact of AI on human labor and jobs, such as the use of deep learning for more accurate skin cancer detection than dermatologists (Esteva et al. 2017; Leachman and Merlino 2017), the augmentation effects of AI on knowledge workers (Davenport and Kirby 2015), digital technologies as the driving force of work and life (Brynjolfsson and McAfee 2016), the growth of low-skill service jobs in the U.S. labor market due to automation (Autor and Dorn 2013), and AI-enabled workplace redefinition (Chui, Manyika, and Miremadi 2015).

The observation that AI constitutes a major source of innovation, yet is increasingly replacing service jobs, motivates us to explore more fully and rigorously the way AI will reshape service. Jobs that are replaced by AI mean that employees lose their jobs and customers lose the opportunity to obtain human service.

We merge the two research streams to try to answer important questions: when, how, and to what extent should service be provided by AI, and how will this use of AI reshape service provision and the job skills required by employees? We develop a theory of AI job replacement to describe and predict the way AI is likely to replace tasks and jobs and change the ways service is provided. This theory contains three key elements.

First, based on a synthesis of HI and AI development, we specify four ordinal and parallel types of intelligence—mechanical, analytical, intuitive, and empathetic—listed in the order of difficulty with which AI masters them. We then address the way firms should decide between humans and machines in the provision of service across the four intelligences.

Second, AI job replacement occurs fundamentally at the task level rather than the job level. AI replaces at least some human labor in a service when AI can do some of a job's tasks better to meet a firm's strategic goal, such as profit. This transition stage is commonly known as augmentation in the literature (Davenport and Kirby 2015). AI then progresses to replace human service labor when it has the ability to take over all of a job's tasks.

Third, this replacement occurs for "lower" (easier for AI) tasks first, starting with mechanical tasks, and then moving up to higher intelligence tasks. We have already seen widespread instances of smart robots replacing unskilled employees. Eventually, AI will be capable of performing even the intuitive and empathetic tasks. By specifying various AI replacement mechanisms for service, we conclude that innovative ways of providing service are emerging and inevitable, and the scale of job replacement may be more substantial than many people realize.

We contribute to the service literature, in that this theory of AI job replacement is not only descriptive (for current AI applications) but also predictive (for future AI applications), providing insights for firm strategic decisions in the fourth industrial revolution. We explore the implications with regard to which intelligences will increase or decrease in importance for human labor as AI advances. For example, business analytics degrees are booming in recent years as the result of big data, but our theory of AI job replacement suggests that analytical intelligence may not be the comparative advantage of human experts for long, and at that point, education should instead emphasize intuitive intelligence for making sense of analytical results and leave the analytical tasks to AI. In general, our conclusions argue for "softer" skills (e.g., intuitive and empathetic) being the most lasting areas of advantage for human service employees.

In the following sections, we first define the four intelligences involved in performing service tasks. We then develop our theory based on the four intelligences and draw from it to produce a set of propositions and elaborate and support these propositions using literature from multiple disciplines, along with real-world applications. Table 1 provides an overview of the structure of the paper and a summary of the theory.

Four Intelligences

The provision of service involves both employees and customers and can be provided by humans and/or machines. Depending on the nature of service, different intelligences are required. Synthesizing from the literatures of HI and AI, we distinguish four intelligences, in the order of their developmental history in AI. They are mechanical, analytical, intuitive, and empathetic. The four intelligences may be both ordinal and parallel: They are ordinal because some HIs (e.g., intuitive and empathetic ones) are more difficult to be mimicked by AI and thus take longer to develop successful AI applications. They may be parallel because once AI has reached a certain intelligence level, all lower AIs can coexist to provide service. For convenience, we refer to the intelligences that take AI longer to emulate as "higher" levels of intelligence.

The HI literature considers intelligence the ability to learn from experience and adapt to the environment (Gardner 1983, 1999; Sternberg 1984, 2005). Sternberg (2005, p. 189) defines intelligence as the ability "to achieve one's goals in life, within one's sociocultural context." Gardner (1999, p. 34) considers intelligence as "a biopsychological potential to process information . . . to solve problems . . . " Intelligences can be considered as skills that humans learn over time to adapt to their environment (Schlinger 2003). The AI literature focuses on developing machine intelligence to mimic HI such as the ability of knowledge and reasoning, problem-solving, learning, communicating, perceiving, and acting (Russell and Norvig 2010).

The following section discusses the four intelligences, highlighting their characteristics, their relevance to both humans and machines, and their applications to service. Figure 1 illustrates the four intelligences.

Table 1. Intelligences, Nature of Tasks, Job Replacement, and Service Implications.

Intelligences			Job Replacement	
AI	Skill/Labor	Nature of Tasks	AI Applications	Literature
Mechanical				
• Minimal degree of learning or adaption • Precise, consistent, and efficient • For example, self-service technologies and service robots • Rely on observations to act and react repetitively	• Skills that require limited training or education • Call center agents, retail salespersons, waiters/waitress, and taxi drivers	• Simple, standardized, 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	• Service robots get jobs done autonomously (Colby, Mithas, and Parasuraman 2016) • Low-skill manufacturing labor reallocates to service occupations (Autor and Dorn 2013; Buera and Kaboski 2012) • Productization replaces repetitive manual tasks (Sawhney 2016)
Analytical				
• Learns and adapts systematically based on data • Logical, analytical, and rule-based learning • For example, IBM's chess player Deep Blue • Rational decision-making	• Technical skills requiring training and expertise on data and analysis • Technology-related workers, data scientists, accountants, financial analyst, auto service technicians, and engineers	• Analytical, rule-based, systematic complex tasks • Tasks require logical thinking in decision-making • Data, information, and knowledge-based service	• Toyota's in-car intelligent systems replace problem diagnose tasks for technicians • IBM's Watson helps H&R Block for tax preparation • Penske's onboard technology takes over navigation tasks	• Marketing analytics take on the data and analysis tasks (Wedel and Kannan 2016) • Machines replace and augment knowledge workers (Davenport and Kirby 2015) • Smart services leverage customer information (Wünderlich, Wangenheim, and Bitner)
Intuitive				
• Learns and adapts intuitively based on understanding • Artificial neural networks-based or statistical-based deep learning • For example, Watson's Jeopardy, Google's DeepMind AlphaGo, and AI poker player Libratus • Boundedly rational decision-making	• Hard thinking professionals that require creative thinking for problem-solving skills • Marketing managers, management consultants, lawyers, doctors, sales managers, and senior travel agents	• Complex, chaotic and idiosyncratic tasks • Tasks require intuitive, holistic, experiential and contextual interaction, and thinking • Personalized, idiosyncratic, experience- and context-based service	• 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	• Robot managers take on managerial tasks (Young and Cormier 2014) • High-paying jobs, such as portfolio managers, physicians, and senior managers, can be automated using current technology (Chui, Manyika, and Miremadi 2015) • Image-recognition AI outperforms dermatologists for skin cancer diagnosis (Esteva et al. 2017)
Empathetic				
• Learn and adapt empathetically based on experience • Emotion recognition, affective computing, and communication style learning • For example, Hanson's humanoid robot Sophia and chatbot Replika • Decision-making incorporates emotions	• Soft empathetic professionals that require social, communication, and relationship building skills • Thinking jobs requiring people skill, for example, politicians and negotiators or feeling jobs, for example, psychiatrists	• Social, emotional, communicative, and highly interactive service • Tasks that require empathy, emotional labor, 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	• Artificial empathy to infer a consumer's internal states (Xiao and Ding 2014) • Incorporating emotions into marketing modeling (Roberts et al. 2015) • Frontline emotional labor performed by AI (Rafaeli et al. 2017)

Note. AI = human intelligence; IBM = International Business Machines Corp.

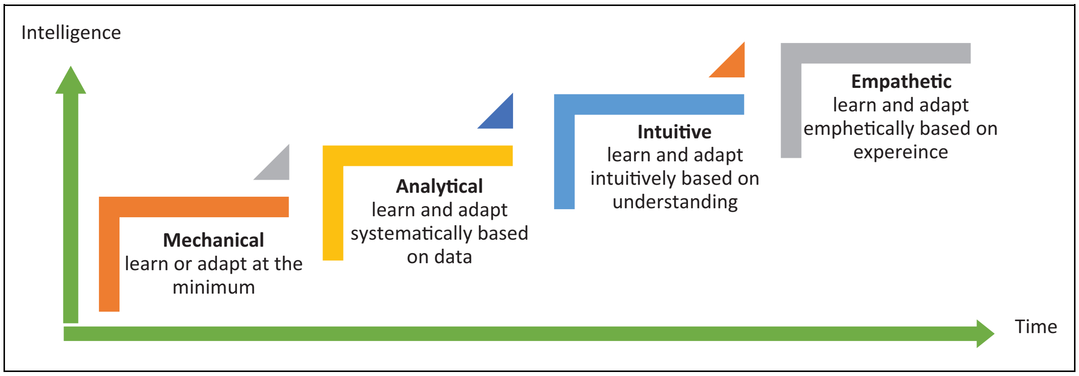

Figure 1. The four intelligences.

Mechanical Intelligence

Mechanical intelligence concerns the ability to automatically perform routine, repeated tasks. It may appear not especially smart but is essential for many tasks. For humans, mechanical processes do not require much creativity because the processes have been performed many times and thus can be done with little or no extra thought (Sternberg 1997). For human service, mechanical labor is unskilled labor, which typically does not require advanced training or education. Call center agents, retail salespersons, waiters/waitresses, and taxi drivers are some examples of jobs that require mostly mechanical skills.

To mimic human automation, mechanical AI is designed to have limited learning and adaptive ability to maintain consistency. Robots are one typical application. Service robots are "technology that can perform physical tasks, operate autonomously without needing instruction, and are directed by computers without help from people" (Colby, Mithas, and Parasuraman 2016). They are rule-based and rely on a priori knowledge and continuous sensor perception to observe and react to the physical and temporal variability in the service environment. They don't understand the environment and can't adapt automatically; instead, their knowledge is updated in an ad hoc manner and infrequently due to the repetitive nature of their environments (Engelberger 1989, pp. 108-109). More advanced versions can incorporate automatic updating functions (Kim 2007), but most service robots are designed to be just intelligent enough to perform the necessary tasks (Engelberger 1989, pp. 108-109). Intelligent search by Google, Bing, or other search engines are another application. They use powerful servers to do the computation and use intelligent algorithms to figure out the meaning of queries and return with the right results. Such search is still mechanical, in that those engines use intelligent algorithms to figure out which pages are more relevant than others but do not understand the content of the pages (Del Prado 2015).

Mechanical AI has the relative advantage over humans of extreme consistency (e.g., free from human fatigue, and responding to the environment in a very reliable manner). The repetitive, without much variation, nature of the tasks renders learning over time of limited value (nothing new to learn over the course of service transactions or relationships). Instead, it relies on observation to act and react repetitively.

Analytical Intelligence

Analytical intelligence is the ability to process information for problem-solving and learn from it (Sternberg 1984, 2005). This is about information processing, logical reasoning, and mathematical skills (Sternberg 1999). Those difficult skills are gained from training, expertise, and specialization in cognitive thinking; for example, computer- and technology-related workers, data scientists, mathematicians, accountants, financial analysts, auto service technicians, and engineers all heavily use analytical skills.

Machine learning and data analytics are the major analytical AI applications. There are various types of machine learning, and typical analytical AI mainly uses algorithms to learn iteratively from data to find insightful information without being programmed where to look for a particular piece of information (SAS Institute, Inc. 2017). International Business Machines Corp.'s (IBM) chess computer Deep Blue, which uses rule-based learning, is one example. Such AI will commit the same mistake twice if the rule remains unchanged. In the AI literature, analytical AI is considered "weak AI" because although such AI applications may exhibit seemingly intelligent behavior, they cannot easily simulate intuition. A common view is that this limitation occurs because such machines have no conscious states, no mind, and no subjective awareness (Azarian 2016).

This intelligence is required for performing complex, yet systematic, consistent, and predictable tasks; for example, for those that are data- and information-intensive. Their systematic nature renders them suitable for mass personalization based on big data from customers, with collaborative personalization being one example. Based on big data, such AI moves further away from being stand-alone machines such as service robots to networked machines that generate collective intelligence. This is considered to be the most profound widespread change that AI has brought to service so far—machines that are able to process and synthesize large amounts of data and learn from them.

Intuitive Intelligence

Intuitive intelligence is the ability to think creatively and adjust effectively to novel situations. It can be considered wisdom based on holistic and experience-based thinking (Sternberg 1984, 1999, 2005). Intuitive intelligence includes hard thinking professional skills that require insights and creative problem-solving; for example, marketing managers, management consultants, lawyers, doctors, sales managers, and senior travel agents all make heavy use of intuitive intelligence.

Understanding may be considered as the key defining characteristic of intuitive AI that distinguishes it from analytical AI. The AI literature considers intuitive AI as "strong AI," in that AI is designed to function more flexibly, more like a human. AI is built to emulate a wide range of human cognition and learn similarly to a human child (but much faster due to its computing power and connectivity). In this way, machine intelligence may be thought of as no different from HI (Kurzweil 2005, p. 260).[1] Del Prado (2015) states that if you had a machine that could read all the pages and understand the context, instead of just throwing back 26 million pages to answer a user's query, it could actually answer the question. You could ask a real question and get an answer, just as if you were talking to a person who read all those millions and billions of pages, understood them, and synthesized all that information. Some even assert that intuitive AI includes self-awareness, sentience, and consciousness; all features of HI (Azarian 2016). Intuitive AI will not as easily commit the same mistake twice because it learns from experience. Watson's Jeopardy can learn intuitively, Google's DeepMind AlphaGo simulates instinct, not just calculation (BBC News 2016), and the AI poker player Libratus can do strategic thinking with incomplete information (which is similar to human poker players; The Wall Street Journal 2017). Currently, IBM is quite advanced regarding the Business-to-Business (B2B) applications of intuitive technology. Its Watson can understand, reason, learn, and interact and has become one of the major AI platforms for business (IBM 2017).

Tasks that are complex, creative, chaotic, holistic, experiential, and contextual require intuitive intelligence. The complex yet idiosyncratic nature of the tasks renders them relying on intuition for successful service provision. For example, a customer relationship can help to get to know a customer's idiosyncratic needs better over time. Such insights may not be as easily obtained from mining the data of seemingly like-minded customers. Complex and personalized travel service arrangements, luxury food provision, entertainment, and sports are some examples that require intuition to provide better service.

Empathetic Intelligence

Empathetic intelligence is the ability to recognize and understand other peoples' emotions, respond appropriately emotionally, and influence others' emotions (Goleman 1996). It includes interpersonal, social, and people skills that help humans to be sensitive to others' feelings and work well with others (Gardner 1983; Johnson 2014). Specific skill examples include communication, relationship building, leadership, advocating and negotiating, work–life balance (Caprino 2012), social, teamwork, cultural diversity, and charisma. Empathetically skilled professionals are found in jobs that require people skill such as politicians and negotiators and feeling jobs such as psychiatrists. They can be skilled professionals, such as psychologists, or relatively unskilled frontline workers such as flight attendants.

Empathetic AI describes a machine that can feel or at least behave as though it has feeling.[2] Picard (1995) defines affective computing as computing that relates to, arises from, or influences emotions. She states that the essential role of emotion in both human cognition and perception, as demonstrated by neurological studies, indicates that affective computers should not only provide better performance in assisting humans but also might enhance computers' abilities to make decisions. The defining characteristic of empathetic AI is "experience," the ability to experience things. McDermott (2007) defines this as the "hard problem" in computationalism, which is "the problem of explaining how it is that a physical system can have vivid experiences with seemingly intrinsic 'qualities,' such as the redness of a tomato, or the spiciness of a taco" (p. 2).

There is debate about whether AI can feel the same way humans do. In the philosophy and psychology literatures, emotion is considered a biological reaction and subjective experience that may not be easily disentangled into binary computing elements and processes. Thus, according to that way of thinking, it is difficult to imagine how machines can be programmed to experience emotions as humans do. Alternatively, in the AI literature, emotion is no different from cognition and can be similarly programmed, given sufficient programming skill, just as reasoning and cognitive abilities can. For example, Minsky (2006) in his book *The Emotion Machine* argues that all mental functions, whether cognition or emotion, are computations. Therefore, AI applications can experience emotions in a computational manner. The debate reflects whether or not AI simulating emotions in a cognitive way is different from how humans experience emotions. However, just as in the Turing test, as long as AI "demonstrates" emotions, for the purpose of service provision, it may not matter how they achieve that. The debate about the nature of empathetic AI employs arguments similar to those the debate about whether intuitive AI can think like humans.

Empathetic AI is the most advanced generation of AI, and current applications to service are still very few. Some examples include Replika, which supplies artificial people (personal bots) for psychological comfort or well-beings (Huet 2016), and Sophia, the human like AI from Hanson Robotics (Campanella 2016), which is designed to look and act like humans. Sophia is so convincing that the Saudi government has recently awarded her citizenship (Maza 2017). The purpose of these applications is different from those of analytical and intuitive AIs that are designed based on functional considerations, for example, how analytical AI applications look is not usually a concern. Very often, they are deliberately designed to look like machines, to avoid looking like humans.

Empathetic tasks are high-touch services that require a higher level of social presence (Giebelhausen et al. 2014;

Table 2. Skill Requirements for Different Intelligence Tasks.

Jobs	Call Center Agents	Tax Accountants	Physicians	Psychiatrists
Intelligences				
Empathetic intelligence	Empathize with customers (calm customer down)	Empathize with clients (commiserate with clients who have to pay a high amount of tax)	Empathize with patients (tell a patient she/he has cancer)	Empathize and communicate with patients for emotional support and solutions
Intuitive intelligence	Understand why customers complain (contextual understanding)	Understand the sources of the high tax and creatively find ways to minimize taxes	Understand the symptom and diagnosis	Understand from diagnosis symptoms and come up with solutions for patients
Analytical intelligence	Analyze customer problems	Figure out which tax rules applied to which client's particular situation	Analyze clinical decision support system	Analyze conversation
Mechanical intelligence	Scripted responses to simple customer issues	File tax returns annually and routinely	Listen to heartbeat, check pulse, and read/write medical records (e-medical records systems)	Keep conversation notes

Wünderlich, Wangenheim, and Bitner 2013). Such tasks are social, emotional, communicative, interactive, and relational. Emotional labor, whether genuine or simulated, plays a key role. Emotional labor is the management of feelings and expressions to fulfill the emotional requirements of a job. Employees are expected to display the appropriate emotions when interacting with customers, whether superficially or deep from their hearts (Yoo and Arnold 2016). As we have seen, AI is making inroads in all four intelligences, with some faster to develop than others. We next explore how this advance of AI is likely to impact human service jobs.

A Theory of AI Job Replacement

To make the best use of the continuing advances in AI, firms need to make the strategic decision of whether and when to use AI of a particular intelligence to perform service tasks. Employees also need to equip themselves with the right skills to maintain employability to counter possible loss of their jobs to AI.

Based on the four intelligences framework, we build a formal theory of AI job replacement to enable us to make predictions about how AI will impact human service labor. We start from distinguishing between jobs, tasks, and labor, explaining that tasks is the level of replacement in our theory. We then identify two relevant service of AI characteristics that help enable them to outperform HI in many cases. Finally, we build a formal model of AI job replacement to predict when and how AI will impact human service labor.

Service Jobs, Tasks, and Labor

Jobs. A job is comprised of a set of tasks that an employee performs. It requires the employee to have certain skills to get the tasks done. Jobs include, for example, the service-providing occupations listed in the Bureau of Labor Statistics' Standard Occupational Classification (Moncarz, Wolf, and Wright 2008), such as customer service representatives, sales representatives, and sales managers. Jobs are comprised of tasks for back-end operations (e.g., data scientists) and front-end interactions (e.g., frontline employees) and can be in either virtual or physical workspaces.

Tasks. A single job typically consists of numerous tasks. These tasks are activities involved in an occupation (Chui, Manyika, and Miremadi 2015). The nature of tasks involved in a job varies. Some tasks are simple and mechanical, some are technical and systematic, some are complex and chaotic, and some are social and emotional. For example, a customer service manager's job may include basic daily routines (simple, routine, and mechanical tasks), analyzing customer preferences (analytical and complex tasks), developing customer service strategies (complex, intuitive, and creative tasks), and communicating and empathizing with customers (communicative, empathetic, and emotional tasks). Table 2 uses four exemplar jobs to illustrate tasks requiring mechanical, analytical, intuitive, and empathetic intelligences. It shows that jobs at different job statuses and pay levels may involve all four intelligences.

Labor. Labor is humans (employees and customers) involved in coproducing service. The service literature has long recognized employee–customer coproduction as a key concept (e.g., Vargo and Lusch 2004). Labor varies in skill levels ranging from unskilled labor performing routine tasks to skilled labor performing abstract, creative, problem-solving, and coordination tasks (Autor and Dorn 2013).

Service AI

We identify two dominant characteristics of AI that matter most to service: (1) self-learning and (2) connectivity.

Self-learning. Self-learning in AI implies a machine that can automatically improve with experience (Mitchell 1997). Self-learning can be achieved by algorithm-based machine learning that learns from data and makes predictions (Soucy 2016), by artificial neural networks (deep learning) that observe the world and generate their own internal representation based on sensory data (Genmod Project 2013), and by even automated machine learning to learn from other AIs (Simonite 2017). Regardless of the methods of self-learning, the key is that sufficiently intelligent AI can self-improve. For example, Amazon or Netflix's machine learning algorithms can improve their own recommendations over time based on customers' responses to the recommendations. Adaptive personalization systems (Chung, Rust, and Wedel 2009; Chung, Wedel, and Rust 2016) observe a customer's behavior and adapt the service over time.

Connectivity. The advance of the Internet and communication technologies significantly scale up AI's self-learning ability to the entire network rather than individual machines. Networked AI gives rise to the emergent phenomenon of collective intelligence. AI pioneer Marvin Minsky's (1986) book, *The Society of Mind*, reflects the view of the mind as comprised of individual agents with limited agendas. Individual agents try to achieve disparate goals, and a more complex intelligence emerges from it.

An example of such connectivity is the Internet of Things (IoT) that enables smart service–based simple sensors (Hoffman and Novak 2016; I. C. L. Ng and Wakenshaw 2017). For example, in the 2016 documentary, "Lo and Behold: Reveries of the Connected World," Raj Rajkumar, a Carnegie-Mellon professor who is working on self-driving cars, said that AI will learn much faster than people, because when a self-driving car makes a mistake, all self-driving cars will learn from it because of connectivity. A B2B example is that IBM's (2017) Watson leverages cognitive document visibility across all supply chain partners or the entire collaboration network to build a strategic integration platform that improves performance for the entire network.

When Does AI Replace Employee Labor?

To investigate this issue, we build a simple and stylized mathematical model based on the observed order of development of AI with respect to the four intelligence. We start by making a series of assumptions that are supported by the existing literature and then use them to develop testable propositions. In spite of the simplicity and relatively uncontroversial nature of the assumptions, some of the conclusions that result run counter to the current conventional wisdom. The technical proofs and derivations are provided in the Appendix.

Assumptions

Assumption 1: The advent of AI job replacement happens first for mechanical tasks, then for analytical tasks, followed by intuitive tasks and empathetic tasks.

Tasks require corresponding human or machine intelligence to accomplish. We separate the use of AI for service into five stages: Stage 1, starting at time $t = 0$, in which AI is used for mechanical tasks; Stage 2, starting at time $t = T_1 > 0$, in which AI begins to be used for analytical tasks; Stage 3, starting at time $t = T_2 > T_1$, in which AI begins to perform intuitive tasks; Stage 4, starting at time $t = T_3 > T_2$, in which AI begins to provide empathetic service; and Stage 5, as $t = >\infty$, in which AI can provide all kinds of service better than humans can.

Assumption 1 considers that AI service provision generally occurs first with tasks that require lower intelligence. For example, mechanical tasks tend to be homogeneous and repetitive and can often be easily and directly automated by AI. Sawhney (2016) argues that tasks that are performed frequently (high volume) and require little sophistication (meaning knowledge or intelligence) are ideal for productization, that is, machine replacement. Chui, Manyika, and Miremadi (2015) consider that tasks that do not require knowledge are more likely to be automated.

Even if some jobs are more heterogeneous and require higher intelligence, as long as the jobs can be broken down into homogeneous tasks, they can be replaced by AI. For example, the systematic nature of analytical service renders it easier to be broken down into more homogeneous tasks to be performed by AI. Baidu's chief scientist, Andrew Ng, in a recent *Wall Street Journal* interview (A. Ng and Jacobstein 2017) states that, as a rule of thumb, any tasks that can be done in less than 1 s of mental thought can be replaced with AI. He uses the example of a security guard monitoring security footage to illustrate this argument: such a job is complex, but the job can be broken down into a lot of smaller tasks, with many of the smaller tasks involving 1 s of cognitive thinking. AI can automate those 1-s tasks and leave the other tasks to the security guard.

Assumption 2: AI job replacement for a particular intelligence is proportional to AI task replacement.

If AI is able to replace half of all mechanical tasks, then we assume that only about half of the original number of people will be required to provide the same service. As an example, consider telephone customer service phone menus. Those automated systems replace the relatively mindless mechanical labor that was formerly performed by low-paid employees. It is clear that the number of telephone customer service personnel has declined as telephone customer service has become increasingly automated (U.S. Department of Labor 2008). For example, we have witnessed that ATM replaces human tellers in handling repetitive cash withdraws and deposits, and robotic servants replace human waiters/waitresses to serve customers at restaurants.[3] A recent *New York Times* reports that robots are predicted to win the race for American jobs (C. C. Miller 2017). For one more robot per thousand industrial workers, the employment to population ratio is predicted to reduce .18% to .34% and wages by .25% to .5% (Acemoglu and Restrepo 2017).

This assumption links task replacement to employee labor replacement. The more tasks of a job that AI takes on, the fewer

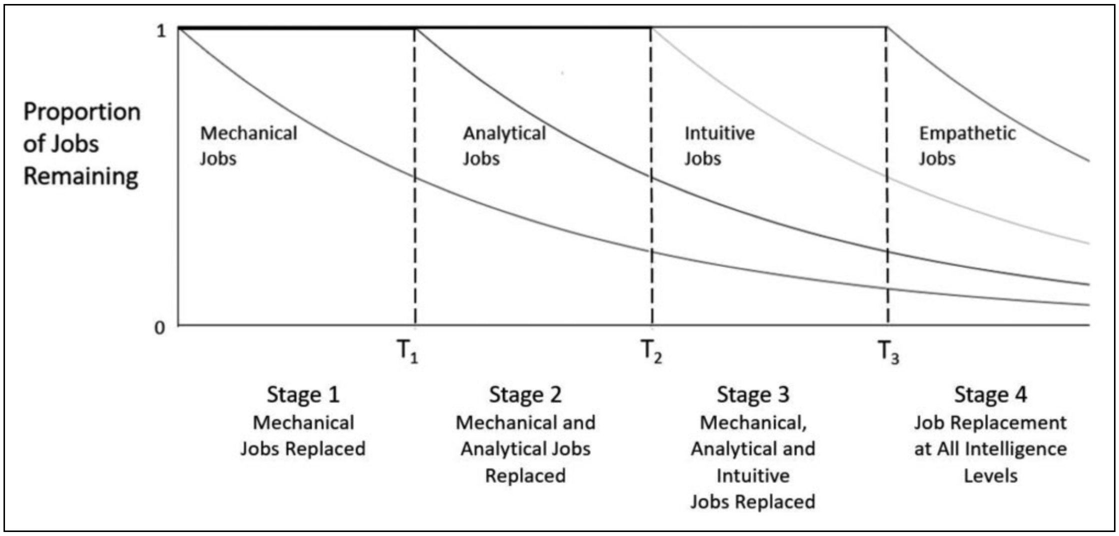

Figure 2. Stages of job replacement.

employees are needed for doing that job. The transition stage when a job is partially done by AI and partially done by employee labor is commonly known as augmentation (Davenport and Kirby 2015). However, as long as AI continues advancing its intelligence and taking over more tasks, employee labor will be steadily replaced. This can be evidenced in that even just for recent years, the prediction that skilled jobs will be more secure (e.g., knowledge workers in Davenport and Kirby 2015) has changed, with portfolio managers being replaced by big data AI (Javelosa 2017). Therefore, task replacement directly implies employee labor replacement.

> **Assumption 3:** The rate of AI job replacement within a specific intelligence is proportional to the number of human workers within that intelligence.

This assumes that job replacement happens at a fixed rate proportional to the number of workers. If there are many human workers, there is more potential for replacement. As the number of human workers approaches zero, the number of workers replaced declines. Similar assumptions are employed by the Bass model of new product diffusion (Bass 1969; Mahajan, Muller, and Bass 1990) and its many variants. As in the Bass model, this assumption is concisely stated using differential equations. In our case, applying Assumptions 1 and 2, we have:

$$dM(t)/dt = -k\,M(t),\ \text{for } t > 0, \tag{1}$$

$$dA(t)/dt = -k\,A(t - T_1),\ \text{for } t > T_1, \tag{2}$$

$$dI(t)/dt = -k\,I(t - T_2),\ \text{for } t > T_2, \tag{3}$$

$$dE(t)/dt = -k\,E(t - T_3),\ \text{for } t > T_3, \tag{4}$$

where $M(t)$, $A(t)$, $I(t)$, and $E(t)$ are the proportion of the original workers associated with mechanical, analytical, intuitive, and empathetic tasks, respectively, and $k > 0$ is the rate of AI job replacement. For simplicity of exposition, we use the same rate of job replacement across intelligences.[4] Some may argue that the lengths of the stages should increase over time, reflecting the greater difficulty of devising higher intelligence AI; our model is fully general to this possibility, and none of the propositions would be affected.

The above first-order differential equations may be solved to provide the following closed form expressions for $M(t)$, $A(t)$, $I(t)$, and $E(t)$:

$$M(t) = \exp(-kt) \quad \text{for } t > 0. \tag{5}$$

$$A(t) = \exp(-k(t - T_1)) \quad \text{for } t > T_1. \tag{6}$$

$$I(t) = \exp(-k(t - T_2)) \quad \text{for } t > T_2. \tag{7}$$

$$E(t) = \exp(-k(t - T_3)) \quad \text{for } t > T_3. \tag{8}$$

Figure 2 provides a graphical illustration of the proportion of jobs remaining for each intelligence over time, as related to the five stages of AI replacement discussed previously.

We also wish to explore the relative importance of the intelligences over time for human service employment because if the relative importance of an intelligence changes over time, this would have implications on the kinds of skills that service workers should have, and the kind of education and training that they should receive. To evaluate this, we define the relative importance of an intelligence at time t as being the proportion of the original number of jobs related to that intelligence, normalized by the sum across all intelligences. For example, the relative importance of mechanical intelligence, $M^*(t)$, is defined as:

$$M*(t) = M(t)/\text{SUM}(t), \tag{9}$$

where $\text{SUM}(t) = M(t) + A(t) + I(t) + E(t)$. $A^*(t)$, $I^*(t)$, and $E^*(t)$ are defined analogously.

We now explore Stages 1 through 5 individually and derive propositions about how the service jobs environment will

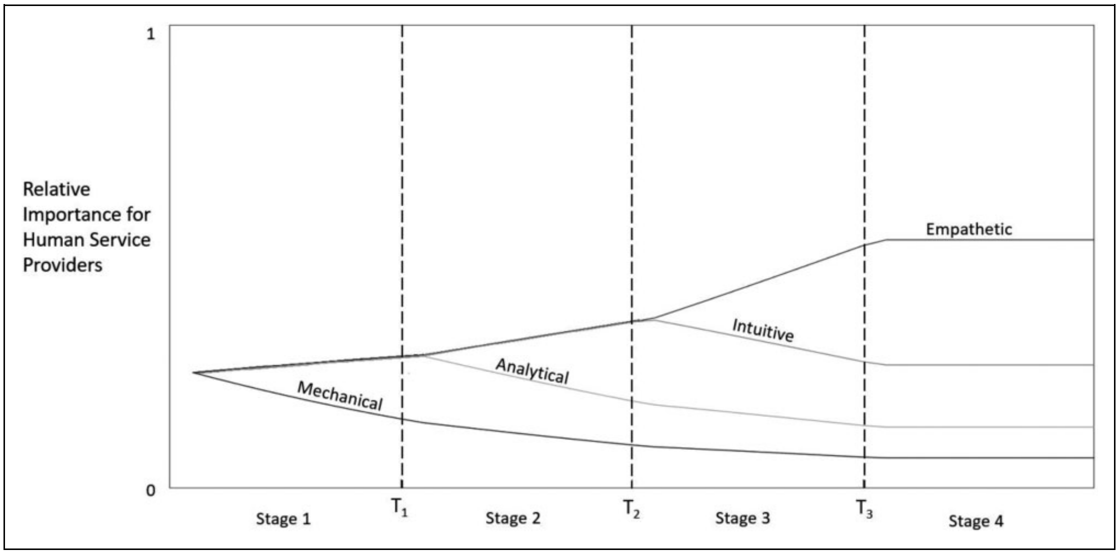

Figure 3. Relative importance of intelligences for jobs.

change. All derivations and proofs of propositions are supplied in the Appendix.

Stage 1: AI Replaces Mechanical Jobs

Proposition 1: In Stage 1, the relative importance of mechanical intelligence declines, and the relative importance of analytical, intuitive, and empathetic intelligences increases (proof in the Appendix).

This stage is mostly what we have observe in recent years. We can see that relatively unskilled labor, who worked on mostly mechanical tasks, has been experiencing a much more difficult time finding employment (Lerman and Schmidt 1999). For example, McDonald's frontline workers are becoming obsolete as McDonald's rolls out the "Create Your Taste" touch screen kiosks (Johnson 2016). At the same time, we see increasing emphasis on analytical, intuitive, and empathetic skills (R. Miller and Chandra 2015). Figure 3 shows the relative importance of the various intelligences over time, across the five stages.

In this stage, mechanical AI takes over standardized and repetitive service tasks, while additionally having the advantages of cost efficiency and quality consistency. Therefore, this is the intelligence for which we can immediately expect to see a large-scale job replacement. Early examples of automation include using voice-recognition telephone menus to automate service delivery, using process technologies to streamline service processes, and using productivity technologies in fast-food chains to provide consistent service. Recent development includes various robots that can do jobs autonomously. Pepper, a humanoid robot made by Softbank Robotics, equipped with facial recognition capabilities, is an example of autonomous AI used for industries that rely on frontline customer service interactions such as hotels, cruise ships, airports, or other places (Halzack 2017).

AI replacement at this stage shifts the demand for human labor from mechanical skills to higher intelligent skills and leaves the mechanical tasks to machines. For example, R. Miller and Chandra (2015) report that, in 2015, there were 5 times as many U.S. positions posted in 2014 requiring computer or mathematics skills, as there were unemployed people. Sawhney (2016) argues that although productization replaces repetitive manual tasks, the flip side is that workers with the best skills keep their jobs.

In facing this replacement, workers need to upgrade their skills to move to a role that uses higher intelligent skills. This is the trend we observe with the shift of jobs from unskilled labor to skilled labor in the United States or the shift of jobs from the United States to foreign cheap labor economies (e.g., outsourcing); both achieve the same replacement effect, but one with replacement by machines and the other with replacement by cheaper, foreign unskilled labor. Autor and Dorn (2013) find that labor markets dominated by routine tasks experienced reallocating low-skill labor into service occupations, adopting information technology, and receiving skilled labor inflows between 1980 and 2005.

Stage 2: AI Replaces Both Mechanical and Analytical Jobs

Proposition 2: In Stage 2, the relative importance of mechanical intelligence continues to decline, and the relative importance of analytical intelligence also declines, while the relative importance of intuitive and empathetic intelligences increases further (proof in the Appendix).

This stage still looks somewhat unfamiliar to us because the AI replacement of analytical jobs is just now emerging. It is notable that analytical intelligence, which in the early days of

AI job replacement has been gaining relative importance, is predicted to soon decline in relative importance. The "soft" skills of intuition and empathy are meanwhile predicted to assume unprecedented relative importance.

In Stage 1, analytical skills were a comparative advantage of human workers. We can see marketing analytics in strong demand both in academic education and in business world (PricewaterhouseCoopers 2017; Wedel and Kannan 2016). The dominant thinking in the existing literature is that as long as humans are skillful and knowledgeable, they don't have to worry about being replaced by AI (e.g., Davenport and Kirby 2015). However, this may not be the case for too long because in Stage 2, analytical skill starts to become a comparative advantage of AI over HI; thus, analytical tasks may be straightforwardly taken over by more advanced AI.

In this stage, workers can secure their jobs by further strengthening their intuitive skills. Unlike analytical skills that are more commonly used at the back end, intuitive skills can be used at both the back end and front end. Complex front-end services, such as negotiation with customers, can be expected to be more difficult to replace with AI.

Intuitive intelligence is of great value for the task of relationship-based personalization. This is different from the data-based personalization in which data are mainly from peer customers not necessarily from the focal customer. When there is an opportunity to observe a customer's behavior or journey over time, direct information can be obtained from the focal customer to provide even more relevant and fine-tuned personalized service to the customer. Such data are not real "big" data and require intuition to gain insights. The provision of such service is considered an example of "smart services" that leverage information collected from a customer via microchips, software, and sensors to serve customers that feature awareness and connectivity (Wünderlich, Wangenheim, and Bitner 2013).

The division of labor between AI and intuitive workers can be that analytical AI does the heavy-duty data and information preparation, calculation, and analysis for intuitive workers to make wise decisions. That is, AI provides analytical decision support. Big data analytics provide a good illustration of this division of labor. Big data are just a massive amount of various types of data. Without human intuition and interpretation, they are useless. For example, in an International Conference on Information Systems 2015 Chief Information Officer Symposium panel, a Toyota executive illustrated that the modern car has become too complicated for the repairmen to fix. Those technicians need to rely on the in-car data and information to diagnose what the problem is and then fix it. Sawhney (2016) states that algorithm-driven automation and data analytics can free well-paid professionals to focus on jobs that require more sophistication. We have even witnessed BlackRock replacing its portfolio managers using big data AI (Javelosa 2017). Without being intuitive and creative in managing customers' investment portfolio, but relying solely on their data and analysis skills, managers who are "too analytical" risk being replaced by AI.

Stage 3: AI Replaces Mechanical, Analytical, and Intuitive Jobs

> **Proposition 3:** In Stage 3, the relative importances of mechanical and analytical intelligences continue to decline, and the relative importance of intuitive intelligence begins to decline, while the relative importance of empathetic intelligence increases even more (proof in the Appendix).

In this stage, even intuitive tasks will not be immune from takeover by AI, contrary to the current conventional wisdom. AI is eroding human dominance in this intelligence already. Esteva et al. (2017) and Leachman and Merlino (2017) report that image recognition AI with deep neural networks is as good as or even outperform dermatologists for skin cancer classification. Edelman and Singer (2015) propose that in contextual interactions, AI can use knowledge about where a customer is in the decision journey to enable a series of interactions that strengthen the journey experience. They illustrate this with the Starwood Hotels example, which rolls out an app that texts a guest with her room number as she enters the hotel, checks her in with a thumbprint scan on her smartphone, and, as she approaches her room, turns her phone into a virtual key that opens the door. The app then sends well-timed and personalized recommendations for entertainment and dining.

Stage 4: AI Replaces Mechanical, Analytical, Intuitive, and Empathetic Jobs

> **Proposition 4:** In Stage 4, all human jobs decrease, with empathetic intelligence still being the most important (proof in the Appendix).

Empathetic AI is currently being developed for all aspects of service, both in the front end and back end. For front-end interaction, for difficult or communication intensive customer service, emotional bots can lighten the load of customer service reps and alleviate consumer irritation (Poggi 2017). The chatbot, Replika, doesn't just talk to people but also learns and mimics their texting styles, which can further personalize frontline communications (Huet 2016). Affectiva's emotion recognition software development kit has been embedded into games, via a Unity3D plugin and other platforms, so gameplay can morph to address a player's psychological responses. Stuart (2017) reports that emotion-aware digital devices can detect that a consumer is sad, and zoom off to the kitchen to make coffee, or at least instruct the IoT system to open the blinds and let the sunshine in, and Hollywood is also using it to tweak trailers to ensure sold-out crowds on movies' opening weekends.

For back-end support, empathetic AI applications can provide emotional analytics for customer experience and engagement. For example, Affectiva measures and analyzes human expressions and categorizes them into emotions (sadness, happiness, anxiety, joy, etc.). Those then can be used to track not just what customers say but how customers really feel (Stuart

2017). Such AI can identify customer emotions, so that employees can figure out the right responses or the firm can deliver the right service at the right time. Based on a similar concept, Xiao and Ding (2014) consider artificial empathy as a model-based approach to infer a consumer's internal states (cognitive, affective, physical) based on the information he or she emits (audio, video, or other formats) as well as to infer a consumer's reaction given a particular set of stimuli. They use face recognition to recommend faces to be used in ads. Kmart Australia uses machine learning to decide the way emotions should be incorporated into its TV commercials to increase likelihood to choose its store and increase its earnings (Roberts et al. 2015).

In this stage, it should be clear that all human jobs are under threat from AI. All intelligences are in decline, but empathetic skills remain the most important. Service workers thus need to develop empathetic skills to cope. Upgrading intuitive skills to empathetic skills is a more natural extension than upgrading analytical skills to intuitive or empathetic skills because analytical thinking, to a great degree, takes place in a different part of the brain (mostly the left cerebral cortex) than the kind of holistic thinking that is necessary for intuition and empathy (mostly the right cerebral cortex). At the risk of oversimplifying, right brainers are more intuitive and creative (making decisions with incomplete information), whereas left brainers are good at calculation and analysis skills (making decision with compete information). Bianchi (2016) argues that in this big data analytic world, to stand out, marketers need to have the ability to balance right brain and left brain and to look beyond the numbers and tools and focus on how to connect with people.

Stage 5: Human Replacement or Integration

> **Proposition 5:** In Stage 5, AI either replaces all human jobs or completely integrates with human workers (proof in the Appendix).

The ultimate path for AI can be replacement or complete integration with human workers. In Stage 5, AI has become at least as intelligent as humans in all four intelligences. Since AI can think and feel like humans, it has the ability to take over all tasks/jobs. Therefore, the best case scenario between humans and machines is that they work together seamlessly. There are multiple possibilities for this integration:

- *Dual service provision*. This reflects a segmentation view that some customers may want to pay a premium for human interaction or human touch. Just as the emergence of TV watching replaced movie going, but there are still some people who enjoy going to movie theaters, it is possible that some people will still prefer knowing that they are being served by humans, even though the service may be inferior in every other way. In this possibility, both humans and machines end up providing service, but each serving its own target segment. In other words, human jobs still exist but as a niche preference.
- *Human–machine division of labor*. In this possibility, humans and machines work together to provide service. It may stimulate insights for high-touch service because some believe that the human brain (feel in a holistic way) and empathetic AI (feel in a logical way) experience emotions in different ways. This view considers that HI is biological and can't be fully described by computational methods (Winkler 2017). In this view, better AI can only make humans more powerful. Russell, a computer scientist and founder of the Center for Intelligent Systems at the University of California and the coauthor of *Artificial Intelligence: A Modern Approach* (Russell and Norvig 2010), concluded in an interview with Tech Insider (Del Prado 2015) that "the way I think about it is everything we have of value as human beings—as a civilization—is the result of our intelligence. What AI could do is essentially be a power tool that magnifies human intelligence and gives us the ability to move our civilization forward."
- *Machines serving humans*. In this possibility, AI does the tasks/jobs that humans don't want to do, while humans can cherry pick the tasks/jobs they want to keep and have a better quality of life. This is a human-centric view such that AI continues to serve humans' needs, even if it can be smarter than humans. To the extreme when all tasks can be done by AI, it may mean that it is a world in which humans no longer need to do any work but may focus on just enjoying their lives. It is a humanity achieved with machines doing all the work and humans enjoying recreation. The concern is that an economy run by AI for machines may not find value in letting this happen.
- *Machine-enhanced humans*. In this possibility, humans are physically or biologically integrated with machines, and AI becomes a technological extension of humans. We have seen some experimental use for medical service, for example, connecting paralyzed people's brains with mechanical devices by implants or brain monitors to help them write and move, using only their thoughts (Winkler 2017). Elon Musk, SpaceX and Tesla CEO, launched Neuralink, a venture to merge human brains with AI to help people keep up with machines. The purpose is to implant tiny electrodes in human brains to improve memory or allow for more direct interfacing with computing devices. Musk considers this is a merger of biological intelligence (HI) and digital intelligence (Winkler 2017). A more dramatic application is human augmentation. Meabh Quoirin, co-owner and CEO of the Foresight Factory & Future Foundation, says that one possibility for AI is "beyond human," which adds human bio-enhancements, prosthetics, or implants. It may also work from a shorter term customer experience perspective to enhance customer experience.

- *Internet of brains*. Researchers have recently demonstrated a connection of the human brain to the Internet (Andrews 2017). From there, it is a short leap to humans connecting together with each other in a big AI network, like the IoT, only connected to people's brains as well. This scenario mimics AI's connectivity for collective intelligence and can be viewed as the "Internet of brains." Such connectedness will greatly accelerate learning in the service environment—expanding service capability just as the beehive expands the capability of individual bees.

Alternatively, the worst case scenario is that AI completely replaces humans (i.e., all service labor, customers, as well as employees). This is the singularity concern about technology becoming completely dominant in all forms of intelligence over humans (Kurzweil 2005). Both Stephen Hawking and Bill Gates share this pessimistic concern (Azarian 2016; Briggs and Scheutz 2017; Rometty 2016). Neuroscientist and author Sam Harris, who presented a TED Talk on humanity's potential to lose control of AI, said on his podcast *Waking Up* that AI's growth will keep advancing unless something much worse happens to society first. The biggest threat is not the intelligence of individual machines but is the connectivity of all machines that amplifies the aggregate machine intelligence (Vinge 1993).

One key argument for machines to win is that humans are more likely to make mistakes. Briggs and Scheutz (2017) in their Human Robot Interaction Laboratory set out to program robots that have reasoning ability to reject human command when carrying out these orders may hurt humans. They argue that humans make mistakes in creating or mastering robots, which could result in disobedient machines. In this thinking, we are programming computers to evolve in the same manner as human brains, due to natural selection, but in a much faster manner. It means that the evolution rate can be very fast, and thus computers will become smarter at a faster rate. The result of the evolution of AI may be an unpredictably complex form that goes beyond the programming rules that produced it. Figure 4 illustrates the idea that the ultimate state is either integration or replacement.

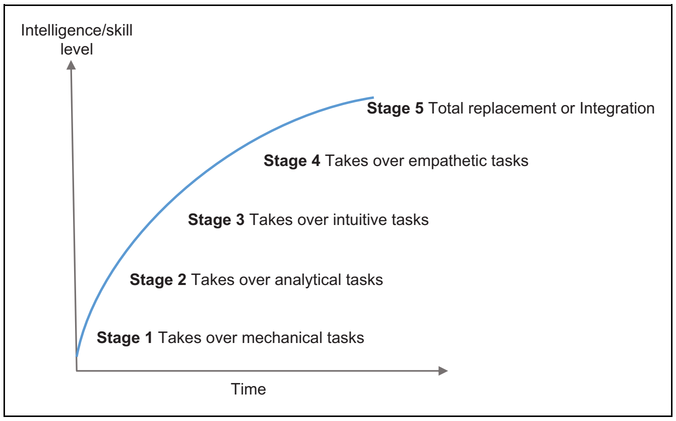

Figure 4. Stages of artificial intelligence job replacement.

Discussion

Our theory of AI job replacement provokes several additional issues for researchers and policy makers to consider in facing the AI revolution in the service economy. It also provides practical guidelines for managers in formulating their strategic decisions of whether and when to replace workers with AI as well as suggestions for business educators about how to train our students. Table 3 summarizes a set of future service research topics based on the major conclusions from our theory.

Should Firms Replace Employees With AI?

The decision should be at the task level, not the job level, which means that a firm needs to think of the task portfolio of a job and optimize the division of labor between human workers and AI. There are several factors that a firm can consider:

- *Nature of tasks*. Tasks that require a lower intelligence should be replaced first. The more tasks that can be replaced by AI, the fewer human workers will be needed. Jobs that are comprised of tasks requiring different intelligences will be the best candidates for human–machine integration.
- *Nature of service*. In the short run, transactional service (i.e., relational benefits are limited) will benefit more from AI replacement, whereas relational service can be expected to benefit more from human workers for higher customer lifetime value (Huang and Rust 2017). Service that demands a stronger human interaction or human touch will be more difficult for AI to replace (Giebelhausen et al. 2014).
- *Strategic emphasis of firms*. Given that AI applications tend first to occur for cost reasons, firms that employ a cost leadership strategy will use more AI replacement, whereas firms that employ a quality leadership strategy will use more human labor and less AI. As AI develops intelligence greater than HI, even quality strategies will employ AI.

How Should Firms Replace Human Labor With AI?

The multiple possibilities for human–machine integration provide directions for firms to design AI service strategies:

- Segment the market into segments having stronger preference for either human or machine service. The key considerations for this strategy are whether there is consumer preference heterogeneity for service and whether the firm has the comparative advantage in either human or machine service.
- Have both humans and machines provide service. In this strategy, it can be humans supporting machines or machines supporting humans. The keys for this strategy are whether humans or machines should play the

Table 3. Implications for Service Research.

Major Conclusions	Service Research Topics
Nature of task, service, and strategic emphasis determines whether firms should replace employees with AI	• What tasks require what composition of intelligences and what combination of HI and AI? • What services require what composition of intelligences and what combination of HI and AI? • What strategic emphases require what composition of intelligences and what combination of HI and AI?
Firms should design human–machine integrated service strategies to stay competitive	• How to identify consumer heterogeneity for preference for human or machine service? • How to streamline processes for human and machine service providers? • How to fully automate service at the four intelligences levels? • How to enhance human service providers with machines at the four intelligence levels? • How to connect humans and/or machines for collective intelligence?
Policy makers should carefully consider the impact of AI on the economy	• Identify the job migration for the service economy at the higher intelligence level • Identify the form of the postservice economy
Intuitive and empathetic skills will be the most lasting comparative advantages of human service	• How to retrain workers for intuitive and empathetic skills to remain employability? • How to educate students for intuitive and empathetic skills to remain employability?

Note. HI = human intelligence; AI = human intelligence.

dominant role in service provision, and the degree to which the service process can be streamlined to include both humans and machines.

- Have machines provide all service. Firms should fully automate service when there is a sufficient cost advantage, there is a sufficient quality advantage, or both. Amazon Go is one such mechanical intelligence example such that no service people are required in the entire store.
- Have machines enhance labor. This can include both the possibilities of enhancing customer or employee labor. For example, marketers could find interest in tools for performance improvements of the average person; ways to burn calories, eat well, work faster, and move better, especially considering the success of gadgets such as the FitBit (Conick 2016).
- Have machines enhance labor connectivity for collective intelligence. For service employees, though individually they may have limited intelligence, collectively they can support each other. Customers can similarly benefit from collective intelligence. For example, social media that facilitate customer interactions provide a rudimentary example of this strategy.

What Is Going to Happen to Service Jobs?

In the postindustrial age, when the lower intelligence jobs were taken over by machines, the proportion of jobs in every developed economy shifted from manufacturing to service because the latter requires heterogeneous contextual interaction, compared to mechanical AI, which emphasizes consistency and precision. Now when analytical jobs are taken over by AI, what is going to happen to those jobs? Our theory predicts that those workers will need to upgrade their intuitive and empathetic skills, and ultimately even intuitive skills will become less important than empathetic skills. In short, soft people skills will increasingly become the most important factor for employability.

A relevant issue is what will be next, after the job migration from manufacturing to service, after AI acquires all HIs and is capable of taking over jobs? What is the postservice economy? The hope for human workers seems to be to explore all the possibilities for human–machine integration discussed earlier.

What Skills Will Become More Important?

Our theory provides direct implications as to how service workers should equip themselves with the right intelligence skills that have higher survival value and what kinds of intelligences firms should look for in deploying their AI replacement strategies. An interesting and important trend we observe, by applying this theory, is concern about our current business analytics education. With the boom in offering business analytics programs in major universities, our theory implies that we should be careful about oversupplying analytics skills, as such skills will soon become a comparative advantage of machines, and can be expected to be supplied by more advanced AI. The key to remaining important will become the interpretation and decision-making based on the analytic results not the data and analysis skills per se. Therefore, in training students, such programs should emphasize creative thinking and intuition in interpreting data or making decisions rather than training students to be data and analysis machines that can lose their importance sooner.

Our theory also provides important insights regarding how the negative impact of AI replacement can be redirected into the new skill development. It may be seen in the popular press that as AI replaces lower skilled jobs, workers who lack the training or ability to function at a higher intelligence level often become unemployed (C. C. Miller 2017). Ignatius (2015), the *Harvard Business Review* (HBR) editor in chief, states that HBR has considered the robotic threat over the years, from the 1981 article by labor expert Robert Schrank, to Davenport and Kirby's (2015) "Beyond Automation," to Brynjolfsson and McAfee's (2016) "The Second Machine Age." All these articles have a common theme regarding whether a large-scale displacement is inevitable. Evolving to a higher intelligence, and especially acquiring intuitive and empathetic skills, appears to be the most promising self-development and education strategy.

Conclusion

We develop a theory for understanding the nature of service work and how/why AI can substitute for or ultimately replace humans in each type of task/job. This theory of AI job replacement provides a road map about how AI advances to take over tasks requiring different intelligences, how AI can and should be used to perform service tasks, and finally how workers can and should shift their skills to achieve a win–win between humans and machines. We conclude that the advance of AI in all four intelligences creates opportunities for innovative human–machine integration for providing service but also results in a fundamental threat for human employment.

Appendix

Proposition 1: In Stage 1, the relative importance of mechanical intelligence declines, and the relative importance of analytical intelligence, intuitive intelligence, and empathetic intelligence increase.

Proof:

$$dM*(t)/dt = \mathrm{SUM}(t)(dM(t)/dt) - M(t)(d\mathrm{SUM}(t)/dt). \tag{A1}$$

Noting that $d\mathrm{SUM}(t)/dt = dM(t)/dt$, we can rewrite the above as:

$$dM*(t)/dt = (\mathrm{SUM}(t) - M(t))(dM(t)/dt). \tag{A2}$$

The first term is positive and the second term is negative, proving that the product is negative, and thus, $dM*(t)/dt < 0$ (the relative importance of mechanical intelligence declines).

$$dA*(t)/dt = \mathrm{SUM}(t)(dA(t)/dt) - A(t)(d\mathrm{SUM}(t)/dt). \tag{A3}$$

Because $dA(t)/dt = 0$ in this stage, the left term is zero. Because $A(t) > 0$ and $d\mathrm{SUM}(t)/dt < 0$, we have:

$$dA*(t)/dt > 0. \tag{A4}$$

The derivations for $dI*(t)/dt$ and $dE*(t)/dt$ are identical to the above.

Proposition 2: In Stage 2, the relative importance of mechanical intelligence continues to decline, and the relative importance of analytical intelligence also declines, while the relative importance of intuitive intelligence and empathetic intelligence increases further.

Proof:

To get $dM*(t)/dt$, we note that $d\mathrm{SUM}(t)/dt = dM(t)/dt + dA(t)/dt$, enabling us to rewrite Equation A1 as:

$$dM*(t)/dt = (\mathrm{SUM}(t) - M(t))(dM(t)/dt) - M(t)(dA(t)/dt). \tag{A5}$$

Plugging in the expressions from Equations 5 through 8, and noting that $I(t) = E(t) = 1$ at this stage, we obtain:

$$dM*(t)/dt = -2\,k\,\exp(-kt) < 0. \tag{A6}$$

Similarly, we have:

$$\begin{aligned} dA*(t)/dt &= (\mathrm{SUM}(t) - A(t))(dA(t)/dt) - A(t)(dM(t)/dt) \\ &= -2\,k\,\exp(-k(t - T_1)) < 0. \end{aligned} \tag{A7}$$

$$dI*(t)/dt = (\mathrm{SUM}(t))(dI(t)/dt) - I(t)(d\mathrm{SUM}(t)/dt). \tag{A8}$$

Because $dI(t)/dt = 0$ and the right term is negative, we have $dI*(t)/dt > 0$.

The derivation for $dE*(t)/dt$ is identical, resulting in $dE*(t)/dt > 0$.

Proposition 3: In Stage 3, the relative importance of mechanical intelligence and analytical intelligence continues to decline, and the relative importance of intuitive intelligence begins to decline, while the relative importance of empathetic intelligence increases even more.

Proof:

We note that $E(t) = 1$ at this stage. Again using Equations 5 through 8), we have:

$$d\mathrm{SUM}(t)/dt = dM(t)/dt + dA(t)/dt + dI(t)/dt. \tag{A9}$$

Using Equation A1, we get:

$$dM*(t)/dt = (\mathrm{SUM}(t) - M(t))(dM(t)/dt) - M(t)(dA(t)/dt + dI(t)/dt) = (A(t) + I(t) + 1)(dM(t)/dt) - M(t)(dA(t)/dt + dI(t)/dt) = -k\exp(-kt) < 0. \tag{A10}$$

$$dA*(t)/dt = (\mathrm{SUM}(t) - A(t))(dA(t)/dt) - A(t)(dM(t)/dt + dI(t)/dt) = (M(t) + I(t) + 1)(dA(t)/dt) - A(t)(dM(t)/dt + dI(t)/dt) = -kt\,[\exp(-2kt + kT_1 + kT_2) + \exp(-k(t - T_1) - \exp(-2kt + kT_2))]. \tag{A11}$$

The argument in the first term is greater than the argument in the third term, which ensures that the expression in brackets is positive, and that $dA*(t)/dt < 0$. The derivation for $dI*(t)/dt$ is analogous, which provides $dI^*(t) < 0$. We also leave for the reader the formal derivation of $dE*(t)/dt$, given that the declining values of $M(t)$, $A(t)$, and $I(t)$ ensure that $E(t) = 1$ is an increasing proportion of the sum.

Proposition 4: In Stage 4, all levels of human jobs decrease, with empathetic intelligence still being the most important.

The derivatives of equations of Equations 5 through 8 are all negative, which shows that all levels of human jobs decrease. Noting that $(t - T_3) < (t - T_2) < (t - T_1) < t$, we have, from Equations 5) through 8), that $E(t) > I(t) > A(t) > M(t)$, which ensures that empathetic jobs retain a higher percentage of their original number than intuitive, analytical, and mechanical, respectively.

Proposition 5: In Stage 5, no human jobs exist.

Proof:

From Equations 5 through 8, we have:

$$M(t) = \exp(-kt) \quad \text{for } t > 0. \tag{A12}$$

$$A(t) = \exp\Big(-k(t - T_1)\Big) \quad \text{for } t > T_1. \tag{A13}$$

$$I(t) = \exp\Big(-k(t - T_2)\Big) \quad \text{for } t > T_2. \tag{A14}$$

$$E(t) = \exp\Big(-k(t - T_3)\Big) \quad \text{for } t > T_3. \tag{A15}$$

The limit of each of these expressions as t goes to infinity is equal to zero, implying that AI will ultimately replace all human jobs.

Relaxing the Assumption of the Same Rate of Replacement Across the Intelligence Levels

In this scenario, we allow k_M, k_A, k_I, and k_E be the AI rates of replacement for mechanical, analytical, intuitive, and empathetic, respectively. In this more general case, Propositions 1 and 5 and their proofs are unaffected. We replace Propositions 2 and 3 by the following more general propositions:

Proposition 2a: In Stage 2, the relative importance of mechanical and analytical intelligence declines relative to intuitive and empathetic, and the relative importance of intuitive intelligence and empathetic intelligence increases further.

Proof:

$dM(t)/dt < 0$, while $I(t) = E(t) = 1$,

$$d[M*(t)/I*(t) + E*(t)]/dt = d[(M(t)/\mathrm{SUM}(t))/((I(t) + E(t))/\mathrm{SUM}(t))]/dt = dM(t)/2 < 0, \tag{A16}$$

and similarly for $A^*(t)$,

$$dI*(t)/dt = d(I(t)/\mathrm{SUM}(t))/dt = -d\mathrm{SUM}(t)/dt > 0, \tag{A17}$$

and similarly for $dE*(t)/dt$.

Proposition 3a: In Stage 3, the relative importance of mechanical, analytical, and intuitive intelligence declines relative to empathetic, and the relative importance of empathetic intelligence increases even more.

Proof:

$dM(t)/dt < 0$, while $E(t) = 1$

$$d[M*(t)/E*(t)]/dt = d[(M(t)/\mathrm{SUM}(t))/(E(t)/\mathrm{SUM}(t))]/dt = dM(t) < 0, \tag{A18}$$

and similarly for $A^*(t)$ and $I^*(t)$,

$$dE*(t)/dt = d(E(t)/\mathrm{SUM}(t))/dt = -d\mathrm{SUM}(t)/dt > 0. \tag{A19}$$

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Notes

1. Although the strong artificial intelligence (AI) hypothesis considers that AI has the full range of human intelligence, it focuses on the cognitive thinking aspect and does not explicitly consider an empathetic aspect of AI.
2. AI pioneer, Alan Turing, devised a thought experiment that is now known as the Turing test. In that experiment, if an outside observer cannot tell apart a computer versus a human, based on their behavior, the computer can be thought to think like a human. The Turing test could also be used to test empathetic AI.
3. As mechanical tasks are replaced, even if the job remains, its nature will likely change—moving more toward the higher intelligence levels. Thus, a bank teller may become more of an adviser and less of a clerk.
4. In the Appendix, we show that allowing these rates to vary across intelligences results in a set of more general propositions that yield many of the same conclusions.

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Author Biographies

Ming-Hui Huang is a distinguished professor of electronic commerce in the Department of Information Management, College of Management, National Taiwan University.

Roland T. Rust is a distinguished university professor and David Bruce Smith chair in marketing and executive director of the Center for Excellence in Service and the Center for Complexity in Business at the Robert H. Smith School of Business, University of Maryland.