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Engaged to a Robot? The Role of AI in Service

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Abstract

This article develops a strategic framework for using artificial intelligence (AI) to engage customers for different service benefits. This framework lays out guidelines of how to use different AIs to engage customers based on considerations of nature of service task, service offering, service strategy, and service process. AI develops from mechanical, to thinking, and to feeling. As AI advances to a higher intelligence level, more human service employees and human intelligence (HI) at the intelligence levels lower than that level should be used less. Thus, at the current level of AI development, mechanical service should be performed mostly by mechanical AI, thinking service by both thinking AI and HI, and feeling service mostly by HI. Mechanical AI should be used for standardization when service is routine and transactional, for cost leadership, and mostly at the service delivery stage. Thinking AI should be used for personalization when service is data-rich and utilitarian, for quality leadership, and mostly at the service creation stage. Feeling AI should be used for relationalization when service is relational and high touch, for relationship leadership, and mostly at the service interaction stage. We illustrate various AI applications for the three major AI benefits, providing managerial guidelines for service providers to leverage the advantages of AI as well as future research implications for service researchers to investigate AI in service from modeling, consumer, and policy perspectives.

Keywords

artificial intelligence, human intelligence, replacement, augmentation, service strategy, robots, automation, mechanical AI, thinking AI, feeling AI, service process, engagement, standardization, personalization, relationalization

The purpose of this article is to delineate a strategic framework for using artificial intelligence (AI) to engage customers in service. This framework addresses the critical strategic decision that service providers need to make: When to use which AI more in service as opposed to human intelligence (HI). Let's share a business example that illustrates the essence of the framework:

> USAA, a financial services provider for the military community that is renowned for excellent service, member engagement, and brand loyalty, collaborates with IBM using its Watson Engagement Advisor to help serve military members transitioning from the military to civilian life.
>
> The use of this application starts from IBM Watson establishing, analyzing, and understanding a database based on more than 3,000 USAA documents on topics exclusive to military transitions. Military members then can visit the USAA website or use their own mobile device to ask Watson questions specific to leaving the military, such as job searching, home purchasing, and military benefits, using text or natural language. Watson then searches the database it has established for answers. This ask-and-answer process iterates and accumulates knowledge over time that personalizes answers with greater precision and relevancy.
>
> The service can be as simple as self-service. USAA members can access anytime anywhere by visiting the USAA website or using their own mobile device for routine, non-thinking, frequently asked questions (mechanical AI for standardization).
>
> The service can scale up by learning with continuing use, accumulating new information from new questions and more members. It provides personalized advice based on individual members' characteristics and specific situations (thinking AI for personalization).
>
> The service can go further to counsel members, as the transition into civilian life often is highly uncertain (members often don't know where or how to start the daunting process), and involves both the member and family. In addition to evidence-based, informed advice, counseling can give members peace of mind (feeling AI for relationalization).
>
> Eventually it helps create exceptional personalized experiences for USAA members, engaging them deeper, and enhancing brand loyalty (IBM 2014).

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The above opening case illustrates how AI can be used to engage customers at various service levels and throughout different stages of the service process. At a basic level, a major service firm like The United Services Automobile Association (USAA) can leverage mechanical AI for robotic self-service for routine, nonthinking tasks. Then, it can leverage thinking AI to make service recommendations to customers based on their current portfolios and prior record of service adoption. Finally, it can leverage a combination of thinking and feeling AI to counsel customers (specifically military members) as they transition into civilian life. Those AIs are in common use. They are not science fiction.

Our framework has its theoretical roots in the work of Huang and Rust on AI in service. Rust and Huang (2014) point out that technology (e.g., machine learning, big data, cloud computing) is a primary force for the expansion of the service economy. (Huang 2016; Rafaeli et al. 2017) develops a three-generational framework for technology innovation—automated technology, thinking technology, and feeling technology—that illustrates how different technologies can be used for different goals in the frontline service context. Huang and Rust (2018) refine this framework into four AIs: mechanical, analytical, intuitive, and empathetic, which predicts the timing of when AI would/will replace human service labor. Huang, Rust, and Maksimovic (2019) simplify the four AIs into three to demonstrate empirically that AI is driving the economy from mechanical, thinking, to feeling.

The view that there are multiple AIs serves as the important conceptual basis of the framework proposed here. The framework directly answers the critical question mentioned above. Regarding when to use more AI in service, service providers need to realize that there are multiple AIs—mechanical, thinking, and feeling—that can be used in service to engage customers. The more complex, idiosyncratic, and emotional service is, the higher the level of AI (in terms of how difficult for AI to perform the service function) is required. When AI at a given intelligence level is used more, HI (human service employees) is used less. Regarding which AI to use to engage customers, service providers need to understand the strengths of each AI, with mechanical AI being good for standardization, thinking AI being good for personalization, and feeling AI being good for relationalization; different AIs can be applied based on considerations of the nature of service.

In the following sections, we first provide a working definition of AI in service and delineate the key decisions for using AI in service. We then provide managerial implications for service providers for using various AIs to engage customers. Finally, we provide modeling, consumer, and societal implications for future research to further shape the use of AI in service.

AI in Service

Defining AI in Service

AI is machines that exhibit aspects of HI. AI is distinct from general information technology in that it involves technologies that *can* learn, connect, and adapt. AI can learn, but it is not always designed to learn, depending upon the needs of the application. AI may have varying degrees of learning ability, adaptivity, and connectivity. For example, hotel housekeeping service robots are appropriately designed as being capable of performing mechanical tasks such as making the bed and vacuuming the floor on a routine and consistent basis rather than chatting with customers interactively. Such AI applications are designed with a low level of learning capability or are only reprogrammed on an occasional basis. There are two defining characteristics of AI that result in AI being able to adapt to changing needs (Huang and Rust 2018; Huang, Rust, and Maksimovic 2019):

Self-learning. AI can self-improve automatically by learning from various inputs (e.g., big data and machine learning). That is why AI can adapt. Learning implies AI can act and adapt based on what has been learned. The deeper the learning, the more AI demonstrates human thinking and feeling capabilities. For example, AI assistant Alexa continuingly learns customer needs and requirements over time, and its algorithms can adapt to customer personal needs to serve customers better (Dawar 2018; Kaplan and Haenlein 2018).

Connectivity. AI is seldom standalone machines; even for Roomba that appears to stay at its home base quietly, the vacuuming robot can map a customer's house floor plan and can be connected to Amazon's Echo and Alexa to enable voice control by sharing the floor mapping information. It's all connected to make the service even better and easier. The connection can be machine to machine, machine to customer, or machine to employee. When Roomba connects with Amazon, Apple, or Google, it is a scenario of machine-to-machine connection. When Roomba takes your commands and cleans your bedroom, it is machine-to-customer connection. When Roomba sends your floor information to iRobot (its manufacturer), it is machine-to-employee connection. The connectivity of AI is most manifested by the Internet of Things (IoT) such that machines, humans, and objects are all connected together, and data flow and shared ubiquitously that facilitate learning. For example, Hoffman and Novak (2018) state that in the IoT, both smart objects' and consumers' experiences are enabled and constrained by the network. Ng and Wakenshaw (2017) state that IoT as a service system is socio-cyber-physical and is liquifying information and data.

AI in Service

AI that can learn, connect, and adapt is increasingly utilized in service, and today is a major source of service innovation and revolution (Rust and Huang 2014). For example, service robots interact with customers with scale and consistent quality (Wirtz et al. 2018), automate social presence in the frontline (van Doorn et al. 2017), and have become part of routine service experiences (Mende et al. 2019). Big data and machine learning applications personalize recommendations to customers

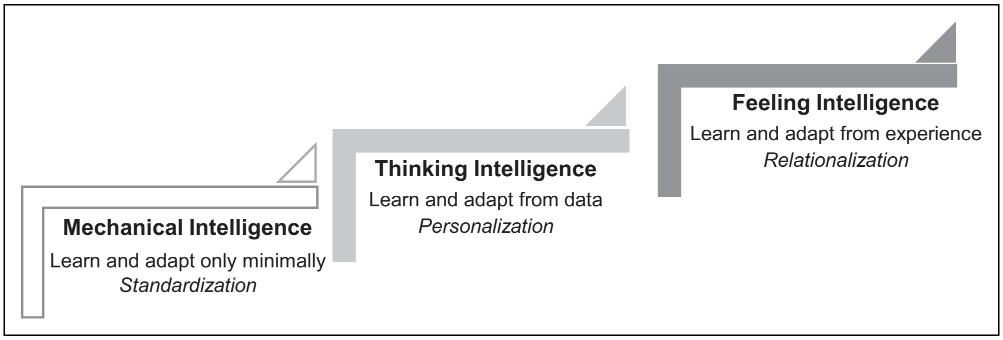

Figure 1. Three artificial intelligences and their benefits to service.

(Chung, Rust, and Wedel 2009; Chung, Wedel, and Rust 2016) and marketing analytics personalize marketing (Wedel and Kannan 2016). Anthropomorphized consumer robots make consumers feeling warm (Kim, Schmitt, and Thalmann 2019), and natural language–based social robots engage customers (Lee, Hosanagar, and Nair 2018). These common and emerging usages of AI for various functions in the service process reveal that service providers need to carefully consider how to use AI to engage customers in a more systematic and strategic way.

AIs and Their Benefits to Service

Based on the multiple AIs view of Huang and Rust (2018) and Huang, Rust, and Maksimovic (2019), we propose that there are three AIs—mechanical, thinking, and feeling—that can be used differentially in service for customer engagement. This multiple AIs view maintains that there are multiple AIs, with each designed to perform different tasks, with mechanical AI used for simple, standardized, repetitive, and routine tasks, thinking AI for complex, systematic, rule-based, and well-defined tasks, and feeling AI for social, emotional, communicative, and interactive tasks. The development of AI is cumulative. Once AI advances to a higher level, it also typically possesses the lower level intelligence capabilities. Mechanical AI is the lowest and easiest, meaning that current AI can handle service tasks that require such intelligence proficiently. Thinking AI, currently a mainstream research and application focus, can analyze big data and make some intuitive decisions. Feeling AI is the most advanced, but its full potential is not yet realized.

We propose that each of the three AIs can deliver its unique benefits to service. Specifically, mechanical AI is ideal for service standardization, thinking AI for service personalization, and feeling AI for service relationalization (i.e., personalized relationship). Figure 1 illustrates this differential benefits view of the three AIs.

Mechanical AI for Service Standardization

Mechanical AI generally learns and adapts only to a minimal degree. It is designed with the goals of maximizing efficiency and minimizing variability. Thus, it is ideal for service standardization (Huang and Rust 2017, 2018). The more goods-like the service is, the more appropriate for it to be automated for scale and efficiency. This is similar to the McService strategy proposed in Huang and Rust (2017); when customers have homogeneous demand for the service and are low in potential customer lifetime value, technologies should be used to automate service for efficiency. Examples are fast-food ordering and delivery, self-service, budget service, and customer service for routine issues. In this use of mechanical AI, routine and repetitive human service is transformed into self-service or is mass produced. For example, for routine purchases, AI assistants offer convenient, uninterrupted household operations (Dawar 2018). Another common mechanical AI application is service robots, for example, hotel housekeeping service robots, which replace human employees to perform this routine service.

Thinking AI for Service Personalization

Thinking AI learns and adapts from data. It can be analytical or intuitive. Analytical AI is designed with the goal of exploring customer diversity to identify meaningful patterns (i.e., data mining, text mining). The more advanced intuitive AI is designed for maximizing decision-making accuracy (i.e., solving problems, maximizing the accuracy of answering questions in data science language). Thus, thinking AI is ideal for service personalization for optimal service productivity (Rust and Huang 2012). As AI capabilities are cumulative, intuitive AI also may process all of the capabilities of analytical AI.

Thinking AI is ideal for service personalization, especially when there are abundant customer data available and when the problems are well-defined, for example, predicting which new services will be appealing to which customers. In this situation, there are ample existing customer preference data that can be used to suggest different new services to different customers.

The analytical subtype of thinking AI is good for uncovering or discovering meaningful patterns in data as the basis of personalization. Using analytical AI for service personalization is similar to the customized transaction strategy for service in Huang and Rust (2017); when demand is heterogeneous and the potential customer lifetime value is lower, analytical AI can be used to capture the individual differences in service preference based on cross-sectional data (e.g., other like-minded

Table 1. Nature of Service to Consider Whether to Use AI or HI More and Which AI Intelligence to Use.

Nature of Service	Levels of AI/HI		
	Mechanical AI/HI	Thinking AI/HI	Feeling AI/HI
Service task	Mechanical tasks should be performed mostly by mechanical AI. Mechanical HI is often replaced	Thinking tasks should be performed by both thinking AI and HI. Thinking HI is augmented	Feeling tasks should be performed mostly by HI. Feeling HI may be augmented by lower level AI
Service offering	Transactional service	Utilitarian service	Hedonic service
Service strategy	Cost leadership	Quality leadership	Relationship leadership
Service process	Service delivery	Service creation	Service interaction

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

customers). For example, for complex shopping decisions, AI assistants can learn consumers' criteria and optimize whatever trade-offs the consumers are willing to make (e.g., higher price or greener; Dawar 2018). Amazon's product recommendation system also falls into this category.

The intuitive subtype of thinking AI has the capability to learn and adapt based on a deeper understanding of the context (i.e., deep learning), not just based on observable systematic patterns. Deep learning is AI that tries to replicate the human brain (neurons, neural network, brain-like virtual neural network, etc. ; Singh 2017). IBM Watson is such an intuitive AI application that has been adopted by various sectors. With its more humanlike thinking capability, intuitive AI is good for more profound and adaptive personalization. For example, some studies have demonstrated that AI can be used to build adaptive personalization systems that can personalize increasingly effectively for an individual customer over time (Chung, Rust, and Wedel 2009; Chung, Wedel, and Rust 2016). Using intuitive AI for dynamic personalization is similar to the relational service strategy in Huang and Rust (2017), such that dynamic (longitudinal) small data for each specific customer over time are available for personalization. For example, AI assistants as consumers' decision aids are less biased and less forgetful. They will retain every last bit of information and analyze the data to provide objective recommendations to consumers (Dawar 2018).

Feeling AI for Service Relationalization

Feeling AI learns and adapts from experience. Experience is defined as data that are contextual- and individual-specific. This level of AI may possess all the mechanical and thinking AI capabilities but applies these capabilities to experience-based data. Feeling AI is ideal for service relationalization, defined as personalized relationship, and for customer satisfaction and retention (Huang and Rust 2017, 2018). It is critical for maintaining customer relationships, in which interaction, communication, understanding, and experience are critical. All relationships are by nature personal, and feeling AI that can handle such data is ideal for this purpose.

There are two polarized applications of feeling AI. At the low end, feeling AI applications, such as virtual agents and chatbots, are widely used to deliver mechanical AI-like customer service. This is similar to the relational service strategy in Huang and Rust (2017), in which demand is homogeneous and potential customer lifetime value is high. Emotional analytics that operate like thinking AI but with emotional data or extracting emotions from data are typical applications. Affectiva (Dwoskin and Rusli 2015) and Magids, Zorfas, and Leemon's (2015) emotional-connection analytics are examples of emotional analytics. The current dialog systems popular in the consumer market, like Alexa, Cortana, and Siri, are another type of application that uses natural language processing to interact with customers but in a rather mechanical manner.

At the high end, feeling AI has potential for customer care that requires empathy and understanding, not just serving as a customer contact interface. Automatic speech emotion recognition is considered to be the next big thing of AI (i.e., the next-gen AI) that can be applied widely to health, retrieval, robotics, security. Such AI needs to be able to truly read human emotions and react to the emotions like a human conversational partner would (Schuller 2018). Sophia and more sophisticated chatbots are examples of such applications. Feeling AI is still in its early stages of development, and thus, feeling mostly remains the territory of human service employees for the time being.

Applying AIs to Engage Customers

We propose that in making the strategic decision of using AI to engage customers, service providers need to realize that each of the AIs—mechanical, thinking, and feeling—can provide its unique benefits to service for engaging customers. Summarizing from the literature and based on our theory, we consider that there are four major factors that shape the role of AI in service: the nature of service task, service offering, service strategy, and service process. Table 1 illustrates some suggestions along the four factors, and Figure 1 illustrates some suggestions for the combinational use of AIs. Below we elaborate the four factors involved in the decision.

Nature of Service Task

Tasks are activities involved in a job (Chui, Manyika, and Miremadi 2015). For AI, they are service functions to be performed. AI applications do not necessarily replace HI (human employees); rather, they are designed to perform specific service tasks. In the end, some tasks may be performed by humans, and others by AI, meaning AI and HI work as a team (Wilson and Daugherty 2018). Nevertheless, the more service tasks involved in a service job can be done by AI, the fewer human employees will be needed, and the remaining human employees will focus more on the tasks not performed by AI (Huang, Rust, and Maksimovic 2019).

Tasks (or service functions) that require a lower intelligence level should generally be replaced first. That is, mechanical/routine/repetitive tasks should be performed mostly by mechanical AI. Given the current AI level, many mechanical HI tasks should be mostly replaced by AI. For manufacturing, the nature of this type of tasks is more straightforward. Such tasks are mostly mechanical, in a well-specified context, and lack variation, and thus can often be easily done by manufacturing robots. For service, there are variations in this type of tasks: Some are as mechanical as in manufacturing, such as cash withdrawals done by ATM (Meuter et al. 2000), whereas some are routine and simple but require context or involve variations, such as restaurant table waiting service that cannot be done easily by mechanical AI.

Thinking tasks should be performed by both thinking AI and HI. This is the type of task where augmentation (skilled service employees augmented by thinking AI) is most likely to occur. For example, managers can use business analytics to support their decisions, and physicians can benefit from health-care applications to aid their diagnosis. The more analytical the service task is, the more likely the analytical subtype of thinking AI can address the task with limited human intervention, while the more intuitive the service task is, the less likely it is that AI can successfully address the task without human intervention. Future progress in the intuitive subtype of thinking AI is likely to change this conclusion in the not-so-distant future. At that point, as thinking AI applications advance to the intuitive level, most of the thinking tasks can be done by machines.

Feeling tasks should today be performed mostly by HI. Feeling HI may be augmented by lower levels of AI applications (i.e., mechanical and/or thinking AI). For example, for low-end applications, mechanical feeling AI, such as chatbots, has been widely applied to handle standardized and routine customer service. For high-end applications, Siri, Alexa, and other similar voice recognition personal assistants that possess analytical capability are used to search for information for consumers and respond to consumer queries, using a human voice.

Nature of Service Offering

The nature of service offering can vary in the utilitarian-hedonic continuum and the transactional-relational continuum, and the three AIs can be combined in various ways to cater to the nature of the service offering. Service offerings that lean toward the utilitarian end should use thinking AI more. Utilitarian service mainly provides instrumental, functional, non-sensory benefits to customers (Huang 2003, 2005). They may be considered as high-tech and are naturally suited for thinking AI. For example, cloud data service (e.g., Amazon) and financial analysis (e.g., IBM Watson) can be done by thinking AI. In contrast, service offerings that lean toward the hedonic end should use feeling AI more. Hedonic service mainly provides sensory benefits such as fun, playfulness, and pleasure to customers (Huang 2003, 2005). They may be considered high-touch and can benefit from feeling AI. For example, computer games can use emotion-detection AI to engage players in a flow state, and smart houses (i.e., houses that are equipped and connected with smart devices so that customers can remote control the temperature, surroundings, and issue commands to adjust the house for their needs) can use feeling AI applications to further transform the houses into "feeling homes" that provide emotional comfort to owners.

The nature of service offering can also vary in degree of transactional-relational. Transactional service has little to gain from a customer relationship and will benefit more from AI replacement (Huang and Rust 2017). For example, fast-food restaurants can use more mechanical AI to serve customers without undermining their value proposition, whereas high-end French restaurants should use less. In contrast, relational service can benefit from having a solid relationship with customers because a higher customer lifetime value can be expected; thus, service providers should strive to use feeling AI more.

In brief, utilitarian service should use thinking AI more, whereas hedonic service should use feeling AI more. Transactional service should use mechanical AI more, whereas relational service should use feeling AI more. Together, the continua of utilitarian-hedonic and of transactional-relational suggest four possible AI/HI portfolios. Figure 2 illustrates the combinational use of AIs based on nature of service.

Utilitarian transactional service. This type of service should use analytical AI more, which is thinking AI but mostly performs mechanical analyses. Analytical AI performs logical, analytical, and rule-based learning. The nature of learning is mechanical, but the capability reaches the thinking level due to rule-based learning from big data to achieve data- and analytics-based personalization. Analytical HI will be gradually replaced as analytical AI gets more dominant for data- and computing-based learning.

Utilitarian relational service. This type of service should use both intuitive AI and HI. Intuitive AI is the more advanced subtype of thinking AI that is closer to feeling AI. It is thinking AI that is capable of bounded rationality and commonsense thinking. Current AI has not yet achieved the full capability of human meaning–based thinking, and thus, both AI and HI should be involved in this type of service. For this use of AI, the customer relationship is built based on the deep understanding of customer preferences, while not necessarily involving an emotional connection with customers.

Hedonic transactional service. This type of service should use mechanical feeling AI more and HI less (i.e., unskilled human employees). Mechanical feeling AI is mechanical AI with some feeling capability. Such AI learns and adapts from limited emotional data and can do some relationalization. A lot of conversational bots providing customer service are at this level, in which the nature of service requires communication and emotions, but mostly are repetitive.

Hedonic relational service. This type of service should use both feeling AI and HI (i.e., skilled human employees with high emotional intelligence). Such AI learns and adapts from emotional data to build connections and relationships with customers. For example, the AI companion, Replika, provides emotionally personalized everyday conversation with customers. Natural language processing dialog systems based on generative machine learning methods and embedded social caretaking are some applications of such AI (McDuff and Czerwinski 2018). Given the current AI level, this type of service should be offered mostly by HI.

Strategic Emphasis of Service Providers

Extending Treacy and Wiersma's (1993) three market leadership strategies—operational excellence, product leadership, and customer intimacy—to service, we recommend that service providers that emphasize cost leadership (i.e., operational excellence) use mechanical AI more, quality leadership (i.e., service performance) should use thinking AI more, and relationship leadership (i.e., customer intimacy) should (eventually) use feeling AI more.

Cost leadership emphasizes operational excellence by automating service processes to reduce costs. The more service processes can be standardized, the more process automation can be achieved by mechanical AI. For example, McDonald's uses robots to deliver ordered foods to customers, firms use virtual bots to deliver customer service, and Amazon attempts to use drones to deliver products.

Quality leadership emphasizes achieving premium quality for customer experience. Such a competitive strategy may not always involve big data as there is a higher degree of customer heterogeneity in quality expectation that cannot be sacrificed for scale economies. Thinking AI that maximizes diversity for service personalization can be used to address individual customers' needs and requirements. For example, trip planning for travelers may take each traveler's unique preferences into consideration, such as a trip that can relax his or her mind or a trip that can see most of a city. Such planning is more complicated than just buying air tickets and booking hotels, and thus, analytical AI that can analyze like-minded travelers' preferences and intuitive AI that can come up with a recommended travel plan are appropriate.

Relationship leadership emphasizes customer intimacy for customer satisfaction. For high lifetime value customers, service providers might eventually leverage feeling AI to engage customers on an ongoing basis. This strategy also involves personalization and further focuses on using emotions as a differentiator. For example, airlines provide both high-quality ground services and aircraft facilities to achieve quality leadership that can achieve relationship leadership but achieve best results if they additionally provide emotional care and high-touch service by ground staff and flight attendants. The latter high-touch service promises to benefit from feeling AI by analyzing, recognizing, and understanding customer emotions (Schuller 2018), and responding and serving them in an emotionally appropriate manner on an individual customer basis.

Stage of Service Process

We refer to a service process as how a service is provided or delivered to a customer. The service process view recognizes that the service outcome depends on the dyadic interaction process between customers and service providers (Ma and Dube 2011). It means that value is created continuously by engaging customers and service providers jointly and interactively (Ramaswamy and Ozcan 2018). As a result, customers experience the quality that providers deliver and reach an outcome evaluation about the quality (not necessarily the same as what was objectively delivered; Golder, Mitra, and Moorman 2012). Bitner, Ostrom, and Morgan (2008) provide a detailed service blueprinting about how a service process can be broken down into subprocesses for service innovation.

We break down the service process into three stages—delivery, creation, and interaction—and order them in this way based on the three AI levels, from mechanical, to thinking, and to feeling. The three stages are reciprocal; they do not necessarily follow a sequence, as in physical goods manufacturing from production to delivery. Instead, each process stage is likely to give rise to the other process stages. Figure 3 illustrates this reciprocal process. Table 2 summarizes the key managerial questions for service providers to address, the dominant AI at each process stage, the major service tasks to perform, and the respective AI application examples. For each contact point (or process stage), a mix of AI can be used. For example, the service provider can use mechanical AI to complete the transaction and deliver the service (e.g., Amazon Prime Air's delivery drones), use thinking AI for market prospecting (e.g., Gap uses AI for predicting fashion trend), and use feeling AI to provide customer service (chatbots for customer service). It is important to note that breaking down the service process into the three stages is for the purpose of illustrating which AI suits best for each stage. Not all services have a clear-cut boundary between the stages, for example, for haircutting service, delivery, creation, and interaction all occur simultaneously. For insurance, service creation is

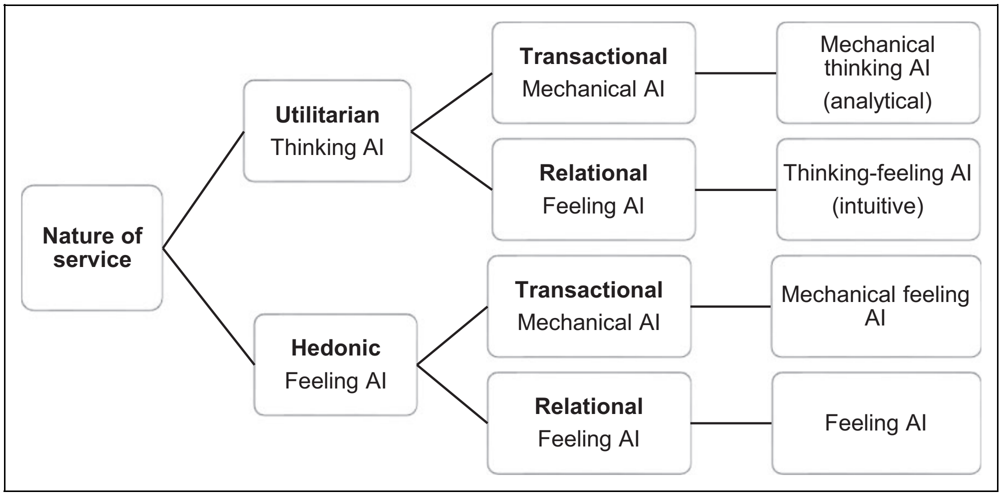

Figure 2. Combinational use of artificial intelligences based on nature of service.

Table 2. AI-Enabled Service Process.

Service Process	Key Question to Address	Dominant AI	Service Tasks	AI Applications
Service delivery	How to deliver service efficiently?	Mechanical AI automates	• Shipping • Delivery • Payment	• Service process automation • Robotic self-service • AI assistant to a consumer's daily life (not as the firm's customer service agent; Dawar 2018)
Service creation	How to create valuable service to which customers?	Thinking AI predicts	• Identify new market • Develop new service • Personalize service	• Predictive analytics (Agrawal, Gans, and Goldfarb 2018) • Computing creativity • Data mining
Service interaction	How and what to communicate with customers?	Feeling AI engages	• Engage customers • Personalize service adaptively • Interact with customers • Customer service • Customer care	• Speech emotion recognition (e.g., Alexa, Cortana, Siri; Schuller 2018) • Sentiment analysis (the recognition of emotion from text, Schuller 2018) • Deep learning • Convolutional neural networks • End-to-end learning • Chatbots • Dynamic optimization

Note. AI = artificial intelligence.

figuring out what kind of policy to offer, delivery arises when there is a claim, and interaction is the relationship between the agent and the customer. In other words, there may be services in which two or more of the three stages combine (e.g., coproduction).

Below we delineate how the three AIs can be matched to the service subprocesses of delivery, creation, and interaction. We also provide strategic suggestions for using AIs to engage customers along the service process.

Mechanical AI for service delivery. At this process stage, the key question that service providers need to ask is as follows: How to deliver service efficiently? The service delivery tasks, such as shipping, delivery, and payment, are more routine and repetitive than tasks involved in the other two process stages. The goal is to maximize service productivity. Use of AI may improve delivery efficiency for service providers and convenience for customers.

This is the stage that mechanical AI dominates. Mechanical AI has the advantages of consistency, reliability, and efficiency; thus, service providers can leverage these advantages of mechanical AI to deliver service. Two major applications of mechanical AI for service delivery are to (1) automate the service process and (2) automate the offering of service to customers.

Automating the service process, such as automated payment or automated delivery (e.g., Amazon's drone delivery), is intended to streamline the service process such that customers can experience a smooth and uninterrupted service process. This is often a backend automation in which customers do not

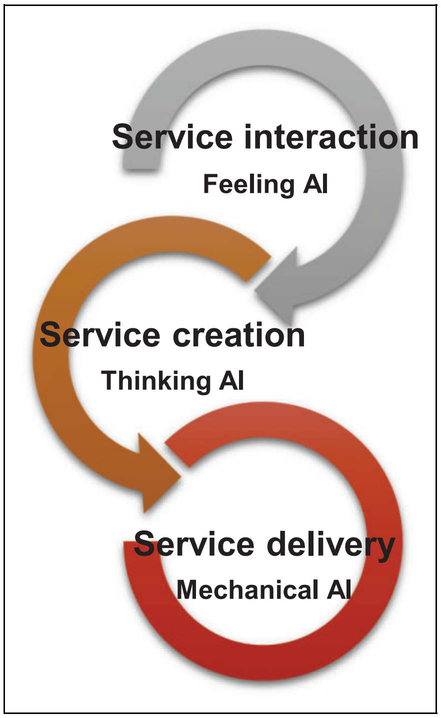

Figure 3. The circular service process with dominant artificial intelligences.

interact directly with the mechanical AI, but service providers deploy it on the backend to automate the process. Amazon's one-click buying is a classic example that allows customers to purchase with one click without having to go through the multiple steps of filling shopping cart, providing shipping information and credit card information, and so on. Being an e-commerce giant, Amazon invests heavily and experiments with various mechanical AI applications to deliver its offerings (goods and service) to customers, such as Amazon Prime Air's delivery drones and Amazon Go. Many AI applications have also been used to streamline the payment process, such as mobile money transfer, digital wallet, and virtual banking. AI start-up Elementum's intelligent automation deploys AI on top of automation technologies to achieve more efficient processes and services. Elementum automates supplier management processes that enable its clients to get early warnings of potential problems and manage the problems before their competitors even know the problems (Wallis and Santiago 2017). AIoT is another instance for mechanical AI, which is the application of AI on top of IoT.

Automating the offering of service to customers is delivering service as self-service. Robotic self-service, such as Pepper and Roomba, and AI assistants, such as Alexa, use intelligent devices to deliver service automatically. This is a frontend automation in which customers interact with the mechanical AI directly.

Thinking AI for service creation. At the service creation stage, the key question to address is how to create valuable service for individual customers. Service creation involves two related questions: What service to create, and which customers would consider it valuable. Major service tasks involved include identifying new markets, developing new service, and personalizing service.

The dominant AI at this stage is thinking AI. In terms of AI applications, predictive analytics can be used to predict customer preferences, computing creativity can be used to develop new service, and data mining (or any other types of pattern mining) can be used to identify like-minded customers for creating personalized service. Deep learning could help in customer segmentation and provide different promotion campaigns for different groups of customers by experience from learning from lots of data. Furthermore, deep learning may even help in prediction of the trends in the industry because of its continual learning from internal and external data.

For developing new service, thinking AI can be used to extract value from systematic patterns from data. For example, Gap, the fashion retailer, removed the position of creative director and replaced it with a big data-driven collective creative ecosystem to identify the fashion trend for the next season (Israeli and Avery 2017). Netflix uses data to decide which new series and movies to develop. Their CEO, Reed Hastings, said such a decision can be considered as "informed intuition" because data science alone is insufficient to predict which product will hit (Israeli and Avery 2017).

For predicting customer preferences, Amazon's anticipatory shipping and Gap's relying on data to predict fast fashion trends are examples of predictive analytics. Such uses of analytical AI, such as in-car intelligent systems with big data analytics, create service that is data-, information-, and knowledge-intensive.

For creating personalized service, thinking AI can be used to predict (e.g., fashion trend prediction) and create service (customer/market prospecting) based on systematic patterns from data. For example, Harley-Davidson uses "Albert," an AI-driven marketing tool to adjust its marketing strategy instantly to different customers, which increased New York sales leads by 2,930% in 3 months (Power 2017). Albert analyzes the existing customer data to identify what high-value customers are like and what kind of marketing campaigns would be most successful with them. It then automatically changes campaigns to make them more attractive to important potential customers.

Feeling AI for service interaction. At this stage, the key question to address is how and what to communicate with customers. The dominant AI involved at this stage is feeling AI, which is used to perform the service tasks of engaging customers, personalizing service adaptively, and providing customer service. AI applications need to be able to detect, understand, and respond to customer emotions adaptively to perform those tasks. This is often the most important service process stage but currently has the lowest level of AI involvement due to the less mature AI applications at this intelligence level.

Feeling AI delivers social-, emotional-, and relational-based service to customers. It can be used to provide emotional support and emotional satisfaction to customers (e.g., customer interaction, customer service, and customer experience). Feeling AI learns and adapts empathetically based on experience and understanding and thus can provide emotional support and emotional satisfaction to customers.

Feeling AI is important for service interaction, which can be divided into two subprocesses: the marketing communication stage and the after-sale customer service stage. For marketing communication, service providers need to emotionally connect with customers to differentiate themselves from competitors (Magids, Zorfas, and Leemon 2015). For customer service, service providers often face emotionally charged customers (e.g., customer complaints) that require feeling AI to handle. Wallis and Santiago (2017) use the example of Capital One Eno to illustrate that AI actually needs to be empathic in interacting with customers. Eno is a natural language chatbot. Customers can text Eno anytime to review their accounts, pay credit bill, and ask general questions. Capital One surprisingly learned that their customers tend to build relationships with those chatbots even while knowing that they are talking to a bot. Nevertheless, most service providers currently rely on text-based chatbots to provide customer service that are not very effective in handling customer complaints.

By being able to act and react empathetically, according to Wallis and Santiago (2017), AI can be used to improve interactions and deepen trust. For improved interactions, AI can deliver superior experiences to customers based on hyperpersonalization and the curation of real-time information. On top of overall satisfaction improvement, this can also generate greater acquisition and retention rates among customers. For deepened trust, AI can more effectively prevent and detect anomalies. It also provides the ability to significantly reduce false positives. As Dawar (2018) points out, AI platforms will even know whether consumers are likely to adapt their requirements in different contexts—for example, if a person on a diet will make an exception for dessert when celebrating.

Discussion

We outline a framework for using various AIs in service to engage customers. The framework helps service providers to decide when and how to use mechanical AI for service standardization, thinking AI for service personalization, and feeling AI for service relationalization, taking into consideration the nature of service task, service offering, service strategy, and service process.

Managerial Implications

Taking the four factors involved in the strategic decision into consideration, we provide the following suggestions for using different AIs in service:

Using mechanical AI for standardization. Service providers should use mechanical AI more when the nature of service task is mostly standard, routine, repetitive, and can be performed without considering context; when the nature of service offering is transactional, that is, with limited relational benefit; when the service strategy emphasizes low cost as the major benefit to customers; and when at the stage of service delivery to enhance the convenience benefit to customers. In all these situations, mechanical AI can be used to automate service process from the backend (process efficiency) and automate service offerings and delivery to customers from the frontend (convenience benefit).

Using thinking AI for personalization. Service providers should use thinking AI more when the nature of service task is mostly data-based, analytical, predictive, thinking; when the nature of service offering is utilitarian, that is, customers obtain functional, high-tech benefits from the service; when the service strategy emphasizes high quality as the major benefit to customers; and when the service creation stage requires figuring out valuable new services for specific customers. Thinking AI can be used to predict new markets, create new services, prospect new customers, and customize service.

Using feeling AI for relationalization. Service providers should use feeling AI more when the nature of service task is mostly experience-based, emotional, and requires interaction and communication; when the nature of service offering is hedonic, that is, customers obtain sensory, fun, high-touch benefits from the service, or relational, that is, higher customer lifetime value; when the service strategy emphasizes customer relationship as the platform for continuing improving service for customers; and when at the service interaction stage provides an opportunity to communicate and interact with customers about the value of the service. Feeling AI can be used to engage customers, personalize service adaptively over time, and provide customer care and customer service.

Research Implications

The strategic use of the three AIs in service also shapes the research about AI in service. We discuss the implications for modeling, consumer behavior, and societal research respectively, along the three service benefits of AI:

Modeling implications. For service modelers, key challenges for the three benefits of AI include:

- For mechanical AI-enabled standardization, developing new algorithms and models that can accommodate service variability without losing the efficiency benefit of standardization is a key challenge.
- For thinking AI-enabled personalization, personalization can be achieved using both cross-sectional and longitudinal data. Cross-sectional personalization leverages the benefits of big data, but the personalization is achieved by inference from like-minded customers. Longitudinal personalization can capture a specific customer's preferences along his or her lifetime, but such data tend to be small and sparse. Therefore, developing

new algorithms and models that can personalize based on a combination of both cross-sectional and longitudinal customer data is desirable.

- For feeling AI-enabled relationalization, algorithms and models that can handle emotional data (i.e., data that are individual- and context-specific) are still not well-developed, and thus, more studies are needed to bring it fully to fruition. Challenges include the difficulty of capturing emotional data, due to context tending to be lost in the data capturing process, and the difficulty of modeling such data due to emotional data being multimodal and containing more nuance than rational cognitive data.

Consumer behavior implications. For consumer researchers, a better understanding about consumers' heterogenous preferences to service automation, concerns about trading personal information for personalization, and reactions to having relationships with AI are major issues.

- Many services have been automated using various embedded and embodied mechanical AI applications, yet consumers react to service automation differently: some prefer AI service, some prefer HI service; thus, it is essential to have a better understanding about how consumers react to AI-enabled service standardization.
- With thinking AI able to do more refined personalization using more personal data, consumer concerns about privacy may also be heightened (Rust, Kannan, and Peng 2002). Understanding consumers' preferred degree of personalization, relative to the degree of privacy concern, is imperative.
- How consumers react to AI that is used to establish and maintain a relationship with them is a hot issue. Given the uniqueness of human emotions having a physiological basis, a potential future avenue of research is to take a neuroscience approach to capturing and understanding the full spectrum of consumer emotional reactions to feeling AI.

Societal implications. For policy makers, mitigating the negative impact of mechanical AI displacing unskilled human service employees, making thinking AI and HI work together, and how and to what extent to develop feeling AI are major issues.

- Using more mechanical AI for standardization is bound to result in displacement of mechanical service employees. We have witnessed such displacement when the service economy began replacing the manufacturing economy in the turn of the 20th century. Where will those unskilled service employees go and how we can retrain and relocate them are pertinent issues that economists, policy makers, and service providers need to consider.
- Thinking AI supports skilled service employees and can sometimes even perform such service functions on its own. Thus, how to have AI and HI work together is a major challenge. There are also general concerns about whether thinking AI will displace even thinking workers, not just unskilled mechanical workers, and policy research looking into this issue will have important implications for the future economy.
- Biological emotions are human characteristics that AI, even the current feeling AI, cannot mimic. This AI technological bottleneck has been demonstrated to give rise to the Feeling Economy because employment and wages will be more attributable to feeling tasks and jobs when thinking AI can do most of the thinking tasks and jobs (Huang, Rust, and Maksimovic 2019). The possibility that the continuing advancement of feeling AI will result in true emotional machines generates the concern of singularity, that is, AI becomes completely dominant in all levels of intelligences over humans (Kurzweil 2005). The issue of how best to approach feeling AI thus is likely become a major policy challenge at some point in the future.

Conclusion

We provide a theoretically driven strategic framework for when to use more AI (as opposed to HI) and which AI should be used in service. The proliferation of AI in service diffuses in order from mechanical, to thinking, and to feeling. As AI advances to a higher level, more AI of that intelligence level should be used and less HI at that intelligence level be used. Thus, at the current level of technological development, mechanical service should be performed mostly by mechanical AI, thinking service should be performed by both thinking AI and HI (thinking HI is augmented), and feeling service should be performed mostly by HI.

Regarding which AI to use, in general, mechanical AI can standardize service, thinking AI can personalize service, and feeling AI can relationalize service. Thus, mechanical AI should be used more when the nature of the service task (i.e., service function) is routine and repetitive, the service offering is transactional (i.e., goods-like and having limited relational benefits), the service strategy is cost leadership, and the service process is at the delivery stage. Thinking AI should be used more when the nature of service tasks is data-based, analytical, and predictive; the service offering is utilitarian (i.e., high-tech service); the service strategy is quality leadership; and the service process is at the creation stage. Feeling AI should be used more when the nature of service tasks is mostly experience-based, emotional, and requires interaction and communication; the service offering is relational (i.e., high customer lifetime value) and hedonic (i.e., high-touch service); the service strategy is relationship leadership; and the service process is at the interaction stage.

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