DIGIT 2019 Proceedings

Diffusion Interest Group In Information Technology

12-15-2019

From IT to AI Artifact: Implications for IS Research on AI Adoption and Use

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Completed Research Paper

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Abstract

The IS research community has introduced and used several theoretical models and constructs to investigate information technology (IT) adoption and use behaviors in individuals. At this point in time, the community requires coherent guidance towards conceptual and methodological considerations that have the potential to provide new insights into the changing nature of interactions between people and technology. These changes are mostly related to the fact that technology is becoming more of an intelligent agent than a mere tool. Thus, the aim of this paper is to distinguish between IT and artificial intelligence (AI) artifacts and to discuss its implications for IS research on AI adoption and use behaviors. Using UTAUT, D&L IS success model, and TTF as examples, we argue how well-established models used in IS research may need to evolve to capture adoption and use behaviors of people who use or intend to use AI artifacts.

Keywords: IT artifact, AI artifact, artificial intelligence, adoption, use.

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Introduction

For about half a century, understanding information technology (IT) adoption and use behaviors have been one of the major research streams in the field of information systems (IS). Our knowledge on the topic has been crystallized using several well-established IS theories and models like the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al. 2003), DeLone and McLean IS success model (Delone and McLean 2003), and the task-technology fit theory (Goodhue and Thompson 1995). These theories and models have proven robust over time, as they have successfully been used to understand and predict user behaviors of several IT tools in several contexts. However, IT as we know it today is becoming more of an agent than a tool due to artificial intelligence (AI). AI, giving properties of human intelligence to machines, is becoming an integral part of almost every IT we use both in our private lives and at work today. From AI-based digital assistants in our phones like Google Assistant and Siri to advanced computing systems like IBM Watson used in organizations, AI is certainly transforming IT as we know it at unprecedented speeds. This transformation affects the way people interact with IT as well as their use expectations. A classic example is that unlike before, people today expect their smartphones with AI-based digital assistants to provide relevant responses to commands they give or questions they ask. Thus, they expect their phones to understand the context of their question or command and provide a relevant response or action. This is just one of the many ways in which AI is transforming IT. Aspects like this were not part of the conceptual and methodological considerations on which many of the existing IS theories and models were built. Thus, these theories and models need to evolve if they must capture these changing user behaviors and expectations resulting from AI.

Today, most IS are IT-based and many increasingly involve the use of AI. Thus, the IS community needs research that theorizes on AI and that fundamentally distinguishes AI from other forms of technology. This need is manifested for example through a recent call for papers by B. Gu et al. (Gu et al. 2019) in a MISQ special issue on Managing AI. This special issue is motivated by the pervasive economic, societal, and organizational changes brought about by technologies involving AI. This issue is intended to help IS researchers challenge how they conceive AI and how this can help improve their ability to manage AI-based IS while dealing effectively with the challenges and opportunities this brings to IS practice.

To fill this research gap, we propose to fundamentally distinguish between the IT artifact and the AI. The purpose is to present evidence of our assertion that there is a fundamental difference between the AI and IT artifact that needs to be explicitly considered in IS research. We base our distinctions on findings from the origins of AI and prominent theories of intelligence that could lead to a holistic understanding of AI. Our evidence is based on a review of key literature on the IT artifact and on the review of literature that has shaped mankind's understanding of human intelligence. We examined each article in the IT artifact to present what fundamentally characterizes this artifact. For each article on intelligence, we examined how this could help improve our understanding of AI and how this fundamentally distinguishes AI from the IT artifact. Thereafter, we use our findings to analyze three well-established IS theories and models as examples to clearly show some conceptual and methodological issues that may limit their ability to capture user adoption and use behaviors of AI. We expect our contribution to challenge IS researchers even more into analyzing and revising existing IS theories in the same manner and to use this as the basis for the development of new ones.

In section 2, we discuss the IT artifact. We highlight key discussions on the definitions and fundamental characteristics of an IT artifact. In section 3, we try to fundamentally define and explain what an AI artifact is. We conclude this section with the fundamental differences between the IT artifact and the AI artifact. In section 4, we analyze how AI is changing traditional IS theories and models that captured the adoption and use of IT that did not involve AI. In section 5, we discuss the implications of our findings for IS research on AI adoption and use.

The IT Artifact

Debates on the IT artifact became a hot topic in 2001 when Orlikowski and Iacono (2001) highlighted the desperate need to theorize this artifact in IS research. They define the IT artifact as "bundles of material and cultural properties packaged in some socially recognizable for such as hardware and/or software" (p. 121). They highlighted five major perspectives of the IT artifact: the tool view, the proxy view, the ensemble view, the computational view, and the nominal view. However, they demonstrate that the IT artifact is usually ignored or underemphasized in IS theories and research resulting in them being conceptualized as some discrete, independent, stable and fixed entities, which is quite the opposite. Thus, they suggest that IS research should be more explicit about IT artifacts in their studies irrespective of their conceptual perspectives or methodological orientation. The fundamental characteristics of IT artifacts they propose are: not natural (man-made), neutral, universal, or given (used by people in a social context, shaped by people's interests, values, and assumptions); always embedded in some time, place, discourse, and community (material and cultural context cannot be ignored, abstracted or overlooked); consists of interconnected components; neither fixed nor independent but emergent from ongoing social and economic practices (undergoes transitions (co-evolution) over time through human interventions; not static or unchanging but dynamic (users adapt artifacts to their needs).

Benbasat and Zmud (Benbasat and Zmud 2003) in their 2003 paper on the IS identity crisis define the IT artifact as "the application of IT to enable or support some task(s) embedded within a structure(s) that itself is embedded within a context(s)" (p. 186). They suggest that structures, routines, norms, and values of the context in which the IT artifact is found are all packaged into the hardware/software design of the artifact. Lee et al. (Lee et al. 2015) conceptualize technology artifact as "human-created tool whose raison d'être is to be used to solve a problem, achieve a goal, or serve a purpose that is human-defined, human perceived, or human-felt" (p. 6).

Nevertheless, some authors argue that the term "IT artifact" is quite ambiguous and should be retired from IS literature because it has lost its meaning over time [9, 10]. Demetis and Lee (Demetis and Lee 2017) argue that this shift is because of technology's subtle transition from artifact to systems of which humans are agents as humans continue to outsource their decision making to algorithms and technology in general. As technology becomes more intelligent, the more we rely on it for technologized decision making, which brings us to AI artifacts.

The AI Artifact

To better understand the AI artifact and how it differentiates itself from the IT artifact, we need to understand the origins of AI and its fundamental characteristics. John McCarthy is recognized worldwide as the founder of the AI discipline. The first appearance of the term AI was in 1956 during a Dartmouth summer research project on AI proposed by John McCarthy and his colleagues (McCarthy et al. 2006). They explain that the fundamental principle of AI is to give machines the ability to simulate learning and other features of human intelligence. This includes communicating using natural language, forming abstractions, solving problems, and improving themselves, all of which are abilities that were limited to humans. Some of the problems they highlighted that could limit the development of AI include: (i) the lack of computational speeds and memory capacities to simulate higher human functions; (ii) inability to write programs that can fully simulate these higher functions; (iii) limited ability to program the rules of reasoning and conjecture in human language for machines to understand context; (iv) how to connect "neurons" to form concepts; (v) identifying and measuring the size of a calculation to determine the most efficient solution; (vi) giving machines the ability to improve themselves; (vii) identifying and classifying levels of abstraction; (viii) and giving intelligent machines the ability be creative.

Today, advances in technology have made AI researchers overcome most of these challenges faced in the 90s, justifying the tremendous growth of AI applications in the last decade. From Hz to GHz and from bytes to terabytes, computational speeds and memory capabilities to enable high-level AI capabilities are no longer an issue. Higher-level programming languages, natural language processing, and computational linguistics are all fields that have helped solve problems (ii) and (iii). Progress in neural networks has helped with problem-solving (iv) while progress in machine learning and deep learning are helping with problems (v), (vi), and (vii). The last and most challenging part of AI is giving a machine the right amount and type of randomness needed to be as creative as humans. At this point, machines will be able to make educated guesses and make decisions based on hunches just like humans. Based, on this analysis, we can already begin to see in our environment what is and what isn't AI.

However, McCarthy and Hayes (McCarthy and Hayes 1981) recognized that research on AI could be improved if we have a clearer understanding of the concept of intelligence. Using a purely behavioral definition, they suggest that "a machine is intelligent if it solves certain classes of problems requiring intelligence in humans, or survives in an intellectually demanding environment" (p. 4). This limits AI to fact manipulators based on the human conception of the world and does not integrate emotional sensations. However, this definition by itself with the idea of surviving in an environment is more or less characteristic of every species. Thus, it positions AI as a man-made (artifact) agent learning and adapting to its environment for survival. To better understand the AI artifact, we need to push further in our understanding of the fundamentals of intelligence and how intelligent agents interact with other entities in their environment. To this end, we build on theories of intelligence that describe intelligence in relation to the environment. This would help provide more clarity to the capabilities of AI that make it survive in "intellectually challenging environments" unlike other technologies and IT artifacts.

To have a holistic understanding of intelligence, we reviewed three groups of theories on intelligence. The first group of theories presents intelligence from a general perspective that describes intelligence as an innate potential to make sense of situations and act on this information. This gives us a more global understanding of what it means to be intelligent according to humans. The second group of theories explains intelligence from a cognitive perspective. These theories focus on the intellectual functions and processes of the brain. This will help us understand the attributes of intellect we are trying to get AI to simulate such as experience, reason, and decision making to meet our intellectual demands. Finally, the third group of theories focuses on the interaction between organisms and their environment. These theories guide our understanding of how AI could adapt to intellectually challenging environments. The complementarity between these sets of theories would help us identify the fundamental characteristics of AI artifacts that distinguish them from IT artifacts and other technologies.

AI from the Perspective of General Intelligence

Some early researchers suggest that intelligence could be characterized by energy levels and levels of sensitivity (Galton 1883). Thus, the more energetic (capacity to do work) and sensitive (smell, sound, light…) one is, the more information they gather for their intelligence to act on. They suggest that there are two factors of intelligence which are general intelligence and specific intelligence (Spearman 1904). General intelligence consists of bonds (Thomson 1939) or learned connections (Thorndike et al. 1926) that represent how well and how fast an individual can understand and respond to situations. Thus, intelligence can be perceived as an innate potential (Hebb 1949) that the test for intelligence tests (Boring 1923). There are two main types of intelligence, ideational intelligence (uses logical analysis and verbal reasoning) and instinctive intelligence (uses feeling - lack of logical thinking) (Binet and Théodore Simon 1916). This line of thought forms the basis of many intelligence quotient (IQ) and emotional quotient (EQ) tests today.

Using these characteristics to describe the AI artifact, we can refer to them as intelligent machines capable of performing tasks and sensing their environment. These capabilities should be measurable and testable.

That is, we should be able to distinguish between two AI artifacts based on their capacity to do work (e.g. their computational abilities and speed at which they deliver expected results) and their ability to detect changes in their environment (e.g. voice command, temperature change…). With these measures, we can measure who is smarter between Google Assistant and Siri when given the same command on their respective smartphone systems, for example. In a simple case, we can compare how sensitive the smartphones are to voice commands and how quickly they can compute the command and provide a suitable response. Thus, the intelligence of an AI artifact can be determined by how well and how fast it can respond to situations. Thus far, AI artifacts only simulate ideational intelligence and not instinctive intelligence.

AI from the Perspective of Cognitive Intelligence

From a cognitive perspective, intelligence is presented in terms of the processes of human thought and the architecture that holds together these processes. This school of thought suggests that an understanding of cognitive phenomena must include a consideration of the environments in which cognitive processes develop and operate. Thus, cognition refers to knowledge or awareness of the environment arising in the course of a transaction between an agent and the environment in which the agent and the other entities therein are logically interdependent (Smelser and Baltes 2001). In this context, direction (knowing what has to be done and how to do it), control (criticizing thoughts and actions), and adaptation (choosing and evaluating course of actions) are the three main elements of intelligence (Binet and Theodore Simon 1916). Therefore, intelligence can be defined as the ability to interact with and adapt to new situations or environments (Piaget and Cook 1952).

Based on this school of thought, we can derive that AI artifacts need to evolve in an environment in which cognitive processes develop and operate. They need to be aware of their environment and evolve with it through interactions with known entities in the environment. Thus, an AI artifact must have direction, control and adaptative capabilities vis-à-vis its environment. AI artifacts evolve both in the physical and in the digital world and must be able to interact with and adapt to new situations and environments

Still using Siri or Google Assistant as examples, we can demonstrate how these AI artifacts interact with both worlds and adapt to their environments. In the physical world, these assistants have to stay aware of their environment in case you call on them to perform a task. Of course, their first task is to learn your voice so that they can know when it is you talking to them. After that, they learn to adapt to your specific needs as time goes on, based on the interactions you have with them. They demonstrate direction and control in the digital world by knowing what you requested them to do (e.g. asking them where the next soccer world cup will take place), deciding how to do it (e.g. identifying the most reliable source of information), and taking action (e.g. providing you will the right feedback). As you would observe, these assistants would interact with the user and their environment and will adapt to different users accordingly.

AI Artifact from the Perspective of Ecological Psychology

This perspective emphasizes the importance of how environmental perception *affords* various actions to organisms. For successful adaptation, organisms need to perceive changes in their environment regarding specific events then adapt through accommodation or assimilation (Piaget and Cook 1952). Senses represent evolved adaptations to an environment and require sensory systems that directly and accurately depict the environment (Gibson 1966). Sensations are produced at some receptor surface of the organism and these sensations are the information on which the organism relies for its perceptual knowledge of its environment (Gibson 2014). Perceptions, on this account, are constructed out of sensations with the aid of memory, habit, cognitive strategies, innate plans. Perception is direct in that (i) it does not require manipulations of internal representations, and (ii) it occurs as (or simply is) an integral part of coordinating the ongoing conduct of given organism in an integrated system encompassing both organismic and environmental activities. Thus, organisms and their environments are an inseparable pair and are attuned to variables and invariants of information in their activities as they interact as participants with other systems in their environment. Therefore, information is found in meaningful aspects of that environment and is obtained by, not presented to agents (Greeno 1994).

The situation theory shows that abilities in activity depend on attunements to constraints, and affordances for an organism can be understood as conditions in the environment for constraints to which the organism is attuned (Cooper et al. 1990). This theory defines a constraint is a regularity involving situation types. A situation refers to the state of affairs at a given time. A state is an object with an argument (information conveyed in a sentence/statement) and a polarity (positive or negative). Two situations are the same if they are held together in the same state. A situation type is a class of situations with objects that have a specified property of relation. Attunement to constraints is a basis for making inferences.

The term affordance refers to whatever it is about the environment that contributes to the kind of interaction that occurs. This broad view of affordances includes both recognized and perceived affordances. Affordances are invariant and differ according to situations and species and are perceived directly from the pattern of stimulation arising from them. They do not change as the needs of observers change; affordances have both objective and subjective properties, becoming a fact of the environment and a fact of behavior. On the other hand, the term ability (a.k.a. effectivity or aptitude) refers to whatever it is about the agent that contributes to the kind of interaction that occurs. In any interaction involving an agent with some other system, conditions that enable that interaction includes some properties of the agent along with some properties of the other system. There is no affordance without ability and vice versa (given that there is no environment without an agent and vice versa).

From this perspective, we can analogize that AI artifacts need to adapt to the environment through accommodation or assimilation: accommodation in the sense that the AI artifact can modify its internal configurations or representations to adapt to a changing knowledge or reality; assimilation in the sense that the AI artifact should be able to apply generally recognized patterns to particular instances. AI artifacts need to have sensory systems that directly and accurately depict the environment. This will determine the artifact's perceptual knowledge of the environment constructed based on memorized patterns, frequency, and other strategies or innate plans pre-programmed into the artifact. Thus, as AI artifacts interact with their environment, they are not presented with meaningful information but obtain it themselves within the constraints and affordances in any given situation. Google Assistant and Siri for example, always have to adapt to their environments through accommodation and assimilation. They perceive the physical environment mostly using your device's mic and voice recognition software. Thus, your assistant's ability to accurately depict the physical environment (in this case detect your voice and capture your wordings properly) depends on the reliability of these sensory systems. These sensory systems just have to transmit the unmanipulated voice to your assistant and using technologies like natural language processing (NLP), the AI artifact will process the voice and use it accordingly. Also, AI artifacts are an inseparable pair with their user it is through their interactions that they learn from each other and interact with other agents or systems in their environment. Thus, your assistant has no reason to conduct a video search on YouTube unless you ask it to. It could also learn to fetch videos only on YouTube if it notices that it is your preferred video website (assimilation). It would not make music recommendations either unless it recognizes or understands your tastes in music (accommodation). Indeed, your assistant uses pattern recognition, memory, machine learning, and other AI enablers to ensure the artifact adapts to its environment.

Table 1 summarizes the fundamental characteristics of the AI artifact derived from our understanding of intelligence from three sets of theories of intelligence. We observe that intelligence is described as a property possessed by an agent that it uses to sense, comprehend, act, and learn in a given environment. Thus, the AI artifact needs to possess each of these characteristics to some extent. We also summarize the differences between AI artifacts and IT artifacts in Table 2, revealing the main dimensions through which one can distinguish between the artifacts. Nevertheless, these artifacts have some similarities. They include: man-made; human-centered; embedded in a context; interconnected components; hardware/software; task-oriented; and fact manipulators.

Table 1. Fundamental Characteristics of the AI Artifact Identified from Theories of Intelligence

Dimensions	Perspective		
	General	Cognitive	Ecological
Sense (environment)	Sense	Aware	Sense

Comprehend	Understand situations	Direction, knowledge	N/A
Act	Perform tasks	Control	N/A
Learn / Adapt	Learned connections	Evolve, adapt, logically interdependent	Adapt (through accommodation or assimilation)

Table 2. Main differences between IT Artifact and AI Artifact

Dimension	IT artifact	AI artifact
Neutrality	Neutral	Not neutral (depends on user)
Evolution	Evolves only through human intervention	Evolves without need for human intervention
Adaptation to users	Users adapt IT to their needs	AI adapts to user needs
Learning capabilities	No learning capabilities	Has learning capabilities
Adaptation to the environment	Cannot adapt itself to the environment	Can adapt itself to the environment
Perception	Shaped by the interest of the development team	Shaped by the interest of the user over time

Using these new insights on AI artifacts and how they fundamentally differ from IT artifacts, IS researchers can start challenging their understanding of AI and its implications for the adoption and use of AI-based IS. These fundamental differences impose the need to revisit our cumulated body of knowledge on technology use and adoption that has been crystallized over the years through IS theories and models. These theories and models need to be revisited through the lens of the dimensions that characterize the AI artifact. Perceived rather as an intelligent agent than as a mere tool, IS literature on technology adoption and use must consider these new dimensions to keep their discussion on AI relevant for the IS community. To demonstrate how these dimensions could be used to revisit existing IS theories and models on technology use and adoption, we revisit the unified theory of acceptance and use of technology (UTAUT), DeLone and McClean IS success model, and task-technology fit (TTF).

Revisiting Some IS Theories and Models

Some researchers have conducted studies on the most influential theories and models in IS research [29, 30]. Three of the IS theories and models that have shaped the IS community's understanding of technology acceptance and use are UTAUT, the IS success model, and TTF. Based on the specificities of the AI artifact, we revisit these models by discussing conceptual and methodological issues that need to be considered if these models should be used to capture AI adoption and use.

Revisiting UTAUT & TAM

UTAUT is one of the main IS theories as concerns IT adoption and use (Venkatesh et al. 2003). Founded in 2003, this theory explains user intentions to use a technology and subsequent use behavior using four constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. The theory builds on the technology acceptance model (TAM) and seven other influential theories and models in IS to capture drivers of technology acceptance by users. Thus, our analysis applies to the constructs of UTAUT as well to all the constructs used to derive those of UTAUT. TAM is a widely used model in IS research used to understand user acceptance of IS. This model postulates perceived usefulness and perceived ease of use are of primary relevance for computer acceptance behaviors (Davis et al. 1989). "Perceived usefulness (U) is defined as the prospective user's subjective probability that using a specific application system will increase their job performance within an organizational context". "Perceived ease of use (EOU) refers to the degree to which the prospective user expects the target system to be free of effort" [26 pg. 985]. These items are operationalized and measured using six-item scales each (Davis 1989) which need to evolve conceptually leading to their modification or the creation of new ones. While perceived usefulness conceptually assumes that IT will increase a user's job performance in the organizational context, users are rather worried about AI artifacts replacing them in the same context (Smith and Anderson 2014). IT artifacts do not understand natural language and context. This is a whole new dimension to EOU as AI artifacts can now interact with users as other humans do. In fact, unlike IT artifacts, AI artifacts are not tools but agents that users interact with to achieve specific goals. Thus, items related to becoming skillful at using IT might need to be revised given that some AI artifacts may not require skills to use them per se. However, a new construct that could be used to extend TAM is what we call 'perception of continuous relevance'. This construct can be defined as the degree to which the user expects the AI artifact to adapt to their needs. We posit that 'perception of continuous relevance' is of utmost importance to AI acceptance behaviors. This is based on the assumption that the more an AI artifact can adapt to the use of its user, the more likely the user is to accept the AI. This could influence the perceived usefulness and perceived ease of use of the AI artifact given that the artifact would have learned and adapted to the user and its environment. This can be operationalized using items that measure the AI's perceived self-improvement, environmental awareness, and sensitivity to environmental changes.

TAM2 (Venkatesh and Davis 2000) extends TAM by proving that social influence processes and cognitive instrumental processes significantly influence user acceptance. Social influences are represented using subjective norm, voluntariness, and image, while cognitive instrumental processes are represented using job relevance, output quality, and result demonstrability.

One way TAM2 could be improved to take AI artifacts into account is at the level of constructs measuring cognitive instrumental processes. These constructs are based on the assumption that people are more likely to perceive technology as useful if it is capable of helping them do their jobs. However, operationalizing these constructs for AI artifacts could be quite tricky conceptually. One challenge faced with AI artifacts is the fact that in as much as they solve for the most efficient solution, they hardly can explain their decisions and actions to users [30, 31]. This raises questions on how we can demonstrate relevance, quality, or tangibility of results we cannot explain. How does one tell others about the results or communicate its consequences without being able to explain them? Given that one can hardly explain the results, it is hard to tell if the results are relevant in context, or if the quality is up to standard, which might not positively influence the perceived usefulness of the system. Thus, conceiving items or new constructs that capture the concept of explainability and adaptability could help improve or extend this model to better capture user acceptance of AI artifacts. However, experience remains a key moderator as AI artifacts are expected to adapt and evolve based on interactions with users. Thus, the more the user has been working with a particular AI artifact, the more likely it is to influence the relationship between the cognitive instrumental processes and the perceived usefulness as well as the intention to use the system.

TAM2 was also extended by TAM3 through the addition of other determinants of perceived ease of use (Venkatesh and Bala 2008). These determinants include computer self-efficacy, perception of external control, computer anxiety, computer playfulness, perceived enjoyment, and objective usability. The fact that AI artifacts can adapt to their users require these constructs to be reevaluated to capture user acceptance. Traditional IT artifacts required users to have some skills to use them in their jobs. Today, AI artifacts can perform several tasks autonomously without help from the user. Thus, there could be a new construct called AI self-efficacy that may rather be perceived as the degree to which users believe the AI artifact can perform a specific task/job. This could be operationalized through items such as, the AI could complete the job - without my help; if I just gave it basic instructions; if I trained it on how to do the job; if I had done a similar job before this one and the AI just had to do the same. This will measure users' appreciation of AI's ability to learn which may influence their perceived ease of use of the system.

Revisiting DeLone and McLean IS Success Model

Another well-established model in the IS field is the DeLone and McLean IS success model (Delone and McLean 2003). The model categorizes determinants of IS success and measures the interdependencies between them. The model posits that a system's information, system, and service quality affect the subsequent use or intention to use that system and eventually the user's satisfaction; using the system will yield some net benefits which are also affected by the user's satisfaction with the system; the user's satisfaction with the system also influences the was the use or intention to use the system. With IT becoming intelligent, the model could also be revisited to incorporate dimensions that are specific to AI artifacts. The updated version of the model that was published in 2003 was evaluated in the context of e-commerce. In that context, system quality currently measures usability, availability, reliability, adaptability, and response time as the desired characteristics of an e-commerce system in the internet environment. However, many e-commerce platforms today make use of conversational agents like chatbots to relate with customers. These chatbots interact with users using natural language (voice or text) to facilitate communication between users and the computer system (AbuShawar and Atwell 2016). In such an environment, system quality would have to measure sensitivity (awareness of the user's needs and environment), understandability (ability to interpret the contextual needs of the client). Both of these aspects are points that make chatbots very appealing for organizations seeking to improve their customer services, hence user satisfaction.

Service quality currently measures assurance, empathy, and responsiveness. However, if the IS success model seeks to capture the service quality of a chatbot, it might have to measure the emotional intelligence of the system as an operationalization of empathy. The explainability of AI will also be an essential measure of service quality, especially if users are to understand and trust the services offered through the AI artifact.

Revisiting Task-Technology Fit (TTF)

The TTF theory was proposed by Goodhue and Thompson in 1995 (Goodhue and Thompson 1995). This theory proposes for IT to have a positive impact on user performance, it must be utilized and must match the task it was designed for (p. 213). Tasks refer to actions that individuals execute to turn inputs to outputs; technology refers to computer systems and user support services that help users perform their tasks, and; TTF is the extent to which technology assists individuals to perform their tasks (p. 216). This theory was measured by the founders using eight factors: data quality, locatability of data, authorization to access data, data compatibility between systems, production timeliness, systems reliability, ease of use/training, and IS relationship with users. These factors can be used to diagnose whether IT tools and services are meeting user needs.

Analyzing these TTF measures through the lens of the dimensions of the AI artifact, we can focus this model on the AI artifact rather than on the individual. In that case, TTF could refer to the extent to which technologies in the AI ecosystem could help AI perform tasks since AI making technology more of an agent than a tool to be used. Applying the TTF measures to an AI agent, we can eventually diagnose whether an AI meets user needs as a partner more than as a tool. Looking at the measures for data quality for example, with AI, it is not only about having current and relevant data at the right level of detail. It is also about data consistency and reliability and of the data sources given that AI artifacts could use this data to learn, make inferences and predictions that are required for timely decision making. Locatability is also crucial for the AI artifact especially when this construct is operationalized through meaning. For example, the AI artifact has to be capable of explaining data fields and data elements to users. As discussed earlier, this is not currently one of AI's strong points. At the level of authorization, AI artifacts may have the authorization to access necessary data that individuals might not be able to access for their jobs. This may be as a result of issues of confidentiality. Thus, AI artifacts may be able to access confidential data, analyze them and make recommendations to users. However, the artifact might not be able (or allowed) to explain the results to the user because of the use of confidential information. This conflict between authorization and explainability should be reflected in the measurements of TTF when using AI as this situation may impact user performance and eventually their use of AI. On the other hand, AI can be deprived of access to confidential data which is crucial for decision making for this same reason. If the AI artifact can explain itself, then it may reveal confidential data. As a result, they may be deprived of access to this data.

Table 3 summarizes our analyses of UAUT, IS success model, and TTF by highlighting some of the conceptual aspects that challenge their ability to effectively capture user behavior as concerns the adoption and use of AI.

Table 3. Revisiting UTAUT/TAM, IS Success Model and TTF using Dimensions that Distinguish between IT and AI Artifacts			
Dimension	Revisited UTAUT / TAM	Revisited IS success model	Revisited TTF
Neutrality	Needs a new construct to capture the neutrality of the AI.	N/A	N/A
Evolution	Needs a new construct to capture the evolution of AI over time.	Evolved systems may influence system and service quality.	Evolution may affect the compatibility between the AI and the task over time.
Adaptation to users	Needs a new construct / items to capture AI's adaptation to user needs in their jobs	Needs to measure understandability (ability to interpret the contextual needs of the user).	Needs to diagnose whether an AI meets user needs.
Learning capabilities	Users are worried about AI learning their jobs and replacing them.	Learning capabilities of AI may influence system and service quality.	Needs to measure data consistency and reliability of data sources.
Adaptation to the environment	Needs to capture explainability of AI; Needs a new construct to capture the effect of AI self-efficacy.	Needs to measure sensitivity (awareness of the user's environment).	AI may be trained to learn a task even if it didn't fit the task initially.
Perception	Needs new construct called 'perception of continuous relevance' and it may influence U and EOU.	N/A	N/A

Discussion and Future Research

In this paper, we evoke differences between the IT artifact and AI artifact that could help the IS community understand AI. We argue that as IT artifacts become more intelligent through AI, IS knowledge on IT crystallized through existing IS theories and models on IT adoption and use need to evolve to stay relevant. Also, new ones need to be developed to better deal effectively with the challenges and capture the opportunities AI brings to IS. To this end, we explored discussions on the IT artifact in IS literature to have a clear understanding of what this artifact is. Given that the expression "IT artifact" has been used by several authors to express different things in IS literature, we sought understanding from the origins of the term. We were able to identify the original meaning and fundamental characteristics of the IT artifact.

To differentiate the IT artifact from the AI artifact, we had to seek the meaning and fundamental characteristics of the AI artifact as well. We started our quest for knowledge from the very beginning of the term as well, given that it has also been used by many different researchers to mean many different things. Based on the project proposal that initiated the AI field, we were able to identify some fundamental characteristics of AI. However, the founders of AI acknowledge that the evolution of AI research significantly depends on our understanding of the concept of intelligence. Thus, we decided to expand our understanding of AI by seeking in-depth knowledge on the concept of intelligence from theories of intelligence. Drawing from three complementary sets of theories of intelligence, we were able to understand intelligence from a general, cognitive, and ecological perspective. Based on these theories, we were able to derive four main dimensions of the AI artifact, and six dimensions that fundamentally distinguish between IT and AI artifacts.

According to the theories of intelligence, all intelligent agents must be able to sense, comprehend, act and learn within the context of a given environment. Thus, the agent must possess all four characteristics before it can be referred to as an AI artifact. We demonstrated how technologies like machine learning, deep learning, and natural language processing are used in the AI discipline. Based on our understanding of the AI artifact, all these technologies can be referred to as AI enablers and not AI artifacts because the give AI capabilities to a technology or system. The AI artifact possesses the four stated capabilities that are enabled by technologies called enablers since the "enable" these capabilities. We highlight the fact that there is indeed a difference between weak AI (designed for a specific task) and strong AI (designed for general tasks). Nevertheless, both must possess all four capabilities. The difference lies in the range of tasks they are designed to execute and their level of intelligence compared to human intelligence. All general applications of AI used today both privately and at work are weak AI.

AI artifacts differ from other IT artifacts in terms of neutrality, evolution, adaptation to users, learning capabilities, adaptation to the environment, and perception. The notions of learning, evolution, and adaptation shifted technology adoption to a highly temporal state. The same AI artifact you use today would behave differently at a different point in time under the same or different circumstances or contexts without being reprogrammed by man. This gives technology adoption and use a whole new perspective both conceptually and methodologically. Conceptually, this implies that one cannot study AI without understanding its environment at the time of interest. Given that the AI artifact and its users are logically interdependent and interact with other systems in their environment, research on AI adoption and use will have to take into account many more parameters for a single study. Without these considerations, research on AI would be methodologically pointless. As AI artifacts tend to adapt to their users, the user's characteristics like personality and habits are bound to be taken into consideration. This would be particularly useful for studies that seek to predict the behavior of AI. Also, measurement instruments will have to evolve as well. Many IS theories and models on adoption and use used questionnaires as survey instruments. Thus, IS researchers should strive to conduct studies that are balanced between the artifact and theory. Given the ever-changing nature of AI, more longitudinal design science research would be a more suitable approach to investigate AI adoption and use. To obtain optimal results, AI artifacts must be represented in every research project and resulting theories or models, including the expected goal and impact of the specific AI in the given context at a given point in time

Using the dimensions that distinguish IT from AI artifacts, used UTAUT/TAM, IS success model, and TTF to demonstrate how IS literature on IT adoption and use could be revisited. Thus, we urge other IS researchers to use the dimensions highlighted in this paper to revisit other IS theories and models. IS scholars and researchers continuously strive to increase their understanding of how IT artifacts are conceived, developed, implemented, used, supported, evolve, and impact the context in which they are embedded (Benbasat and Zmud 2003). Thus, as IT transitions to AI artifacts, their managerial, methodological and operational capabilities need to be at the center of upcoming IS research. IT is at the core of the IS discipline and it is changing to become AI. Thus, the IS discipline needs to study AI as a core subject and not as a peripheral issue as it did with IT artifacts. As AI continues to spread rapidly, the IS community has to keep up with theorizing the AI artifact to capture its evolution and the maturity of different types in several contexts. At the organizational level, transitioning from IT artifacts would require several institutional changes that need to be studied critically, including the nature of work, and the choice of AI artifact to purchase. With AI capable of adapting to its environment, institutional culture becomes even more relevant depending on the AI to be adopted. Confidentiality issues become even more accentuated as well as technology may have to start explaining itself at some point.

The boundaries of the IS field are shifting from IT artifacts to AI artifacts. Recognizing this early enough and acting on it will give the IS field legitimacy on the topic and make it more attractive for AI researchers and institutions implementing AI. Thus, we recommend that IS research on the adoption and use of AI artifacts should: focus on theorizing the AI artifact; increase collaboration with other disciplines; and pay as much attention to the AI artifact as to the context and environment in which the AI is used or to be used.

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