Impact of Non-Human Actors in Communicating Meaning: Towards a Knowledge Translation Framework

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Abstract: Knowledge Translation is a core research topic in the field of knowledge sciences. To date, traditional research on knowledge translation has come from medical and health sciences. This is not surprising because in health sciences and medicine, there is a long tradition of review of evidence-based research, information dissemination and translating theory to application. While providing a strong foundation for understanding knowledge translation, research focused on the healthcare domain overlooks the scope or the scale of knowledge translation we all encounter every day in the course of living in the 21st century. In the knowledge economy, knowledge exchange and simple sharing represent an economic transaction. Wherever and whenever knowledge is exchanged, knowledge transactions should be as effective and efficient as possible to ensure the flow of knowledge is maximised. Knowledge exchange frequently occurs between human and non-human actors. In contrast, the traditional knowledge translation literature focuses on human-to-human knowledge translation. This paper looks at knowledge exchanges between human actors and non-human actors in two specific environments. The first is human-to-machine knowledge translation in service call centres. The second environment focuses on doctor-patient conversations during patient visits, with the participation of third-party non-human actors, e.g. machine transcription applications. These non-human actors create persistent records of exchanges between doctors and patients. They also have been found to generate high rates of errors in knowledge translation. The problems, challenges and opportunities involved in each of these fields are the focus of this paper. The authors identify factors that contribute to knowledge translation failures.

Keywords: Knowledge translation, Knowledge economy,Human-nonhuman interactions, Call centers, Doctor-patient dialogs

1. Introduction and Research Rationale

Knowledge Translation is a core research topic in the field of knowledge sciences. To date, traditional research on knowledge translation has come from medical and health sciences. It is not surprising because there is a long tradition of reviewing evidence-based research, information dissemination and translating theory to application in health sciences and medicine. In that field, the goal is to ensure that state-of-the-art medical research and knowledge are deployed as soon and as safely as possible to the field, where these can significantly impact those who require the research results for patient care.

In the knowledge economy, what we refer to as knowledge exchange, knowledge sharing, knowledge transfer, knowledge dissemination, and knowledge absorption is all part of a knowledge transaction. Knowledge translation must be as effective and efficient a transaction to ensure knowledge value is maximized for all parties. Therefore, knowledge translation is vital to all organizations, all groups and even individuals. Furthermore, knowledge translation is vital to today's managers in a knowledge economy where optimal use of knowledge is a competitive advantage. Therefore, every knowledge organization's core business activity is effective knowledge translation.

In addition to expanding our work in knowledge translation to every domain and every level, we must now add a third dimension – the role of non-human actors. In our world, there is an increasing role of non-human actors in everyday and professional knowledge transactions. However, there is little foundation for this new dimension in the literature on human-to-human knowledge translation. This paper examines knowledge exchanges between human and non-human actors in two specific contexts. The first is the role of non-human actors in automated call centers. The second is the role of non-human actors as recorders and transcribers in medical conversations during patient visits.

1. Knowledge Translation – Definition and Characterizations

Several definitions of KT are reported in the literature (Dal Mas et al., 2020; Savory, 2006; Semeone Secundo and Schiuma, 2017; 2018; D'Andreta & Scarbrough, 2015; Hodgins & Dadick, 2015; Jull, Giles & Graham, 2017). Strifler et al. (2015) identified 159 different theories, models, and frameworks for knowledge translation in their comprehensive review of the literature. In general, the definitions and frameworks found in the literature today represent three perspectives, including (1) research utilization and uptake; (2) evidence-based research; and (3) information dissemination. The emphasis in these perspectives is on translation from source to target. The

authors noted that a perspective focusing on the knowledge component is generally absent from the peer-reviewed literature.

There is a growing consensus that the optimal definition and conceptual model are those proposed by Baumbasch et al. (2008). Their definition and model include knowledge and translation's fundamental elements and processes. Paraphrasing Baumbasch et al., knowledge translation is an interactive and reciprocal process involving synthesizing knowledge within a complex system of interactions. They conceptualize knowledge translation as a dialog, interaction, communication, and collaboration between actors with different perspectives and domains.

The Baumbasch et al. definition and model focus on knowledge translation from unidirectional, linear research utilization and evidence-based practice models toward a complex, dynamic model. This model provides new research opportunities to explore and better understand the complexities of translating knowledge among humans who have different levels of understanding and come from different cultures and contexts. Knowledge translation is much more complex than translating research into practice.

2. Research Goals

This paper presents exploratory research. The authors have both short and long-term goals for their work. In the short-term, we expect to: (1) raise awareness of the everyday knowledge translation activities between humans and non-humans, and non-humans to non-humans; (2) explore the nature of knowledge translation among diverse actors where one or more actors are non-human, representing varying types and levels of knowledge; and (3) explore the capacity of non-human actors to articulate, absorb and engage in transactions with humans and other non-human actors. In the longer term, we hope to (1) develop a theory about the role that non-human actors can effectively play in knowledge translation and to identify their advantages and disadvantages; (2) to provide reliable and valid guidance to intelligent non-human actors to ensure there is a built-in capacity for knowledge awareness, articulation and absorption; (3) explore these questions in an extended scope and scale of engagement - from the simplest conversations to everyday collaborations, to business transactions, to complex diplomatic conversations, to interacting with automated help center agents, and even doctor-patience consultations.

3. Conceptual Model and Framework

This exploratory research is grounded in a conceptual model to reduce the complexity of integrating research from multiple disciplines (Figure 1). The conceptual model draws from the traditional literature and existing models but expands it based on knowledge drawn from the communications literature, the field of linguistics, business management practice, and the knowledge sciences literature. And, unlike the current literature, the conceptual model is domain, sector, and goal agnostic. It is both knowledge ecosystem- and scale-aware. It incorporates but goes beyond the existing models. The model provides a foundation for identifying and organizing influence factors, competencies, and capabilities by anchoring in the four components- knowledge, translation, scope, and scale.

The model provides a holistic description of the essential components of knowledge translation and the factors that influence them. The model is grounded on but expands the work of Baumbasch et al. The model has two core components – knowledge as substance and translation as a process. We expand the model to include two additional components: the translation's scope and scale.

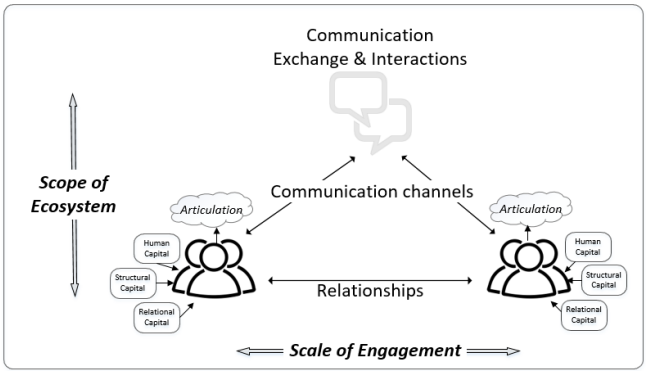

Figure 1: Foundational Components of a Knowledge Translation Conceptual Model

Knowledge translation is effective when a shared understanding and meaning among actors is achieved. To achieve this shared level of understanding, we must consider: (1) the knowledge being shared; (2) the translation process; (3) the knowledge ecosystem; and (4) the scale and scope of the communication. Each of these is comprised of multiple factors. Each knowledge translation action is unique because the goal, the context, the agents, and the knowledge is unique. When we can "see" the factors in play, we can better understand its uniqueness and how to improve its effectiveness. The literature is rich in discussing factors, but we do not have a comprehensive and inclusive picture of where they fit in any translation. A comprehensive conceptual model and a framework grounded in the model can act as a guide to identify which factors may be relevant. And a framework tied to competencies and capabilities can help us to gauge how effective that translation might be. This chapter presents a conceptual model with four components, the elements comprising each component, and critical questions for each element. The framework is grounded in the conceptual model, aligns critical questions, and calls out competencies and capabilities.

The conceptual model also translates into a framework. Because it is grounded on the conceptual model, the framework provides a comprehensive view of the translation landscape. From the framework, we can develop a checklist and set of key questions practitioners can leverage to design an optimized picture of knowledge exchanges and translations.

Table 1: Knowledge Translation Framework

Component	Parts
Knowledge	Knowledge Asset Actors Relationships
Translation	Communication and Interaction Channels Articulation
Scope of Ecosystem	Diversity of Actors Range of Goals Range of Domains Range of Languages (Linguistic) Range of Cultures Range of Status and Roles Range of Communication Styles Range of Capabilities
Scale of Engagement	# of Actors # of Channels # of Interactions The Extent of the Impact

The guiding framework is structured around the four components of the conceptual model – knowledge, translation, the exchange's scope, and scale. Within each component, key elements are identified and described. Finally, the framework offers guiding questions for each element to help anyone achieve an effective outcome.

4. Research Methodology

We have chosen two business cases to explore the role of non-human actors and their role in knowledge translation. In each case, we apply the conceptual model and framework to develop a full accounting for all four components. The first case explores non-human actors' role in automated service and calls systems. The second case explores the role of non-human actors in medical information systems and their capacity to capture, record and transcribe conversations between medical professionals and patients. In both business cases, the scope is limited to a single domain, common goal, controlled vocabulary, and common expectations to allow us to derive important observations about the actors. Also, in both business cases, the scale is limited to micro-level transactions to allow us to focus on the nature and characteristics of the non-human actors.

5. Business Case 1: Knowledge Translation in Automated Service Center Dialogs

Automated service centers are integral parts of every domain and every economic sector. Every individual encounters some form of automated service every day. They are found in banking, restaurant services, home improvement stores, appointment scheduling, retail services, library services, pharmacies, insurance, human resource, and transportation services.

Service and call center automation replace human agents with non-human agents to reduce human labor costs and improve the accuracy and quality of service requests. Non-human agents are comprised of various software and technology components. These non-human agents are designed to perform routine, time-consuming tasks and processes (Hardy et al., 2004; Legos, 2021; Paek & Horvitz, 2004; Salcedo-Sanz, 2008). The expectation is that these non-human agents will reduce the need for human intervention. However, while cost reduction may be achieved, the literature and practical experience suggest that non-human agents have not yet achieved the

same quality or efficiency of service as their human counterparts. To date, the peer-reviewed literature has assessed the performance of these non-human actors using quantitative methods applied to logs and recorded interactions. In this business case, we consider how applying the knowledge translation framework might help us identify and address challenges.

5.1 Applying the Framework to Automated Service Centers

We define service and call center interactions as focused dialogs between humans and non-human actors. We begin by profiling each component in the call pr service center dialog (Figure 2).

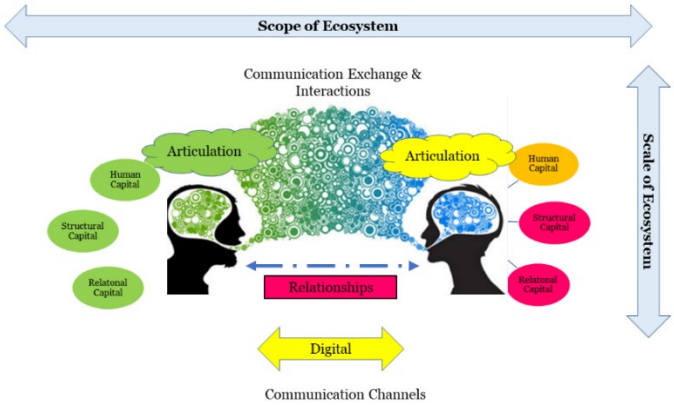

Figure 2: Automated Call and Service Centers in the Knowledge Translation Framework

Let's walk through each of the components in the framework. As a starting point, we have coded each component to suggest the challenges, limitations and constraints it brings to the task.

The ecosystem

We first want to understand the ecosystem's scope and scale when applying the framework. These two components describe two dimensions of complexity that may increase the translation challenge. In this case, the scope is minimal, as the dialog takes place in a specific domain and is related to a select set of options. It means that the vocabulary and the knowledge base will be well-known to all actors.

At first glance, the scale is also limited because the dialogue is between a single human and a non-human actor. However, our understanding of the scale changes when we realize that the non-human actor is designed to interact not only with a single actor but with any possible actor. In this case, the scale is different for each actor. The human actor is dialoguing with a single non-human actor. But the non-human actor is dialoguing with any one of potential thousand or millions of human actors. The non-human actor is designed to communicate at the meso level – with many actors within a defined domain and activity. Variations in the scale of dialog are the first challenge the framework exposes.

Actors, capabilities and competencies

The *knowledge component* of the framework surfaces variations and imbalances that can lead to miscommunications, misunderstandings and failed dialogs. Focusing on the actors, Figure 2 suggests an imbalance in the knowledge capital the actors bring to the dialog and their ability to develop relationships to improve the dialog iteratively. The human actor brings all three types of knowledge capital to the conversation, including tacit knowledge of the service and their needs, their ability to answer questions, adapt to responses by the non-human actor, develop relationships and adjust their vocabulary to communicate with others.

On the other hand, the non-human agent's knowledge capital is limited to the specific task it is designed to perform. The knowledge base is defined by its human developer. In most cases, the non-human actor's knowledge is embedded in several applications and technologies, including (1) decision support trees comprised of the conditions/responses in the non-human actors' knowledge base; (2) a domain knowledge base and vocabulary sufficient to fill the decision support tree; (3) other applications such as calendars, product descriptions, service descriptions relevant to the domain and the activity; and (4) frequently a collection of frequently asked questions or frequently given answers. The limited knowledge base of the non-human actor can be a challenge depending on the nature of the vocabulary used in the dialog and the semantic variations built into the non-human's semantic repertoire.

We acknowledge that human actors have different capacities for understanding and absorbing knowledge. While there are variations, humans can articulate what they know (e,g., tacit knowledge) and absorb knowledge from other humans. An actor's ability to articulate and absorb knowledge speaks to his ability to learn, unlearn, adapt, relearn and reframe the dialog. It is a challenge for non-human agents for several reasons. First, non-humans can detect when an interaction is not on track, an error has occurred and needs correction, and when there is frustration in the dialog. Second, non-human actors can detect mismatches in options based on coding and semantic capabilities but cannot detect frustration or anger in human speech. Third, they cannot determine when it is appropriate to hand the dialog over to a human actor.

Additionally, human actors can learn from an effective dialog, whereas non-human agents cannot. As a result, human actors will adjust their knowledge base for future dialogs. Only the human developers of non-human actors can make those changes. In general, the knowledge imbalance across actors raises challenges that may be addressed or improved by leveraging lessons learned from knowledge translation.

In the translation component, though, we find the most significant challenges. In a human–non–human dialog, the success of the translation is very much dependent upon the architecture and the capabilities of the non-human actor (Levin, Peraccini & Eckert, 2000; Polzehl et al., 2011; Sarosi et al., 2014; Schmitt, Hank and Liscombe, 2008; Schmitt, Pieraccini & Polzehl, 2010). In this component, we find a significant communication and articulation capacity imbalance between human and non-human actors. Humans have the capacity to articulate what they know, and they can adapt how they articulate to suit others in the dialog. We take all human competencies for granted. These have to be constructed for a non-human actor, however. A non-human actor must have access to voice recognition applications, speech-to-text capabilities to translate what they hear into text for matching or form filling, named entity extraction, natural language processing to understand the response of the human actor, natural language generators, a set of scripted rules for responding, slot filling, vector-based task identification, dialogue act classification applications, and also Bayesian database record selection algorithm.

In addition to these components, non-human actors must also have the capacity to detect emotion in human speech. Detecting emotion is one of many communication problems that may occur and for which there may not yet be solutions (Hirsh et al., 2007; Suendermann et al., 2010; Yongho-Hyun, Kim & O'Keefe, 2014; Zweig et al., 2006). Nevertheless, by leveraging these applications and technologies, non-human agents can achieve some level of understanding of human words, sufficient to make a probabilistic decision regarding their meaning.

From this single business case, we observe that applying the knowledge translation model surfaces challenges that have not yet been addressed by developers building these systems. When we view the interaction from a knowledge translation perspective, there is potential for improving the human interaction with call centers.

6. Business Case 2: Non-Human Actors in Doctor-Patient Dialogs

We begin building out this business case by describing the nature of a doctor-patient dialog. Then, we overlay this dialog with the knowledge translation framework to understand the challenges and opportunities. We are concerned about non-human agents in doctor-patient dialogs because of the increased number of medical errors reported in medical situations that leverage non-human actors in some capacity.

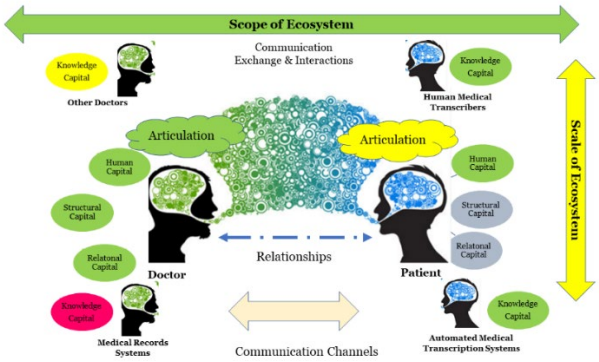

Figure 3: Doctor Patient Dialogs in the Knowledge Translation Framework

The ecosystem

How would we characterize the scale of the dialog? The label would suggest that it is a one-on-one dialog – between doctor and patient – at the micro level. It is what is initially visible. But the scale changes as we look for other invisible actors. There are at least four invisible actors involved in this dialog. The first is a medical information system – a non-human actor whose knowledge base contains records of all previous doctor-patient dialogs and interactions. The second is a community of other doctors who may take the doctor's role in future events or specialists who may provide related care. The third is a human medical transcriber who works with doctors to create medical records. And finally, we now have automated medical transcription systems that may take on the role of the human medical transcriptor to create medical records. We note that as medical records become more widely available and accessible, the scope of the doctor-patient ecosystem will continue to expand to include insurance companies, legal professionals, medical researchers, billing coders, audit contractors, other doctors and the patient. This expanding scope increases the number of opportunities for translation errors and failures. Given what we can see, we suggest the scale is micro-level and meso-level at the invisible and behind-the-scenes levels.

How do we characterize the scope of the dialog? The scope of the dialog is patient-focused – micro level. Depending on the patient's issues and medical situation, the scope may grow to the meso level as more specialists and other supporting actors are brought into the ecosystem. It is highly probable that as the scope increases, each new actor from a related discipline may bring in their non-human actors and automated applications. Scope creep may increase the knowledge translation challenges and opportunities for errors.

Actors, capabilities and competencies

As Figure 3 suggests, the knowledge component of a doctor-patient dialog significantly affects knowledge translation (Carboni et al., 2002; Poder et al., 2018). The two visible and four invisible actors best understand the knowledge component. An ideal dialog between a doctor and a patient is based on one of two conditions. First, the doctor and patient have an existing relationship and are familiar with the patient's condition and situation. They share a joint knowledge base about the patient. Second, the doctor does not know the patient but can gain some knowledge of the patient's condition and situation from medical records. The doctor must have a complete picture of the patient to elicit information from the patient and provide information back to the patient that will be understood, absorbed by, and turned into practice by the patient. So that's our setting. Doctors and patients must have substantial social capital and emotional and psychological capital. Doctors must be able to demonstrate social capital for there to be trust between the two actors. Without trust, the literature suggests the patient may be unlikely to provide additional explanatory or sensitive information essential to a correct diagnosis and medical remedy.

Patient's medical records are held in medical information systems. These are invisible actors in the doctor-patient dialog. These systems have evolved from paper to digital. Medical records have predefined structures, use predefined vocabularies and concepts, and free test fields for doctors' notes, diagnoses, remedies, therapies and general notes about the conversations with patients. Medical records are not just for the originating doctor but other healthcare professionals. While a limited number of people may be present for a given medical encounter, the number of potential actors in the longer-term dialog increases through the use of medical records. Today, these records may be created by doctors, medical transcriptionists, or automated speech recognition systems. While the use of electronic health records is intended to reduce errors, bring down costs, ensure privacy and support patient care. If the information in medical records is inaccurate, poorly organized, or untimely, medical mistakes can occur, affecting the patient's care and health. (Roop, 2009; Star 1999; Star and Griesemer, 1989; Timmermans and Berg, 2003); Garfinkel, 1967)

Medical transcriptionists are important but invisible actors in doctor-patient dialogs. They create medical records for doctors and patients. Their work has been supported or replaced by speech recognition technology in the past decade. However, transcriptionists do more than record a doctor's recordings or notes verbatim (Cora Garcia, David & Chand, 2010; David et al., 2009; Fahini et al., 2009). Medical transcriptionists use a wide range of skills and knowledge to produce accurate records. They rely on the extensive medical knowledge of terminology, anatomy and physiology, procedures, diagnosis and treatment to do their work. In addition, transcription requires an understanding of spoken language, healthcare documentation processes, medical spelling, medical terms, critical medical errors made by dictating physicians, discerning voice inflections for punctuation, and filtering background noise and distractions in the voice recording.

Additionally, transcriptionists leverage professional and sense-making skills and knowledge of how doctors speak and record their notes in their work. These very human professional and common-sense competencies

allow them to discover errors in notes. These competencies add a critical level of defense against inaccurate medical records and resulting medical errors, which existing speech recognition technologies cannot duplicate.

Physicians are increasingly encouraged to create patient records using automated medical transcription applications. Physicians may use these non-human actors as dictation and transcription support as they dictate their notes after the dialog. They may also be invisible non-human actors recording the whole doctor-patient conversation as it occurs. When doctors dictate their notes, the transcription quality will depend on the doctor's articulation and speech skills, vocabulary quality, and knowledge base (e.g., medical knowledge) embedded in the application. Automated medical transcription applications do not always have built-in computational linguistics or grammar-checking components. If a human does not review the transcription, errors could exist and sustain (Brenner et al., 2015; David, Change & Sankaranarayanan, 2014; Hodgson & Coiera, 2016; Wahl et al., 2008).

The translation component is as important as the knowledge component in any knowledge translation action (Blakley et al., 2010; Halkowski, 2011; Ihlebæk, 2020; Lyons et al., 2016; Shaeff, 2017). And communication is the focal point in translation. In the doctor-patient dialog, communication between human and non-human actors is primarily one way – the non-human actors receive, translate and memorialize the communication of medical personnel. There is little interactivity or exchange in the dialog at any point. It presents challenges as the lack of interaction would suggest few checks or validations of the non-human actors' representation of the communication. The literature suggests that the critical review and validation of non-human actors' representation can raise significant concerns.

Knowledge translation between actors is the critical success factor in whether that communication is a success or a failure. A preliminary observation of introducing two non-human actors into this dialog is that the communication model may be shifting. We are prompted to ask whether the invisible non-human actors may be playing more significant roles in the translation of patient and medical knowledge among all the actors. The increased use of non-human actors may be shifting the attention of doctors and other medical personnel towards a dialog with non-human actors during patient consultations. Similarly, non-human actors may now encourage doctors to listen to their "medical data and information" in preference to knowledge from the patient. While these systems provide many new advantages in tracking and providing access to medical data and information, introducing non-human actors has changed the traditional doctor-patient knowledge exchange. These exchanges were historically challenging, but now they are abbreviated or eliminated. Have the non-human agents taken on the role of a translator in the knowledge translation process?

This case raises questions about whether this shift is occurring and, if so, how the shift might be affecting translation between doctor and patient. The authors believe it is worth further exploring how a traditional human-to-human knowledge translation process may be affected. Medical risks and unintended consequences may shift when doctors do not converse directly with patients. We suggest these are important questions to explore while the opportunity to redesign and reshape the design of non-human actors exists. Information in the popular press and gray medical literature suggests that a high percentage of hospitals plan to expand their use of the applications and technologies referenced in this paper. However, standardized methods for evaluating these technologies are currently lacking. An opportunity exists to add a knowledge translation framework to future evaluation methods.

7. Preliminary Observations From the Businesses Cases – Implications for Further Research

The authors offer two observations from their exploratory research. The first is that applying the knowledge translation framework to business cases helps us to identify the critical gaps and challenges in any knowledge translation activity. For example, in the case of knowledge translation in the call center, the translation and communication component exposed the challenges. It highlighted opportunities for improvement, specifically the non-human actor's lack of capacity to communicate with the human actor. In the case of the doctor-patient dialog, the main challenges appeared in the knowledge component – precisely, the non-human actor's lower capacity to accurately represent the knowledge of human actors and the lack of opportunity to discover and correct errors. We suggest the framework has value but requires further testing and elaboration in a broader range of examples.

Our second observation is that although smart technologies are marketed as a cost-effective and efficient way to reduce the use of human labor, they come with significant risks. The knowledge translation literature teaches us that interaction and feedback are critical quality control and assurance factors at any level and scope.

We conclude this work with an invitation to the wider community of scholars and practitioners to consider the importance of knowledge translation in their efforts to embed the latest technologies in fields that have traditionally been driven by human interactions. Our business cases show that –despite their potential to improve processes and add value, the introduction of non-human actors in a traditional dialogue must be part of a carefully designed strategy that also includes the development of key capabilities and competencies within the organisation.

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