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Smart nudging: How cognitive technologies enable choice architectures for value co-creation

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ABSTRACT

People make decisions and take actions to improve their viability everyday, and they increasingly turn to artificial intelligence (AI) to assist with their decision making. Such trends suggest the need to determine how AI and other cognitive technologies affect value co-creation. An integrative framework, based on the service-dominant logic and nudge theory, conceptualizes smart nudging as uses of cognitive technologies to affect people's behaviour predictably, without limiting their options or altering their economic incentives. Several choice architectures and nudges affect value co-creation, by (1) widening resource accessibility, (2) extending engagement, or (3) augmenting human actors' agency. Although cognitive technologies are unlikely to engender smart outcomes alone, they enable designs of conditions and contexts that promote smart behaviours, by amplifying capacities for self-understanding, control, and action. This study offers a conceptualization of actors' value co-creation prompted by AI-driven nudged choices, in terms of re-institutionalizing processes that affect agency and practices.

1. Introduction

Advancements and synergies in the Internet of Things, augmented reality, robotics, intelligence systems, and other emerging technologies are accelerating (EU, 2020). Smart technologies can perform tasks and accomplish objectives that traditionally required human intelligence and capabilities (Kelly, 2015). They thus challenge conventional understanding of what is possible, yet their impact on human actors' agency remains underexplored (Mele et al., 2019). Recent calls suggest the need to investigate new forms of technology-based service interactions and provide insights for more valuable, contextual types of human-to-machine interactions (Corsaro, Hofacker, Massara, & Vargo, 2018).

In answering this call, as highlighted for this special issue of *Journal of Business Research*, we propose a framework of the role of cognitive technologies in actors' value co-creation efforts. We draw from two research streams (MacInnis, 2011): the service-dominant logic (S-D logic) and its view of agency, institutions, and technology, as well as nudge theory, which contributes choice architectures as a design condition that affects actors' agency. According to the S-D logic, all social and economic actors are affected by, and affect, the socio-material context in which they are embedded (Lusch & Vargo, 2014; Orlikowski, 2007). Any antagonism between social and material artefacts can be overcome by a perspective on technologies that consists of the combination of meanings, processes, and practices (Akaka & Vargo, 2014; Mele & Russo Spena, 2019). Beyond being a material artefact, technology is an operant resource—one capable of acting on other resources to create value—so it performs a critical role in ecosystem (re) formation (Vargo, Weiland, & Akaka, 2015).

The exploitation of technology happens in the systemic contexts in which actors perform their practices while trying to resolve contradictions and inconsistencies with changes in institutions and institutional arrangements. In their search to improve their viability, actors act together with technologies to develop new understanding and practices (Akaka, Vargo, & Wieland, 2017). In such a view, smart technologies have strong disruptive potential for actors' practices. Their promise to transform people's lives and society stems from the higher levels of connectedness, greater computational processing, and more complex decision making, involving extraordinary volumes of data, that they promise (Huang & Rust, 2018, 2020). However, the debate about whether and how a process of re-institutionalization arises and changes value co-creation practices, thanks to artificial intelligence, social

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robots, and other smart technologies, is unresolved (Kaartemo & Helkkula, 2018; Mele, Russo-Spena, & Peschiera, 2018b).

Building on an interdisciplinary perspective to extend extant services research, this study leverages behavioural economics, as manifested in nudge theory (Thaler & Sunstein, 2008), according to which humans are heavily influenced by their environments, emotions, and social interactions. "Nudge" in this context refers to "any aspect of the choice architecture that alters people's behaviour predictably without forbidding any options or significantly changing their economic incentives" (Thaler & Sunstein, 2008, p. 6). This concept builds on psychological, economic, and sociological theories that detail how environments shape and constrain human behaviour, far more than people might like to believe (Ross, 1977).

To clarify nudging mechanisms, a key consideration is the role of different technologies and how persuasive cognitive systems might support value co-creation. Digital nudging (Weinmann, Schneider, & vom Brocke, 2016) refers to user interfaces in online decision environments that affect human behaviours, though this concept does not explicitly address the potential of emerging intelligent technologies. To specify how cognitive technologies create nudges and choice architectures that alter human decision making, and thereby increase value co-creation and prompt a re-institutionalizing process, this study focuses on how value co-creation can be framed by perceptions of that context. How can cognitive technologies enable us to make better decisions and prompt value co-creation?

To establish a robust contribution, we carried out empirical research involving 15 case studies. We investigated different actors (providers, users, partners) who provided insights into how cognitive technologies affect agencies, behaviours, and mundane practices. In turn, we offer an integrative framework (MacInnis, 2011) of S-D logic and nudge theory that contributes to service research by delineating the concept of nudging and choice architecture in terms of a re-institutionalizing process, with four main implications. First, we introduce the concept of *smart nudging* to refer to uses of cognitive technologies to affect people's behaviour predictably, though without limiting their options or changing their economic incentives. Second, we identify choice architectures and nudges that affect value co-creation by (1) widening resource accessibility, (2) extending engagement, and (3) augmenting human actors' agency. Third, we establish that though cognitive technologies are unlikely to engender smart outcomes by themselves, they enable the design of conditions and contexts that promote intelligent behaviours, by amplifying capacities for self-understanding, control, and action. Fourth, this study offers a conceptualization of actors' value co-creation, prompted by AI-driven nudged choices, in terms of a re-institutionalizing process that affects their agency and practices.

The remainder of this article proceeds as follows: First, we review literature on four main topics: actors, resource integration, institutions, and value co-creation; cognitive technologies and AI; nudge theory and choice architectures; and digital nudging. Second, we present the methodology and findings. Third, this article ends with a review of theoretical contributions, managerial and ethical implications, and avenues for further research.

2. Literature review

2.1. Actors, resource integration, and value co-creation

The S-D logic proposes a generic actor-to-actor model, in an effort to move beyond economics-based categories of producer versus consumer or the exchange market, in which prices are the primary means to distribute resources throughout a society efficiently. Rather, social and economic actors perform basic activities of integrating resources from various sources, exchanging service for service, and co-creating value (Vargo, Maglio, & Akaka, 2008). In this actor-centric vision of the economy, entrepreneurial actors use their networks, composed of both actors and resources, to gain higher density and enhance their individual and collective well-being (Vargo & Lusch, 2017). Resources refer to anything on which an actor can rely, such that they are not necessarily things but rather reflect an abstraction about how an idea can contribute to achieve a desired end (Koskela-Huotari & Vargo, 2016). They provide the basis for value co-creation. The density of resources is defined by their mobilization, by an actor in a certain time and place; maximum density implies the best combination of resources for an actor in a certain time and a certain place, such that it results in the co-creation of the highest possible value. Because resource-integrating actors aim to improve individual and collective well-being, an actor-centric perspective, by definition, is also value-centric. The S-D logic posits that value is unique, specific to each actor, and, at the moment of its co-creation, simultaneously distinguished and phenomenologically determined (Vargo & Lusch, 2008).

Furthermore, actors have agency and perform "multiple roles, such as facilitators, modifiers, or disruptors in the service ecosystem as part of their value co-creation efforts" (Tronvoll, 2017, p. 10). Agency is both collective and relational (Sewell, 1992); it provides schemas to mobilize resources through interactions and communications with others, through a recursive structuration process (Giddens, 1984). In describing their relational and purposeful actions, the S-D logic suggests that actors seek to establish service exchanges that can result in value co-creation. Yet these actors are not completely rational agents, as predicted by neoclassical economics. Nor can they clearly see the network or system within which they function to predict the future or maximize results. They may consider some steps to take and solve more immediate problems; they are less capable of making sophisticated calculations to solve problems. Overall, the S-D logic posits that actors solve recurring issues by developing institutionalized solutions, but their resource integration might fail (Mele et al., 2018a) if the solutions integrate resources that worsen their viability or the actors lack the capabilities to integrate other resources (Frow & Payne, 2011). As Koskela-Huotari and Vargo (2016, p. 163) describe it, "the resourceness of potential resources is inseparable from the complex institutional context in which it arises." Therefore, it becomes crucial to understand actors' agency and resource, as they are becoming in service ecosystems (Vargo & Lusch, 2016), as well as the institutionalizing process that guides value creation. To address how cognitive technologies affect actors' agency and become resources in context (Koskela-Huotari & Vargo, 2016), by enabling resourceness, it is necessary to delineate connections among human and non-human elements and the practices of resource integration in a socio-material context (Mele et al., 2018b).

2.2. Cognitive technologies and artificial intelligence in service research

Cognitive technologies rely on computational components that deliver cognition as a service (which implies three Ls: language, learning, and levels) and that empower and scale human expertise (Spohrer & Banavar, 2015). These technologies augment human intelligence and capabilities across the spectra of sensory perception, deduction, reasoning, learning, and knowledge (Kelly, 2015). Artificial intelligence (AI), machine learning, natural language processing, speech recognition, and robotics have transformed how actors interact with machines by performing tasks and accomplishing objectives that traditionally required human intelligence (Huang & Rust, 2020). Applying computational technology effectively requires conceiving of modelling, designing, and evaluating joint human–machine cognitive systems (Hollnagel & Woods, 1983). Furthermore, cognitive technologies offer promising ways for actors to innovate (Demirkan et al., 2015; Ng & Wakenshaw, 2017), due to their capacity to use knowledge databases and derive inferences automatically from available information.

Although the topic of cognitive technologies is of fundamental importance for both business scholars and professionals (Lemon & Verhoef, 2016), most studies focus on the exploitation of AI and machine learning from a technological perspective (Schwab, 2017), such as how AI supports new activities, provides alerts and notifications, enables control of product functions, or facilitates self-diagnosis (Dzyabura & Hauser, 2011; Hauser, 2014). In service research, technologies promise broader applications for augmented human–machine interactions (Huang & Rust, 2018; Wirtz et al., 2018) by not only transforming data into usable intelligence but also incorporating digitally empowered systems into human lives (Demirkan et al., 2015). Because AI is used to integrate and augment human capabilities, not replace them, it can enable summative and emergent resource integration processes (Mele et al., 2018b). A few studies specifically address features of AI technologies related to value co-creation (Table 1).

For example, some works identify specific roles for robotics according to their value co-creating or co-damaging potential (enabler, intruder, ally, replacement, extended self, and deactivator), then link these roles to three functions: safeguarding, psychosocial health, and cognitive health (Čaić, Odekerken-Schröder, & Mahr, 2018). Such a perspective promotes a value-centric conceptualization of social robots according to a resource-focused view of technology (Čaić, Mahr, & Odekerken-Schröder, 2019). A social cognition perspective is useful to understand how "users evaluate social robots on their affective and cognitive resources" (Čaić et al., 2019, p. 465). Other scholars combine insights on the role of AI and robotics in value co-creation to specify four themes: generic field advancement, supporting service providers, enabling resource integration between service providers and beneficiaries, and supporting beneficiaries' well-being (Kaartemo & Helkkula, 2018). A recent study introduces the roles (personal assistant, relational peer and intimate buddy) that companion robots can fulfill to mitigate feelings of loneliness through building different types of supportive relationships (Odekerken-Schröder, Mele, Russo-Spena, Mahr, & Ruggiero, 2020).

Table 1
Features of cognitive technologies to value co-creation.

"Features"	Main authors
New ways of connecting actors: • Expanding Interactions: new ways of developing service provisions in the business • Engaging Empowered Actor: prompting actors in take active roles in service provision New ways of knowing: • Exploring knowledge: AI explores and scales data, information and knowledge, encouraging the creation of new knowledge • Exploiting knowledge: exploiting knowledge in a way that new forms for integrating resources can emerge.	Russo-Spena et al. (2019)
Safeguarding: • Enabler role • Intruder role Social contact: • Ally role • Replacement role Cognitive support: • Extended self-role	Čaić et al. (2018)
• Supporting service providers, • Enabling resource integration between service providers and beneficiaries, • Supporting beneficiaries' well-being	Kaartemo and Helkkula (2018)
• Improving the ability to co-create service with users. • Creating new ways for companies to help customers, but also helping customers to help themselves. • Creating new opportunities for customers to receive and share information about their usage • Helping companies understand customers, and customers using technology to monitor and improve their performance. • Helping customers create value in more sufficient ways than before.	Kristensson (2019)
A value-centric conceptualization according to a resource-focused view of technology • Value matching process: Congruence between value propositions and users' values (and users' subjective wellbeing) • Offering users value propositions that leverage affective and cognitive resources • Evaluating value co-creation potential according to the dimensions of social cognition	Čaić et al. (2019)
Roles of companion robots in mitigating feelings of loneliness • Personal assistant: to functional support (e.g. information, instructions). • Relational peer: to compensate for their lack of relationships and mainly perform hedonic activities (e.g. having fun, joking, playing games, etc.). • Intimate buddy: granting it a social identity and experiencing deep attachment	Odekerken et al. (2020)

By moving from specific roles to wider practices, recent research addresses how multiple actors connect, interact, learn, and discover new ways to do things, serve others better, and co-create value through AI (Russo-Spena, Mele, & Marzullo, 2019). This technology offers a new way to expand interactions and engage actors, through actions that prompt resource access and enable new service provision and value co-creation, from an ecosystem perspective. In addition, AI supports the generation and dissemination of knowledge and the ability to increase resource density for value co-creation and innovation. Finally, by adopting a broader view, beyond AI, to include wider future service technologies (Kunz, Heinonen, & Lemmink, 2019), service scholars have addressed the need to understand how technology can lead to value co-creation for customers and users to improve the lives of individuals and organizations (Kristensson, 2019).

Because this study focuses on how value co-creation is framed by the new socio-material context that emerges through human–machine interactions, it is necessary to understand how this context can be designed by service providers to steer actors' decision-making processes. Thus, we integrate nudge theory to set the resource context, frame design conditions, and predict influences on individual decision-making.

2.3. Nudge theory and choice architectures

Thaler and Sunstein (2008) propose nudge theory to understand decision-making behaviour. It provides a way to understand how people think and make decisions, which then can be applied to help people improve their decisions and reduce unhelpful influences. With input from behavioural economics (Vuong, Ho, Nguyen, & Vuong, 2018), this theory details the consequences of bounded rationality (as introduced by Simon, 1957), social preferences, and a lack of self-control, as well as how human traits can systematically affect individual decisions and market outcomes. The environment can be altered to direct people to make better choices, in interaction with the context. As a fundamental premise, nudge theory identifies two archetypes of individual thinking: thoughtful and impulsive (Thaler & Sunstein, 2008). When people function as "econs," they react to economic incentives and make thoughtful choices; impulsive thinkers instead choose a satisfactory rather than perfectly optimal option (Kahneman & Tversky, 1979).

These intuitive processes are guided by heuristics and biases (Kahneman & Thaler, 2006), or rules of thumb, which support decision making by reducing the required amount of information processing. Heuristics contribute to natural or human thinking, which can be irrational, instinctive, emotional, subjective, and unhelpful, even if it also is typical of human decision making (Tversky & Kahneman, 1974). A nudge leverages these heuristics to influence human behaviour. For example, describing a cafeteria, Thaler and Sunstein (2008) reveal that it is possible to increase consumption of healthy food by changing the arrangement of food on shelves, such as putting fruit at eye level, which evokes the availability heuristic. A nudge can be any small intervention in complex decision-making situations that overcomes cognitive errors and helps people select certain, beneficial alternatives, though without limiting their ability to make different choices. That is, a nudge refers to indirect encouragement, not direct instruction or enforcement.

The choice environment or decision context, which constitutes the choice architecture, also has vast importance in terms of altering "people's behaviour in a predictable way," because "what is chosen often depends upon how the choice is presented" (Johnson et al., 2012, p. 488). A choice architecture includes and influences any external forces that can guide decisions; it structures the context, design, and layout of options and information and thus shapes human behaviour. In turn, the existence of a choice architecture implies a choice architect, who creates nudges within the architecture to alter behaviour in a predictable way (Thaler & Sunstein, 2008).

Thaler and Sunstein (2008) also identify the tools of the choice architect (for additional insights, see Table 2). Johnson et al. (2012) elaborate on this classification by distinguishing tools used to structure the choice task and those used to describe the choice options. Sunstein (2014) also extends the number of nudges to ten; Hansen and Jespersen (2013) suggest a classification into type 1 nudges, which aim to influence automatic behaviours and automatic thinking, and type 2 nudges, which make people aware of their decisions. Then an epistemic distinction arises between transparent and non-transparent nudges (Hansen & Jespersen, 2013), so as to distinguish manipulative from other uses of nudges. Münscher, Vetter, and Scheuerle (2016) instead suggest three categories—decision information, decision structure, and decision assistance—that reflect different aspects of the decision-making process. Similarly, Baldwin (2014) distinguishes three degrees of nudges, based on the cognitive, volitional, and emotional functions they promote. On the basis of the target of the nudge, Hagman, Andersson, Västfjäll, and Tinghög (2015) differentiate pro-self versus pro-social nudges; they find that pro-self nudges are viewed more favourably.

Beyond these categories, nudges differ from other interventions, in that they seek to preserve freedom of choice (Thaler & Sunstein, 2008). Appropriately designed and applied, nudges allow an architect to shift a user's attention to a particular choice aspect and thus trigger specific heuristics and corresponding associations (Michalek, Meran, Schwarze, & Yildiz, 2015; Mont, Neuvonen, & Lähteenoja, 2014). Some authors predict that nudges work best in situations that involve habitual behaviour or low involvement (Mont et al., 2014), though they require the actor to be motivated to change behaviours. Three key features of a nudge emerge (Rachlin, 2015): (1) it manipulates means and not ends and can be recognized as an intervention; (2) it offers freedom of choice in the offered alternatives; and (3) the reward or cost is small compared with different choice consequences. Moreover, a nudge does not involve any obligation for people to make a choice, in that it essentially encourages or guides behaviour without the use of financial incentives or penalties (Halpern, 2015).

2.4. *Digital nudging*

As increasing numbers of people make choices by relying on digital devices, within digital environments, user interface designers have become choice architects who, knowingly or unknowingly, influence people's decisions (Weinnmann et al., 2016). Such digital nudging entails "the use of user interface design elements to guide people's choices or influence users' inputs in online decision environments" (Weinmann et al., 2016, p. 433). Digital choice environments include user interfaces, such as web-based forms and screens that require people to make judgments or decisions. Therefore, an effective nudge reflects the digital context in which people approach problem solving, the biases people bring to the situation, and how people interact or cooperate within a wider group.

The few studies of nudge design mostly focus on differences in behaviours and how people respond differently to various digital nudges, which then can be taken into account to inform design recommendations (Matz & Netzer, 2017; Weinmann et al., 2016). Some scholars propose a nudge design process model (Schneider, Weinmann, & vom Brocke, 2018; Weinmann et al., 2016), which would address how information systems (e.g., personalization, data availability, real-time tracking) can afford the ability to tailor nudges to people's unique characteristics. Other studies focus on the benefits of digital tools, such as smart devices or apps, for applying gentle pressures that encourage virtuous behaviours (Matz & Netzer, 2017; Yeung, 2017). With real-time tracking and analyses of user behaviour, as well as personalization in the user interface, these options can optimize the effectiveness of digital nudges. They provide information, reminders, or automatic prompts as status bar messages, pop-ups, phone vibrations, or LED displays (Okeke, Sobolev, Dell, & Estrin, 2018). In addition to being relatively simple and intuitive, digital nudges can feed off of socially acceptable group behaviours and spread quickly throughout groups to induce people to think or act differently (Yeung, 2017). With these advantages, information systems allow for rapid content modification and visualization to

Table 2
Typologies of choice architectures.

Choice architecture typologies	Main authors
● Default: give individuals options that are in line with their goals and reflective thoughts. ● Expect error: anticipate human errors and make them irrelevant ● Give feedback: help guide decisions ● Understand mapping: help people improve their ability to map and select options ● Incentives: Give incentives for making certain choices ● Structure complex choices: shape the answer to a question or the outcome of a choice	Thaler and Sunstein (2008)
Structure the choice task ● Reduce the number of alternatives ● Use technology and decision aids ● Set defaults ● Adjust the time frames ● Adjust the sequences of the choices Describe the options ● Partition the options and attributes ● Design the attributes	Johnson et al. (2012)
● Default rule: (e.g., automatic enrolment in programmes, including education, health, savings) ● Simplification: make the programmes easily navigable and intuitive. ● Use of social norms: emphasize what most people do ● Increase ease and convenience: make low-cost options or healthy foods visible ● Disclosure: make clear the economic or other costs associated with some use (i.e., environmental cost of energy) ● Warnings, graphic or otherwise: large fonts, bold letters, and bright colours can be effective in triggering people's attention ● Precommitment strategies: strategies by which people commit to a certain course of action ● Provide reminders ● Elicit implementation intentions ● Informing people of the nature and consequences of their own past choices	Sunstein (2014)
First degree nudge ● Supply simple information ● Provide a reminder Second Degree Nudge ● Behavioural or volitional limitations Third Degree Nudge ● Frame strategies, ● Emotional responses ● Covert techniques are used to influence the decisions or shape preferences	Baldwin (2014)
Decision information ● Translate the information (reframe, simplify) ● Make the information visible ● Provide a social reference point (norm, opinion leader, etc.) Decision structure ● Change the choice defaults ● Change the option-related effort (i.e., physical/financial effort) ● Change the range or composition of the options ● Connect the decision to a benefit/cost Decision assistance ● Provide reminders ● Facilitate self/public commitment	Münscher et al. (2016)

achieve the desired nudging effect. A similar phenomenon has been discussed in recent literature on intelligent software agents (ISAs) (Burr, Cristianini, & Ladyman, 2018), which influence decision-making by using emotional associations, social effects, or other methods to bias choices. Once ISAs learn the personality traits of individual users from their behavioural signals, they use this information to match market offerings to consumers' preferences at the appropriate moment (Matz & Netzer, 2017). In field experiments, Matz, Kosinski, Nave, and Stillwell (2017) find that persuasive appeals that match the psychological needs of the target audience result in up to 40% more clicks and 50% more purchases than mismatched or impersonal advertising. In addition, ISAs can steer humans toward decisions they would not otherwise make. These decisions can be beneficial, as in the case of positive health interventions, or detrimental, such as decisions to continue excessive consumption of online entertainment. However, emerging research linking cognitive technologies and nudging is still in its infancy, so we consider it worthwhile to study empirically how an AI-based context can alter individual behaviour and frame value co-creation.

3. Research method

This research adopts a qualitative method, in an attempt to specify what people do in practice and the sociocultural contexts within which they live (Gummesson, 2017). Emerging research areas can benefit from the use of interpretative data collection methods (Eisenhardt, 1989), which potentially allow for in-depth theoretical insights (Gummesson, 2005). Therefore, we sought deep, detailed, rich data to explicate complex issues and advance existing knowledge (Dubois & Gadde, 2002; Gummesson, 2005). Using theoretical sampling, we did not pursue representativeness but rather aimed to understand the phenomenon (Strauss & Corbin, 1998). The empirical study lasted 15 months (June 2017–October 2018) and involved 15 case studies, related to cognitive technologies (Table 3). To gather information about companies, we started with Google searches, then enriched them with business reports and information from additional sources (blogs, social networks). In selecting the final cases, we considered access to potential data, the commitment of the interviewees, and the availability of additional documentation; we halted our case search when we achieved theoretical saturation, such that no new data emerged (Gummesson, 2017).

3.1. Data collection

In collecting data from different sources, we focused on both new technologies and solutions and the different actors (providers, users, partners) they connected, as well as new processes and practices that they enabled. The primary sources were in-depth interviews with managers, employees, and customers, which took place via Webex and Skype or through email. Two researchers conducted the interviews separately and encouraged participants to talk about pertinent issues by asking open-ended questions designed to explore their knowledge, experiences, meanings, and personal themes. Particularly, we invited the managers to provide insights on how technologies affect users' behaviours and mundane practices (e.g., "Can you tell me about a situation where your technologies are used?" "Which kind of benefits do they provide?" "What changes do they prompt?" "In what ways do users and other actors obtain benefits?"). The users were prompted to talk about their personal experiences using new solutions. The 64 interviews each took 40–60 min and were recorded, then listened to and reflected on independently by two researchers. The researchers also provided sufficient flexibility for respondents to introduce original or unexpected issues, to be investigated in more detail. Supplementary data collections included analyses of company reports and internal documents, press releases, official websites, videos, blog posts, and other media dedicated to cognitive solutions. This data collection created triangulation and the development of converging lines of inquiry.

Table 3
The investigated cases.

AI tools (company)	Features	N. interviews
Alex posture tracker (by Namu)	Smart wearable device that encourages good posture habits by measuring the angle of the neck. If a user's neck bends too far into a "poor posture angle", ALEX will gently vibrate to alert the user to correct their posture.	N. 3 Customers N. 1 Manager office
Nutrino App (by Nutrino)	Data driven nutrition based on an intelligent platform that leverages machine learning and optimization to offer consumers highly personalized, contextual and science-based nutrition recommendations	N. 1 Chief health officer N. 2 Users N. 1 Co-founder and chief science officer
Fitbit Coach Ace (by Fitbit)	Smart wearable fitness tracker for children and adults. Fitbit Ace opens up a direct line of communication across the family to help parents and their children understand how physical activity impacts overall wellbeing and health	N. 1 CEO of fitbit N. 1 Digital strategy & Ix lead N. 3 Users
Jenoptik speed sensors (by Jenoptik)	Speed exhibitors integrating a radar sensor to measure the speed of a vehicle reliably and precisely. The intelligent tool shows a smiley face to road users who are complying with the required speed limit	N. 2 Users N. 1 Head of the design competence group
Upright Go (by Upright Technologies)	Fitness smart wearable device worn on a person's upper or lower back to correct their posture. The Upright Go device has been referred to as both wearable and trainable tech.	N. 3 Users N. 1 CEO of upright technologies
CaféWell Concierge (by Welltok)	An intelligent platform to help employees take charge of their health, nutrition and fitness. It is provided by Welltok and powered by Watson technology. It encourages behaviour towards better choices, as judged by themselves, without restricting the diversity of choices.	N. 1 Chief health officer N. 1 Chairman and CEO N. 2 Users
Under Armour cognitive coaching (by Under Armour)	Cognitive coaching is a smart wearable technology based on sensor data, other personal information, and external data sources that nudges personalized health and fitness with recommendations.	N. 1 Founder and CEO N. 1 Senior vice president N.3 Users
HAPIfork (by Hapi)	An electronic fork that helps people monitor and track people eating habits. The intelligent tool alerts people with the help of indicator lights and gentle vibrations when they are eating too fast.	N. 2 Customers N. 1 Executive it architect
Mabu (by Catalia Health)	A personal healthcare robot to help patients dealing with chronic illness. The social robot has an engaging interface to improve patient care via daily check-ins.	N. 1 Founder & CEO of Catalia health N. 3 Patients
Triax sensor (by Triax Technologies)	A device that tracks the force and frequency of head impacts during play and delivers that information to the side lines in real-time. The intelligent tool is worn in a headband or skullcap. It is a platform to help prevent head injuries and to better understand an athlete's behaviour.	N. 1 Co-founder and CEO N. 2 Athletes N. 1 Athlete's parent

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Table 3 (*continued*)

AI tools (company)	Features	N. interviews
ElliQ (by Intuition Robotics)	A small desktop device that consists of a stylized domed "body" and a separate detachable screen. A key purpose of the conversation agent is to act as an easy interface to access existing services such as social media, messaging programs, and audio and video streaming.	N. 3 Elderly N. 1 Network services lead N. 1 It specialist networking
Neosurance (by Neosperience)	The intelligent platform is delivered as-a-service and paid on performance. Neosurance is flexible, scalable and easily customized to insurers' and communities' needs. It evolves with new features, enabling recurring revenue models with increased revenues for insurers and communities.	N. 4 Customers N. 1 Global account director
Nest Learning Thermostat (by Nest)	A Nest thermostat uses sensors and machine-learning to understand the thermal properties of buildings and occupancy habits. The intelligent tool shows people how to save energy. People collect the Nest Leaf on the thermostat screen and in the Nest app.	N. 2 Users N.1 Advisory solution consultant
Eco-bot (by Dexma)	An energy efficiency conversational agent that can deliver personalized information on disaggregated energy usage through an intelligent and interactive virtual assistant. The chatbot enables seamless communication in a more natural and interactive way than offered by traditional mobile applications or websites.	N. 3 Users N. 1 Project manager N. 2 Strategist and research projects
Ellcie Healthy (by Optic 2000)	Optic 2000 emphasizes its commitment in health prevention in general, and drivers' comfort and road safety in particular with AI eyewear. The smart wearable device collects data through sensors then processes it and sounds an alarm if needed.	N. 3 Users N. 1 Director of research innovation & technology N. 1 Chief digital officer

3.2. Data analysis

We analysed our data in four steps, using open, axial, reflective, and selective coding (Scott & Howell, 2008). The open data coding process relied on thematic analysis, which takes "raw data and rais[es] it to a conceptual level" (Gummesson, 2017, p. 205). Two researchers analysed the text, to identify primary categories and seek a preliminary understanding. Then categories were linked and organized by relationships in a process of axial coding to understand what the central phenomenon and its patterns were. The axial coding allows us to expand the codes and also return to the primary categories (Scott & Howell, 2008).

Next, we built reflective coding matrices, useful for developing a picture or storyline that can explain the dimensions and conditions of the central phenomenon. The main objective of constructing a reflective coding matrix as a relational hierarchy was to identify the core category, subcategories, and their relations (Strauss & Corbin, 1998). The analysis of different themes and the inclusion of detailed descriptions allowed distinctions to emerge, providing a useful basis for mapping the dynamics of the phenomenon and enriching the explanatory power of the empirical investigation (Halinen & Törnroos, 2005).

Then, through an interpretive process of selective coding, the researchers engaged in constant comparisons of categories to understand the construction of interrelationships through which the concepts were categorized, and thus conditions and dimensions were developed (Scott & Howell, 2008). By explaining the storyline, a theoretical framework emerged (Strauss & Corbin, 1998), with the smart nudge concept as a core category that relates to three other categories, namely, cognitive technologies, choice architectures, and value co-creation.

We discussed the results to obtain consensus and performed the process repeatedly, starting with different steps of the data analysis each time to increase the credibility, reliability, and validity of the findings (Denzin & Lincoln, 1998; Gummesson, 2005; Piekkari, Lakoyiannaki, & Welch, 2010). In addition, we followed recommendations by Wood and Kroger (2000) and explain the emergence of the interpretations of the individual segment of talk; the emphasis in the presentation of the findings accordingly is on illustrating excerpts of stretches of talk (Rod, Lindsay, & Ellis, 2014). Finally, during two workshops, we presented the theoretical framework to gather external feedback about any weaknesses in the identification of patterns and categories (Creswell, 2007).

4. Findings

We developed a theoretical framework of how smart nudges contribute to value co-creation. A synopsis of the process is depicted in Fig. 1.

Four groups of solutions, based on cognitive technologies, represent different choice architectures and nudges: smart wearables, intelligent tools, conversational agents/social robots, and intelligent platforms. First, smart wearables are technological devices that can be worn as clothing and accessories. They have sensory and scanning features and perform computational tasks. They record, track, store, and elaborate on actors' data and context. They also have communication capabilities that allow the wearer to access information in real time. Second, intelligent tools can be handled or used but not worn. These instruments are powered by AI and machine learning. They track, analyse, and act on unstructured historical and real-time data about actors to elaborate on interactions and connections. Third, conversational agents/social robots engage in different kinds of social interactions and cognition. Some are sociable and proactively engage with humans. Others are socially situated, sensing and reacting to a social environment, or socially intelligent, showing aspects of human-style social intelligence, based on deep models of human cognition and social competence. Fourth, intelligent platforms exploit machine learning to improve the reliability, performance, and security of data analyses and the elaboration of actors' connections. They can integrate with web and mobile apps, cloud services, and the Internet of Things to provide superior experiences, regardless of the customer's location or device being used.

Such solutions in turn offer opportunities to design three kinds of choice architectures: greater resource accessibility, extended actor engagement, and augmented agency. Each architecture employs specific nudges as resource context and design conditions. Together, choice architectures and nudges support decision-making and increase value co-creation by (1) activating capabilities, (2) affecting emotions, and (3) enacting social bonds.

4.1. Widening resource accessibility: Providing predetermined and dynamic content

Digital tools empowered by cognitive technologies enable decisions, based on wider access to real-time and enriched resources (information, data, relations, interactions) that would not otherwise be available to human beings. Greater resource accessibility emerges as a new choice architecture that is prompted by cognitive technologies through the active design of choice contents. Such technologies help people make better decisions based on massive data and multiple interactive responses. Smart wearables influence actors by proposing multiple, predetermined choices based on real-time data that match each actor's needs. This opportunity is based on a design that enables users to acquire, set, and manage information, with a certain amount of variability.

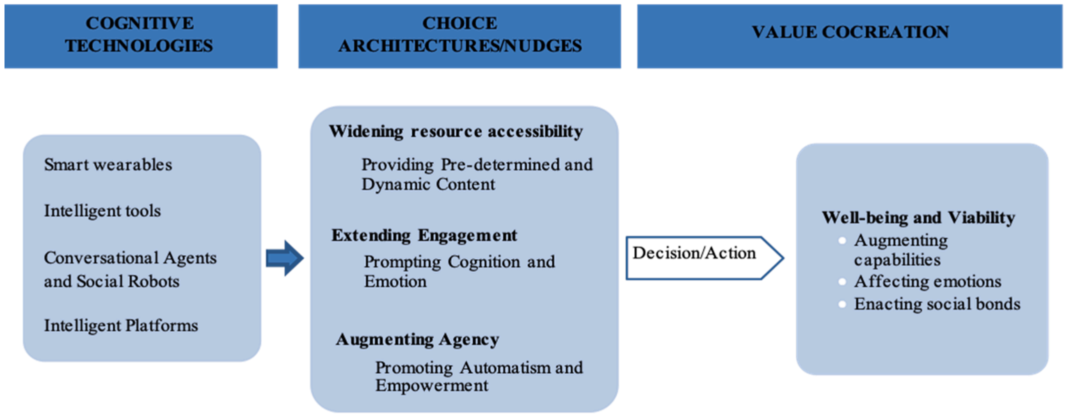

Fig. 1. Smart nudging: cognitive technologies, choice architectures and value co-creation.

Smart wearables also can provide actors with insights so that they can establish commitment and consistency, leading to increased motivation. By focusing on pertinent information and using analytical processes, these solutions widen opportunities that actors can pursue, thus reducing their sense of risk and cognitive efforts. For example,

The Alex Posture Tracker is a smart wearable device that encourages good posture habits by measuring the angle of the neck. When a person's neck bends too far into a 'poor posture angle,' the wearable defines a set of options to demonstrate the correct position in real time, elaborated by acquiring, setting and managing information about the habitual neck position of the person. In this way the Alex Posture Tracker nudges people, through gently vibrating, to make a better decision about their lifestyle (source: Interview 11, Namu Manger Office).

In other cases, cognitive technologies, such as conversational agents or social robots, enhance actors' ability to act by providing dynamic contents, configured around the actors' on-going, recursive choices and behaviour. The actors' needs are not addressed on the basis of pre-defined problem analyses and settled problem formulations. Instead dynamic, cognition-based propositions are co-created through continuous, real-time elaborations on data and information. The nudges then are based on an advanced understanding of the actor's behaviour in real-life settings and interactions. Through a dynamic series of on-going interactions about the nature, content, and context of the specific problem, they provide decision support in an individualized way to help actors make choices that reflect their current and emerging needs.

The Nutrino App encourages future mothers to do the right thing for their health and well-being in general with real-time, personalized and contextual nutritional advice. It combines Nutrino's nutritional deepening platform with Watson's natural language skills. Through the continuous documentation of daily main meals, food preferences of future mothers and lifestyle the app is able to offer a highly personalized nutritional program suited to address multiple health objectives, dietary needs, food preferences and specific eating habits (source: Interview 38, Nutrino Co-Founder and Chief Science Officer).

By enabling the intertwining of different types of data and information, these technologies may drive changes in human behaviour in both predetermined and dynamic manners. The past, present, and future of an actor's behaviour are connected; the continuous documentation and reconstruction of everyday life form the basis for relevant recommendations for the future. They also may give a deeper look into an actor's stories and experiences, including their sense of urgency during interactions, and promote the creation of more meaningful links among their needs, personalization preferences, and expected behaviour.

The Fitbit Coach Ace is a wearable device that supports kids in taking care of themselves. It analyses the everyday activities of children and their behaviour such as monitored steps, active minutes, and sleep stats in such a way as to integrate and connect their data. The Fitbit provides kids with personalized exercises that adapt according to the activity carried out and the objectives to be pursued. From the playground to sports activities, children need a tracker that is suitable for every situation. The Fitbit buzzes with celebratory messages each time kids achieve a goal and rewards them with fun, collectible badges. Kids and parents see their stats, badges, and progress towards their goals and more in the Fitbit app on their phone (source: Interview 21, Fitbit Digital Strategy & Ix Lead).

4.2. Extending engagement: Prompting cognition and emotion

Extending engagement is a further result of the new choice architectures prompted by cognitive technologies. The use of information and real-time data allows actors to operate with a mechanism that copes with changes in their information or social perceptions. By prompting cognition, intelligent tools track users' habits. Actors also feel engaged through mobile devices, apps, and platforms, which can help them track their progress and gain insights to improve their habits and overall health.

The HAPIfork is an AI tool able to help people monitor and track their eating habits. The smart device alerts people with the help of indicator lights and gentle vibrations when they eat too fast, and in this way, it shifts individual behaviour rather than the traditional method of correcting behaviour. It can also be viewed as a weight loss and health product with a lot to offer with today's dietary trends. Information is elaborated from data about the person's meals and minute/intervals between 'fork servings.' The fork, which tracks the user's eating speed as it's used, can also be connected to an app so that users can track their eating 'progress' and improve their habits and overall health (source: Interview 7, Hapi Executive It Architect).

Through the combination and elaboration of data from multiple sources, these technologies transmit more useful information to actors, who make sense of the opportunities and the available resources to address their needs timeously. The engagement of users and other actors (including relatives, friends, and other care providers) results from the large amount of personal data and connections (including different actors, processes, and knowledge), which in turn enables users to adopt long-lasting changes.

Triax's platform and intelligent tools are tapping into Watson's Personality Insights application programming interface to combine data from the sensor to help measure the risk of head injuries from sports and help actors make decisions by activating informational states. Different actors, such as coaches and athletic trainers, see if their players are risk-takers off the field and adjust the athlete's training and habits accordingly with a sense of urgency and care during interactions, thus creating a more meaningful link with actors and their needs. The intelligent tool tracks the force and frequency of head impacts during play and delivers that information to the sidelines in real-time. Athletes can create customizable profiles by establishing a history of head impacts throughout their athletic career, which helps identify trends that may signify risky play or improper technique (source: Interview 13, Triax Technologies Co-Founder and CEO).

Social robots and intelligent platforms contribute to reducing asymmetries (in information, data, or resources) among actors and prompt their engagement. Social robots tailor conversations to each actor to obtain hard-to-get, real-time data about treatment, challenges, and outcomes on a daily basis. This way of engaging allows the tracking and analysis of behaviour, feelings, and needs, as well as personalization of the user interface; both outcomes help nudge decisions. Robotic designs that feature big eyes or different facial expressions can enact emotional bonds during conversations, in a way that keeps people engaged and creates stronger relationships.

Mabu is an intelligent, socially interactive robot whose conversations are tailored to patient engagement (thanks also to Catalia Health's platform). The name Mabu is short for *mabutaki*, a Japanese word meaning to blink and *mabudachi*, or best friend. It is designed as a small robot that can make eye contact while carrying on a conversation with someone and perform simple gestures with its head and eyes. Its aim is to help patients with the challenges of chronic diseases and ensure that they maintain their medication regime. The intelligent platform learns about each patient's personality, interests, and treatment challenges over time. Mabu can have conversations that resonate with patients' unique personalities and circumstances. The structure of these conversations is based on proven psychological behavioural models that promote behavioural change (source: Interview 4, Catalia Health Founder & CEO).

Social robots and cognitive technologies also are distinctive with regard to their capabilities for decision framing through feelings or other forms of sensitive influence and engagement. They can boost an actor's experience, activating behavioural, emotional, and social responses. Social robots can give suggestions to prompt actors' decision making, create emotive connections, and foster social interactions.

ElliQ is an emotionally intelligent social robot that consists of a stylized domed 'body' and a separate detachable screen to nudge older people to stay social and active. It can encourage a higher degree of social engagement. EllyQ uses big-data analytics to analyse the behavioural patterns observed in real time to infer people's personalities, cognitive styles, and emotional states. It works by offering indirect suggestions to help elderly people make decisions about their social life. The connection allows the system to perform real-time analysis of emotional information and detect usual unhealthy events with a friendly approach towards patients (source: Interview 9 Intuition Robotics It Specialist Networking).

4.3. Augmenting agency: Promoting automatism and empowerment

Cognitive technologies offer different contributions to actors' resource integration by enabling broader applications for augmented agency. Intelligent tools and smart devices vary, from objects to applications that make information and resources actionable. They collect and elaborate on data about an actor's behaviour to inform that actor about her or his actions, interests, and choices over time. In turn, they support people with on-going feedback, alerts, and recommendations that are appropriate for each particular human actor's choice and use contexts.

Neosurance's intelligent platform is designed in an AI framework to suggest the right action at the right time, enabling the partner insurer, through a stored consumer behaviour database, to offer the right coverage information about better choices or actions when the customer actually needs it. The offer is made through a personalized push notification to customers' mobiles with the proposed micro insurance coverage for a specific event. Neosurance enables continuous data exchange and helps the partner insurer make sense of information … revealing new insights and enabling consumer decision-making (source: Interview 29 Neosurance Global Account Director).

Most smart wearables, intelligent tools, and platforms enhance actors' choices through visualized feedback and automatic stimuli. They enable users to elaborate data over time and provide prompt guidance for decisions, thereby influencing their behaviour. The ready-to-use information encourages agents to perform their tasks autonomously, thus reducing the risk that they might get stuck in limited action space. Through a multidimensional analysis of massive information, these technologies enable actors' classification, prioritization, and evaluation processes. Because their articulation of their expectations and needs thus is facilitated, actors can exploit their knowledge and exert more control over decision-making. Technology contributes to expanding the capability and commitment of individual users and their social contacts.

With CaféWell Concierge powered by IBM Watson, there is a new level of empowerment in healthcare. The foundation is Welltok's CaféWell health optimization platform that guides and incentivizes consumers to optimize their health. The AI platform enables consumers to visualize and use data over time and provides prompt guidance at the point of a consumer's decision, thus influencing their behaviour. By using natural language processing and spatial and temporal intelligence, CaféWell offers on-demand guidance to encourage agents to perform their tasks autonomously which empowers them to make healthier choices anytime, anywhere (source: Interview 42, Welltok Chief Health Officer).

Cognitive solutions play a crucial role in how actors, data, and objects combine and how actions and resources get mobilized for knowledge-based actions. They can represent problems that have many solution methods, involve many perspectives and knowledge types, and be solved by collaboration with other actors. In addition, AI fosters emergent learning processes within situated actions that empower human actors' knowledge-based reasoning, especially if an established set of rules, data, or actions does not match a newly encountered context or if more reflexive behavioural decisions are needed to ensure their self-interest. Active choices can be encouraged through higher levels of perceived awareness. The AI technology stimulates agents' ability to achieve their goals in a wide range of choice settings and encourages a sense of purposefulness in their situated action.

Under Armour has created a cognitive coaching system that provides personalized health and fitness recommendations based on sensor data, other personal information, and external data sources, which is delivered on smartphones and other portable devices. The capacity of this intelligent tool to learn the health data of any problem situation fosters emergent learning processes and, in this way, empowers the actors to elaborate information based on knowledge and nudges personalized health and fitness with recommendations to create and provide meaningful data-backed health and fitness insights (source: Interview 15, Under Armour Senior Vice President).

4.4. Value co-creation

Through systemic interactions involving real-time data, contextual resources, design conditions, and informed action, actors can leverage all three types of choice architectures to change their behaviour and increase their ability to achieve value co-creation, including enhanced well-being and viability. The result then is augmented human cognition capabilities, which increase the actor's chances of actualizing the potential value co-creating process.

Great intelligent tool. I follow a daily training programme, and Upright Go warns me whenever my posture is not correct and suitable to achieve the desired goal. By training me every day, I often think about posture even when I'm not using it. In this way it increases my ability to act towards a fixed goal (source: Interview 34 Upright Go user).

I truly think it is useful in getting help when I need personal information on disaggregated energy. I really like it because with natural communication I have an on-going interaction with it that informs me about better actions! (source: Interview 20, Eco-bot user).

Cognitive solutions affect interactions among different actors in such a way that competing interests and pressures can be cognitively addressed and solved. By connecting different information sources and synthesizing contextually relevant information, technologies support actors' value co-creation in every use context, thereby contributing to the establishment and maintenance of an actor's well-being.

The Triax sensor allows us to obtain health care at a distance. A virtual environment provides athletics with basic information about the frequency of head impacts. We are able to improve our ability to act towards the reduction of head injuries (source: Interview 52, Triax sensor user).

Smart nudges also can influence individual behaviour by exhibiting sensitivity to the person's decision-making process. For example, AI-based solutions induce emotional behaviours by mitigating the effect of an actor's sense of conflict and misbehaviour, which then initiates virtuous cycles for self-empowerment.

Mabu robot enables me to self-check, monitor, and continually record behaviour data and transmit it to doctors. Mabu engages in daily conversation with me and affects my emotions because the conversation's tailored to my personality, my behaviours and my treatment needs. It sends responses to my healthcare provider and improves my well-being (source: Interview 36, Mabu user).

ElliQ interacts with me, with the naturalness of a companion, thanks to its emotion detection capabilities. For this reason, it helps me to manage information and communicate better with my caregivers to maximize assistance and improve care and well-being (source: Interview 52, ElliQ user).

Changes to behaviour happen not only when actors make decisions and perform actions that reflect their augmented cognition and affective motivation but also in broader contexts, involving other actors. Notably, AI-informed social interactions lead to multiple potential choices, due to the mutual awareness that they provide regarding what different actors can do for one another. Thus, various consequences are expected, and the effects on individual well-being are amplified in scope and time.

I really like ElliQ because it helps me stay in contact with my family. It alerts me when my grandchild has posted a new photo on Facebook, shows it to me on the screen, and allows me to comment using speech-to-text technology. In this way I have new social interactions (source: Interview 61, ElliQ user).

CaféWell Concierge is able to change my health behaviour. While I'm using CaféWell, many informed social interactions with my personal trainer and/or doctor are implemented through the app. They lead to my behaviour changing and optimal health. For this reason, I love this platform (source: Interview 62, CaféWell Concierge user).

Moreover, through smart technologies, actors can undertake mutual learning processes to determine how to act, by expanding their social bonds. Multiple interactions prompt systemic reflection; such understanding then informs individual and collective actions toward value co-creation.

I'm very, very excited to use Ellcie Healthy Connected Eyewear. I feel protected by it, which in turn sets me free to drive my car without causing danger to other people or me. It will make the phones of connected and identified passengers ring in order to address drowsiness. In this way passengers know my actions and can interact with me (source: Interview 45, Ellcie Healthy Connected Eyewear consumer).

5. Conclusions

Considerations of cognitive technologies are growing in both academic and business circles. Their promise to transform people's lives and society stems from the higher levels of connectedness, greater computational processing, and more complex decision-making, involving extraordinary volumes of data, that they promise (Huang & Rust, 2018; Kaartemo & Helkkula, 2018; Mele et al., 2018b). Although academics have long focused on technological issues, a bigger question may be: How can cognitive technologies enable us to make better decisions and prompt value co-creation? To encourage research interest in this topic and provide some initial findings, regarding how cognitive technologies effectively influence human agency and support actors in value co-creation, this study builds on S-D logic and behavioural economics literature, particularly research pertaining to nudge theory and choice architectures. We offer an integrative framework (MacInnis, 2011), delineating the concepts of nudging and choice architecture in terms of a re-institutionalizing process that extends the conceptualization of value co-creation processes, as well as showing how smart nudging can enact resources in context and guide individual decisions. In this section, we discuss the theoretical contributions, address some managerial and ethical implications, and suggest avenues for further research.

5.1. Theoretical contributions

This study offers four main contributions to on-going discussions of how cognitive technologies affect human agency, in that it frames the ways these technologies enact choice architectures and nudges to contribute to value co-creation. First, the concept of smart nudging accounts for recent developments in cognitive computing; it is defined as the use of cognitive technologies to affect people's behaviour predictably, without excluding options or significantly changing their economic incentives. Smart nudging enables actors to make better decisions by providing cognitive resources that would otherwise not be available, extending engagement to construct data that otherwise are not available, and augmenting humans' agency to use the insights from these data.

Second, our analysis identifies choice architectures and nudges prompted by cognitive technologies. Moving past the limited view of digital nudging as simple user interfaces in online decision environments (Weinmann et al., 2016), we address smart nudging as AI-mediated choice architectures that contribute to overcoming people's cognitive, emotional, and social limitations when they make decisions and perform actions that contribute to value co-creation. We distinguish three kinds of choice architectures that shape smart nudges, namely, those that widen resource accessibility, extend actor engagement, and augment agency. Cognitive technologies widen resource accessibility by providing both predetermined and dynamic choice content. Predetermined nudges are based on real-time data; dynamic nudges are based on predictions that AI makes about an actor's possible future. Both exert behavioural influences by personalizing information choice environments. In addition, extended engagement choice architectures prompt cognitive and emotional ties by increasing an actor's data-based engagement and social interactions. Finally, cognitive solutions augment human agency. By promoting automatism and empowerment, they help actors continuously monitor, update, and refine their decisions and execution.

Third, cognitive-based solutions influence value co-creation in relationships that are nonlinear and indirect. In support of the configuration of new choice architectures and smart nudges that alter human behaviour, AI provides guides for decisions and actions that improve value co-creation. By moulding the actor's understanding of surrounding resources (e.g., information, meaning, emotion, social ties), smart nudging can set the design conditions and guide human actors toward decisions that affect their well-being. Although varied in nature and characteristics, all three architectures driven by data analytics provide smart decision support, beyond a simple provision of input. They require human intervention and constitute an action-enabling design. In a context that fosters cognitive, emotional, and social issues, people can augment their ability to act. Designed as complex decision guidance (Yeung, 2017), AI-embedded choice architectures nudge humans to make informed and relevant decisions. What emerges from this study is the notion that cognitive technologies are unlikely to engender smart outcomes by themselves; rather, they enable the design of a smart behavioural context that promotes smart actions. The role of cognitive technologies stems from a pervasive nudge that shapes contexts and amplifies capacities for self-understanding, control, and action. In Hansen and Jespersen (2013) classification, smart nudging constitutes a type 2 nudge, which influences behaviour characterized by action and results from deliberation, judgement, and choice.

Fourth, this study offers a deeper conceptualization of value co-creation processes (Vargo & Lusch, 2017). We suggest that value co-creation relies on a decision process based on the integration of resources, the direction of actions, and the orientation of interactions, consistent with an actor's present and prospective needs. The actor's ability is critical to value co-creation, but it is important to develop a deeper understanding of how this ability, as well as new forms of self-understanding and self-development, can be shaped by AI, through the enactment of cognitive, emotional, and social surroundings in the actor's context. Consistently, we claim that smart nudging allows actors to not only choose differently but also behave differently in practice.

In summary, this study details how value co-creation emerges from the AI-driven, nudged choices of actors, who choose on the basis of their ability to read and understand context, connect and leverage emotions, and enact social ties. Smart nudging enables actors to explore *resourceness* in a dynamic way, balancing the opportunities of integration options against the performativity of achieving them. By multiplying and unbinding the range of actors' possible choices, smart nudging contributes to activating actors' agency, thus boosting value co-creation. In the S-D logic lexicon, smart nudging enacts a re-institutionalizing process that affects actors' agencies and practices. By offering a different view on problems and solutions, as well as increasing interaction and collaboration between humans and machines, this study reveals how actors can develop shared, routinized behaviours around a new solution with shared meanings and understanding, which then enables the application of problem-solving behaviours.

5.2. Managerial implications

The concept of smart nudging and the framework we present offer important insights for practitioners. First, managers need to see themselves as choice architects. This role requires an accurate understanding of how to use cognitive technologies to design contexts and tailor smart nudges to individual users, by leveraging user data to effect individual choices and behaviour. Second, practitioners should integrate discussions of smart nudging into their strategic and managerial processes. They also need a better understanding of how cognitive technologies affect actors and wider systems (e.g., markets, societies). In particular, they require more insights into which combinations of cognition and sensing, automation and personalization, machine and human will be accepted. Third, in evaluating how smart choice contexts affect value co-creation, practitioners should be aware of the implicit interactions taking place in the wider, socially co-constructed, cognitive context. When making decisions, users often engage in processes of social sense-making, including an evaluation of service providers' intentions as choice architects and the cognitive resources that other actors make available. Managers should devote more attention to factors that can moderate the success or failure of social sense-making in choice architectures.

5.3. Ethical implications

We note some important ethical, privacy-related (Horvitz & Mulligan, 2015), and regulatory issues. Although we hope to ignite interest in smart nudges, in research and in practice, it would be ethically problematic if smart nudging functions to widen digital divides across different groups of actors (e.g., elderly, people with disabilities). Due to the heterogeneity and changes in how human actors interact with digital devices, policy makers should provide cultural instruments to address the visible hands of the nudging process. Scholars and policymakers also should reflect on the dark side of smart nudging to determine solutions that ensure that cognitive technologies improve well-being, without requiring substantial invasions of privacy. New regulatory views on privacy similarly highlight the legitimate owner of personal data and define rules for how data can be used and shared. Security and trust issues thus represent a central challenge, considering the powerful impacts that smart nudges can have on individual decision-making and behaviour.

5.4. Limitations and further research

The limitations of this study can inform avenues for further research. First, the theoretical sample is based on successful cases. Understanding of how smart nudging and choice architectures contribute to human actors' decision-making and value co-creation could be enriched by failed cases—that is, examples in which nudges worsen actors' well-being. Second, we do not take measures of value co-creation and well-being into consideration. Further studies could address ways to assess the effectiveness of nudges and how much a nudge improves a decision in the eyes of the person being nudged, for example.

Third, research might focus on designing, implementing, and evaluating the effectiveness of smart nudges through lab or real-world experiments. It is essential to clarify the interpretation schemes and the values and purposes of actors, which in turn affect their understanding of contexts and situations. Fourth, studies could go deeper into the understanding of how the co-existence of alternative or overlapping institutionalized views on problems and solutions might affect a re-institutionalizing process. It is important to foster research into how institutional complexity might create new opportunities for interaction and collaboration between human actors and machines to foster value co-creation.

Fifth, cognitive technologies are shaping service ecosystems and enabling new practices, so a broader focus should be assigned to actors' decision-making, taking into consideration the larger service ecosystems. It is of paramount importance to analyse how human and nonhuman actors interact and make decisions within shaping digital ecosystems. Actors' decisions, intertwined with cognitive technologies, determine such shaping, through consequent actions that can reform and renew practices, as well as by following such practices and making them institutionalised.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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