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How Artificial Intelligence affords digital innovation: A cross-case analysis of Scandinavian companies

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A R T I C L E I N F O

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A B S T R A C T

Artificial Intelligence (AI) is fuelling a new breed of digital innovation in Human Resource Management (HRM) by creating new opportunities for complying with General Data Protection Regulation (GDPR) during data collection and analysis, decreasing biases, and offering targeted recommendations. However, AI is also posing challenges to organisations and key assumptions about digital innovation processes and outcomes, making it unclear how to combine AI affordances with actors, goals, and tasks. We conducted a qualitative multiple-case study in Scandinavian organisations offering HR services. Grounded theory guided our data collection and analysis. Input-Process-Output framework and affordance theory supported the analysis of specific information processing constraints and enablers. We developed a framework to explain how AI affordances enable digital innovation and address the calls about definitional boundaries between innovation processes and outcomes. We showed how AI affordances are actualised and how this leads to reontologising decision-making and providing data driven legitimisation. Our study contributes to digital innovation research by elucidating AI affordances and their actualisation in organisations. We conclude with the implications to theory and practice, limitations, and suggestions for future research.

Introduction

Artificial intelligence (AI) is radically changing the process and outcomes of digital innovation owing to its specific nature and ontology (Benbya et al., 2021; Haefner et al., 2021; Kohli and Melville, 2019; Nambisan et al., 2019, 2017; Yoo et al., 2012). The nature of the changes triggered by AI is fundamentally different from those triggered by other traditional information technologies as it is developing new ways to collect and process vast amounts of information (Balasubramanian et al., 2020; Haefner et al., 2021). The increasing fluidity and complexity between digital innovation processes and outcomes leads to a significant new way of value creation and differentiation by the competitors (Nambisan et al., 2017; Yoo et al., 2012). This encourages a rethinking of how actors, organisations, AI, and action possibilities may pursue innovative endeavours. Prior studies suggest that AI can support and speed up labour-intensive information processes in Human Resource Management (HRM) (Leicht-Deobald et al., 2019), evaluate candidates with the same criteria consistently (Metcalf et al., 2019), make fairer and less biased decisions compared to human intuition (Cowgill, 2019), and promote diversity in organisations (Daugherty et al., 2019).

However, besides offering distinctive opportunities, AI is posing significant challenges to organisations (Benbya et al., 2021) and key assumptions of innovation management theories (Nambisan et al., 2017). First, innovation is a dynamic combination of the actors' needs, affordances, digital features, and sociotechnical contexts (Nambisan et al., 2017; Yoo et al., 2012). When a new technology is introduced in organisations, such labile couplings are questioned, and old logic does not hold true anymore. Second, prior studies have not incorporated key AI features as explanatory factors of digital innovation, although AI is becoming an active ingredient in fostering innovative initiatives (Lusch and Nambisan, 2015). Third, AI can overcome human information processing constraints such as speed of analysis or a combination of multiple types of information. However, little is known about how to mitigate AI technical constraints when processing information for digital innovation (Haefner et al., 2021).

Although some studies started to study AI development and implementation empirically (Haefner et al., 2021; Mikalef and Gupta, 2021), there is an urgent need to understand better how to combine AI action possibilities with actors, goals, tasks, and surrounding contexts. Such an understanding helps organisations innovate processes and services and differentiate from competitors (Collins and Clark, 2003). Therefore, there is an opportunity for new phenomenon-based theorising

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(Nambisan et al., 2017; von Krogh, 2018) on digital innovation for constructing more accurate explanations of innovation processes and outcomes in the age of intelligent machines (Faraj et al., 2018). Our purpose is to explore the ways in which AI enables digital innovation by examining the information collection and analysis and how the affordances enabled by AI can be leveraged to drive digital innovation. Accordingly, we pose the following research question:

***RQ:** How can organisations leverage AI affordances to drive digital innovation?*

To answer this question, we conducted an inductive qualitative multiple-case study (Eisenhardt and Graebner, 2007; Yin, 2018). Grounded theory (GT) guided our research methodology (Urquhart et al., 2010; Walsh et al., 2015), and the Input-Process-Output framework (Espinosa et al., 2006) supported the identification of key components from semi-structured interviews. Drawing on affordance-actualisation theory, we extracted AI-specific affordances and enfolded the mechanisms and actions of affordance-actualisation that ultimately lead to digital innovation. Our study offers a conceptual framework for explaining how AI enables digital innovation and addressing calls related to fundamental assumptions about definitional boundaries between innovation processes and outcomes (Nambisan et al., 2017).

The rest of the paper is organised as follows. In the theoretical background section, we present the role of AI in organisations, particularly towards digital innovation, and then proceed to present the affordance-actualisation theory in Information Systems (IS). Next, we describe our research methodology, which uses GT on data from multiple case studies. Following the data analysis, we present our findings and the resulting framework for AI-afforded digital innovation. We conclude with a discussion on the contributions to theory and practice as well as some important societal implications of our work.

Theoretical background

Artificial Intelligence (AI) and Digital Innovation (DI)

When defining Artificial Intelligence (AI), scholars refer to *intelligence* as the ability to make sense of the information collected from past experiences and deal with the uncertainty of future actions (Ågerfalk, 2020) and *artificial* as the emulation of human-like cognitive tasks with more transparent approaches (Benbya et al., 2021). Merging these concepts together, our study refers to AI as '*the ability of a system to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals*' (Mikalef and Gupta, 2021).

Advancements in AI are rapidly changing the way information is processed in multiple fields such as recruitment (Baakeel, 2020; Daugherty et al., 2019; Haefner et al., 2021; Robert et al., 2020; Upadhyay and Khandelwal, 2018), medical diagnosis (Constantinides and Fitzmaurice, 2018; Lebovitz et al., 2019), marketing (Davenport et al., 2020; Rai, 2020), financial advisory (Strich et al., 2021), and others. First, AI can mimic complex reasoning and analysis tasks that were previously performed by human experts (Liu et al., 2020; Tschang and Mezquita, 2020), which is leading to a redefinition of professional boundaries between human and machine expertise. Second, it has the potential to accelerate the discovery process (Fleming, 2019) and the development phase of new solutions and services (Lehrer et al., 2018; Lusch and Nambisan, 2015) by leveraging its computational processing power for data analysis even in complex environments. Third, AI can learn from large data sets to develop pattern recognition and make automated predictions months in advance compared to traditional analytical tools (Floridi, 2020; Stahl et al., 2021).

Consequently, AI offers novel approaches for information processing, which is generating new waves of digital innovations (Haefner et al., 2021) defined as *'the creation of (and consequent change in) market offerings, business processes, or models that result from the use of digital technology'* (Nambisan et al., 2017). The new combinations of digital and physical components can produce new products or services and new processes and business models (Mikalef and Krogstie, 2020; Yoo et al., 2010). This can lead to '*a significantly new way of creating and capturing business value*' (Fichman et al., 2014). Prior scholars made a central distinction between two types of innovation and assumed that they are distinctly different phenomena as follows (Fichman et al., 2014).

Digital *process* innovation involves the creation of new ways of operating in organisations with the support of digital technologies, which subsequently influence how decisions are made, transactions are performed, and work is done (Mikalef and Krogstie, 2018; Saldanha et al., 2017). Digital *product/service* innovation refers to the creation of new products or services enabled by digital technologies that create value propositions from firms' resources that improve value creation for customers (Lehrer et al., 2018; Lusch and Nambisan, 2015). Both types of innovation (process innovation and product/service innovation) can be either incremental if organisations make gradual, continuous improvements on existing services or solutions or radical if the new solutions entirely disrupt previous ones and render them obsolete (Van Looy, 2021).

With the introduction of AI in organizations, the assumption that innovation processes and outcomes are distinct phenomenon has been challenged, which is raising the need for alternative conceptualizations (Henfridsson et al., 2018; Nambisan et al., 2017). Specifically, digital innovation processes are breaking down different innovation stages (discovery, development, diffusion, and impact) (Fichman et al., 2014), making less clear when they start and when they end and how they unfold across time and space (Nambisan et al., 2017). Therefore, the dependencies between innovation processes and innovation outcomes such as services are increasingly complex and dynamic, which calls for a deeper understanding of their intermingling (Nambisan et al., 2017).

AI is increasingly implemented in HRM to support and speed up labour-intensive information processes such as evaluating several resumes and conducting numerous interviews (Leicht-Deobald et al., 2019). AI is particularly promising in HRM because it can automatically process candidates with the same criteria consistently (Metcalf et al., 2019), make fairer and less biased decisions compared to human intuition (Cowgill, 2019), and promote diversity (Daugherty et al., 2019). Consequently, AI can help organisations win the '*war for talent*' (Kane et al., 2017; Wirtky et al., 2016) by attracting talent and predicting candidates' added value for organisations (Margherita, 2021). There are at least three AI applications for HR tasks (Strohmeier and Piazza, 2015): (a) androgynous interview robots to collect interviews and score candidates' responses; (b) an AI system for job listing recommendations that match candidates' profiles with available job opportunities; (c) an AI staffing platform (CV parsing) to analyse candidates' information and rank them according to their skills and competence. Therefore, the combination of AI features (storage, analysis, and recommendation) with organisational actors are enabling novel approaches for information processing (Margherita, 2021), contributing to digital innovation (Nambisan et al., 2017).

Investigating how the innovation process unfolds with the introduction of AI in HRM is important for two main reasons. First, the value of the innovation process positively influences the output an organisation produces (Mikalef and Krogstie, 2020). Organisations that develop new internal processes can combine them in multiple ways to improve current outputs or create new ones. Second, organisations can provide new services linked to physical products that play a significant role in competitiveness and sustained performance (Lehrer et al., 2018). Based on these perspectives, our study focuses on innovation processes and innovation outcomes such as service triggered by the introduction of AI. Specifically, we investigate incremental digital innovations but acknowledge that an investigation that departs from incremental innovations might lead to radical changes in organisations as the value of all types of innovations is falling '*along a continuum, ranging from minor incremental changes to major radical innovations*' (Kahn, 2018).

Affordances and affordance-actualisation theory

To understand the role of material features of AI in relation to HR tasks and digital innovation, we adopt an affordance theory perspective. It provides powerful analytical tools for investigating technical and social aspects without privileging one at the expense of the other when studying the relationship between digital artefacts, employees, and goals in organisations (Chatterjee et al., 2019). The affordance theory became increasingly popular in IS research as it allows a better understanding of how technology affords different ways of reciprocal actions to achieve goals (Lehrer et al., 2018; Zeng et al., 2020). Beyond IS research, affordance theory was applied in multiple disciplines such as psychology, sociology, computer science, human computer interaction, and others due to its explanatory power for potential actions to perform with specific technologies (Anderson and Robey, 2017; Chatterjee et al., 2019; Norman, 2013).

Affordances can be analysed at individual and organisational levels to achieve group-level goals (Burton-Jones and Volkoff, 2017; Volkoff and Strong, 2013) to investigate the interrelationship of flexible routines and technologies (Leonardi, 2011), the role of social media technology enacted in knowledge-sharing processes (Majchrzak et al., 2013, p. 39), or recently, the impact of COVID-19 (Hacker et al., 2020; Henningsson et al., 2021; Waizenegger et al., 2020). Affordance theory is increasingly adopted on an organisational level to explore the role of digital artefacts in their situated organisational context while acknowledging the decisive role of actors, their intentions concerning the material properties, and features of a digital artefact (Dremel et al., 2020; Du et al., 2019; Henningsson et al., 2021; Krancher et al., 2018; Lehrer et al., 2018; Strong et al., 2014). Thus, the relational nature of the affordances depicts that the potential contextual value arises from the relationship between material properties and features of digital artefacts, the organisational context, and the actors (Majchrzak and Markus, 2013); Markus and Silver, 2008; Volkoff and Strong, 2013). In our study, we follow the perspective of affordance-actualisation theory defined as '*the actions taken by actors as they take advantage of one or more affordances through their use of the technology to achieve outcomes in support of organizational goals*' (Du et al., 2019; Volkoff and Strong, 2017).

Taking up this perspective of affordance-actualisation, scholars focused on understanding blockchain in the context of FinTech companies (Du et al., 2019), the value realisation of big data analytics (Dremel et al., 2020), and digital innovation (Chatterjee et al., 2019). The purpose was to understand the peculiarities of the different digital artefacts and its realisation of action possibilities to achieve concrete outcomes. Further, scholars suggested maintaining a clear distinction between an affordance—the potential to achieve a goal—and its actualisation—which relates to the details of specific actions that an individual actor performed with the support of a digital artefact—in line with the philosophical rooting of affordance theory in critical realism (Volkoff and Strong, 2017). Such distinction allowed many studies to separate potential action, goals, actors, and consequences achieved (Dremel et al., 2020; Du et al., 2019). Further, scholars underline and call for understanding the dependency between different levels of affordances (Henningsson et al., 2021; Strong et al., 2014; Volkoff and Strong, 2017).

The affordance-actualisation theory helps to address the challenged assumptions regarding the differentiation between innovation process and outcomes by separating digital innovations that emerge during the process of connecting use contexts and features within specific features of technologies (Nambisan et al., 2017). We adopt the affordance-actualisation theory in our study for two key reasons. First, we need to deepen the understanding of dependencies between affordances. To this end, we adopt the notion of salient affordances (second-order affordances) and lower level first-order affordances (Burton-Jones and Volkoff, 2017). The actualisation of first-order affordances may allow or constrain that of second-order affordances (Volkoff and Strong, 2017). Second, we aim to explore affordances and their outcomes in the form of digital innovations that are enabled from the material properties of AI technology in relation to the socio-technical characteristics of the organisations (Strong et al., 2014). AI technology is argued to enable actors to automate tasks such as the collection of online behaviours and augment other tasks such as ranking potential candidates, extracting patterns invisible to human eyes, and augmenting decision-making (Mikalef and Gupta, 2021). On this basis, we applied affordance theory on the task level of HR processes such as recommending online job listings based on prior online behaviour.

Research methodology

We followed GT, an inductive research methodology (Urquhart et al., 2010) widely used in IS to '*engage with the data and participants in order to create theory*' (Walsh et al., 2015). We chose this approach because it allowed us to be open to multiple perspectives, ignore preconceived ideas, and let the data tell its story while combining literature, data, and experience (Urquhart, 2019). Through the Input-Process-Outcome (I-P-O) framework (Espinosa et al., 2006), we extracted social and material elements of AI implementation and use in organisations, while GT enabled us to explain the combination of such elements, the action possibilities organisational actors could perform to innovate processes and services. Additionally, we applied a multiple case study approach, which offers more '*accurate, interesting, and testable*' tools (Eisenhardt and Graebner 2007; (Yin, 2009) to develop a framework grounded in the analysis of the data. To this end, we combined the experience of four case studies to explain how they leveraged AI-affordances to drive process and service innovations.

Research setting

We conducted an explorative multiple case study design with four cases operating in HRM in Scandinavian countries (Table 1). We purposefully decided on a multiple case study design owing to its potential to achieve more robust results (Yin, 2018). The companies were selected based on the following criteria. First, we aimed at companies that use AI technology to innovate daily work routines and practices within the selection and recruitment HR processes. Second, to ensure high adoption of AI technologies and avoid cultural differences, we decided to select our cases from Scandinavian countries as they are deemed to be the most innovative countries in Europe (Breton and Gabriel, 2020). Third, aside from the commonalities, we aimed to obtain a sample of firms from different industries and a diverse set of use cases for adopting AI within organisations. This approach allowed us to compare the cases for both commonalities and differences to identify AI-enabled digital innovation that is not bound to industry or firm characteristics.

Case 1 is about a leading corporate group that operates in the financial sector and a recruitment-staffing agency that aims to create an innovative labour market with advanced technologies for private and public companies. Case 2 is represented by a Scandinavian organisation that offers an online marketplace for multiple services, including job advertisements with the support of machine learning algorithms and collaborative filtering models. Case 3 consists of a corporate group that offers recruitment and staffing services, which is one of the biggest agencies in the Nordics. Finally, case 4 represents an organisation specialised in recruitment and staffing services for healthcare companies and tech start-ups, which provides a virtual staffing assistant for healthcare staffing in private and public sectors. The common goal of the four cases is to combine Scandinavian know-how with cutting-edge technology for providing qualified staff efficiently.

Data collection

We conducted semi-structured interviews, which provided rich empirical data related to situations considered episodic and infrequent (Eisenhardt, 1989; Eisenhardt and Graebner, 2007; Gehman et al., 2018).

Table 1
- List of organisations included in this study.

	Country	Industry	Employees (estimated)	AI vision for HR activities	AI technology
Case 1	Sweden	Finance/banking	400	Deliver innovative solutions, attracting competent candidates, securing equality and diversity	Androgynous interview robot
	Sweden	Recruitment and staffing	250	Create bias-free recruitment, selection, and staffing. Contribute to diverse, sustainable, innovative labor market	
Case 2	Norway	E-commerce	400	Enable recruiters with digital tools to reach competent candidates	AI job listing recommendations
Case 3	Norway	Recruitment and staffing	300 + 120	Creating value and meeting future needs by leveraging new technology and focusing on human development	AI staffing platform
Case 4	Sweden	Staffing	638	Provide customers with qualified staff in the healthcare, social and educational sector at the best price	AI staffing assistant
	Norway	Technology	35	Empowering human potential by combining Scandinavian know-how with cutting-edge technology (healthcare)	

Table 2
- Interviews by role of employees, length, and period.

Case	Role of interviewee	Time	Period
1	Employee Branding, Product Manager, and Recruiter	2 h 30 min	Sept–Oct 2020
2	Product Managers and Developer	2 h 20 min	Oct–Nov 2020
3	CDO, CEO, and Innovation Project Manager	2 h 15 min	Oct–Nov 2020
4	CIO	1 h 30 min	Nov 2020

We focused on information related to participants' thoughts, behaviours, beliefs, and feelings about the implementation of AI in organisations offering HR services. Our respondents were HR practitioners, recruiters, and managers with first-hand experiences implementing or developing AI tools for recruitment or selection processes. We conducted eleven interviews in seven HR companies from September to November 2020 (Table 2). A total number of 67 pages and 41929 words were transcribed.

Data analysis

Following Strauss and Corbin's recommendations (1990), data analysis was performed by coding, memoing, sorting, and writing (Urquhart et al., 2010; Volkoff and Strong, 2017). Memos were written to capture thoughts and ideas about the categories and concepts that emerged from the data. This activity is fundamental to GT as it helps to shape the development of the theory. We went through three rounds of data analysis (Burton-Jones and Volkoff, 2017). In the first round, we coded relevant information about AI, such as input, process, and output, guided by the I-P-O framework (Espinosa et al., 2006). The interviews were coded by two researchers to reach a common understanding of the process (Urquhart, 2019).

In the second round, we focused on the processes described by our respondents. To this end, we followed six principles suggested by Volkoff and Strong (2017). First, we extracted potential actions performed with the support of AI technology to capture the affordances that arose from the relation between the users and the artefact. Subsequently, we made a clear distinction between affordances and their actualisation process. Therefore, we focused on the potential actions and not on their outcomes with the support of the I-P-O framework (Espinosa et al., 2006). Finally, we grouped first-order affordances into second-order affordances. For example, the use of an androgynous robot for *conducting interviews with candidates* came under first-order affordances. The robot was employed for *introducing* itself and *informing* the candidate about the time to prepare for the interview, *asking* questions about personality, competence, work-experience to candidates, and *recording* and *transcribing* candidates' responses during interviews.

In the third round, similar codes were aggregated to create first-order and second-order themes with an iterative coding process. Subsequently, we examined and compared the associated codes and concepts with the new data. Thus, we could enrich existing concepts, form new relations between concepts, or create new ones. The stages were not persistently conducted in a linear fashion as they often overlapped each other and interplayed with the comparison of existing data, concepts, and theories. This process led to the identification of concrete actions to actualise affordances based on the ways organisations applied AI to reach their goals.

Findings

In this section, we present the results of our analysis for enabling digital innovation in organisations with the support of AI. We show how AI affordance-actualisation triggered digital innovation processes that subsequently generated digital service innovation for collecting and analysing information. These two types of innovation influence and reinforce each other and take place continuously until the desired outcomes are met. Subsequently, we introduce an AI-affordance-innovation framework to explain how to combine actors, AI, goals, organisations, and tasks for innovation processes and outcomes in the age of intelligent machines and how to develop unbiased approaches for managing heaps of information and creating added value.

AI affordance-actualisation for collecting information

AI offers novel approaches for collecting online information and respecting the General Data Protection Regulation (GDPR). Specifically, AI generates a new breed of digital innovation process through two second-order affordances—*fine-tuning algorithms* and *identifying patterns in users' interests* (Table 3). Consequently, this fosters the creation of a digital service innovation such as targeted recommendations by combining patterns related to online users' interests and online job advertisements. Subsequently, AI is used to support internal actors of organisations such as employees and external stakeholders such as potential candidates by *facilitating job applications* as follows.

First, organisations can reach a broader audience when publishing online information as they are enabled with *fine-tuning algorithmic parameters* for online services such as online job advertisements. The aim is to show compelling job ads to the most interested pool of candidates to attract competent candidates for specific job positions based on their interests and preferences. This second-order affordance can be actualised with three first-order affordances, including the following: *AB-testing* to test already existing algorithms or create new ones in real time and check their performance; *ranking candidates* from the most to the least relevant for that specific job ad; and *setting a threshold value* to limit

Table 3
- Second- and first-order affordances for collecting information.

		Affordances	Representative quotes
Innovation process	**2nd**	**Fine-tuning algorithms**	We have scraped numerous different models; we test them on a percentage of users. Those that provide better results are implemented in our company.
	1st	AB-testing	We created our own dashboards where we make ab tests for different algorithms and tune different parameters to measure their performance. We lay out different algorithms or new models in real time. If they are good enough, we start using it.
		Ranking candidates	The algorithm ranks all users from the most relevant to the least relevant; you need to figure out where to set the limit (…)
		Setting a threshold value	The threshold value is relevant because this decision will affect the size of the target group (…) we want to move closer to the goal of providing more applicants, not just people viewing and clicking on the ads.
	2nd	**Identifying patterns in users' interests**	We construct a huge matrix and (...) we attach an id, a cookie, to each user as columns and then you have the codes for each job listing as rows (…) we try to find users that have a similar usage pattern as you (online users searching for job), and if these other users have clicked on an ad, then there is a big chance that you are also interested in that ad.
	1st	Collecting online behavioural information	ML models are fond of new data to make recommendations (…) Until now, we have been focused on clicks, getting users to the landing page of the ad. It is a good proxy, but now we want to show job listings to users that will be more likely to apply because they are interested in them and not just because they think those ads are cool.
		Creating clusters of online job advertisements	To fill out the matrix, we need the user ID and the job listing ID. We do not look at the content of the job listings. The users create clusters of ads (…) We do not have to know and make all these rules ourselves; it is the users who do that, indirectly based on what they click on, who decide these connections and correlations that we might not be aware of.
Service innovation	**2nd**	**Recommendin g online job listings**	When you open a listing, we will recommend listings that are similar, so if you click on the first ad (…) we have a model that will show you similar positions. It targets the users in a good way, and several people will click on it (the job listing) and actually end up applying for the position.
	1st	Suggesting keywords	We will take the title of the listing and try to recommend which keywords you should register to the listing. That is also an ML model. When you have filled in a couple of keywords, we try to use both the title and the keywords to get other keywords to make it (the recommendation) more targeted.
		Targeting job listings with users	We have several algorithms; for example, if you have looked at three different positions, then you go out and get back in the day after, and the system will show you ads based on your prior preferences.
	2nd	**Facilitating job application**	You can register using LinkedIn or Vipps; there is a resume parser engine from (a company specialised in AI software), which works well; you just input your resume, and it makes a user based on that information.
	1st	Parsing information	We try to not get this registration-mill that people resist towards when applying for a job, like 'oh, do I need to fill out all this to apply for the job? I do not want to do that'.
		Matching profiles with job listings	We are looking at making the process easier; as we make it easier for the candidates, it often comes along with better quality as well because what they actually register for is done better.

the size of the ranked lists of users.

A higher level of accuracy for recommendations of job listings led to an increased number of generated clicks and a higher percentage of users applying directly for the positions. Through continuous experimentations with different algorithms and incremental improvements to the parameters of existing machine learning models, developers had the opportunity to optimise the outreach towards job applicants. They provided companies with increased, targeted exposure towards open positions. Second, organisations are enabled with *collecting online behavioural information* such as user clicks and time of stay on job listings through collaborative filtering models to analyse the information collected from active users on the organisation's web page, as a product manager mentioned,

> *We construct a huge matrix and (...) we attach an ID, a cookie, to each user as columns, and then we have the codes for each job listing as rows (…) we try to find users that have a similar usage pattern as you* (online user searching for job)*, and if these other users have clicked on an ad, then there is a big chance that you* (online user searching for job) *are also interested in that ad.*

Consequently, the information collected about the behavioural patterns of users showed how many clicks a job ad obtained and the percentage of users who applied for that position. This type of innovation helped organisations to understand users' preferences for offering targeted job listings recommendations. Such action possibilities did not use any private or sensitive information, which is protected by GDPR, as a project manager explained:

> *When it comes to what we gather internally, we store it* (information) *for one year. You* (the user) *have the possibility to opt out of this* (data gathering)*, and then we will not store anything, and we make sure to delete everything that is there or at least anonymise everything.*

Third, the collection of online behavioural information can be actualised through two first-order affordances: *collecting online behavioural metrics*—such as location, type of work, and competences related to the job listings the users looked at online—and *creating clusters of online job advertisements* by grouping users with similar online usage patterns.

> *To fill out the matrix, what we need is the user ID and the job listing ID. We do not look at the content of the job listings. The users create clusters of ads (…) indirectly based on what they click on, and they create the basis for connections and correlations.*

Finally, the system ranked online users from the most to the least relevant and grouped them. The collection of this type of information supported the HR employee to decide the group of users who should receive recommendations about specific job listings by manipulating factors such as outreach methods, application processes, and job descriptions. Next, this information is used to adjust future online job advertisements to attract more attention. Consequently, the digital innovation process creates the basis for digital service innovation, such as targeted recommendations by *recommending online job listings* for candidates via platforms such as digital marketplaces, social media sites, and digital newspapers. The recommendations were steered by machine learning algorithms that sought to target users with job listings in which they were likely to be interested.

Job listings recommendations is a novel HR online service that also contributed to increased revenues for the organisation. Indeed, employers, who were searching for competent candidates, were willing to pay a fee for achieving a more targeted and broader reach when they posted job listings online. Based on this necessity, the developers of the websites where the job ads were published started to use machine learning models for suggesting potential candidates for specific job ads. Therefore, they created innovative services online for both employers and employees, which were more expensive than the standard ones. This can be achieved through three first-order affordances: *suggesting keywords* to tag the job listing; *creating connections and correlations* based on users' online behaviour and keywords selection; and *targeting online job listings*. This was explained by a developer:

> *Many customers pay extra to get a broader reach (…) we use machine learning to give them the opportunity to distribute this into different platforms (…) so it gives more clicks on the job listing and hopefully more people applying for the position.*

After having attracted valuable candidates for specific jobs, organisations also use AI to help candidates share their information such as resumes, competencies, and others by *facilitating job applications*. To actualise the affordance of this second-order affordance, HR employees performed two first-order affordances: *registering and parsing candidates' information* automatically into the organisations' applicant tracking system (ATS) and *matching online candidate profiles with online job listings* based on how well their competencies matched the job description. Consequently, the recruiters could quickly identify available and competent candidates for job openings. Therefore, organisations collected a minimal amount of information in the initial stages, and potential candidates would upload more information later. This helped save time for candidates—they did not need to fill out complete applications, which was time-consuming and possibly intimidating—and recruiters, who could review only specific information they required for the initial steps.

AI affordance-actualisation for analysing information

The use of AI for analysing information collected from multiple sources and multiple types led to the creation of digital service innovation through the second-order affordance for *optimising online recommendations*. This triggered digital innovation processes such as *reontologise decision-making* and *data-driven legitimisation* (Table 4). Contrary to information collection procedures, we identified that AI contributes to the development of new online services and enables organisations to develop new and unbiased approaches for data analysis with objective and evidence-based reasoning.

To optimise online recommendations, staffing coordinators used NLP algorithms for *parsing job requests* from the different employers. These were sent to the staffing bureau through e-mails as Word documents, Excel sheets, or other formats. AI is particularly useful for the interpretation of text from different digital formats, which did not have structure and made the staffing coordinators' work even more challenging. Subsequently, staffing coordinators proceeded with *reviewing the pool of available candidates,* owing to the information inserted by available candidates in the AI system, such as their interest in a position, qualifications, time availability, and others. Later, organisations used an AI staffing assistant for automatically *matching candidates with open positions* based on job requirements, candidates' competence, availability, location, and other factors. This played a pivotal role in organisations' work activities because it constituted the core of the services they provided to hospitals and other healthcare organisations. A CEO described how the staffing assistant automated mechanical tasks:

> *We combine that* (information from job requirements) *with the data that exists about candidates in the applicant tracking system (…), and based on all that data, we manage to match the job and the candidates that exist in the database (…).*

Finally, AI was used for *ranking potential candidates* in a decreasing order for each open position based on the information processed in the previous steps. Staffing coordinators opened the files automatically elaborated by AI and received a list of the most suitable candidates for those specific positions. This allowed staffing coordinators to optimise the analysis of heaps of information, which improved the coordination with other colleagues. The algorithm provided more transparent and

Table 4
- Second- and first-order affordances for analysing information.

		Affordances	Representative quotes
Service innovation	2nd	**Optimising online recommendations**	We immediately get a matching of the candidates, a score to weight how well they fit the position. AI system then learns from prior decisions and provide better results.
	1st	Parsing job requests	For us, [the motivation for using the AI-assistant] is to simplify a time-consuming process, and especially, from the big volume customers (…) we needed a fast way to automatically review all documents of job requests.
		Reviewing the pool of available candidates	We use an AI assistant to review descriptive information of candidates and check mandatory job requirements such as driving licence, language certificates, professional education, etc.
		Matching candidates with open positions	We combine that (information from job requirements) with information about candidates we collected with the applicant tracking system (ATS). The AI assistant then matches job requirements with potential candidates.
		Ranking candidates for open positions	They (candidates) are ranked depending on how well they fit the job description based on their competencies. However, you must make them (staffing coordinators) trust AI recommendations.
Innovation process	2nd	**Androgynous robot for interviews**	Many candidates said they responded more honestly when they talked with the robot. I think they perceived AI as fair process because they were evaluated based on their competences and not on similar interests or past experiences.
	1st	Providing introductory information	The robot introduced itself, informed the candidate that the interview would start in 15 minutes, and said it would ask questions from certain topics.
		Asking questions about competence	The robot asks questions similar to the Big 5 model; it asks structured questions about the candidate's competence. A combination of answers with an automatic personality test makes a really good foundation.
		Transcribing responses	The robot recorded and automatically transcribed each interview for the next phase analysis.
	2nd	**Assessing objectively candidates**	The robot elaborates scores for each candidate, makes predictions of how well that candidate will be doing at work, and creates a list. We then choose the candidates that are more interesting related to their work performance.
	1st	Competence based evaluations	Many would rule out candidates based on their looks, their age, sex, ethnicity, or tattoos. With the robot, we evaluate candidates on their competencies and scientific indicators for job performance. The subjective evaluation is moved as late in the process as possible to give the right people the right opportunity.
	2nd	**Data-driven decision making**	You will always be able to show why you gave a specific person the job; with our robot, you get data driven documentation, and you can demonstrate objective reasons for hiring decisions.
	1st	Unbiased information analysis	You also get time efficiency (…) you can plan better as the robot manages the interviews and is unbiased; it scores candidates' answers, and the evaluation is not focused on candidates' appearance.

competent-based recommendations for temporary jobs while avoiding personal judgements. This streamlined the complex and time-consuming process for analysing job requests and enabled staffing coordinators to save time from mundane tasks for performing higher-level tasks such as attracting new customers.

Regarding the digital innovation process, organisations started to use androgynous robots to *conduct automatic interviews* with candidates. Specifically, the HR employees had to perform a requirement and competence analysis to identify which skills and competences were relevant for a specific position. This was used to decide which questions the robot would ask the interviewees and helped candidates provide more transparent responses, as an HR adviser explained. Subsequently, the HR managers filtered out candidates based on automatic tests, which the recruiters used to measure the candidates' characteristics and abilities. The organisations used automatic personality-tests to narrow down the candidate pool to interview with the robot, as explained by an HR adviser:

> *Everyone who applied was anonymised directly, so we did not know who had applied (…) were then able to go on to the next round and use the robot for a second interview.*

The robot was used for *providing information* regarding the interview, *asking competence-related questions*, and *recording and transcribing candidates' responses* during interviews. This allowed to anonymously review the answers from the competence tests and combine their scores with the results provided by the robot's personality indicator. Candidates experienced a fairer selection process as they were asked the same questions and evaluated mainly based on their answers to pre-determined questions. Moreover, candidates had more time to respond to questions and were less stressed about making a good impression with the HR manager.

This opportunity brought important advantages to organisations working in small municipalities, where there is a high risk of people knowing each other's private information. It also provided more privacy and respect for candidates as they could respond without perceiving any feedback from the HR manager. Finally, the robot was advantageous in maintaining social distance during the pandemic.

Considering this together, we noticed that AI enabled organisations to develop unbiased approaches for data analysis by *objectively assessing candidates* with the support of the Big 5 personality model and by making competence-based evaluations. HR recruiters analysed candidates' resumes and provided scores on personality traits such as conscientiousness. Subsequently, these psychological test scores were combined with other evaluations by the robot for predicting which candidates would perform better in that position. A recruiter explained how this led to better hiring decisions:

> *Many would rule out candidates based on their looks, age, sex, and ethnicity and if they have tattoos. But here they are judged based on their answers and what science tells us indicates good job performance. After that you get to the subjective part, which is moved at the end of the process to give the right people the right opportunity.*

The goal was to help HR employees filter out candidates based on objective factors linked to work performance instead of subjective judgements about personal letters and resumes and legitimise each decision at each step. Consequently, HR employees conducted personal interviews with the most suitable candidates suggested by the robot only in the last stage of the selection process, thus reontologising the decision-making.

> *You will always be able to show why you gave a specific person the job; with our robot, you get data driven documentation, and you are able to say, 'this is why we chose to go further with this candidate'.*

AI-affordance digital innovation framework

In this section, we present an AI-affordance digital innovation framework (Fig. 1) to explain how the actualisation of AI affordances lead to digital process and service innovation in organisations. We identified three types of digital process innovation (complying with GDPR, reontologising decision-making, and data-driven legitimisation) and one type of service innovation (targeted recommendations and their optimisation) that primarily aim to develop unbiased approaches for managing heaps of information. We identified the key material features of AI, such as storage (record and transcribe interviews, collect online behaviour, register, and parse information), analysis (training and testing of model prediction, pattern recognition, and match), and recommendation (display and rank information). By leveraging AI affordances, organisations can create digital process and service innovation, which contribute to organisations' performance in terms of a higher degree of perceived fairness, less biased decision-making, transparent feedback, increased communication, and others.

We provide an overview of the framework by describing AI features, key actors, AI affordance-actualisation for collecting and analysing

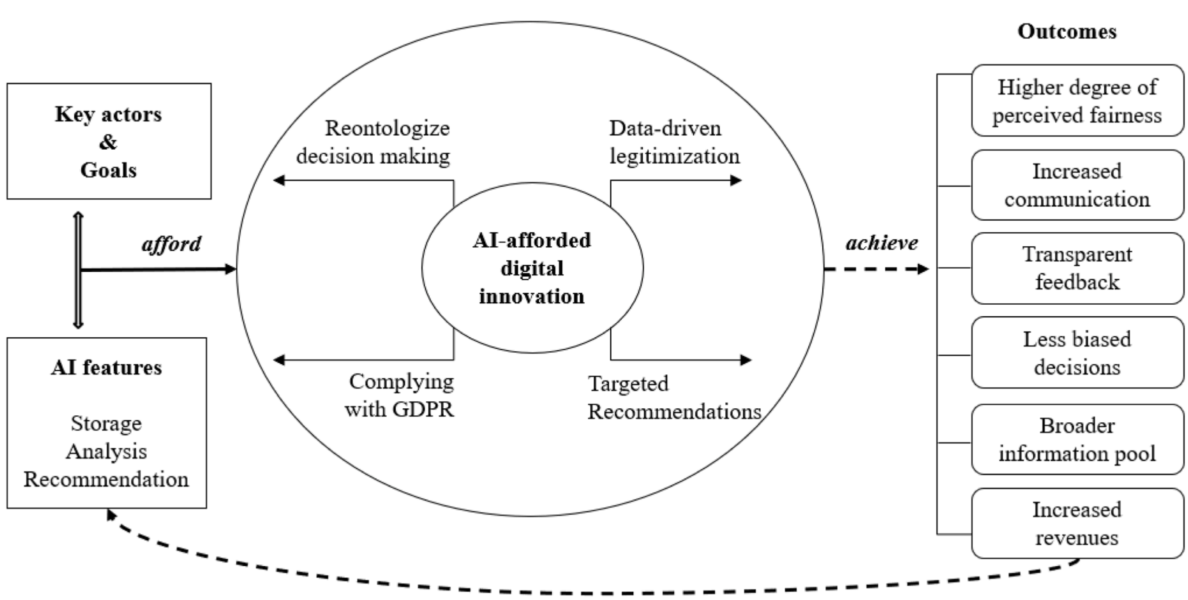

Fig. 1. - AI-affordance digital innovation framework.

information, and the outcomes achieved.

Key actors and AI material features

The advancements of AI can change the direction of strategic management towards unbiased approaches for handling heaps of information. The development of AI tools emerges with the combination of strategies regarding differentiation, technical needs for digital innovation, developers, and employees. Top management actors such as the Chief Information Officer (CIO), Chief Data Officer (CDO), and Chief Executive Officer (CEO) play a key role in supporting the implementation and use of new technology such as AI as they deal with high-level strategic decisions and the ways to achieve those decisions. After the implementation phase of AI, the actual users of AI such as AI developers, HR employees, and others significantly contribute and determine the successful use of the new technology. Three main features are inscribed in AI technology. First, the storage feature functions to collect information in digital formats for multiple uses. Second, the analysis feature enables organisations to process information, compare it, and extract insights invisible to human eyes. Third, the recommendation feature displays lists of the most important information for decision-making. Notably, although AI enables actors to perform tasks with evidence-based procedures and data, AI acts only with the intervention of actors, who decide the type of information to collect, when to process it, and based on which criteria. AI provides the necessary conditions and opportunities to act, but the actualisation of potential actions is supervised by actors. Our framework shows the interrelationship between actors, AI material features, action possibilities, and outcomes of digital innovation.

AI-afforded digital innovation process and digital service innovation

For managing heaps of information, organisations followed two main phases—information collection and information analysis. Information collection refers to the action possibility of gathering information in multiple formats from multiple sources (websites, digital marketplaces, social media sites, and digital newspapers) in line with privacy and security regulations such as GDPR. Information analysis refers to the opportunity of developing unbiased approaches for evidence-based data analysis. In both phases, AI can foster digital process and service innovation as follows.

Regarding the information collection, actors are enabled with specific second-order affordances (action possibilities), including fine-tuning algorithms, identifying patterns in users' interests, recommending online information, and facilitating the collection of online information. These affordances are further decomposed into first-order affordances such as AB-testing, ranking relevant information, setting a threshold value, collecting online behavioural information, creating clusters of online job advertisements, targeting job listings with users, parsing information, and matching profiles with job listings. Notably, the actualisation of first-order affordances influences that of second-order affordances. It is possible to actualise the second-order affordances only when all first-order affordances are properly actualised, which contributes to achieving organisational goals.

AI has the potential to foster a *digital innovation process* by developing new and evidence-based approaches for data collection. First, it helps to adjust specific parameters to attract a broader audience when the information is published online. Second, organisations are enabled with collecting online behavioural information and save it for a specific time (i.e. one year) in line with the GDPR regulation. Notably, this type of information is not considered private or sensitive as it refers to the interaction of online users with organisations' websites, which is currently not regulated. This creates new opportunities for the blue ocean strategy in an area not yet explored regarding the use of heaps of information in line with current privacy rules, which is a sensitive and pivotal topic at present. Third, organisations can analyse online users' interests to extract patterns and make predictions.

A deeper understanding of online users' preferences allows organisations to adjust the parameters to publish online information and reach a broader audience. Moreover, AI can facilitate the process of sharing online information with simpler and easier steps to insert information in online portals. Consequently, the actualisation of AI affordances that lead to digital innovation process also contribute to foster *digital service innovation* by developing targeted recommendations for specific categories of online users. Relying on online behavioural information collected previously, organisations can combine patterns of online users' interests with potential online services such as job advertisements.

In the information analysis phase, actors actualise four second-order affordances—collecting information through an androgynous robot, objectively assessing information, data-driven legitimisation, and optimising online recommendations. Each of these affordances is decomposed into first-order affordances such as matching needs with services, transcribing information, competence based evaluations, unbiased information analysis, and others. The same logic is also valid for information analysis. The actualisation of first-order affordances is strictly linked to that of second-order affordances determining the action possibilities of digital innovation. This allows the organisations to extract and select valuable information for differentiating their online services from the competitors.

AI is likely to stimulate *digital service innovation*, such as optimisation of targeted recommendations by matching needs and solutions based on the information collected from online users. Achieving this is possible by parsing the information of the needs such as job requests from other organisations, reviewing the pool of solutions such as available candidates, matching them based on objective parameters, and ranking potential solutions. Moreover, the solutions are continuously optimised owing to the continuous analysis of online behavioural information. After identifying the most suitable solutions, AI enables organisations with a *digital innovation process* that reontologises decision-making and offers data-driven legitimisation as follows. First, the androgynous robot standardises and objectifies the data collection process by applying the same criteria and procedures to each candidate. Subsequently, it transcribes the new information and anonymises it for future analysis for human actors and proceeds with automatic competence-based evaluations. This approach aims to diminish human biases during decision-making as much as possible. Finally, AI affordances provide data-driven legitimisation for each decision at every stage, increasing the transparency and objectivity during the analysis of heaps of information.

Outcomes of AI-afforded digital innovation

The actualisation of AI affordances for collecting and analysing heaps of information leads to important outcomes that help organisations to differentiate their online services and gain competitive advantage as follows. First, online users such as online candidates perceive a higher degree of fairness regarding the way their personal information is collected and analysed. This can be achieved with the support of an androgynous robot to automate tasks, follow the same procedures, and apply the same parameters each time. Second, AI increases the communication between key actors inside an organisation such as employees and external actors as potential candidates, online customers, and others. The results of each decision made by key actors inside the organisation can be instantly communicated to external actors, thereby increasing their asynchronous communication. Third, AI enables new approaches for analysing heaps of information and providing a transparent feedback for every step of the data analysis. This is beneficial to internal actors, who can justify every step performed and every decision made, as well as external actors, who can understand better the reasons of the results achieved. This type of information is beneficial to both types of actors to improve their personal and organisational performance further.

Fourth, AI enables internal actors to develop and use unbiased approaches during the decision-making process to provide similar opportunities to multiple users, which can subsequently contribute to organisational performance (Trocin et al., 2021). Fifth, AI enlarges the pool of information organisations that can reach, collect, and analyse to target their online services and solutions better for specific categories of users. Sixth, by leveraging AI processing capabilities, organisations can identify patterns in online users' preferences and interests. This helps them to identify current gaps in online market, which helps to create new online services or update the current ones. Moreover, such granular information about clients' needs enables organisations to segment their online services with different prices for each segment generating new revenues, especially for requested services such as matching needs with solutions. This can be achieved only with the support of specific parameters inscribed in ML algorithms.

Consequently, the process of AI affordance-actualisation for digital innovation and the outcomes achieved deeply influence and determine the strategies developed by key actors in organisations, the definition of organisational goals, the development of AI features, and the strict relationship among these factors.

Implications for theory and practice

Our study offers several contributions to theory and develops the following propositions. First, we contribute to digital innovation research in the age of intelligent machines by explaining how AI enables novel approaches for complying with GDPR when collecting and analysing heaps of information (Haefner et al., 2021; Lusch and Nambisan, 2015; Nambisan et al., 2017). Specifically, we develop alternative conceptualisations regarding the assumption that innovation processes and outcomes are distinctly different phenomenon. To this end, we show how they unfold and reinforce each other in a nonlinear fashion through the affordance-actualisation theory. We incorporate key AI features, such as storage, analysis, recommendation, and their entanglement with actors, goals, and action possibilities as explanatory factors of digital innovation. This is because AI is increasingly used to discover new patterns and ideas and develop new combinations of existing services. Therefore, we create novel explanations of innovation processes and outcomes through phenomenon-based theorising (Nambisan et al., 2017; von Krogh, 2018; Steininger et al., 2021). In line with this, we develop Proposition 1: *Organisations' goals and actors' capabilities are positively related to the potential offered by AI to afford digital innovation.*

Second, we provide alternative conceptualisations about digital innovation processes and outcomes by developing an AI affordance digital innovation framework. We explain firm innovativeness and associated mechanisms to differentiate themselves from the competitors (Liu et al., 2020) by developing unbiased and evidence-based approaches for managing heaps of information. The objective of this theoretical perspective is to understand the actions organisations should perform to realise competitive gains from digital innovation. Thus, we present the journey of developing and implementing AI in organisations relying on affordance-actualisation theory to explain how affordances are actualised (Chatterjee et al., 2020; Du et al., 2019). We make a clear distinction between actors involved, AI technologies used, affordances, and their actualisation and outcomes, guided by the I-P-O framework. Accordingly, we suggest Proposition 2: *AI recedes the distinctions and accompanies the duality between innovation processes and outcomes.*

Third, our study contributes to the growing body of research on AI by offering insights into how AI can be implemented and used for fostering digital innovation. As an emerging phenomenon, AI is attracting scholars' attention since its inception in the 1950s. However, the extant studies have mainly focused on hypothetical impacts and potential use. Little is known about how AI is implemented in organisations and how AI can contribute to digital innovation and competitive advantage (Ågerfalk, 2020; Liu et al., 2020). Specifically, we contribute to the knowledge regarding how AI is implemented in organisational settings and how key actors actualise its technology affordances for innovation (Dremel et al., 2020; Du et al., 2019). Thus, we develop Proposition 3: *AI positively influences professional expertise and its evolution in the age of intelligent machines.*

Apart from the research implications, this study also provides some important practical contributions by guiding practitioners to effectively implement AI within their organisations and extract value from their investments. First, we present the possibilities of developers to use AI technology for innovation purposes. We show how the selection of parameters of collaborating filtering models deeply influences and defines the success of recommendation systems. This can help AI practitioners to understand how such technologies can enhance organisational processes and how this can complement companies' strategies for gaining competitive advantage. Accordingly, we develop Proposition 4: *AI enables and constrains automatic predictions (filtering) about the interests of a user by collecting preferences or taste information from many users.*

Finally, our study presents the challenges HR departments face in a competitive environment, and we show how innovation processes can push further technological development. The findings show that the competitive pressure operates as a prompt for managers to adopt AI-based innovations to remain competitive. This outcome suggests that building a digital strategy is a strong requirement for organisations operating in competitive environments. The proposed framework and the mechanisms described can serve as guide for practitioners to initiate their AI-based projects. Based on the specific requirements of their industries, the framework can be used to identify what types of outcomes need to be strengthened using AI-based innovations and understand how such digital innovations should be developed. Thus, we suggest proposition 5: *The power of AI positively supports the realisation of organisational logic, goals, and intentions towards digital innovation.*

Limitations and future work

Our empirical study has some limitations. First, although we intended to interview employees with different working backgrounds in organisations, there was an overrepresentation of employees at higher-level positions. We collected valuable insights from managers, CEOs, and CIOs about the implementation process and their reasons for implementing AI. Nevertheless, this study lacks the perspective of other employees that use AI during their work. Therefore, future studies might consider including more employees from all levels of an organisation to broaden the perspective of how AI is influencing their work. Second, to understand how AI is used, we asked questions that mainly considered information collection and analysis. Although these two processes play a critical role in organisations, they are not sufficient to describe other daily activities. Therefore, this limits our understanding about the other processes in the field, such as decision-making, planning, data analysis, and others. Third, the use of AI-technology was at an early and explorative stage in the companies involved in this study. Consequently, exaggerated expectations or prejudices about AI may have impacted this study. Additionally, most respondents felt almost uncomfortable to say that they were using AI tools and preferred to specify that they used robots, machine learning, and collaborative filtering models to perform their work. Fourth, this study focused mainly on Scandinavian companies that might present trends typical of a specific geographic area. Therefore, future studies might conduct research in other countries that implemented AI in organisations, which could provide other perspectives and trends driven by the specific location, thus enriching our knowledge.

Conclusions

This study investigates how organisations can leverage AI affordances to drive digital innovation. With an inductive qualitative multiple-case study, we explain the actualisation process of AI affordances to collect and analyse heaps of information with an unbiased and fair approach in line with GDPR guidelines. Based on the I-P-O framework, we analyse the entanglement of actions, AI technology, and HR employees. Guided by GT, we describe the associated actualisation processes through affordance-actualisation theory by explaining the strong link between first- and second-order affordances. This study elucidates the awareness about the stimulating conditions of affordance actualisation for fostering digital innovation, which leads to competitive advantage. In addition, this study opens the black box on how to integrate AI technology in organisations for digital innovation processes and outcomes.

CRediT authorship contribution statement

Cristina Trocin: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing. **Ingrid Våge Hovland:** Investigation, Writing – original draft. **Patrick Mikalef:** Conceptualization, Writing – review & editing. **Christian Dremel:** Writing – review & editing.

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