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How AI revolutionizes innovation management – Perceptions and implementation preferences of AI-based innovators

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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

The application of AI is expected to enable new opportunities for innovation management and reshape innovation practice in organizations. Our exploratory study among 150 AI-savvy innovation managers reveals four different clusters in terms of how organizations may use and implement AI in their innovation management ranging from (1) AI-Frontrunners, (2) AI-Practitioners, and (3) AI-Occasional innovators to (4) Non-AI innovators. The different groups vary not only in their strategy, organizational structure, and skill-building but also in their perceived potential, understanding of the required changes, encountered challenges, and organizational contexts. Our study contributes to a better understanding of the current state of AI-based innovation management, its impact on future innovation practice, and differences in organizations' AI ambitions and chosen implementation approaches.

1. Introduction

The prospects for (AI) in business and the global economy are thrilling. The idea that AI – and machine learning in particular – will increasingly match or exceed human performance, take on work roles, fundamentally transform the operational foundation of business, and disrupt management practices holds considerable potential (Agrawal et al., 2017; Lakhani and Iansiti, 2020; von Krogh, 2018). Generally, the premise is that AI will enhance human capacities, perform tasks or solve problems faster, deliver better outcomes, and deliver higher efficiencies (Agrawal et al., 2019; Wilson and Daugherty, 2018).

AI is not only a new technology leading to game-changing products and services and transforming existing processes to be done faster, cheaper, and with higher quality; it is considered the most important general-purpose technology of our times (Brynjolfsson and McAfee, 2017). AI is expected to transform every industry, just as the Internet did 30 years ago or electricity 100 years ago, creating an estimated GDP growth of $13 trillion between now and 2030 (Bughin et al., 2018).

AI will fundamentally change the way companies work – how they operate and how they compete (Lakhani and Iansiti, 2020). AI will also challenge the core axioms and assumptions underlying the innovation process and its management (Benner and Tushman, 2015; Cockburn et al., 2019; Haefner et al., 2021; Keding, 2021; Nambisan et al., 2017). The central proposition is that AI has the potential to transform the innovation management practice by enabling a much more effective and efficient innovation process and so herald a new innovation era. However, our knowledge of how to apply AI for innovation management is still sparse, and managers are struggling to find the most appropriate approach for applying AI in their innovation efforts. The objective of this article is to fill the gap by exploring how managers perceive the potential of AI for innovation management and what kind of impact they expect on the setup of their innovation processes. More precisely, we explore how innovation managers differ in their views on how AI may impact their innovation management practices as well as how they plan to implement and use AI for certain innovation tasks within their organizations. In doing so, we define AI-based innovation management as the application of AI technologies that extend, complement, or even substitute human capabilities to efficiently and systematically develop and promote innovations in organizations, ranging from the identification of promising opportunities to successful market launch.

In our exploratory study with 150 AI-savvy innovation managers, we reveal four major insights into the upcoming AI-based innovation management era. (1) AI-based innovation management has the potential to usher in a new seventh paradigm of innovation management. Our

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Table 1
Evolution of innovation process models.

Generation	Model	Features
First – 1950s-	Technology push	Simple linear sequential model; emphasis on R&D
Second – mid-1960s-	Market pull	Simple linear sequential model; emphasis on marketing
Third – early-1970s-	Push-pull	Integration of R&D and marketing
Fourth – mid-1980s-	Parallel processing	Combinations of push and pull
Fifth – early-2000s-	E-integration	Integration of information technology (IT) into innovation systems
Sixth – mid-2000s-	Network innovation	Systems integration and extensive networking, continuous innovation

Source: Modified from Rothwell (1994), Tidd and Bessant (2013).

findings show that a vast majority of innovation managers agree on the high potential of AI to significantly increase the effectiveness and efficiency of certain innovation tasks. Our findings further show that (2) AI-based innovation management requires substantial technical and organizational changes to cope with the associated challenges; our group comparisons reveal that AI-innovators vary in the implementation challenges they face, such as insufficient access to data or a lack of technical expertise. In terms of organizational challenges, they mainly differ in their experience with and expertise in AI, as well as in the size of the company, which may limit the available resources that can be allocated to AI-based innovation initiatives. Our study further shows that (3) AI-based innovation management cannot be implemented with a one-size-fits-all approach. Organizations clearly differ in their preferences of how they may use and implement AI-based innovation management. Building on a systematic perspective of the innovation process (Roberts, 2007), we identify four major implementation clusters: AI-Frontrunners (37.3%), AI-Practitioners (25.3%), AI-Occasional innovators (26%), and Non-AI innovators (11.3%).

Furthermore, our findings show that (4) AI-based innovation management needs adequate implementation to tap the full potential. AI implementation managers must ensure that major internal stakeholders and external partners are aligned and compliant with the AI-based innovation management goals. Our findings also provide practical guidance for organizations and their innovation managers regarding the potential benefits and barriers of AI-based innovation management as well as success factors for implementation. Overall, organizations consider AI technologies as powerful means to improve their innovation performance and assist innovation teams in their innovation activities.

The paper is structured as follows: First, we provide the theoretical background for our study and provide an overview of current innovation management practices. We conceptualize how AI may affect innovation management – how it may change it and help boost current innovation practices. Building on the theoretical background, our empirical study explores how managers and innovation practitioners perceive the potential of AI for innovation management and how they plan to apply AI in their innovation processes. Then, we discuss our findings, and the theoretical and practical implications.

2. Theoretical background

2.1. Innovation management

Understanding how to manage innovation is fundamental, especially when innovation is crucial for corporate growth and competitive advantage (Ahmed and Shepherd, 2010). The innovation process typically describes the sequence of various activities performed to realize an opportunity and bring an idea to market (Ahmed and Shepherd, 2010; Tidd and Bessant, 2013). In innovation management literature, diverse approaches to manage innovation or broader R&D processes have been attempted, with various stages ranging from idea generation through the implementation and launch of a product (Cooper, 1986; Rogers, 2003; Rothwell, 1994; Tidd and Bessant, 2013) Roberts (2007, p. 36)., states that ''innovation is composed of two parts: (1) the generation of an idea or invention, and (2) the conversion of that invention into a business or other useful application [...] innovation includes all of the stages from the technical invention to final commercialization." To better represent the complexity as well as the variety of activities within the innovation process, scholars applied a more granulated approach and divided the innovation process into various phases ranging from three to seven phases. Exemplarily, Tidd and Bessant (2013) illustrate an innovation process involving four phases: (1) *searching* – analyzing the internal and external environment for, and managing relevant signals about, threats and opportunities for innovation; (2) *selecting* – deciding based on the innovation strategy how the organization can respond to the signals; (3) *implementing* – pursuing relevant ideas to develop new products and services; (4) *learning* – building the knowledge base and constantly improving the innovation process through this cycle.

Roberts and Frohman (1978), for example, suggest a technological innovation process along seven stages: opportunity recognition, idea formulation, basic/applied research, prototype solution development, standardization, manufacturing, and commercialization Kumar et al. (1996). define five stages: initial projection, commercial evaluation, development, manufacturing launch, and initial commercialization.

While innovative organizations adapt their innovation process and define the sequence and granularity of activities, various approaches to managing innovation have been evolved over the years, beginning with simple linear models (first and second generation) to increasingly complex interactive models (fourth-sixth generation) (Ahmed and Shepherd, 2010; Tidd and Bessant, 2013) Table 1. shows the evolution of the innovation model, and the phases further help define the trajectory for future progress in the management of innovation (Rothwell, 1994; Ahmed and Shepherd, 2010; Tidd and Bessant, 2013). Within the first generation (the 1950s) – known as technology-push – new technological opportunities increased productivity among various sectors and industries. Organizations emphasized research and development to further improve products (Rothwell, 1994). As competitive pressure intensified over time, it became clear that technology-push was failing new market environments and the second-generation innovation model – also referred to as the market-pull model – was developed. While the technology-push model emphasized research and development, the market-pull model incorporated the market focus into the innovation process to overcome the technology-push's blindness to customers' needs. Within this generation, most companies adapted existing products to meet changing customer requirements. By doing so, companies began to suffer from a further weakening of research and development and risked being outstripped by radical innovators. To counter these weaknesses, in the third generation (the early 1970s) – push-pull innovation – a combination of technology-push and market-pull was developed. The innovation model is also known as the interactive, "coupling" model, which combined a sequential process with feedback loops (Rothwell, 1994). With time, while markets became further internationalized, competition increased, and product life cycles shortened, it became clear that the pace of development was essential to stay competitive. The fourth generation (the mid-1980s) emerged and focused on integration and parallel development, and was therefore also referred to as interactive-parallel processing innovation. While traditional innovation approaches – like the popular stage-gate model – have been developed for new product development in stable and predictable environments (Cooper, 1986; Smith, 2007), organizations need to adjust to unpredictable occurrences in the face of change. Faster product life cycles, constantly changing customer needs, emerging technologies, and high uncertainties challenge organizations to exploit current competitive advantages while simultaneously exploring new potential advantages (O'Reilly and Tushman, 2011). Traditional innovation processes were often criticized as being too linear and rigid to handle more innovative and dynamic projects; thus, later research suggests a next generation innovation process should be more adaptive, flexible, agile, and accelerated (Cooper, 2014). This process consists of multiple spirals or iteration loops, allowing more experimentation with users and faster learning. Besides integrating external networks (such as suppliers) in the early phases of innovation, the innovation process can also be improved and accelerated by simultaneously aligning and integrating the activities of different functional parties (working on the innovation) in parallel rather than sequentially. Progress in information technology (IT) further developed the innovation model and induced integrated and concurrent product development. Thereby the fifth generation (2000) – e-integrated innovation – focused on integrating IT-based tools to speed up the innovation process and add more flexibility. The sixth generation (the early 2000s) – also referred to as network innovation – is seen as the latest innovation model and puts greater emphasis on networking as well as the horizontal and vertical integration of external partners via strategic collaborations along the supply chain (Ahmed and Shepherd, 2010; Tidd and Bessant, 2013). Innovation management literature further embraced open innovation approaches to foster collaboration with internal and external partners like universities, research institutes, companies from different industries, and start-ups as sources of inspiration and innovation (Chesbrough, 2003). Various agile and lean innovation formats like innovation labs, jam sessions, lean start-up camps, corporate incubators, and accelerators have evolved to spur innovation management agility and benefit from start-up thinking (Chesbrough, 2003; Fecher et al., 2020; Kohler, 2016).

Companies have experimented with diverse approaches to managing innovation processes over the years (as shown in Table 1), starting with rather rudimentary approaches and building to more sophisticated and complex innovation management systems; AI, however, may take the idea-to-launch innovation process to the next even more advanced seventh stage (Haefner et al., 2021). The next (r)evolution in innovation management and innovation process models may be AI-based and rely on the potential of AI to make innovation management more efficient and reduce risks. While systematic innovation processes provide answers to crucial questions, e.g. how we can systematically identify opportunities and realize them (Tidd et al., 2005), AI can strengthen the innovation capabilities and support current human-centered decisions to sense opportunities in the environment and predict changes (Cockburn et al., 2019). The ingredients for a breakthrough in innovation management are in place as computational power is growing notably, algorithms are becoming more available and effective, and vast quantities of data are generated every day. The following sections discuss AI-based innovation management in more detail.

2.2. AI-based innovation management

Machines powered by AI are already capable of handling many tasks today that not long ago were assumed to be "human" tasks that required human cognition. For instance, machines can identify complex patterns, synthesize information, draw conclusions, provide predictions, or execute problem-solving duties (Agrawal et al., 2019; Brynjolfsson and McAfee, 2017). Thus, we are interested in how these AI-based applications change how we innovate and allow for better and more efficient innovation management.

To frame our discussion and demonstrate how AI can improve, accelerate, or partially-autonomously conduct tasks along the idea-to-launch innovation process, we will build upon the previously discussed innovation process defined by Rogers (2003). The innovation process follows four phases, and in the following, we discuss examples of associated tasks AI could support:

(1) opportunity identification and idea generation – e.g. identifying user needs, scouting promising technologies, generating ideas;
(2) idea evaluation and selection – e.g. idea assessment, evaluation;
(3) concept and solution development – e.g. prototyping, concept testing; and
(4) commercialization launch phase – e.g. marketing, sales, pricing.

(1) Opportunity identification and idea generation phase: AI may help overcome humanity's information processing constraints in the opportunity identification and idea generation phase. AI systems use machine learning algorithms that demand and process vast amounts of data (Brynjolfsson and McAfee, 2017). They can recognize problems, opportunities, and threats above and beyond local search routines and knowledge domains, which may be helpful to discover and generate new ideas (Haefner et al., 2021). Indeed, we find several interesting applications of AI across various domains. A German manufacturer of personal care products used AI algorithms to analyze online discussion forums and extract new customer needs from almost two million posts related to body care. An American manufacturer of semiconductor chips used AI to identify potential lead users and derive key problem areas associated with their products based on their internet postings (Kakatkar et al., 2020). As the examples show, AI offers promising methods for idea and opportunity generation, especially by identifying relevant consumer needs and problems. AI provides further information to generate novel ideas in at least two different ways. In the first, smart algorithms, using extensive training data and xisting rules, supported by ever-increasing information-processing power, make it possible for AI systems to provide valuable insights to generate novel ideas by exploring solutions much more efficiently (Haefner et al., 2021). As a consequence, novel insights are generated by solving previously unsolvable problems. This is especially true in "structured" fields like biology, chemistry, materials science, and drug discovery, where previously search for solutions was very slow and expensive, as it asked for exploring vast combinatorial spaces. Probably, the most visible example of how AI provides the basis for novel ideas generation in this way is AI (i.e., machine learning) solving the "protein folding problem", one of the most significant remaining scientific challenges (DeepMind, 2020). In a second way, AI is used to create novel ideas by completing more creative tasks, such as generating original music (TNW, 2020a, 2020b); short movies (Ars Technica, 2021), and graphical designs (TNW, 2020c). For example, Nikolay Ironov, an AI-powered graphical designer, was developed by Art.Lebedev Studio (Lebedev Studio, 2020). Nikolay created several original visual identities for companies ranging from logos to entire brand identities, which were commissioned and paid for before it was disclosed that Nikolay was not a human. To generate novel ideas, a neural network needs to be trained on a dataset of text-image pairs, supplemented by applying additional algorithms that scale, smooth, and simplify the design, and generate different color schemes and fonts (TNW, 2020c). However, we are still facing constraints and downsides as the generation of novel ideas is based on decomposing existing solutions rather than on creating entirely new ideas. AI-based idea generation is still highly dependent on the context and available data.

(2) Idea evaluation and selection phase: The idea selection phase requires knowledge and experience to identify the best from a multitude of ideas. While a clear set of evaluation criteria and having trained people on the selection team are critical for idea selection, decisions are often based on limited or partial information, subject to cognitive biases and limited knowledge. Furthermore, idea selection is often dependent on network connections and highly subjective (Hofstetter et al., 2018). The HiPPO method – relying on the highest-paid person's opinion – still commonly serves as the dominant selection criteria (Lakhani, 2016). With the advent of machine learning, information processing and decision-making can be supported and in some cases even taken over by AI (Verganti et al., 2020). AI has the potential to substantially support idea selection by providing more and nonbiased information and insights. It may improve the organization's ability to select and invest in ideas that could create its next competitive advantage (Haefner et al., 2021). An American food company, for example, applied unsupervised machine learning to support the selection of best product ideas. They applied the LDA topic model to textual descriptions of solutions (i.e.,

flavor, color, taste, etc.) and further applied a supervised random forest machine learning algorithm to identify which features of the product ideas contribute to excellent evaluations (Kakatkar et al., 2020). The example shows how the advent of AI may change the way information is processed and support innovation managers in selecting ideas through an AI-based content analysis.

(3) Concept and solution development phase: The concept and solution development phase aims to develop and build ready-to-use solutions that can be brought to the market. Prototypes are built and tested to drive the new product or service through a series of validation cycles to learn and optimize its feasibility, desirability, and viability and bring it closer to commercialization. Build-measure-learn loops are commonly applied for developing, testing, and obtaining feedback when introducing new products (Ries, 2011). While feedback gathering and analyzing methods remain immensely important in the concept and solution development phase, AI provides several possibilities to learn faster and improve these experimentation cycles. Data-oriented decision-making and seamless testing have been infused into the product prototyping process with the support of AI. For example, generative design applications (Krish, 2011) based on machine learning algorithms offer benefits by providing a more comprehensive range of design options and optimizing for materials, costs and manufacturing methods. General Motors, for example, leveraged generative design and explored 150 design permutations to reduce the weight of its vehicles – making the parts 40% lighter and 20% stronger than the original components (Autodesk, 2018).

(4) Launch and implementation phase: The launch and implementation phase entails marketing, distribution, logistics, and customer-facing activities. Organizations can leverage individual customer information and AI technology to offer curated products and services (Gioia and Chittipeddi, 1991; Kumar et al., 2019). AI may help organizations gain insights from a vast number of customers and transaction data – involving numeric, text, voice, image, or facial expression data – to predict what customers are likely to buy and deploy targeted digital advertising in real-time (Davenport et al., 2019). Netflix and Amazon, just to name two examples, monitor customers' online activities and apply recommendation algorithms to individualize the service and make product recommendations about what to watch or what to buy (Antonio, 2018).

By breaking down the innovation process into various phases and constituent activities, we see how AI may affect the innovation game. However, the innovation process does not occur within a vacuum, and research indicates a range of contextual factors that may impact organizations' decisions about deploying AI-based innovation management (Ahmed and Shepherd, 2010; Rothwell, 1994; Tidd and Bessant, 2013).

2.3. The organizational setup for AI-based innovation management

Purposeful innovation management and its activities are rather complex tasks. They require consideration of a sound innovation strategy, an effective organizational structure, and dedicated people equipped with the right mindset, necessary skills, and appropriate innovation tools (Clark and Wheelwright, 1995; Roberts, 2007) Roberts (2007). defines three critical dimensions of successful innovation management: (1) skills, (2) structure, and (3) strategy. In the following, we discuss how these dimensions may be affected by AI-based innovation management.

(1) *Skills:* Attracting the right people with the needed skills and mindset is essential for every innovating organization. AI-based innovation projects need dedicated people with relevant skills and sets of expertise. Formalized expert knowledge and domain specialists with various backgrounds like data scientists, developers, or IT infrastructure engineers are means to actualize opportunities created by AI technology (Keller et al., 2019). Organizations also rely on existing staff, who need to apply the technology skillfully across innovation tasks and processes. Training to stimulate interest should target potential AI implementors with more technical backgrounds and decision-makers and employees at a larger scale. A pronounced integration of people and technology and the right managerial actions to maximize productivity are essential success factors in AI-driven innovation management (Barro and Davenport, 2019).

(2) *Structure:* Organizational structures are crucial for organizational performance since they influence organizations' ability to act and react effectively. They reflect the formal scheme of relationships, communications, decision processes, procedures, and systems and therefore facilitate the capacity of the organizations to adapt to change, learn, or innovate (Chen and Huang, 2007). Internal structures of organizations have evolved, and the most common structures are functional organizations – with hierarchical division of work between workers and their supervisors – and matrix organizations – retaining functional specialization while improving cross-functional integration (Ahmed and Shepherd, 2010). The adoption of a specific organizational structure is highly dependent on the context of the organization – the nature of the business in which an organization is engaged. Whereas functional structures are geared for high efficiency within a stable environment, matrix structures seem to better cope with uncertainty and change in dynamic markets. Organizational structures also reveal how information and knowledge are distributed within an organization, which further affects their efficiency. Decentralized organizational structures are chosen when decision-making has been disaggregated into several subunits or divisions, each making its own decisions. Contrarily, within centralized organizational structures, decisions are made at headquarters and at the level of the whole organization. With the implementation of AI-based innovation, organizations need to evaluate which type of organizational structure is suitable Christensen (1997)., for instance, argues that a rapid and effective response to major transformations in the competitive landscape may require new organizational structures and the creation of an independent business. Other scholars argue that organizations may engage in a mix of new exploratory initiatives while pursuing existing initiatives within the same structural context (Brown and Eisenhardt, 1997; Tushman and O'Reilly, 1996). Organizational structures further have to support organizational learning and innovation. Innovation networks and open innovation principles may foster collaboration with external partners and joint development of new skills and capabilities (Chesbrough, 2017; Füller et al., 2014). To facilitate AI-based innovation management, setting up devoted cross-functional teams in project matrices or venture teams, even outside the official bureaucracy of the company, may be necessary to scale innovation and ensure company growth and prosperity (Cooper, 2014; Roberts, 2007). As AI has the most significant impact when it is developed by cross-functional teams possessing mixed skills and perspectives (Fountaine et al., 2019), companies need to address the pressing challenge of integrating essential functions. In our case, potential organizational setups to embrace AI-based innovation management may include temporary decentralization and collaboration with open innovation networks with subsequent integration of new AI-based competencies.

(3) *Strategy:* An innovation strategy is needed to cope with an external environment that is complex, ever-changing, and has considerable uncertainties about present and future developments in technology, competitive threats, and market demands (Tidd and Bessant, 2013). To cope with the mentioned challenges and make innovation happen, organizations may increasingly embrace AI in their innovation strategy. Companies have to understand how AI supports value creation and how AI contributes to the overall strategy as a driving force of digital transformation (Hess et al., 2016; Kane et al., 2015). Furthermore, an organization's strategy determines its position as a leader, follower, or imitator. Therefore, organizations must determine the resources they need and how much they want to allocate to AI-based innovation management to reach their ambition. Many organizations struggle with the allocation of appropriate resources for innovation management. Research identifies three levels of innovation goals (Nagji and Tuff, 2012): (1) enhancement of organizations' core offerings, (2)

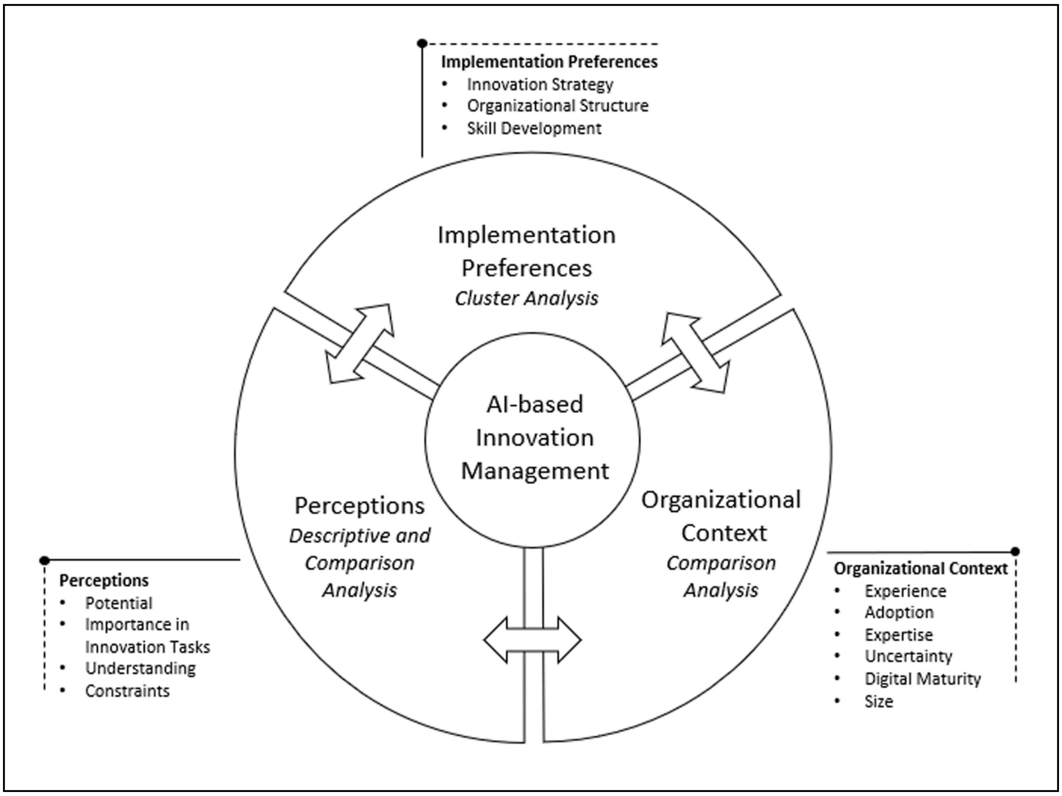

Fig. 1. Research Framework.

pursuit of adjacent opportunities, and (3) ventures into transformational, often disruptive, territory. The industrial manufacturers studied by Nagji and Tuff (2012) show a strong preference for innovating core offers (70%) complemented by a few breakouts for adjacent opportunities (20%) and only a minor share (10%) for transformational innovations. Similarly, Roberts (2007) argues that in practice, companies usually understand how to manage incremental innovations (and spend 80–90% of their tech budgets on upgrades, modifications, and extensions) but often struggle with and fail to manage more exploratory innovation. These studies show that most organizations focus on incremental innovation and allocate relatively small budgets at the transformational level, indicating rather low levels of innovation ambition. Furthermore, company structures and innovation processes are often not set up to execute transformational innovations such as AI-based technologies. Companies should think more in terms of platforms than stand-alone products and more in terms of ecosystems than isolated partnerships in order to build winning innovation strategies. In the new platform- and ecosystem-based environment, AI innovators may primarily focus on building and managing links with organizations outside their current networks but control vast amounts of data or collect them easily (e.g., hospitals, schools, city councils). At the same time, they may reinforce collaboration with start-ups (as a key to creating an efficient ecosystem and benefiting from it by accessing new tech and skills) and universities (as a way to secure access to talent and the latest knowledge). The challenges related to AI will require companies to make additional efforts to become more open towards the external environment. Nowadays, open innovation is the "new normal" rather than the exception for innovation. Innovation occurs increasingly in open ecosystems where the boundaries between organizations, customers, users, and start-ups become blurry (Nambisan et al., 2018).

Summarizing the previous discussion, we can conclude that AI's impact on the innovation process is different from that of *traditional* digital technologies. In addition to making what people already do faster and more efficient (which was the main result of the previous advancements in digital technologies), AI may allow data-driven innovation management and may even automate problem-solving, excluding humans from it (Verganti et al., 2020). Thus, the focus of innovation teams may shift from conducting certain innovation activities and designing the innovation process to designing AI-based innovation tools that assist with or even automatically conduct the innovation activities for them. This change, together with AI's power to solve previously unsolvable problems (e.g., protein folding), is why AI's impact on the innovation process may be disruptive and why AI is expected to transform the nature of innovation management. However, as highlighted above, this requires different skills, access to data, open, collaborative approaches, and shifts in strategy and the organizational setup. The impact of AI on innovation management may be on a similar magnitude to the Internet, which allowed for open innovation and innovation ecosystem approaches. Similarly, innovation management may be improved using AI-based innovation tools fed with various data sources and allow to search, analyze, and identify the most promising trends and ideas and create the most appropriate solutions.

2.4. Perceptions and organizational context

Research on information systems using an affordance theory perspective suggests that the adoption and implementation of information technologies do not solely depend on the perceived potential of the features and functions of the technology (Majchrzak and Markus, 2014), AI in our case, but also on the organization's capabilities and goals (Markus and Silver 2008), the organizational fabric (Zammuto et al., 2007) and other factors such as organizational context (Bygstad et al., 2016). Recently, the theoretical perspective focusing on individual and organizational perceptions has been used to analyze the adoption and implementation of various popular technologies ranging from Blockchain (Du et al., 2019) and Big Data analytics (Zeng et al., 2020) to AI technology (Keller et al., 2019). Therefore, we assume that intended applications and usage of AI for innovation management are not only contingent on perceived application possibilities of AI and the advantages and disadvantages that innovation managers identify, but also on organizational context, as well as previous experiences, expertise, and knowledge about AI-based technologies.

From an organizational point of view, the key challenge for innovation is to develop the most suitable process and structures that will fit the particular task and context (Tidd and Bessant, 2013). Current innovation practices propose that organizations do not automatically follow one best practice but rather adopt commonly applied models and manage their innovation processes based on the companies' specific contexts such as industry, company size, the company's stage of development, or their competitive position (Nagji and Tuff, 2012; Ortt and Van Der Duin, 2008). This is also in line with contingency theory, attributed to the fundamental assumption that there is no one best way to organize due to various internal and external factors and constraints (Ginsberg and Venkatraman, 1985; Luthans and Stewart, 1978) Volberda et al. (2012). claim that managers carefully cater to both internal and external factors to pursue operational excellence. Thus, in our research, we particularly investigate innovation managers' perceptions of how much potential they ascribe to AI technologies for their organizational context. More precisely, we investigate how innovation managers evaluate the future importance of AI applications at various innovation tasks along the idea-to-launch process and accordingly identify their AI implementation strategies. While the claims about the promise and peril of AI are abundant and growing, we also explore preferred implementation patterns of AI-based innovation management relative to organizational contexts such as company size, degree of maturity, skill sets, and AI affinity.

3. Empirical study

3.1. Research design

We assume various perceptions, affordances, constraints, and preferences regarding AI-based innovation management, depending on the context as well as organizational characteristics. Thus, we follow an exploratory and inductive research approach which is useful to generate a rich understanding of new phenomena such as AI-based innovation management (Cockburn et al., 2019), where our knowledge is still limited and where it is difficult to come up with up-front propositions or research hypotheses (Christensen, 2006; Faems, 2020; Jebb et al., 2017; Spector et al., 2014). Nevertheless, our research framework is clearly guided by theoretical insights from innovation management literature, affordance and contingency theory.

Our research framework (Fig. 1) consists of three key domains: (1) perceptions – to determine the perceived potential to improve innovation performance through AI-based methods and the importance of AI for various innovation tasks, as well as the current understanding of the impact of AI-based innovation management and perceived barriers and challenges in the innovation units; (2) implementation preferences – to learn more about what role AI plays in the innovation strategy and organizational setup, to measure the investments and resource allocations and identify preferred approaches on skill development; and (3) organizational context – to capture the experience with AI in general, the adoption of AI-based innovation management, the AI expertise in the innovation unit, and the related uncertainty, as well as more general information such as the organizations' digital maturity, size, and industry. Within this framework, we seek to explore the current usage of AI in innovation management, different implementation preferences, and differences among organizational and contextual configurations by reaching out to AI-savvy innovation managers using a quantitative online survey.

In this context, Faems (2020) argues that quantitative data can be a viable source for inductively deriving insights into emerging innovation phenomena and highlights cluster analysis as a promising method in this endeavor. As an inductive approach, cluster analysis determines common patterns in samples where we do not know if and how many groups exist prior to the analysis (Afifi et al., 2003). For researchers in strategic management and management of information systems, it presents a valuable tool to unravel natural groupings and configurations in a research sample given a rigorous implementation of the method and theoretical justification of the solutions (Balijepally et al., 2011; Ketchen and Shook, 1996). Previously, several exploratory studies in the field of innovation management applied cluster analyses to quantitative survey data. Based on innovation-related factors, Hollenstein (2003) grouped firms into different innovation modes and compared the characteristics of the configurations Gruber et al. (2010). identified clusters within technology ventures that deploy different resources and capabilities Block et al. (2015). revealed distinct trademarking motive clusters and investigated their characteristics in a comparison analysis Verbano et al. (2015). explored distinguished open innovation profiles and analyzed them in terms of determinants, performance, contextual factors, barriers, and motivations.

Before designing the survey, we conducted semi-structured interviews with eleven innovation managers working in AI-related fields. The interviewees covered a broad range of AI-expertise and covered CEOs, department heads, innovation managers, and IT experts in the fields of AI-based recruitment, health care, and finance, as well as Conversational AI, Emotional AI, computer vision, and applied-AI consultancy. The purpose of the interviews was two-fold: on the one hand, the explorative character of the interviews enabled us to gain a first impression of how innovation managers think about AI for innovation; and on the other hand, the semi-structured interviews allowed us to reflect on the applied theory with insights from practical experiences and helped us to refine and test questions and items used for the subsequent online survey. All constructs and items we applied to operationalize our framework were either derived and adopted from previous studies or inspired by our interviews.

3.2. Measures

3.2.1. Perceptions

To capture the perceived potential of AI for innovation management applications, we derived seven items from Wilson and Daugherty (2018) and asked managers to evaluate the expected improvement in innovation outcome, innovation process, speed of development cycle, diffusion and scalability of innovations, operational flexibility, decision-making, the individual fit of products and services, and cost management on a scale from 0% to 100%. Based on previous literature on stages of the new product development process (Bartl et al., 2012; Keum and See, 2017; Roberts and Frohman, 1978), we measured the expected importance of AI in eight tasks along the idea-to-launch process – need and trend identification, technology scouting, idea generation, idea selection, concept development, generative design, prototyping, and marketing. To account for the ongoing discussion about the superiority of machines relative to humans in specific task types, recognized in our interviews as well as in literature (e.g Agrawal et al., 2017.), we asked the participants in which skills - analytics, administration, esthetic sensibilities/design, creativity, empathy, experimentation, intuition, social and people skills – machines will outperform humans or vice versa in the next five to ten years. The understanding of AI and its implication for change with respect to innovation dynamics, data requirements, innovation strategy, organizational structure, and skills was measured with five items adopted from Kane et al. (2015). We also included seven items out of the interviews dealing with organizational challenges on the ability to integrate AI for innovation and adapted five items from Bughin et al. (2018) to assess the specific challenges associated with data and AI algorithms.

3.2.2. Implementation preferences

Concerning innovation strategy, to quantity financial commitment to the transformational efforts related to AI (Nagji and Tuff, 2012), we

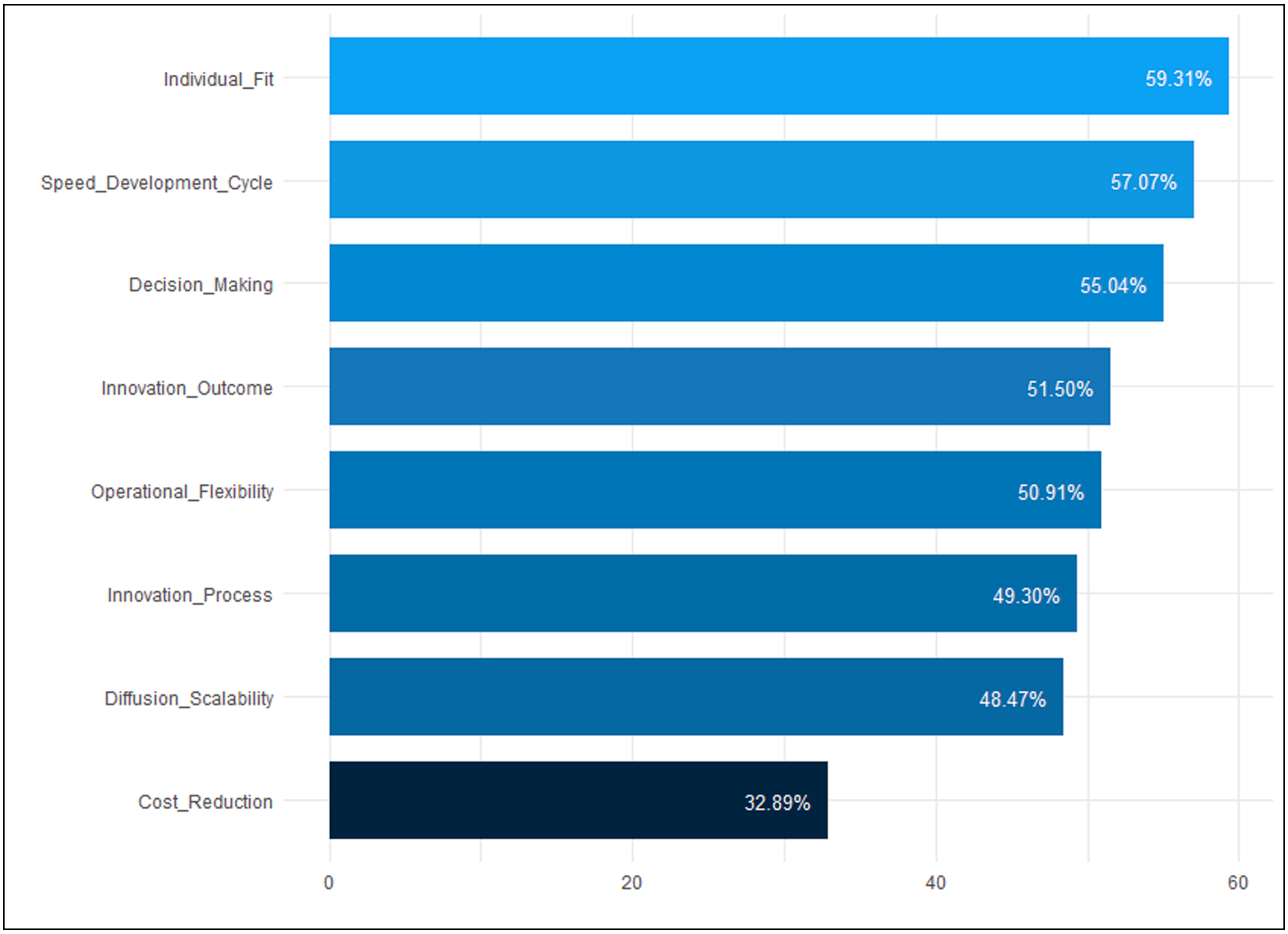

Fig. 2. Perceived Potential of AI-based Innovation Management "I expect that AI will improve … by …% within the next five to ten years."Perceived importance in innovation tasks.

asked for the percentage spending of the innovation budget (0–100%). We established an item referring to intellectual property management to learn if more protective or more collaborative approaches are chosen in dealing with new ideas and solutions for AI-based innovation management (Manzini and Lazzarotti, 2016). Two items in line with the literature by O'Reilly and Tushman (2011) were derived to measure strategic priorities in terms of exploration and exploitation.

Concerning organizational structure, we asked about the extent of integration of the AI initiatives (Ransbotham et al., 2018) and the chosen organizations' structure to set up AI initiatives, and derived semantic differentials of decentralized vs. centralized (Roberts, 2007) and existing vs. new-built structures (Fountaine et al., 2019). We also measured the relevance of open innovation and open source approaches (Chesbrough, 2003; von Hippel and von Krogh, 2006) to implementing AI in innovation management.

Concerning skill development, we measured the investment in training for the existing staff and hiring of AI talent by adapting five items suggested by Ransbotham et al. (2019). Further, we modified two items from MIT SMR Connections (2019) to quantify the extent of AI development to improve innovation performance and summarized four items to measure the extent of collaboration with external partners in the innovation ecosystem such as companies, universities, start-ups or innovation hubs in the AI context (Fecher et al., 2020; Kohler, 2016; Nambisan and Baron, 2013).

3.2.3. Organizational context

AI experience and adoption of AI-based innovation methods were measured with two items adopted from Ransbotham et al. (2017), while the level of AI expertise and uncertainty in the orientation towards AI-based innovation management were derived from the preliminary interviews with the innovation managers. Digital maturity was split into early stage, in development and mature stage (three-point Likert), adopted from Kane et al. (2017). Company size was measured by the indicated revenue in the previous fiscal year (seven-point Likert, e.g., 1 < €100 million, 7 > €25 billion) (Ransbotham et al., 2017).

Unless otherwise noted, we applied five-point Likert scale types, (1) "strongly agree/not important" and (5) "strongly disagree/very important", within our survey. We used multiple-item measures and single-item measures in our study. Single-item measures can be both reliable and valid when a measured construct is concrete and one-dimensional, the semantic redundancy of multi-items would be high, the sampled population is diverse, and the sample size is limited (Bergkvist and Rossiter, 2007; Fuchs and Diamantopoulos, 2009) Table A.1. (Appendix A) and Table B.1 (Appendix B) show all items and constructs applied in the online survey with measures from exploratory factor analysis. The measured constructs meet the required quality standards in terms of reliability and validity. Before we reached out to our survey sample, we checked the questionnaire for comprehensibility and meaningfulness with 5 innovation managers and adapted it.

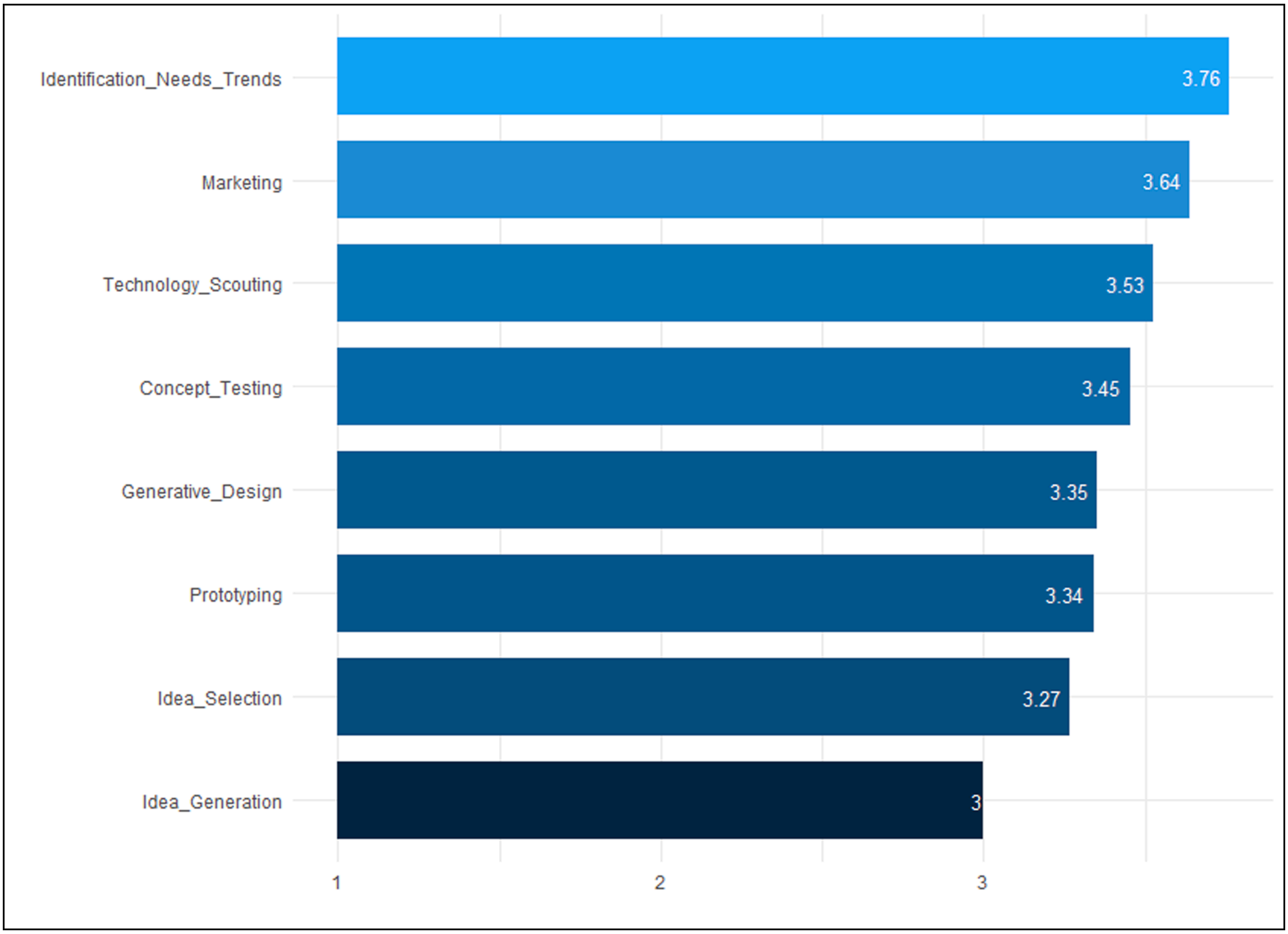

Fig. 3. Importance of AI-based Methods in Innovation Tasks "Please evaluate the importance of AI within the following innovation tasks for the next 5–10 years." 1=not
important, 5=very important on a 5-Point Likert.

3.3. Sample description

For data collection, E-mails with a link to the online survey were sent to innovation managers ranging from publicly listed to medium-sized organizations. 195 managers accessed our survey, of which 150 managers also completed the survey and form the basis for our analysis. The mean responses of the participants that did not go through the whole survey do not deviate significantly in terms of responses from the others who completed the survey. Concerns of missing data due to unfinished surveys are similar to issues of nonresponse bias in the data collection process (Hair et al., 2014). Thus, it may be a sign for no or only low nonresponse bias in our sample (Armstrong and Overton, 1977).

The responding managers represent mostly medium to large-sized organizations. While the majority of the respondents (47.3%) indicated a revenue below €250 million in the last fiscal year, our sample also contains a substantial number of larger-sized companies with revenue above €1 billion (41.1%). Further, our sample covers a wide range of industries including media and telecommunications, professional services, financial services, consumer goods, industrial, healthcare, energy, and the public sector. Most respondents were from the industrial sector (29.9%), followed by professional services (22.2%) and media and telecommunications (18.8%). Almost half of the responding managers (46%) work in top-level management positions (e.g., C-level executives, president, VP), and around a third (30.9%) are in middle management positions (e.g., business unit managers, department heads). The vast majority of participants regard innovation as important or very important in their current job position (81.4%). The managers were predominantly male (82.7%) with a median age of 46 years.

4. Findings

4.1. Status Quo

Concerning the status quo of AI for innovation, we find that a clear majority of the 150 responding managers already have some experience applying AI in their overall business operations (n = 95; 63.3%), and another substantial share of organizations plan to use it in the near future (n = 47; 31.3%). Only a small share of them indicated that their organization has no experience and no plans at all to deal with AI technology in their overall business operations (n = 8; 5.3%). When specifically asked about the application of AI in innovation management, almost a quarter stated that they incorporated the technology into their innovation processes and offerings (n = 34; 22.7%). Another quarter of them have already tested it in one or more pilots (n = 39; 26%), and more than a third of the organizations plan to adopt AI-based innovation management in the near future (n = 60; 40%), while only a minority indicated they have no plans to apply it at all (n = 17; 11.3%).

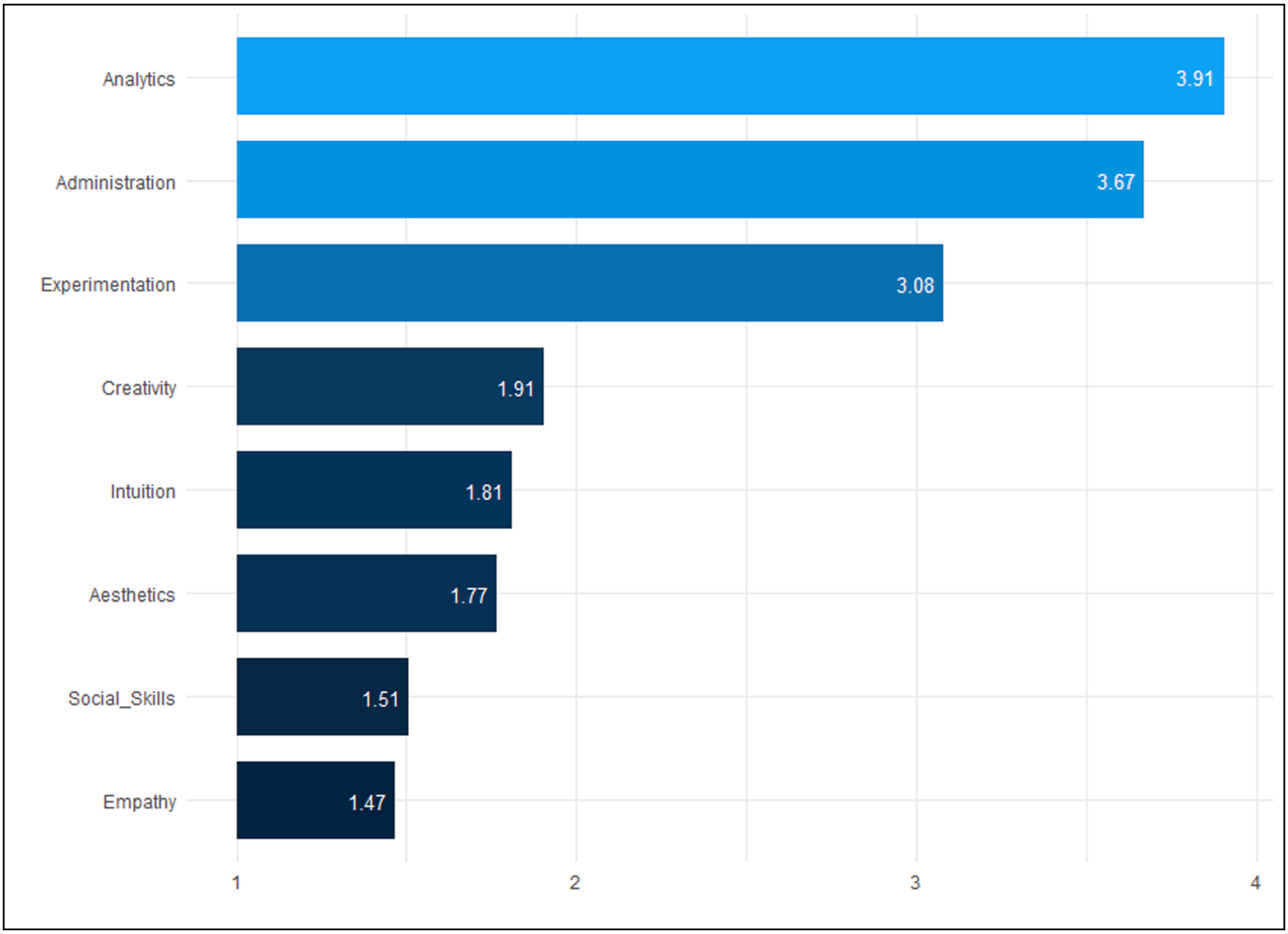

Fig. 4. Human vs. AI Skills, Within the next 5–10 years, which skills do you see humans and which skills do you see machines better at in the innovation unit? 1=Humans with better skills, 5= Machines with better skills on a 5-Point Likert.

4.2. *Perception of AI for innovation*

4.2.1. *Perceived potential*

When focusing on the perceived potential of AI-based innovation management, managers expect the biggest improvements through an increased fit with more individualized products and services (by 59.31%; SD=26.74), as well as faster development cycles (by 57.07% faster; SD=26.45) and more accurate decision-making processes (by 55.04%; SD=27.93) within the next five to ten years (Fig. 2). The participants assume that AI-based innovation methods may significantly contribute to the effectiveness of innovation management by improving the innovation outcome (by 51.5%; SD=24.46) and operational flexibility (by 50.91%; SD=28.84). Further, AI may also contribute to the efficiency of innovation management by increasing the scalability of innovations (by 48.47%; SD=26.65) and reducing costs (by 32.9%; SD=21.33).

When focusing on importance along the idea-to-launch innovation process, the application of AI for the identification of needs and trends (mean=3.76; SD=1.16) is expected to be most important in the next five to ten years, followed by marketing (mean=3.64; SD=1.15) and technology scouting (mean=3.53; SD=1.15), which are expected to be the second and third most important tasks along an AI-based innovation process (Fig. 3). The technology is perceived as relatively less important for idea generation (mean=3; SD=1.04) and idea selection (mean=3.27; SD=1.05). The results shown in Fig. 4 indicate that machines are expected to outperform humans in analytical tasks by the most (mean=3.91; SD=1.05) – followed by administration (mean=3.67; SD=1.19) and experimentation (mean=3.08; SD=1.13) – while other relevant skills like creativity (mean=1.91; SD=0.85) or intuition (mean=1.81; SD=1.03) are perceived to be better implemented by humans. These results are well aligned with the previously discussed finding that AI is estimated to be most important in analytical tasks, such as the identification of needs and trends, technology scouting or marketing, and least important in the generation of ideas where a fair share of creativity and intuition is required. Overall, compared to the perception of AI's importance in specific tasks, clear differences can be observed between lower and higher rated item categories.

4.3. *Implementation preferences for AI-based innovation*

Along with the expected potential and relevance of AI for different innovation tasks, we are also interested in the kind of implementation preferences that organizations aim for. We explore implementation preferences along the following three dimensions: (1) strategy – represented by the budget, intellectual property management approach, and exploration and exploitation focus for AI-based innovation management; (2) organizational structure – represented by the integration of AI initiatives, project structures, locus of responsibilities, and innovation culture for AI-based innovation management; and (3) skill development – represented by the investment in training, investment in hiring, internal technology development, and external collaboration to enable AI-based innovation management.

Table 2
Implementation preferences of AI-based innovators.

		Cluster 1:**AI-Occasional*n* = 40**	Cluster 2:**AI-Practitioner*n* = 41**	Cluster 3:**AI-Frontrunner*n* = 52**
Strategy	**Budget**	Low	Medium	High
	IP Management	Mixed	Collaborative	Protective
	Exploration	Low	High	Medium
	Exploitation	Low	High	Medium
Structure	**Integration**	Separated	Connected	Tightly integrated
	Project Structures	Existing	Mixed	New
	Locus Responsibilities	Mixed	Mixed	Mixed
	Innovation Culture	Closed	Open	Mixed
Skills	**Investment Training**	Low	Low	High
	Investment Hiring	Low	Low	High
	Technology Development	Low	Medium	High
	External Collaboration	Low	High	High

4.3.1. *Cluster analysis*

In this study, we cluster participants in our survey representing their organizations to identify differences in preferred implementation patterns for AI-based innovation management. In doing so, we aim to identify the most distinctive but still parsimonious number of groups who share similar configurations within the group but are different across the groups. We consider the organizations that have already adopted AI for innovation management or plan to do so in the near future "AI-based innovators" ($n = 133$; 88.7%). The ones that have not adopted AI for innovation management and do not plan to do so in the future we call "Non-AI innovators" ($n = 17$; 11.3%). In the cluster analysis, we exclude the latter and aim to explore similarities and differences among the 133 AI-based innovators.

4.3.2. *Clustering procedure*

We adopt a two-stage clustering approach using hierarchical and non-hierarchical methods in tandem as recommended in the literature (Balijepally et al., 2011; Hair et al., 2014; Punj and Stewart, 1983). In the first step, we deployed a hierarchical clustering based on Ward's minimum variance method with the Euclidean distance as the similarity measure. We used standardized values to control for the different scales in the set of cluster variables and considered several stopping rules for finding the optimal number of clusters. The results indicated a two-,

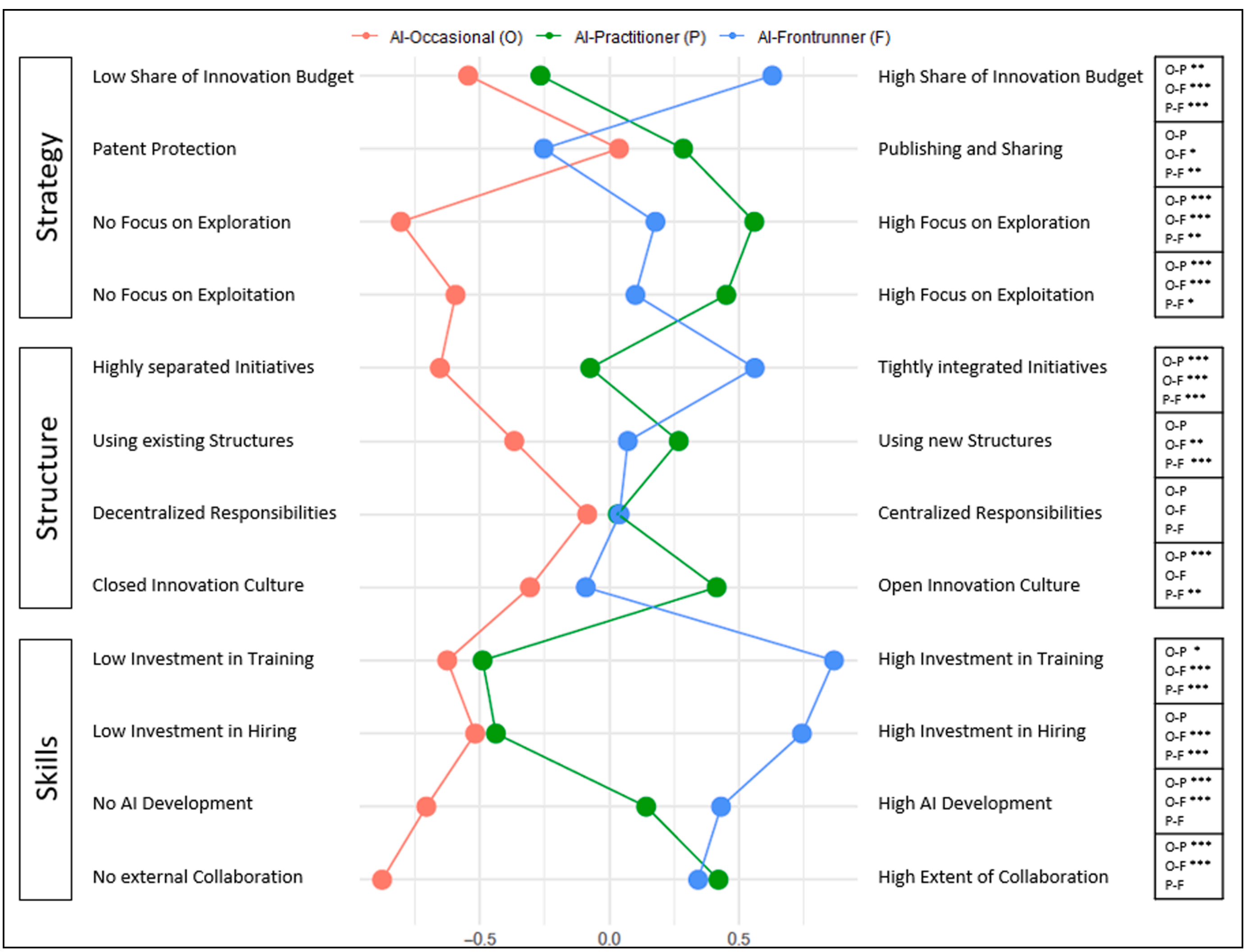

Fig. 5. AI Implementation Cluster Graph of AI-based Innovators,[11] Significant pairwise differences two-tailed Wilcoxon-Test: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

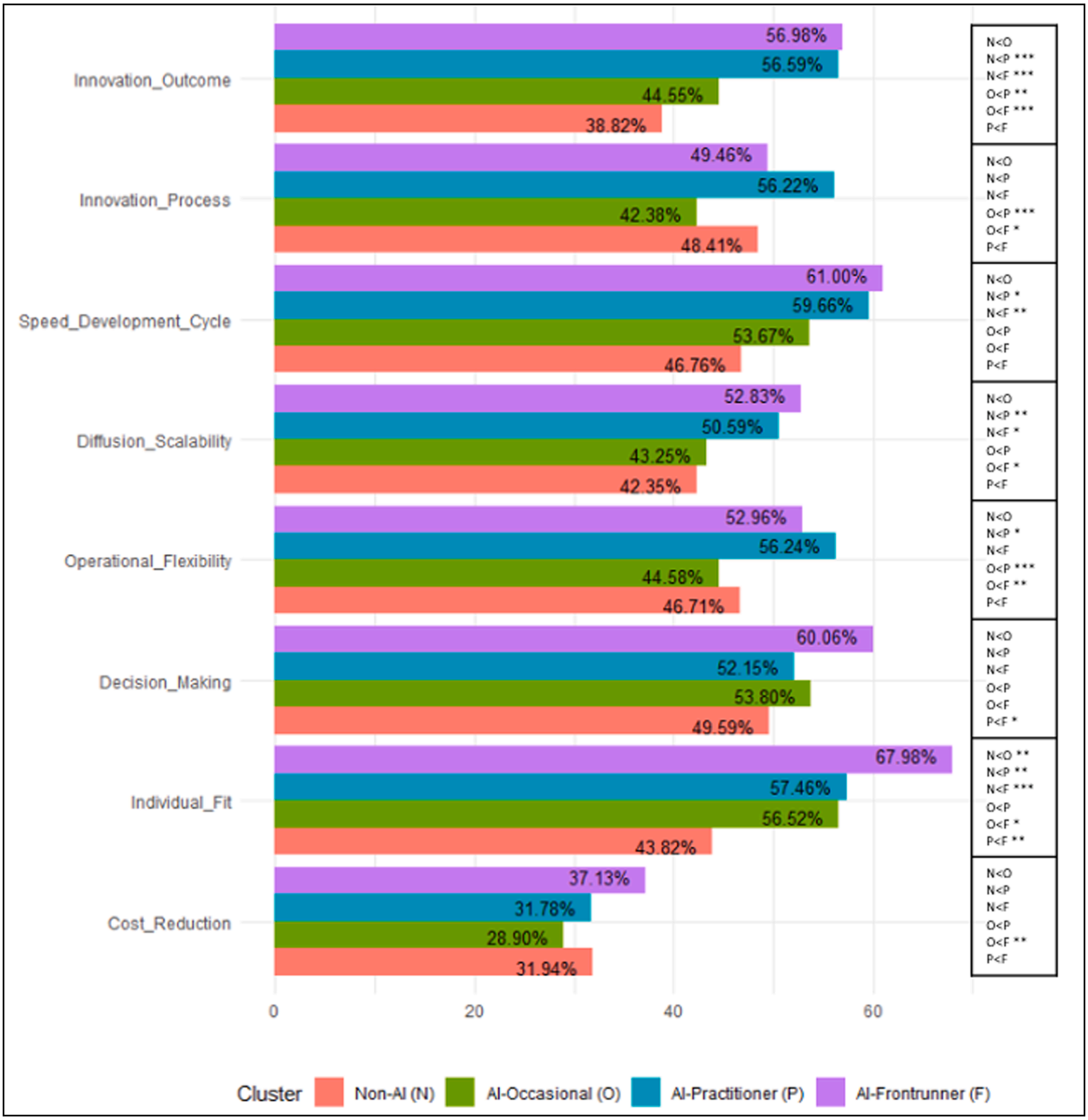

Fig. 6. Perceived Potential of AI-based Innovation Management across Clusters, "I expect that AI will improve … by …% within the next five to ten years." Significant pairwise differences one-tailed Wilcoxon-Test: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

three- and four cluster solution as most appropriate.[2] Thus, in a second step, we performed a non-hierarchical k-means analysis on clusters between two and four groups and evaluated the different groupings from a practical and conceptual perspective (Hair et al., 2014). For each iterative k-means analysis (Hartigan and Wong, 1979), we employed the centroids of the initial hierarchical cluster solutions as a starting point. Finally, we selected the three-cluster solution as the best fitting option in terms of meaningfulness, distinctiveness, and parsimony of the revealed patterns (Hair et al., 2014; Hambrick, 1983). In the process, we verified the stability of our solution using other clustering algorithms. To check the reliability of our cluster solution, we randomly split our sample into two halves and analyzed them separately, yielding consistent results (Balijepally et al., 2011; Hair et al., 2014).

Fig. 4 illustrates the emerging implementation preferences in the three cluster groups, which we labeled as AI-Occasional innovators, AI-Practitioners, and AI-Frontrunners. The labeling orientates on the mean values of the cluster variables and tries to summarize the main characteristics of the different implementation preferences. The cluster means in the three groups significantly differ in eleven out of twelve cluster variables (all except for centrality of responsibilities). The pairwise contrast values between the identified clusters are shown in Fig. 4 Table 2. further highlights the differences and similarities among AI-Frontrunners, AI-Practitioners, and AI-Occasional innovators. In the following, we characterize and describe the implementation preferences of these groups in more detail.

[1] To transform the values of clustering variables that were measured with different scales into a comparable scale, they were centered and normalized before the k-means clustering.

[2] From 23 indices calculated using the *NbClust* package in R (Charrad et al., 2014) seven indicated a two-cluster solution and five each a three-cluster solution and four-cluster solution as the optimal number. However, no criteria is found to be better than others in all situations (Balijepally et al., 2011).

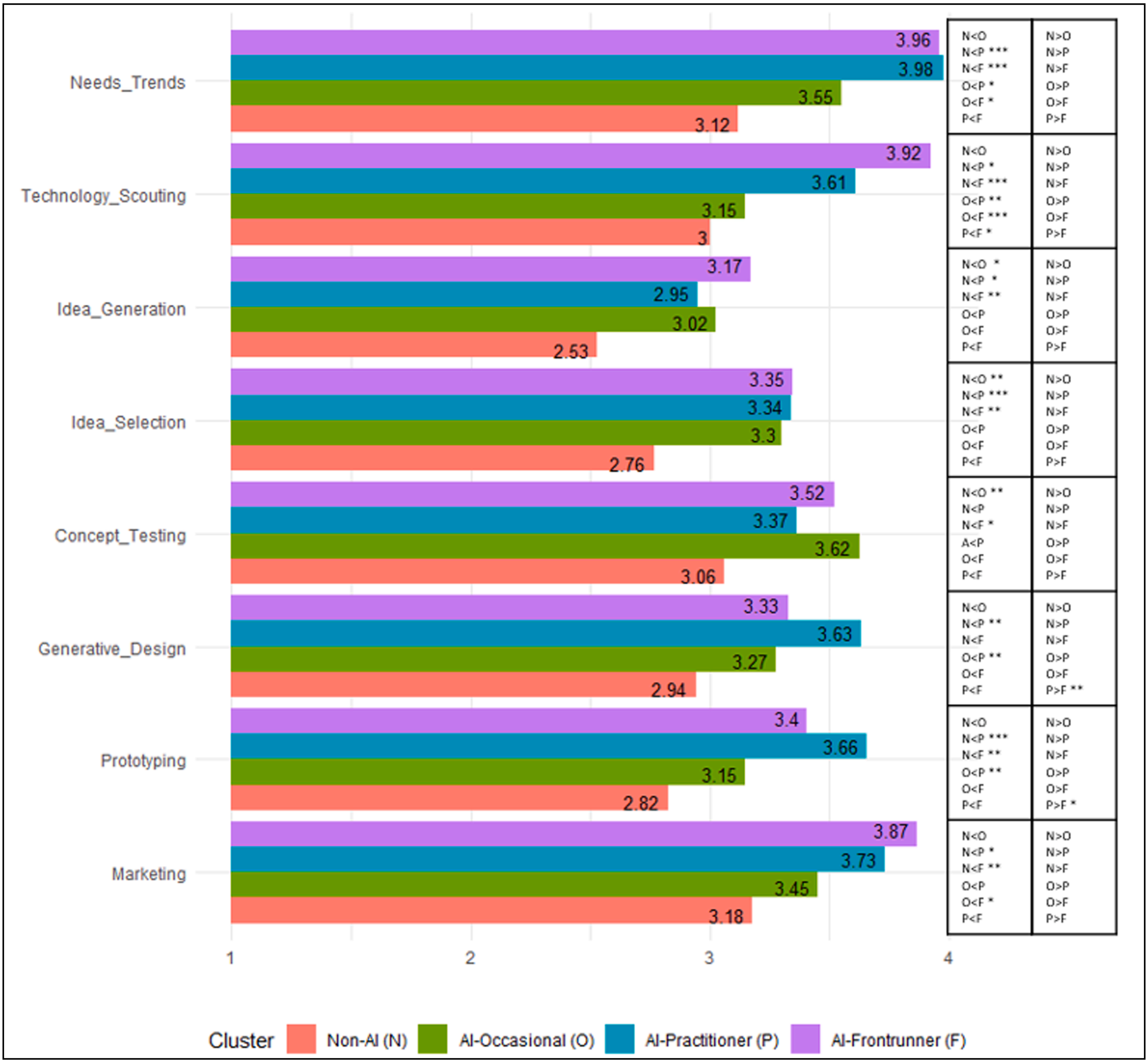

Fig. 7. Relevance of AI in Innovation Tasks across Clusters, "Please evaluate the importance of AI within the following innovation tasks for the next 5–10 years." 1=not important, 5=very important on a 5-Point Likert, Significant pairwise differences one-tailed Wilcoxon-Test: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3.3. *AI-Occasional innovators*

The organizations in the first cluster ($n = 40$) are taking a tentative implementation approach and thus far refrain from making any commitments towards AI-based innovation management. Compared to the other two clusters, they follow a minimum-effort approach with respect to the relevance of AI-based innovation management, reflected in their strategy, organizational structure, and skill development. If at all, they may rely on occasional AI-based innovation pilot projects to experiment with and get familiar with the application of AI technologies for innovation management. Thus, in the following, we use the notion of "AI-Occasional innovators" to refer to organizations assigned to this cluster group.

AI-Occasional innovators currently dedicate a low share of their innovation budget to AI. They pursue a mixed approach of managing intellectual property and navigate between protection through patents and sharing their solutions with others. Open innovation practices and collaborations with partners in the area of AI are rather uncommon. AI-Occasional innovators consider existing and project-based organizational structures as appropriate to match their current ambitions in AI-based management, which has not been anchored in their innovation strategy yet. Thus, it is not surprising that detecting new opportunities for innovation or improving existing processes with the help of AI technology are not appealing to them at the moment. Since they do not have the corresponding skills themselves and do not intend to make large investments in hiring AI talent or training of the existing workforce, it makes sense for them to wait for the opportunities that may arise in the respective areas rather than to control AI centrally in more integrated ways.

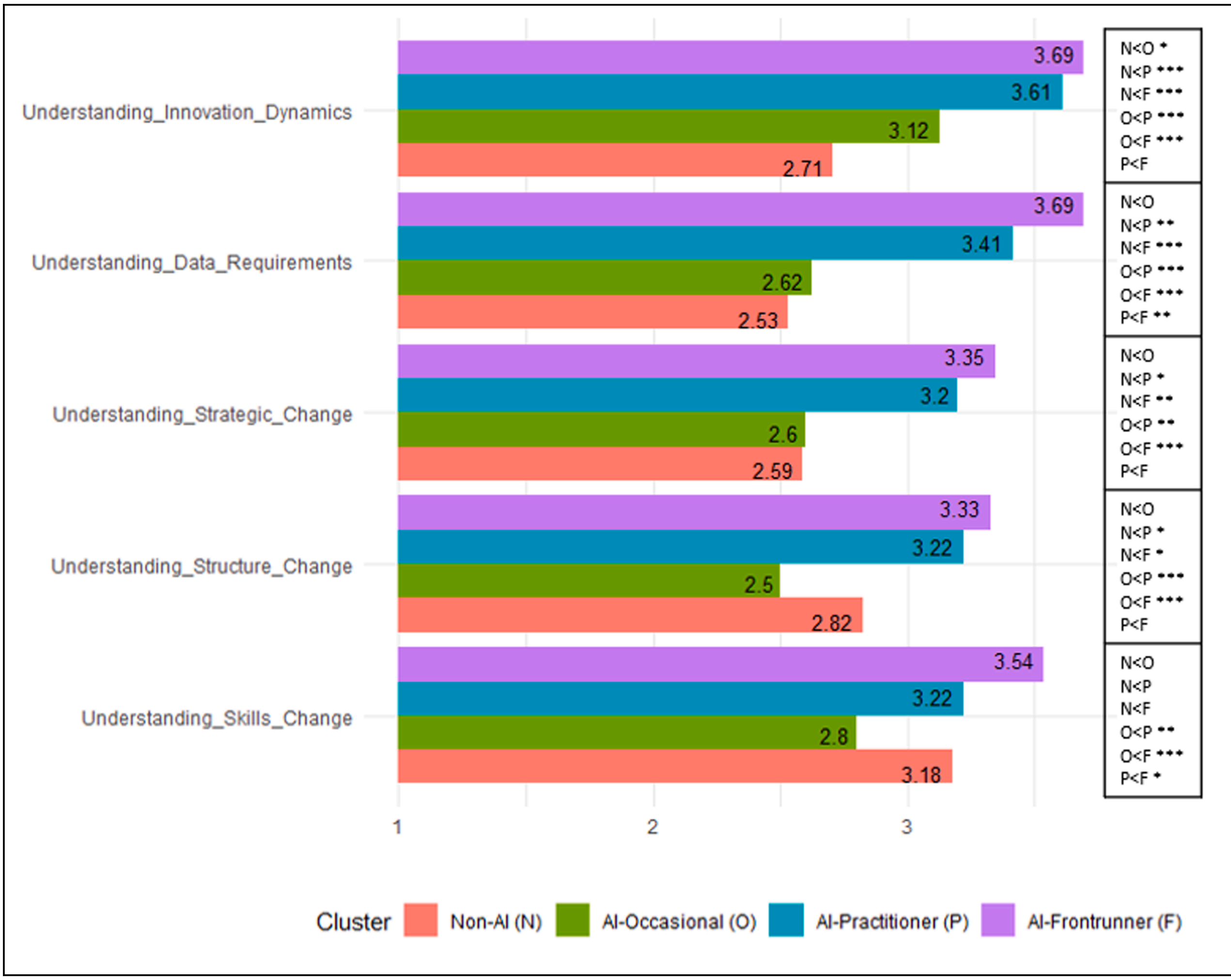

Fig. 8. Understanding of Impact and required Change across Clusters, "We understand…" 1=strongly disagree, 5=strongly agree on a 5-Point Likert, Significant pairwise differences one-tailed Wilcoxon-Test: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3.4. AI-Practitioners

The organizations in the second cluster ($n = 41$) are taking a pragmatic AI implementation approach and trying to achieve solid effects with limited resources. Instead of building up all of the knowledge themselves, they want to apply existing knowledge, routines, and methods. They rely on external collaborations to spur their AI-based innovation practice instead of building up the in-house capabilities necessary to become real experts. Thus, we call them "AI-Practitioners".

AI-Practitioners exceed the sporadic attempts of AI-Occasional innovators but are far away from systematic, scalable, and investment-intensive efforts in AI-based innovation management. Their share of the innovation budget assigned to AI – a proxy of strategic commitment – is at an intermediate level. However, they seem to be excited about discovering practical use cases and follow a highly ambidextrous approach by balancing the exploration of new innovation opportunities and the exploitation of existent processes based on AI. With respect to intellectual property rights when applying AI in the innovation context, they favor the most open and collaborative approach, characterized by publishing and sharing new ideas. Their efforts are well connected and tend to be project-oriented by combining existing and new structures. The pragmatic approach of AI-Practitioners is also reflected in their limited investment in the training of existing staff, as well as the limited ambition of hiring new AI talents from outside. Instead of building up their own internal capabilities, they engage in collaborations with external partners and use open innovation methods in the context of AI. AI-Practitioners can develop some AI technology themselves, even if only sporadically, which points to their ambition to become savvy users of AI-based solutions.

4.3.5. AI-Frontrunners

The organizations in the third cluster ($n = 52$) are taking the most progressive implementation approach towards AI-based innovation management. It seems that they have already discovered use cases and innovation opportunities to implement AI solutions and are making bolder moves in applying and scaling AI for innovation management. Thus, we use the notion of "AI-Frontrunners" when referring to organizations assigned to this implementation cluster.

AI-Frontrunners pursue an AI-dominant innovation strategy by investing substantial amounts of their innovation budget into AI technology. They are eager to avoid their solutions being implemented by

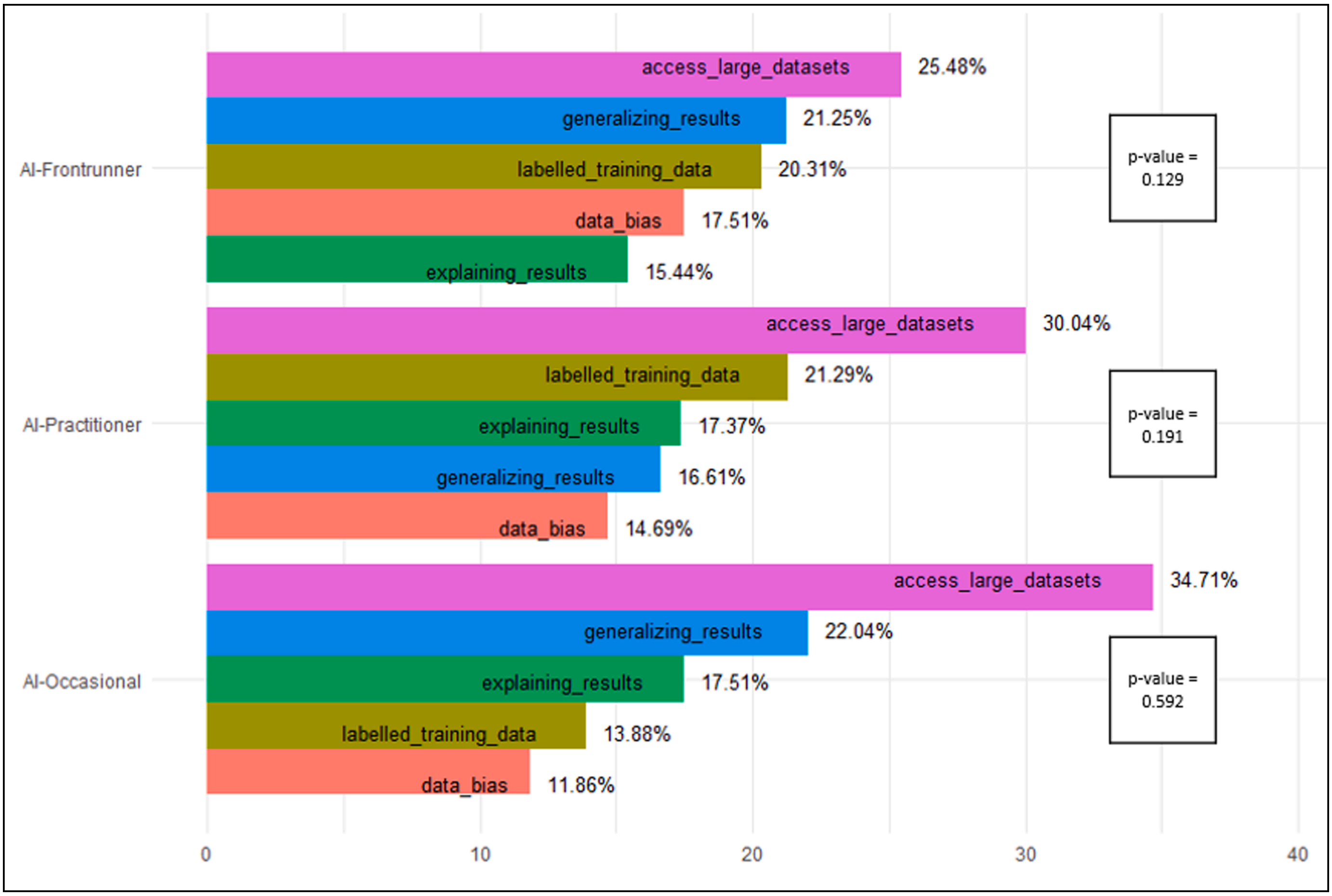

Fig. 9. Ranked Data Constraints across Clusters, "What are the biggest limitations on the ability to apply AI algorithms in the context of innovation? Assign a total of 100 Points"; significant difference Kruskal-Wallis-Test: *** $p < 0.01$, **, $p < 0.05$, * $p < 0.1$.

competitors and therefore manage their intellectual property much more protectively than AI-Practitioners. AI-Frontrunners are interested in exploring new opportunities to come up with new business models, and equally try to exploit existing products and business models by applying AI technology. They prefer new organizational structures for their AI initiatives and complement them with open innovation practices from time to time. AI-Frontrunners anchor and systematize AI in their innovation management by setting up a long-term sustainable infrastructure and invigorating platforms for experimentation with AI algorithms. To build up new capabilities, they follow a dual approach in staffing and skill-building by heavily investing in hiring external experts as well as in the training of the internal workforce. While external collaboration with AI partners is highly appreciated, they develop their own AI capabilities and solutions.

4.4. Cluster comparison – from AI-Frontrunners to non-AI innovators

In the next step, we conducted a comparative analysis to assess whether the four identified groups – AI-Frontrunners, AI-Practitioners, and AI-Occasional Innovators revealed in the cluster analysis as well as the group of Non-AI innovators - differ in their perceptions of the potential and importance of the technology in their innovation units, the understanding of its impact, and challenges related to AI-based innovation management, as well as in their organizational context. Unless otherwise noted, in the comparative analysis, we applied Wilcoxon rank sum tests to identify the pairwise difference in the selected dimensions among the cluster groups, as the normality assumption of residuals was not reached (Hair et al., 2014).

4.4.1. Perceived potential

Overall, all four groups see meaningful potential for innovation management through the application of AI (Fig. 6). While the means of the cluster groups do not differ significantly in all dimensions, the overall tendency that AI-Frontrunners and AI-Practitioners see the highest potential is pretty clear and strong. AI-Frontrunners are particularly excited about opportunities to increase the individual fit of products and services (F: 67.98% - P: 57.46% **, O: 56.52% **, N: 43.82% ***)[3] and make better decisions (F: 60.06% - P: 52.15% *, O: 53.80%, N: 49.59%), where they see significantly more improvement potential than all of the other groups. AI-Practitioners perceive a particularly high potential to increase the speed of the development cycle (P: 59.66% - F: 61.00%, O: 53.67%, N: 46.76% *) and create more flexible operations in their innovation units (P: 56.24% - F: 52.96%, O: 43.25% ***, N: 46.71% *). Interestingly, Non-AI innovators also see substantial potential in the technology at quite similar levels as AI-Occasional Innovators.

[3] F = mean of AI-Frontrunners, P = mean of AI-Practitioners, O = mean of AI-Occasional innovators; significant pairwise differences one-tailed Wilcoxon-Test: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

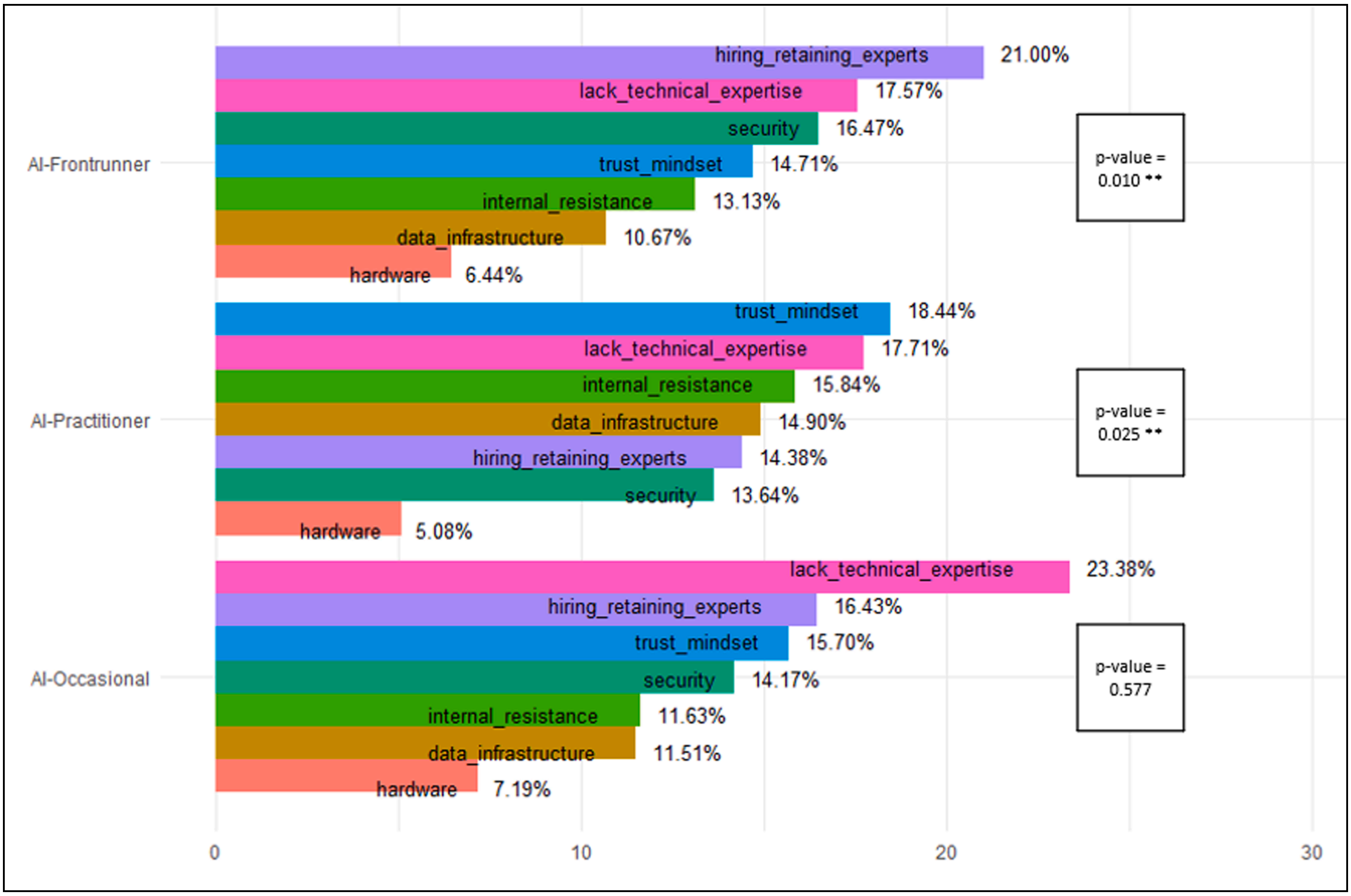

Fig. 10. Ranked Organizational Constraints across Clusters, "Please specify general organizational challenges on the ability to integrate AI for innovation. Assign a total of 100 Points."; significant difference Kruskal-Wallis-Test: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.4.2. Perceived importance in innovation tasks

The analysis also reveals differences in the perceived importance of AI in the eight innovation tasks along the innovation process – need and trend identification, technology scouting, idea generation, idea selection, concept development, generative design, prototyping, and marketing (Fig. 7). Overall, AI-Frontrunners and AI-Practitioners consider the application of AI technologies to their innovation tasks as most important. Not surprisingly, Non-AI innovators perceive the lowest importance of AI in all innovation tasks. Compared to the other cluster groups, AI-Frontrunners see more importance in analytical tasks like searching for new technologies (F: 3.92 – P: 3.61 *, O: 3.15 ***, N: 3.00 **) or marketing (F: 3.87 – P: 3.73, O: 3.45 *, N: 3.18 **). Interestingly, the expectations of AI-Practitioners significantly exceed those of AI-Frontrunners in the experimentation-oriented tasks of automatized generation of designs (P: 3.63 – F: 3.33 **, O: 3.27, N: 2.94) and prototyping (P: 3.66 – F: 3.45 *, O: 3.15, N: 2.82).

4.4.3. Perceived understanding

The results in Fig. 8 indicate that AI-Frontrunners and AI-Practitioners seem to know best how AI will impact the processes in their innovation units, even though the understanding of the former exceeds that of the latter in all five dimensions considered – understanding of the AI-related shift in innovation dynamics, data requirements and AI-related change in innovation strategy, organizational structure, and skills. Most prominently, compared to all other groups, AI-Frontrunners have a significantly better understanding of the essential need for data required to train AI algorithms (F: 3.69 – P: 3.41 **, O: 2.62 ***, N: 2.53 ***). While the understanding of AI-Occasional innovators clearly lags behind the two more advanced cluster groups in all five aspects, it is notable that their understanding of the impact of AI-based innovation management also tends to fall behind those of Non-AI innovators with respect to understanding AI-related change in the organization structure (O: 2.50vs. N: 2.82) and the impact on job roles and necessary skills (O: 2.80vs. N: 3.18). These results suggest that Non-AI innovators are well aware of the required change in structure and skills but may doubt the feasibility of implementation in their company and, thus, decided not to engage in AI-based innovation.

4.4.4. Perceived constraints

Along with constraints concerning data and algorithms – which are central to building useful machine learning models and eventually achieving superior performance in innovation tasks – organizational challenges arise when AI-based innovators try to find the appropriate setup for their innovation management. Overall, the comparative analysis[4] reveals that the different groups of AI-based Innovators seem to agree more on the relative severity of data challenges than on the ranking of limitations on the organizational level, which is more heterogeneous (Figs. 9 and 10).

Out of the five data challenges discussed – labeled training data, access to datasets, explaining results, generalizing results, and risk of bias - access to sufficiently large datasets to empower machine learning

[4] As Non-AI innovators do not even plan to engage in AI-based innovation management, they are excluded from the comparative analysis of encountered data and organizational challenges.

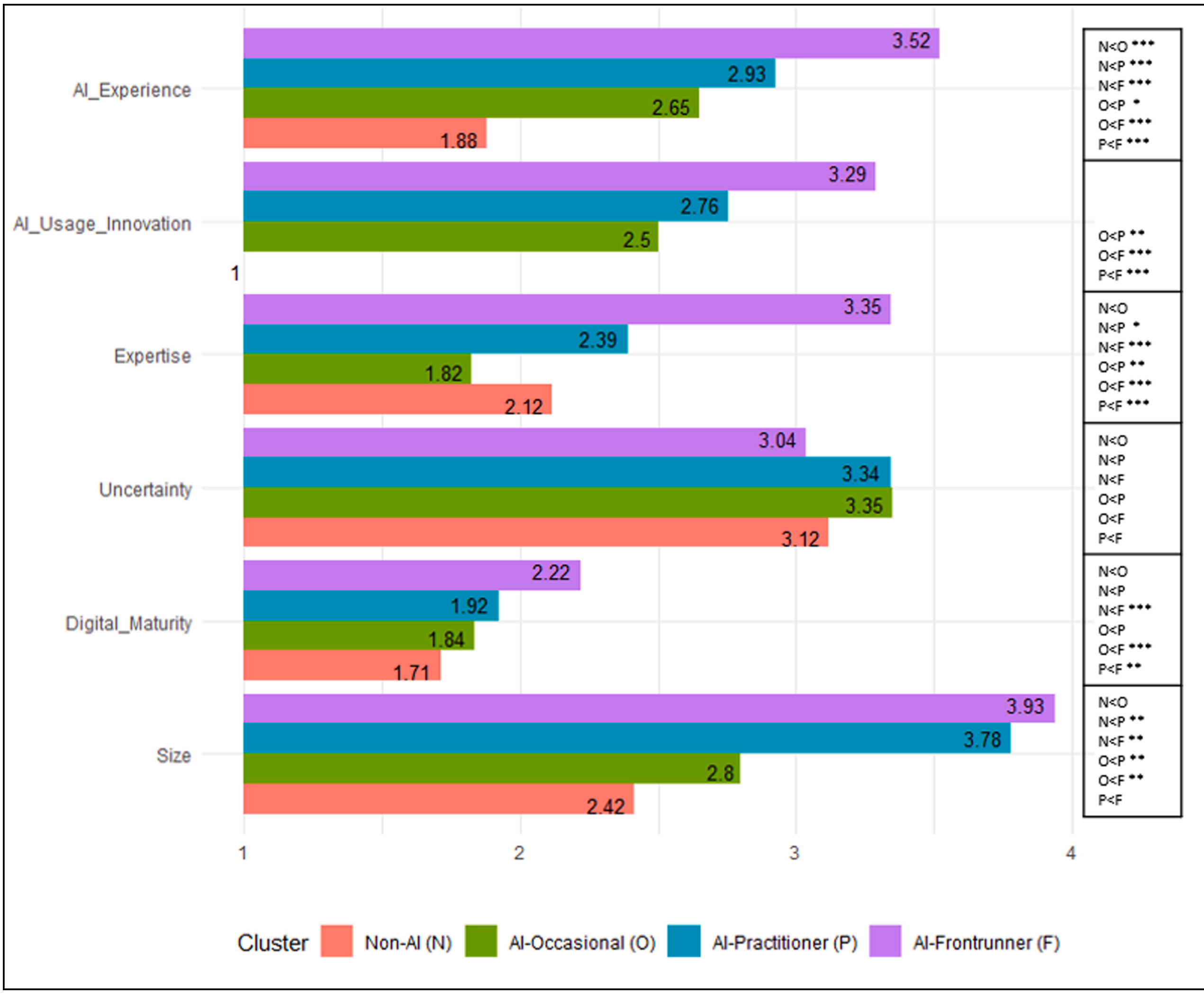

Fig. 11. Organizational Context across Clusters, Significant pairwise differences one-tailed Wilcoxon-Test: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

algorithms turns out to be the major data challenge for all AI-based Innovators. On average, AI-Practitioners and AI-Occasional innovators perceive access to large datasets as more constraining for their AI-based innovation management than AI-Frontrunners. While the availability of labeled training data represents a serious barrier for AI-Frontrunners and AI-Practitioners, AI-Occasional innovators are less concerned about it.

Of the seven organizational challenges discussed – internal resistance, trusting environment and the right mindset, security, lack of technical expertise, hiring and retaining AI experts, hardware and data acquisition and storage - lack of technical expertise is by far the strongest limiting factor for AI-Occasional innovators relative to their perception of other challenges. While AI-Frontrunners would also welcome some more AI expertise in their innovation unit, they are particularly concerned about hiring and retaining AI experts – which makes sense as their preferred implementation pattern is characterized by a strong focus on building up a skilled workforce. AI-Practitioners lack a trusting environment, the right mindset and necessary expertise and also face a higher resistance of internal stakeholders than the other groups when trying to implement AI technology in the innovation process. It seems that they are much less concerned about security topics than the two other groups – which might be related to their open approach to AI-based innovation management, including sharing of intellectual property and collaborating with partners in the field of AI.

4.4.5. *Organizational context*

Fig. 11 shows the results of the comparative analysis of six contextual factors – the organizations' experience with AI technology in general, the current usage of AI in their innovation management, the AI expertise in the innovation unit, the uncertainty in their orientation to AI-based innovation management, the digital maturity and the size of the organization – determining central aspects of the organizational context.

AI-Frontrunners are most experienced with AI technology in general and also apply AI most extensively for innovation compared to other implementation clusters (F: 3.29 – P: 2.76 ***, O: 2.50 ***). They further indicate having by far the highest expertise (F: 3.35 – P: 2.39 ***, O: 1.82 ***, N: 2.12 ***). Although no significant differences across the cluster groups can be observed, the uncertainty of AI-Frontrunners tends to be lower than for other groups (F: 3.04 – P: 3.34, O: 3.35, N: 3.12). In the previous steps of the comparative analysis, we found that AI-Practitioners and AI-Occasional innovators clearly differ in their perceptions about the potential and impact of AI-based innovation management as well as related challenges. Interestingly, when looking at their organizational context, it turns out that they face a quite similar situation across the contextual factors, except for company size. Thus, one might hypothesize that the different implementation preferences that AI-Practitioners and AI-Occasional innovators prefer are predominantly subject to different perceptions of AI-based innovation management rather than contextual factors. Further, the results show that AI-Occasional and Non-AI innovators are on average the smallest in size (e.g., O: 2.80 – F: 3.93 **, P. 3.78 **, N: 2.42). Although even Non-AI innovators have already engaged with AI technology in other business fields, the small size and corresponding lack of available resources might limit their opportunities to experiment with AI technology at all or engage in more ambitious approaches to AI-based innovation management. Interestingly, we find that the expertise of Non-AI innovators is higher than those of AI-Occasional innovators and close to those of AI-Practitioners. In further consequence, this indicates that next to perceptions about AI's potential in the innovation process, the extent of previous experience with AI (N: 1.88 – F: 3.5 ***, P: 2.76 ***, O: 2.77 **), and available resources – rather than solely the domain-specific expertise in the innovation unit – might be decisive factors in whether and how AI is applied for innovation.

5. Discussion and implications

AI technologies have gained a prominent position in the organizational context. This paper explores the current status quo of AI for innovation management and how it may impact the future of innovation management practice through an exploratory study. Our findings from tech-savvy managers reveal four major insights into the upcoming era of AI-based innovation management. They confirm that AI may revolutionize all industries (Lakhani and Iansiti, 2020) and also (r)evolutionize innovation management and take the idea-to-launch innovation process to the next, more advanced stage.

(1) AI-based innovation management indeed has the potential to usher in a new seventh paradigm of innovation management (Ahmed and Shepherd, 2010; Tidd and Bessant, 2013). While we are currently still relying on innovation networks and ecosystems (e.g., Tidd and Bessant 2013), our findings suggest that we are heading towards AI-based innovation ecosystems. This AI-based innovation management paradigm is characterized by real-time analytics of big chunks of various available data that allow making more informed and better decisions. The available AI-based analyses may, for example, help to determine what kind of technologies, trends, and customer needs should be addressed and what concepts and prototypes seem to be most promising. They may also support tailoring and automatizing communication, marketing, and sales of innovations to individual customers. The ongoing feedback about innovations in use may also continuously improve and adjust existing solutions (Nambisan et al., 2017). Our study clearly shows that innovation managers are aware of the enormous potential of AI for innovation management. For example, they believe that AI may improve the overall innovation outcome by more than 50% compared to existing innovation approaches. However, AI-based management is still in its early and experimental state. Within the next five to ten years, AI may become a technology assisting innovation managers rather than supplementing them. Further, AI cannot be considered a plug-and-play technology that can be easily applied to all kinds of innovation tasks. In its current form and within the near future, managers will apply AI for analytical and repetitive administrative tasks such as searching, scouting, structuring, clustering, visualizing, representing, and highlighting available information and knowledge, as well as evaluating, comparing, and optimizing different options (Brynjolfsson and McAfee, 2017; Rhyn and Blohm, 2017). However, the tasks of innovation creation and composition are still dominated by humans with their intuition, creativity, empathy, and sense for aesthetics, rather than by AI-based analytics. Our study confirms that within the next five to ten years, humans will continue to dominate creative tasks (Kakatkar et al., 2020) and be the key in activities related to identifying and selecting problems to be solved. They may concentrate on Sherlock-Holmes-like-thinking tasks (Tekic et al., 2019), which are inherently open-ended and require long chains of logic or reasoning that depend on diverse background knowledge and intuition (Brynjolfsson and Mitchell, 2017). AI may assist innovation teams by providing rich and unbiased data. Humans will be irreplaceable in building AI tools – developing algorithms and training procedures – but less absorbed by repetitive tasks that require one-second-thinking (Ng, 2016).

(2) AI-based innovation management requires substantive technical and organizational changes to handle and successfully cope with the associated challenges. While AI-based innovation management has the potential to revolutionize innovation management, currently, it is still in its infancy stage. Even AI-savvy organizations still have many concerns about how to overcome barriers to make AI-based innovation management work (Haefner et al., 2021; Verganti et al., 2020). Our study shows that organizations must overcome various technical challenges such as access to large datasets, the generation and labeling of training data efforts, and the explanation and generalization of results. In addition, companies need to tackle organizational challenges such as the lack of internal expertise, missing access to talents, distrust, and a skeptical mindset. Our findings show that in order to prepare for AI-based innovation management, organizations have to adjust their strategy (e.g., allocation of budgets or handling sharing of IP), and implement structural changes (e.g., to determine the level of centralization or integration of projects). They also have to invest in capability building and skill development, e.g., offering training, hiring new talents, or developing new tools and technologies. Dealing with AI-based innovation management requires becoming even more open and collaborative than before. It necessitates the integration of data scientists into innovation teams and a thorough understanding of the shift in the innovation dynamics caused by the constant inflow of new insights and findings provided by AI-analytic tools. Thus, our findings suggest that AI-based innovation management may be considered a new, seventh innovation paradigm rather than just another digital technology that allows improving specific innovation tasks (Ahmed and Shepherd, 2010; Tidd and Bessant, 2013). According to our findings, it presents a new era of innovation thinking, structuring, and organizing to benefit from AI (Kiron and Schrage, 2019). These findings contribute to innovation management literature by providing first insights into the topics and dimensions that have to be addressed when thinking of and establishing AI-based innovation management (Cockburn et al., 2019; Haefner et al., 2021; Kakatkar et al., 2020).

(3) There exists no one-size-fits-all approach to implement AI-based innovation management. While most managers agree on the potential and requirements for AI-based innovation management, our findings show that they slightly differ regarding their preferred implementation approach to utilize and familiarize with AI-based innovation management. We identified four different implementation groups: (1) AI-Frontrunners, (2) AI-Practitioners, (3) AI-Occasional innovators, and (4) Non-AI innovators, which mainly differ in their perceived relevance of AI technologies, resources they intend to invest as well as the range and frequency with which they aim to apply these technologies. Besides the differences in their intended use of AI, they also prefer different organizational setups and vary in their view on necessary skill development. Our research further suggests that these differences may be associated with their different perceptions, e.g., regarding the perceived potential and perceived affordances of AI for innovation management, and the organizational context, especially criteria such as previous experience, current usage, and expertise with AI as well as size. These findings confirm insights from affordance theory (Keller et al., 2019; Majchrzak and Markus, 2014; Zeng et al., 2020) as well as contingency

theory (Ginsberg and Venkatraman, 1985; Luthans and Stewart, 1978) suggesting that organizations see different opportunities and use cases for AI technologies and that these may be dependent on the organizational context. Our study provides first empirical evidence that AI affordances for innovation management may depend on factors such as experience, expertise, digital maturity, and organization size. Thus, in line with Haefner et al. (2021), it suggests that organizations need to create a systematic implementation approach to benefit from AI. While the implementation approach may be based on best practice, it may be adopted to the specific organizational context (Ortt and Van Der Duin, 2008), such as size and experience.

(4) Despite the potential of AI-based innovation management, organizations may fail to realize the expected benefits due to inadequate or poor implementation. Although AI-based innovation management seems very promising, organizations still run the risk of means-end decoupling (Jabbouri et al., 2019). This might lead to an implementation gap, meaning that innovation managers may apply AI-based innovation management without realizing the expected benefits (Wilson and Daugherty, 2018). The problem may be especially challenging due to the novelty and complexity of AI-based innovation management. As our study shows, there are technical barriers to overcome as well as organizational barriers, such as different mindsets and distrust in AI technologies. Successful implementation also requires the integration of new team members such as data scientists, as well as intensified collaboration with external actors such as AI consultants and universities. In order to avoid decoupling, AI implementation managers have to ensure that all relevant internal stakeholders and external partners are in line and also compliant with the AI-based innovation management goals (Jabbouri et al., 2019). In order to overcome potential tensions, inertia, and resistance towards AI-based innovation management, organizations have to avoid opaque implementation contexts that lead to compliance barriers such as complex causal patterns, practice multiplicity, and behavioral invisibility (Wijen, 2014). They further have to incentivize adoption behaviors by offering compliance inducements such as setting concrete rules, offering specific incentives, providing best practices and implementation options, and enabling capacity building (Perez-Aleman, 2011; Terlaak, 2007). It is crucial to pick the right tasks for successful AI implementation in the innovation process. First, the tasks must be suitable to be taken over by machines. Second, organizations must be able to obtain sufficient data to train machines. However, more than that, organizations will need to foster collaborative intelligence where humans and AI enhance their complementary strengths to realize the advantages of AI technologies (Wilson and Daugherty, 2018). Combing the best of AI (e.g., processing big data to identify patterns and relations) and humans (e.g., common sense, creativity, tacit and industry domain knowledge) to build an efficient and lasting partnership will be essential for successfully managing AI-assisted innovation processes (Jarrahi, 2018; Keding, 2021; Shirado and Christakis, 2017).

6. Conclusion and research outlook

While our study provides a first glimpse of the application of AI-based management, its potential, affordances, challenges and potential implementation approaches, it also evokes additional research questions and asks for further studies on AI-based innovation management.

We are aware of potential biases and limitations due to our study's given scope and operationalization. Managers with limited or no interest in the topic might not even have started our online survey, leading to potential biases towards the potential of AI-based innovation. Though we included organizations not planning to apply AI-based methods in our comparative analysis, future research could focus more on companies' reasons for not considering the technology. Studies may also explore ways to lower the barriers in case AI-based innovation management makes sense in the specific organizational context. The study has also shown that there is a lack of understanding about the necessary changes and impact of AI-based innovation management, as well as a surplus of perception-based rather than fact-based interpretations of the potential of AI in the innovation context. This represents both a limitation of the current study and an opportunity for future research. Further research may explore and learn from best and worst practices and investigate causal relations between necessary preconditions and their effect on AI-based innovation management. Alternatively, research may try to identify different recipes for successful AI-based innovation management, assuming more than one pathway to it. An additional avenue for future research relates to exploring critical success factors or the actual impact of AI-based innovation management on innovation outcomes. As AI-based innovation management relies on technical and organizational aspects, these dimensions may deserve special focus, as they may determine the extent and the timing of the shift to AI-based innovation management. Other areas of further interest in the context of the current new work debate include the impact of AI-based innovation management on skill and capability development of innovation teams, collaboration across innovation and AI-experts, and the role of and interaction between humans and machines. We look forward to seeing further areas where AI can be applied in innovation management (Fig. 5).

CRediT authorship contribution statement

Johann Füller: Conceptualization, Methodology, Investigation, Resources, Writing – review & editing, Supervision. **Katja Hutter:** Conceptualization, Resources, Investigation, Writing – original draft. **Julian Wahl:** Methodology, Formal analysis, Data curation, Visualization, Writing – original draft. **Volker Bilgram:** Resources, Writing – review & editing. **Zeljko Tekic:** Writing – review & editing.

Table A.1
Final measurement items and psychometric properties of cluster variables.

Variables	Source (derived from)	Mean (S.D.)	FL (EFA)	ITTC	Cronbach's Alpha	AVE
Budget						
(0–100%)						
Share of AI investment in innovation budget	Nagju and Tuff (2012)	21.88 (17.63)				
IP Management						
(5-Point Likert; Patent protection/closed – publishing and sharing new ideas/closed)						
Strategic Orientation to IP Management	Manzini and Lazarotti (2016)	3.05 (1.09)				
Exploration						
(5-Point Likert; no extent – great extent)						
Priority to come up with new business models (Exploration)	O'Reilly and Tushman (2011) Ransbotham et al. (2019)	2.70 (1.10)				

(continued on next page)

Table A.1 (*continued*)

Exploitation						
(5-Point Likert; no extent – great extent)						
Priority to apply AI to improve existing products and business models (Exploitation)	O'Reilly and Tushman (2011)					
Ransbotham et al. (2019)	2.20 (1.10)					
Integration						
(3-Point Likert; completely separate - connected - tightly separate)						
Level of Integration of AI Initiatives	Ransbotham et al. (2019) Keller et al. (2019)	1.90 (0.63)				
Project Structures						
(5-Point Likert; existing structure – new built structure)						
Extent of new structures built for AI initiatives	Fountaine et al. (2019)	2.81 (1.35)				
Locus Responsibilities						
(5-Point Likert; decentralized - centralized)						
Extent of centralization in AI initiatives	Roberts (2007)	2.54 (1.40)				
Innovation Culture						
(5-Likert; not at all - crucial)						
Relevance of open innovation for successful integration of AI in the innovation context	Chesbrough (2003)	2.27 (1.13)	0.94	0.75	0.80	0.69
Relevance of open source for successful integration of AI in the innovation context	Von Hippel and von Krogh (2006)	2.27 (1.13)	0.70	0.75		
Investment Training						
(5-Point Likert; strongly disagree – strongly agree)						
Share of innovation budget invested in building and strengthening AI competence through training of employees	Ransbotham et al. (2017)	2.20 (1.14)	0.73	0.82	0.86	0.76
Share of innovation budget invested in communicating relevant AI use cases to employees	Ransbotham et al. (2017)	2.30 (1.17)	0.97	0.82		
Investment Hiring						
(5-Point Likert; strongly disagree – strongly agree)						
Level of investment in hiring AI talent (e.g. Engineer, AI lawyer, Researcher etc.)	Ransbotham et al. (2019)	2.30 (1.20)	0.51	0.73	0.84	0.65
Level of investment in hiring Data talent (e.g. Data scientist etc.)	Ransbotham et al. (2019)	2.90 (1.30)	0.74	0.85		
Level of investment in hiring IT talent (e.g. IT collaborator, Infrastructure engineer etc.)	Ransbotham et al. (2019)	2.90 (1.30)	0.89	0.74		
Technology Development						
(5-Point Likert; strongly disagree – strongly agree)						
Extent of development of AI applications in-house	MIT SMR Connections (2019)	3.05 (1.41)	1.01	0.68	0.74	0.59
Extent of development of applications using cloud-based ML and DL services.	MIT SMR Connections (2019)	2.9 (1.28)	0.48	0.68		
External Collaboration						
(5-Point Likert; no extent – great extent)						
Extent of collaboration with companies	Nambisan (2017)	3.00 (1.21)	0.61	0.70	0.87	0.65
Extent of collaboration with universities	Nambisan (2017)	3.00 (1.31)	0.66	0.70		
Extent of collaboration with startups	Kohler (2016)	2.90 (1.27)	0.93	0.88		
Extent of collaboration with labs. hubs and incubators	Fecher et al. (2018)	3.10 (1.32)	0.89	0.86		

Table A.2
Correlation table cluster variables.

	Var 1	Var 2	Var 3	Var 4	Var 5	Var 6	Var 7	Var 8	Var 9	Var 10	Var 11	Var 12
Budget	1											
IP Management	0.00	1										
Exploration	0.23 ***	0.04	1									
Exploitation	0.27 ***	0.01	0.63 ***	1								
Integration	0.30 ***	0.20	0.22 ***	0.17 **	1							
Locus Responsibilities	-0.05	0.05	0.01	0.13	0.10	1						
Project Structures	0.15 *	0.00	0.16 *	0.02	-0.06	-0.13	1					
Innovation Culture	-0.09	0.21	0.20 **	0.17 *	0.11	0.11	-0.01	1				
Investment Training	0.49 ***	-0.13	0.13	0.15 *	0.39 ***	0.07	0.13	-0.02	1			
Investment Hiring	0.23 ***	-0.21	0.15 *	0.07	0.15 *	-0.15 *	0.15 *	0.06	0.52 ***	1		
Technology Development	0.21 ***	-0.06	0.16 *	0.26 ***	0.22 ***	0.04	0.16 *	0.09	0.34***	0.31 ***	1	
External Collaboration	0.26 ***	0.02	0.24 ***	0.20 **	0.19 **	0.04	0.22 ***	0.21 **	0.28 ***	0.35 ***	0.38 ***	1

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0$.

Appendix A

Table A.1. Final Measurement Items and Psychometric Properties of Cluster Variables

Table B.1
Final measurement items and the psychometric properties comparative analysis.

Variables	Source (derived from …)	Mean (S. D.)
Perceptions		
Expected improvement of … (0–100%)		
innovation outcome by AI	Own	51.50 (24.46)
the innovation process	Own	49.30 (23.78)
speed of the development cycle by AI	Wilson and Daugherty (2018)	57.07 (26.45)
diffusion and scalability of innovations by AI	Wilson and Daugherty (2018)	48.47 (26.65)
operational flexibility by AI	Wilson and Daugherty (2018)	50.91 (26.84)
decision-making by AI	Wilson and Daugherty (2018)	55.04 (27.93)
individual fit of products and services by AI	Wilson and Daugherty (2018)	50.31 (26.74)
Importance of AI in … (5-Point Likert; not important – very important)		
identification of needs and trends	Roberts and Frohman (1978)	3.76 (1.15)
technology scouting	Roberts and Frohman (1978)	3.53 (1.14)
idea generation	Keum and See (2017) Bartl et al. (2012)	3.00 (1.03)
idea selection	Keum and See (2017)	3.33 (1.60)
concept testing	Roberts and Frohman (1978 Bartl et al. (2012)	3.45 (0.98)
generative design	Krish (2011)	3.435 (0.97)
prototyping	Roberts and Frohman (1978) Bartl et al. (2012)	3.43 (1.01)
marketing	Roberts and Frohman (1978) Bartl et al. (2012)	3.64 (1.15)
Human vs. AI in general tasks (5-Point Likert;1=Humans with better skills, 5= Machines with better skills)		
Analytics	Own	3.84 (1.04)
Administration	Own	3.73 (1.13)
esthetic sensibilities/design	Own	1.75 (0.84)
Creativity	Own	2 (0.94)
Empathy	Own	1.49 (0.83)
Experimentation	Own	3.05 (1.09)
Intuition	Own	1.82 (1.05)
Social and people skills	Own	1.52 (0.77)
We understand … (5-Point Likert; strongly disagree – strongly agree)		
how AI will shift our innovation dynamics	Ransbotham et al. (2017)	3.41 (1.08)
what data is required to train AI algorithms	Ransbotham et al. (2017)	3.1 (1.12)
how AI will change our organization structure	Ransbotham et al. (2017) Roberts (2007)	3.02 (1.05)
how our existing job roles and skills need to change in order to complement AI	Ransbotham et al. (2017) Roberts (2007)	3.21 (1.05)
how the presence of AI machines in the workplace will change our organization's innovation strategy	Ransbotham et al. (2017) Roberts (2007)	3.02 (1.14)
Organizational Context		
Extent of current AI usage in … (5-Point Likert; not adopted AI and has no plans to do so - not adopted AI but has plans to do so in the near future - one or more AI pilot projects - incorporated AI into some processes and offerings – extensively incorporated AI into processes and offerings)		
general	Ransbotham et al. (2017)	2.94 (0.99)
innovation management	Ransbotham et al. (2017)	2.67 (1.09)
Level of uncertainty in strategic orientation regarding AI (5-Point Likert; very low – very high)	Own	3.21 (1.00)
Level of digital maturity in the organization (3-Point Likert; early stage – in development – mature stage; $n = 140$)	Kane et al. (2017)	1.99 (0.62)
Revenue in last fiscal year (7-Point Likert; Less than €100Mio, €100Mio - €249Mio., €250Mio - €499Mio., €500Mio - €999Mio., €1Bn - €5Bn., €5Bn - €25Bn., More than €25Bn; $n = 129$)	Ransbotham et al. (2017)	3.82 (1.97)
Limitations on the ability to apply AI algorithms in the context of innovation (Constant Sum; assign a total of 100 points; $n = 133$)		
Labeled training data	Bughin et al. (2018)	21.35 (18.8)
Obtaining sufficiently large data sets	Bughin et al. (2018)	31.84 (24.3)
Difficulty explaining results	Bughin et al. (2018)	18.79 (17.6)
Difficulty generalizing	Bughin et al. (2018)	21.54 (18.9)
Risk of bias	Bughin et al. (2018)	17.56 (18.0)
Organizational challenges on the ability to integrate AI for innovation (Constant Sum; assign a total of 100 points; $n = 133$)		
Resistance to AI integration of internal stakeholders (e.g. fear of job loss. no personal benefits. loss of control in current position)	Keller et al. (2019) Ransbotham et al. (2017)	19.52 (19.7)
Building a trusting environment/the right mind-set	Keller et al. (2019)	22.05 (19.6)
Security concerns (e.g. cyber fraud)	Ransbotham et al. (2017)	21.48 (17.6)
Lack of technical expertise	Ransbotham et al. (2017)	34.14 (22.8)
Hiring and retaining AI experts	Ransbotham et al. (2017)	23.14 (21)
Hardware (e.g. advanced enough processing power)	Own	11.19 (18.1)
Data acquisition and storage	Own	17.46 (22.4)

Table A.2. Correlation table cluster variables.

Appendix B

Table B.1. Final measurement items and the psychometric properties comparative analysis.

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