This paper was presented at The ISPIM Innovation Conference – Innovating in Times of Crisis, 7-10 June 2020.
Event Proceedings: LUT Scientific and Expertise Publications: ISBN 978-952-335-466-1

Integrated AI and Innovation Management: The Beginning of a Beautiful Friendship

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Abstract: There is growing consensus around the transformative and innovative power of Artificial Intelligence technology. AI will transform which products are launched and how new business models will be developed to support them. Despite this, little research exists today that systematically explores how AI will change and support various aspects of innovation management. To address this question, this paper proposes a holistic, multi-dimensional AI maturity model describing the essential conditions and capabilities necessary for the integration of AI, and guides organisations on their journey to AI maturity. It explores how different elements of the innovation management system can be enabled by AI at different maturity stages. Two key experimentation stages are identified - an initial stage focusing on optimisation and incremental innovation; and a higher maturity stage where AI becomes an enabler of radical innovation. We conclude that AI technologies can be applied to democratise and distribute innovation across organisations.

Keywords: artificial intelligence; innovation management; maturity model; AI innovation; AI maturity; IMS ISO 56002

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1 Introduction

Adoption of Artificial Intelligence (AI) is accelerating - according to McKinsey, 58% of organisations embedded at least one AI capability into a process or product (Cam, 2019), and integrating AI holistically across an organisation has the potential to create competitive advantages and strengthen organisational innovation capabilities (Cockburn et al., 2018; Fountaine et al., 2019; Prem, 2019; Raisch and Krakowski, 2020).

However, very few organisations today are seeing a widespread adoption of AI (Fountaine et al., 2019) and there is limited research available on how integration of AI can support specific challenges related to innovation management (Prem, 2019). Existing models of AI in organisations do not integrate the technical, organisational, and ethical aspects, nor do they address how AI integration is intertwined with innovation management. We propose that strategic integration of AI and innovation management in organisations go hand-in-hand, mutually complementing and enabling each other, and explore the following: What does the journey towards trustworthy integrated AI in organisations look like? And second, how could integrated trustworthy AI act as an enabler of innovation management systems?

Traditionally, for complex issues such as sustainability or general purpose technologies like AI, frameworks are used to create structure and to decompose aspects into specific categories and maturity stages. These frameworks serve an essential role in educating management, creating clarity, ability to act, and accelerating adoption. A number of AI maturity frameworks have been published (see *Figure 1*) that typically cover specific aspects of AI integration, but do not holistically integrate the technical, organisational and ethical aspects. Here, we propose the AI Innovation Maturity Index (AIMI) in an attempt to rectify this.

Further, we consider different elements of the Innovation Management System according to ISO 56002 and explore examples of how AI technologies could be used to support and augment them in order to increase organisational innovation capability. We focus specifically on the application of AI at various levels of AI maturity and its implications for democratising and distributing innovation, increasing diversity, interdisciplinary and cross-functional collaboration, building a learning organisation, and strengthening capacity for sensing future possibilities and embracing uncertainty.

2 Theoretical Background

AI and organisations: current practice and challenges

Many large multinational consulting firms tout significant potential for AI technologies. At the same time, AI is still in an early commercialisation phase with only 8% of firms today seeing a widespread AI adoption across the organisation (Fountaine et al., 2019). There is also limited published, empirical work on challenges related specifically to AI and innovation management (Prem, 2019).

A key pattern in adoption of AI is a separation between incremental use cases that optimise the existing business processes and products and transformational use cases that shift the organisation, its products and sometimes the market. Influenced by the Innovation and Ambition Matrix (Nagji and Tuff, 2012) and inspired by the notions defined by Laszlo and Zhexembayeva (2011) in their work on Embedded Sustainability, we refer to the two ends of the AI spectrum as *Bolt-On* and *Integrated AI*.

Bolt-on AI is implemented in the existing business processes and products through projects in non-critical areas, relatively independent of other parts. It is focused predominantly on optimisation of existing processes, risk management, and short-term return on investment, enabling incremental innovation of the existing business. By contrast, *Integrated AI* considers the company's core domain area and is deeply integrated with overall organisational purpose and strategy. It is more long-term oriented and strategic, focused on the wider ecosystem of the company, creating value across a broader context and closely associated with transformational innovation.

Cultural and organisational barriers is one of the reasons why larger organisations struggle with broader AI integration (Fountaine et al., 2019). Many big systems are rigid, hierarchical, with low levels of flexibility and adaptability and innovation competence and mindset limited to specific parts of organisation, rather than spread across the system. Managers rarely understand that while cutting-edge technology is needed, aligning organisational culture, structure, and ways of working is equally important (Fountaine et al., 2019). Unsurprisingly, some studies show that start-ups have a vital role to play in both the application and deployment of AI innovations in companies as they are considered to be the leaders and main competence carriers in AI technology (Prem, 2019).

Fountaine et al. (2019) suggest that large organisations need to go through various shifts to enable the scaling up of AI, such as moving: 1) from silos towards more interdisciplinary collaboration; 2) from experience-based, leader-riven decision making to data-driven decision making at the front line; and 3) from rigid and risk-averse to agile, experimental and adaptable mindset and ways of working (Fountaine et al., 2019).

Existing AI maturity frameworks

The 'maturity model' concept was introduced in 1986 by Carnegie Mellon with its Capability Maturity Model (Paulk, 2009). Since then, there has been a widespread adoption of maturity models for process optimisation, innovation management, and digital transformation. Such maturity models are most prevalent in domains that are inherently complex, requiring a systematic and structured approach. More recently, there has been a proliferation of digital maturity models (DMMs), driven in part by Industry 4.0 (Teichert, 2019). Just as Teichert found with the early DMMs, we have seen that existing AI-specific models are developed primarily by practitioners rather than academia.

While a complete review of AI frameworks is outside the scope of this paper, in *Figure 1* we show thirteen representative examples. Some of the top patterns we found include:

1. Frameworks tend to focus near-exclusively either on technical aspects of AI integration or strategic and organisational considerations. This means there is a lack of models holistically integrating technical, organisational and innovation management perspectives.
2. Some re-formulate existing digital transformation models, but without addressing specific needs related to the development or implementation of AI.
3. Some frameworks focus exclusively on the ethical, legal and social/technology robustness aspects or, alternatively, these aspects appear as one of the separate dimensions, rather than integrated by design.
4. A number of the models have bolt-on rather than integrated AI as the end goal, sometimes framed as "enterprise cognitive computing," defined as improving business operations by automating repetitive tasks (Tarafdar et al, 2019). These frameworks concentrate on the more technical and operational dimensions, while frameworks looking at more integrated AI use cases focus more on strategy and organisation.

Model	Focus Areas
AI Hierarchy of Needs - Monica Rogati (Rogati, 2017)	Data, tech
AI Maturity Model (Alsheibani et al., 2019)	Technologies & tools, data structure, people, organisation
The AI Maturity Playbook: Five Pillars of Enterprise Success (Etlinger, 2018)	Strategy, data science, product & service development, organisation & culture, ethics & governance
Catalyst Fund - AI Readiness Toolkit (Catalyst Fund, 2018)	Data, technologies,operations & general management, skills, ROI
Element AI (Element AI, 2019)	Strategy, technology & data, people & organisation, governance
Ethics Guidelines for Trustworthy AI (European Commission, 2019)	Ethics
Kaleido Insights - AI Readiness (Groupman, 2018)	Strategy, people, data, infrastructure, ethics
Microsoft - Landing AI Maturity Model (Microsoft, 2019)	Strategy, culture, organisation,capabilities
MMC Ventures - The AI Playbook (MMC Ventures, 2019)	Strategy, people, data, development, production, regulation & ethics
Oracle Data Science Maturity Model (Oracle, 2018)	Strategy, roles, collaboration, methodology, data awareness, data access, scalability, asset management, tools, deployment
Ovum (now Omdia) - How to Achieve AI Maturity and Why It Matters (Pringle et al., 2018)	Strategy, organisation, data, technology, operations
PwC Ethical AI Toolkit (PwC, 2019)	Ethics
The University of Chicago - Data Maturity Framework (UC, 2018)	Data, tech, organisation

Figure 1 Overview of AI maturity models and frameworks

Innovation Management and AI

Current research

There is currently a lack of research providing a systematic overview of how AI can support different elements of the innovation management system. While there are discussions on how AI is integrated into *products, features and services* of an organisation, which can be both incremental or radically new, AI is also used to *enable innovation* by integrating it *in the development* of new products and services (Cockburn et al., 2018). AI methods have been successfully applied for complexity and knowledge management to increase flexibility, and more traditional applications including process optimisation and automation for increased efficiency and quality in product and service development (Raisch and Krakowski, 2020).

Prem (2019) who interviewed experts in Austria on the current use of AI in companies, suggests that the range of applications is quite wide but the emphasis is currently on incremental improvements, with some examples of more radical innovation that would not be possible without AI, such as automation of sign language translation. Despite the potential for *AI to radically innovate business models*, the current focus is still often on quality improvements rather than transforming business models.

AI can strengthen innovation capability by increasing the *organisational ability for sensing changes in the environment and predicting what might happen* (Cockburn et al., 2018). An example would be predicting drug candidate selection by bringing together a vast array of previously disparate clinical and biophysical data, fundamentally reshaping idea generation function in the innovation process of drug discovery (ibid.).

Other *challenges* and barriers exist when it comes to integrating AI in organisations to strengthen their innovation capability. There is a lack of talent in IT fields in general, but even more so when it comes to AI experts (Prem, 2019; Loucks, 2018). There is low AI competence and knowledge among managers, creating unrealistic expectations and disappointment around what is possible with AI, its costs and how long it takes to develop innovative solutions (ibid.). The credibility and trust in AI is also questioned by management due to the lack of explainability of learning systems, and lack of clarity around the responsibility of the smart and autonomous systems' behavior and possible legal implications (ibid.)

Innovation Management System Framework

The Innovation Management System developed by the international standard ISO 56002 is introduced below. The framework is used later in the article to discuss how a more holistic integration of trustworthy AI, guided by the AI Innovation Maturity Index could support different aspects of the innovation management system.

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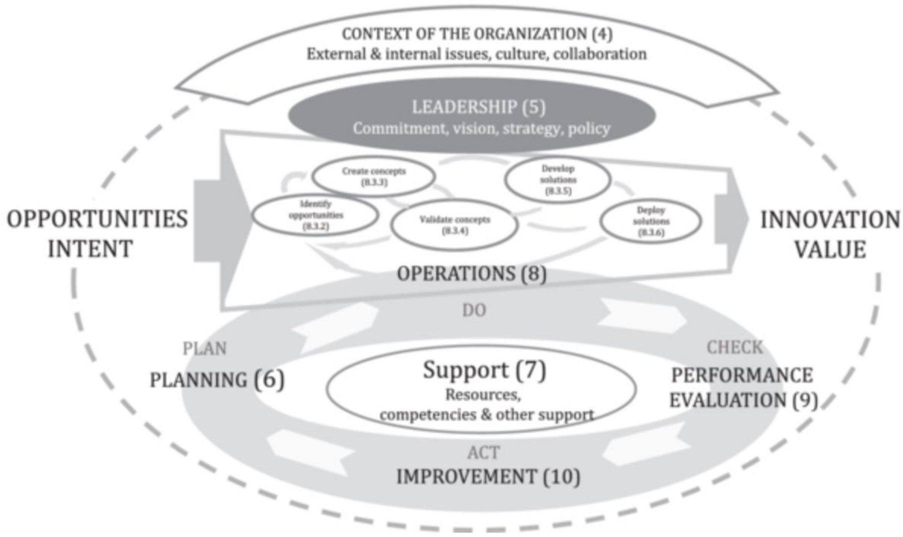

Figure 2 Innovation Management System, ISO 56002

There are seven key components in the framework represented in *Figure 2*. The *"Innovation Context of the organisation"* includes: a) *scanning* and analysing *external* environment and understanding the potential impact of economic, social, cultural, technological, legal, political, and environmental trends on organisation; b) *scanning* and analysing *internal environment* and understanding current managerial and organisational practices, organisation competences and performance, etc.; c) monitoring and *understanding the needs of different interested parties*, such as customers, partners, shareholders, unions, local community, etc. ; d) *promoting innovation culture*, built on openness, curiosity, learning, experimentation, risk-taking, collaboration; and e) developing collaboration internally and externally by *building an innovation ecosystem*.

The "*Innovation Leadership*" includes a) the development of innovation vision, strategy, and policy, b) defining innovation roles and responsibilities, and c) the organisation. Innovation leadership needs to perform the *"Planning"* of innovation objectives, innovation portfolio and organisational structures that support innovation. *"Innovation Operations"* focuses on initiatives and processes.

"Innovation Support" is needed to successfully implement innovation management systems, including people, knowledge management, time, financial resources, physical and virtual innovation infrastructure, tools, methods, and competences. The last two parts of the innovation management system refer to *"Performance Evaluation"* and continuous *"Improvement"*.

3 Methodology

Our development of AI Innovation Maturity Index was influenced by the maturity model development framework proposed by de Bruin and Roseman (2005). Our approach consisted of three sequential and iterative research phases.

Step 1: Define Scope - Analysis of existing models and literature

To scope our framework, we conducted analysis of existing models related to AI adoption and innovation. This was augmented with a literature review, including research papers and articles discussing AI integration. Our background research included consideration of digital transformation maturity literature (Teichert, 2019), as well as design and development principles for maturity models (de Bruin and Roseman, 2005; Mettler 2009). While sparse academic research exists relating directly to AI maturity and its adoption path, we include Alsheibani and Messom's (2019) 'research-in-progress' maturity model in our review of existing frameworks. For our central notion of *Trustworthy* integrated AI we chose the guidelines developed by the European Commission (2018).

Given how new this domain is, we found few academic research papers specifically about AI maturity models. A rare exception was a work-in-progress paper by Alsheibani and Messom (2019). We recognised the need to complement this research with practitioner reports and best practices guides (Groupman, 2018; MMC Ventures, 2019; Ng, 2018, among others).

Finally, to broaden our insights into innovation management capabilities and applicability of AI maturity, we conducted a review of innovation frameworks (among others, ISO 56002, 2019; Tidd and Bessant, 2018; Bozic Yams, 2017; Crossan and Apaydin, 2010) and innovation readiness assessments including the Berkeley Innovation Index (Sidhu et al, 2016) and the KTH Innovation Readiness Level (2015).

Additionally, work on sustainable innovation management and strategy was reviewed as a good proxy for AI innovation, due to its general purposes qualities that require actions that affect whole organisations and ecosystems (Laszlo et al., 2011; McEwan and Schmidt, 2007).

Step 2: Design - Iterative model design

In this phase, we defined the critical dimensions of maturity and *what* represents maturity rather than *how* it can be measured. This approach is recommended in newer domains where there is little evidence of what represents maturity (de Bruin and Roseman, 2005). Inspired by the work of Laszlo and Zhexembayeva (2011), we defined bolt-on AI and integrated AI notions, which were used to map maturity behaviours and the necessary capabilities to build a baseline of what good looks like (Mettler, 2009).

Given the complexity of the domain, the model must be able to tell a simplified rather than simple story. Thus, a *stage-gate* approach is required; providing additional layers of

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detail, in the form of dimension components and subcomponents, that enable more granular maturity assessments for distinct areas (de Bruin and Roseman, 2005).

We reviewed multi-dimensional, staged innovation maturity frameworks (Capability Maturity Model Integrated (CMMI Institute 2020); Berkeley Innovation Index (Sidhu, 2016); KTH Innovation Readiness Level, 2015; Groupman, 2018). The prevalent, underlying entropy in many of the models did not suit our holistic approach to maturity and a converging interwoven design was developed instead with *Trustworthy Integrated AI* in the center. That is, our model, proposes a convergence, by design, towards robust, ethical and legal AI that is embedded within all dimensions of the organisation.

Step 3: Interviews with domain and subject matter experts

We interviewed a cross-functional group of fourteen experts one-on-one. The interviewees included innovation managers, senior public sector employees, AI researchers, data scientists and AI leads within companies, as well as business leads including one CEO and several CEO advisors. The interviews gave insights and understanding around how organisations are currently adapting AI and how it is augmented with their innovation management system. The authors also utilised their own broad industry experience in the AI, business strategy and innovation management sectors (among others at Google, Ericsson, Spotify, GE and Northvolt).

4 Results

AIMI - AI Innovation Maturity Index

We developed an AI Innovation Maturity Index (AIMI)©, providing a comprehensive framework, specifically designed with a goal of *Trustworthy Integrated AI*. This framework combines the essential organisational, strategic and technical conditions necessary for AI-based innovation, while also incorporating the central requirements for ethics, legality and robustness.

The Dimensions of AI Innovation Maturity

The AI Innovation Maturity framework consists of six interconnected and interdependent dimensions, seen in *Figure 3*. A seventh dimension of trustworthiness is incorporated across the framework. It is interdependent with the six main dimensions. To create legal, ethical systems providing long-term durable value and to scale them successfully, this dimension needs to be integrated “by design” (EC, 2019). To grow, organisations must develop maturity across all dimensions. These dimensions are not mutually exclusive and should be viewed as enabling each other.

Figure 3 AI Innovation Maturity Index (AIMI)

The *Strategy* dimension is concerned with the vision, value creation and governance of an organisation. Specifically, it is about the ability to align and integrate AI into the broader business context, including the definition of problem-oriented use-cases and business objectives. In short, it provides the *why* for what AI activities organisations undertake.

The *Ecosystems* dimension is about the level of collaboration, communication and impact that an organisation achieves with its internal and external stakeholders, partners, and collaborators. AI is a complex subject and organisations need to develop a common understanding, vocabulary and story-telling around it both internally and externally. *Communication* quality is an important indicator of maturity. Successfully integrating AI requires *cooperation* across the organisation from strategy to data collection and technology, with similar cooperation needed externally.

The *Ecosystems* dimension is strongly linked to *Strategy*. Notwithstanding AI, digital maturity drives dramatic changes in organisations' business ecosystems, making them larger, more complex and even more critical to business strategy. Ecosystems enable organisations to respond to, and exist in, an increasingly digital environment. They must make conscious strategic decisions about what role they intend to have in this wider ecosystem, whether it be as an observer, a participant or an orchestrator - which in itself defines maturity in this dimension.

The *Mindsets* component is concerned with the behaviour, culture, and systems within organisations. The mindset orientation of the leadership, and the nurturing of an innovation and growth mindset will determine the degree to which an organisation is able to be successful in its AI endeavours. The AIMI framework defines *Mindsets* as the mind orientation and intangible capabilities that create the organisational conditions for the sustainable development and integration of AI.

The *Organisation* dimension includes the people, skills, structure, processes and operations aspects. It is effectively about how a business is able to organise itself for AI. It plays an important role in hiring, training, educating, and upskilling, with regard to AI skills. The organisational elements are also critical to fostering the mindset growth, cross-functional collaboration and more distributed decision making. From a process and operations point of view, this dimension also covers the tools which make internal and external collaboration more frictionless. The *Organisation* can partly be considered a tangible representation of the *Mindsets*.

The *Data* dimension is central for AI, as data represents the underlying fuel for most AI algorithms. It is also essential for evaluating performance of machine learning algorithms, enabling companies to make data-informed decisions. Data can also be a source of competitive advantage via the self-reinforcing *virtuous circle of data* (Ng, 2018), and sustainable data dominance, with data-enabled learning network effects (Hagiu and Wright, 2020). Briefly, this dimension is concerned with *data preparedness, data strategy* and *data-driven decisions* inside an organisation.

The last dimension is *Technology*, often called *data infrastructure* among technical practitioners. It represents software and hardware systems, processes and design principles enabling data, analytics and AI development and deployment. Technology for AI needs to be scalable, support multiple diverse use cases and fast iteration. Good technology selection and data sets allow for internal *data democratisation* - ability for the less technical users to themselves create insights from data. *Data* and *Technology* dimensions together represent the ability to physically create and operationalise AI applications.

Stages of AI Maturity

The progression to trustworthy integrated AI has five stages, from *Foundational* to *Integrated*. It represents growth in AI competency and growth of the organisational mindset towards a more integrated, systems-of-systems, transformative innovation mindset. This mindset growth is important for organisations long-term - not just for AI-enabling innovation, but also for their work with sustainability and other complex technological innovations. The process of AI maturation and organisational mindset growth enable each other.

The five stages of maturity are *Foundational*, *Experimenting*, *Operational*, *Inquiring* and *Integrated*. The summary of the stages is provided in *Figure 4*.

Foundational	Experimenting	Operational	Inquiring	Integrated
General curiosity about AI, limited understanding of it and its applicability to the business / industry.	Less hype around AI. Beginnings of a mindset change in the organization. Developing an understanding of the iterative / experimental process needed for developing AI.	Strategic and organisational alignment, including governance, occurs to scale proven AI use cases.	The business understands the transformational power of AI for the organization / market / industry and develops the necessary strategic orientation and mindset capacities.	Trustworthy Integrated AI is at the core of the business strategy with the capacity to develop new applications and business models and affect the markets and ecosystems.
Some grassroots efforts or small-scale, opportunistic use-cases are likely driven by self-motivated individuals and tend to focus on short-term ROI (efficiency gains, risk reduction), often linked to internal processes rather than the core organization domain.	Move from limited understanding and competence to building their first relevant AI applications, small data science/AI teams and initial data infrastructure.	Investments increase and a solid data infrastructure is in place with a small central team working with AI and analytics/decision support.	Innovation-based product and business strategy exploration gains momentum. The organization becomes more external and future-facing with regards to the ecosystem and R&D	The organization reaches a self-transforming stage - able to learn, evaluate, adjust, invest in the future. It can experiment and explore at multiple levels from strategy to technology.
Little to no data and data infrastructure nor data-driven experimentation culture.	May not have a clear AI strategy and experiments are not directly linked to top-line business strategy. More deliberate planning is underway but the organisation is still siloed with differing goals, resources and vision.	Speed of iterative experimentation increases, backed by knowledge, data and technology. Virtuous cycle of data is activated. There is a transactional approach with the wider ecosystem, where needed, to operationalise current use cases and identify possible new means of value creation.	Organization develops its own external ecosystem with academic partners, other companies, diverse types of specific as well as open-ended collaborations.	Significant and continuous R&D investment enables experimentation, risk-taking and feasibility evaluations, now with clearer systematic understanding of how it shapes future value-creation.

Figure 4 AI Innovation Maturity Index (AIMI) Stages of Maturity Descriptions

It is beyond the scope of this paper to discuss all the patterns and anti-patterns of each stage, but we present their main features in the table above and a brief characterisation below.

Foundational Stage: This stage is characterised by a limited understanding of AI. There may be a nascent curiosity surrounding it, but no clear grasp of the relevant and useful use cases. Some opportunistic bolt-on AI use cases may have started with a focus on return on investment. In more digital organisations, there may also be grassroots efforts from the technical employees to get simple AI projects going. But, generally, no real AI specific budget or process exists at this point.

Experimenting Stage: At this stage, an organisation builds capabilities to execute on more straight-forward AI applications. These include technical capabilities, people capabilities (including hiring and learning) and development of a more experimental mindset. A key feature of this stage is discovering, cleaning and making usable any data the organisation has, as well as instrumenting existing systems to get more quality data. This is an “action” stage, with a focus on a few specific projects based on identified internal needs.

Operational Stage: Here, organisations have a few scaled AI use cases, and the technical and organisational capacity to keep them going. They can start reaping the benefits of built-up knowledge and capacity around AI to create new applications with higher speed. They have good internal analytics and quality data that can be applied to multiple use cases. At this point, organisations tend to move from a business optimisation approach to an outward and forward looking innovation strategy and mindset. Awareness of the importance of the external ecosystem and engagement with it becomes increasingly common.

Inquiring Stage: At this point, major shifts in the leadership mindset and strategic orientation take place. The organisation understands that AI is not just a technology, but the basis for bigger organisation/market/industry transformations. Innovation-based product and business strategy exploration occurs and gains momentum, backed by capabilities developed in the previous stages. The organisation becomes more external- and future- facing with regards to the ecosystem and R&D. Structurally, the business may be moving towards self-organised, flexible teams, driven by a common sense of purpose.

Integrated Stage: Very few organisations today have reached this stage. Examples would include companies such as Google, Amazon, and Baidu, whose competitive advantage derives from AI and the associated virtuous circle of data, that reinforce their existing business and create possibilities for further business innovation and transformation. Furthermore, the enabling structures, processes, technologies and operations are in place to accelerate agility, supported by an understood sense of purpose and strategic alignment centred on value creation and purpose.

While theoretically possible, existing companies (not AI startups) tend to have difficulties in moving toward integrated AI (Fountaine et al., 2019) and more complex behaviours. It first requires building up both technical and organisational capabilities and knowledge with bolt-on applications. While there is some fluidity, our findings from interviews and workshops with companies in Sweden show that most companies today are in the early phase of AI development, using a bolt-on AI approach. This is an example of the style for a subsequent paragraph.

5 Discussion

AIMI & Innovation Management System

AIMI and Innovation Management System (IMS, ISO 56002) models include many shared elements, from strategy, leadership, culture, processes and organisation, ecosystem, and more. It is clear that to fully exploit the potential of AI and to reach higher inquiring and integrated levels of maturity, general conditions for innovation in organisations need to be met. On the other hand, integrating trustworthy AI in organisations can support various aspects of the innovation management system and increase the overall innovation capability of an organisation. Strategic implementation of AI and innovation management in organisations thus go hand-in-hand and can mutually complement and enable each other.

In *Figure 5*, several elements of the Innovation Management System according to ISO 56002 are mapped, and examples given of how AI technologies could be used to support and augment them to increase organisational innovation capability. In general, four recurring topics can be observed.

First, AI technologies can be applied to *democratise and distribute innovation across organisations*, instead of centralising it within a specific function or department. This is done by using AI to automate routine tasks, freeing up employees´ time for innovation and repurposing their work towards innovation as a core activity. By building a data-driven organisation, all employees can use AI-supported systems for more informed decision-making. In order to reach the full potential of democratising innovation with the help of AI, organisations need to reach higher levels of AI maturity, such as inquiring and integrated. While automation of work tasks and processes, and data-driven decision-making starts at earlier stages already, it is usually either optimisation (not innovation) driven or limited to a specific part of the organisation.

Second, integrating trustworthy AI in organisations can *increase diversity, cross-functional and interdisciplinary collaboration*. This is achieved by enabling more diverse talent recruitment and team formation. AI technologies can be applied for breaking down organisational silos, building recommendation systems that matchmake individuals and teams with interesting potential collaborators from within and without an organisation, depending on the challenge they are addressing. AI systems can even be used for assessing the innovation potential of external partners from the wider innovation ecosystem in order to optimise investments in external collaborations. Here again, bolt-on AI approaches might be used in specific functions (such as HR recruitment) in early maturity stages, while the full potential of AI will only be reached at higher inquiring and integrated maturity stages when innovative culture and flexible organisational structures are merged with AI across organisation.

Third, AI technologies can be applied to *increase organisational capacity for sensing future potentialities*. Organisations can move from a reactive to proactive mode based on AI-supported predictions that help organisations sense signals of change in stakeholders´ behavior and macro trends, thus better identifying their possible future needs. Consequently, organisations can become better at embracing risk-taking and uncertainty, reaching higher levels of ambidexterity, complementing incremental innovation with more radical innovation. At earlier stages of AI integration, bolt-on solutions will be used in specific functions, like predictive AI analytics in business intelligence or marketing, while the ability to sense future potentialities will be distributed across organisation only at the later inquiring and integrated stages.

Lastly, AI technologies can *support development of a learning organisation*, where learning is personalised and adjusted to the needs, preferences and learning styles of each employee. Some aspects of knowledge management (like taking meeting notes and systematising knowledge documentation) can be automated with personal recommendation systems used to only share knowledge that is relevant and interesting for individual employees. This stimulates creativity and continuous lust for learning. In the beginning of the AI adoption process, bolt-on applications might be tested to automate parts of knowledge management and to introduce personalised learning in some people development programs. A broader development of a learning organisation enabled by AI will only happen at later stages where AI is embedded and interlinked with innovation, the learning mindset and culture across the organisation.

Innovation context	**Innovation leadership**	**Innovation operations**	**Innovation support**	**Innovation performance**
Scan external environment AI can be used to scan large amount of macro data & trends, industry & competitors data, identifying pain points, in-time recognition of customer/stakeholder needs and prediction of future needs **Scan internal environment** AI can be used to scan internal data and processes, supporting alignment with org values (e.g. to increase inclusion, participation & diversity) **Innovation culture** AI can be used to understand culture/ identify patterns in human behavior that would not be seen through common questionnaires (for example, pattern identification in analysing internal communication) **Innovation ecosystem** AI can be used to support matchmaking with the right innovation partners, assessing their innovation capability	**Innovation vision and strategy** With improved AI-supported sensing of weak signals of change, organisation can become better at sensing future possibilities and possible new lines of business, developing a better data-driven innovation vision and strategy **Organisation for innovation** Data-driven organisation can democratise innovation and enable a more non-hierarchical organisation with distributed and innovative data-driven decision-making on all levels. AI could be used to enable more cross-functional interdisciplinary teams and support a matchmaking and recommendation system within organisation depending on the type of problem/challenge people work with **Innovation roles** AI can be used on one hand to act as assistant to innovation managers better support them in their work through data and insights, and on the other hand it can help them distribute innovation work and capacity across organisation by enabling each employee to become better at identifying pain points and needs of stakeholders they interact with, spotting signals of change that create opportunities for innovation within their own expert domain **Innovation portfolio** AI can be used both for tracking different ideas and their development status in organisation, for merging or connecting them, and as a support to evaluate innovation potential of different ideas	**Identifying opportunities** Data-driven product and service development through identification of pain-points, needs and opportunities with complex AI analytics. **Concept creation & validation** AI can be used to go beyond tunnel vision in the innovation process, identifying unexpected correlations between different concept ideas and broadening concepts by connecting them to other fields. **Solutions development** AI can be used for verification and testing of solutions, analysing trouble reports, and proactively predicting possible failures/defects **Solutions deployment** With a virtuous circle of data you can enable continuous improvement of products and services with iterative loops of feedback data and fast improvements. As development of AI processes and features requires a data-driven experimentation / evaluation cycle, other solutions can get a direct benefit from reusing their experimentation platform	**Attracting & retaining talent** AI supported talent recruitment tools can be used to increase diversity and create a better fit, which increases also retention **Knowledge management** AI can be used for automating and optimising KM, e.g. automated note taking in meetings and making personalised knowledge sharing recommendations **Time & budget for innovation** AI can release extra time and financial resources for innovation work by automating more routine tasks and freeing up more resources for innovation which can thus become a core task of everyone in organisation **Physical & virtual infrastructure/innovation methods & tools** AI-supported innovation tools which can augment human creativity with insights and artefacts from analysing complex and diverse sets of data **Innovation competence development** AI can be used to enable personalised learning (adjusting timing and training methods to specific needs of employees)	**Measure/evaluate performance** AI can be used to track complex sets of innovation performance related data, not only analysing what is happening today but predicting what might happen tomorrow to better manage potential risks and embrace uncertainties, increasing potential for radical innovation **Plan and act for improvement** With the help of predictive analytics, a more proactive (instead of reactive) approach to continuous development of innovation system is enabled, helping organisation not only incrementally improve its IMS, but potentially disrupt it

Figure 5 *Mapping AI support to different aspects of the Innovation Management System*

Despite the potential future impact of trustworthy integrated AI on various aspects of the innovation management system, the current reality is that most organisations are in foundational or experimenting maturity stages of AI integration, running ad hoc pilot projects and applying AI in a single business process (Fountaine et al., 2019). Our assessment is that organisations need to move towards the inquiring and integrated stages in order to start increasing not only incremental innovation, but also strengthening organisational capacity for radical innovation with AI as enabler. This could result in AI-driven innovation, supporting new ways of adaptive organising based on distributed decision-making, innovative business models, and introducing completely new lines of business.

It is interesting to address the question of how the role of innovation management might change in organisations as they reach the highest levels of trustworthy AI integration. We see glimpses of that in some of the AI-driven start-ups today, run by a new generation of progressive leaders that fully embrace the possibilities of human-machine augmentation and self-organisation, where innovation management as an organisational function is not needed anymore, because continuous innovation has become both a core skill and business for everyone in organisation.

6 Conclusion

This paper develops a more comprehensive view of the complex relationship between integrated AI and innovation management. It also raises important questions around how integrated AI could affect the role of innovation management in the future and increase organisational innovation capability. It demonstrates the need for two different experimentation stages - an initial AI adoption level that strengthens organisational capacity for optimisation and incremental innovation (from foundational to operational stages); and one where organisations reach inquiring and integrated AI maturity levels that drives more radical innovation. As this is a fairly new area, this paper introduces the AI Innovation Maturity Index (AIMI) framework that could be used more systematically to support the implementation of innovation management systems designed to increase organisational capability for more radical innovation.

We intend AIMI to be used as a compass, a map and a tool. It enables joint sense-making around best practices needed for a holistic integration of AI in organisations, enabling innovation. For business and public sector organisations, it shows which aspects they need to develop (often in parallel), what the journey might look like, how well they are doing, and what types of help they should engage at different stages of maturity to derive the most value. For innovation management researchers and practitioners it offers suggestions on how AI could be used in various ways as an innovation enabler, moving organisations from incremental towards more radical innovation.

The AIMI model needs to be tested more widely in practice to fully demonstrate its value and application opportunities. For this, an assessment tool could be developed to support the model and enable a systematic evaluation of current AI maturity state, supporting strategic planning for AI integration.

We believe that integrating trustworthy integrated AI in organisations can support various aspects of the Innovation Management System (ISO 56002, 2019) and increase the overall innovation capability of an organisation. AI technologies can be applied to democratise and distribute innovation across organisations, increase diversity, cross-functional and interdisciplinary collaboration, strengthen organisational capacity for sensing future potentialities, and support development of a true learning organisation. Strategic implementation of AI and Innovation Management in organisations go hand-in-hand, and further exploration of their integration could be a beginning of a beautiful friendship.

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