5 Artificial intelligence and public innovations

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Introduction

As artificial intelligence (AI) technology becomes more complex and far-reaching in its implications, we are in danger of education losing the race with technology: our understanding, organizations, policies, and ethics could be buried under an avalanche of technology diffusion and adaptation (Goldin & Katz 2008). A danger is that the pace and direction of AI innovation are dictated by the tech giant's pursuit of profit rather than clear public service strategies meeting citizens' needs. "Break first, think later" – the mentality of commercial AI innovation – may deliver financial and technical success, but meeting social needs is another matter if trust is endangered and social consternation rises (Leslie 2020).

One danger is trying to pursue more from less, with the cost reductions resulting from AI innovation becoming inevitable even if opaque technology is applied to socially intractable problems. Equally dangerous is neglecting technological advances that offer new service solutions simply because the technology is advancing too fast. Avoiding AI is impossible: instead, agents in public services need to grapple with new knowledge flows and the new roles, relationships, and responsibilities posed for citizens, public service providers, and private organizations. This is especially challenging since most public agencies have little in-house AI capacity or AI research capability, meaning that many AI projects are necessarily public–private partnerships (PPPs), which introduces an additional set of complexities for public agencies that perhaps prefer bottom-up modes of innovation (Mikhaylov et al. 2018; Wirtz et al. 2019). Balancing fast-paced technology and slow-moving social and ethical values challenges public service agents to think, plan, and act critically and systematically.

In support of a critical approach to AI innovation, we consider the meaning and practical implementation of mutuality at the city level since mutuality is essential at every stage of design and implementation if AI-enabled new service solutions are to reflect user needs and meet public service standards such as equity, consent, privacy, and transparency. Our research question: Is AI altering mutuality governance in innovations between the private and public sectors?

We consider what mutuality means as a form of governance in the relations between the public and private sectors around AI given the need to blend

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institutional drivers and overcome the uneven distribution of expert knowledge. This is done by drawing on the experiences of the City of Oulu and the City of Tampere in innovating AI.

The chapter begins by conceptualizing AI as a general-purpose technology and then critically assesses previous research on AI innovation, highlighting the challenges posed for public agencies and the case for mutuality in AI innovation. Building an analytical framework on these discussions, we apply it to experiences of AI innovation in Oulu and Tampere, focusing in particular on how mutuality shapes service innovations. After discussing these results, we propose theoretical conclusions and carefully outline generalizable lessons for public agencies implementing AI-enabled service solutions.

Conceptualizing AI in the public sector

AI capability builds upon data digitalization and big data analysis evolving from human-computer interaction (Papert 1993) and decision theory (Minsky 1986). Singularity, i.e., computers imitating human emotional-cognitive ability, has often been predicted (Newell & Simon 1972; Kurzweil 2005), as have artificial superintelligence computers *significantly more intelligent than humans in all respects* (Barrett & Baum 2017). However, this remains to be achieved (Russell 2019), though general intelligence is perhaps close to today's advanced machine learning (Searle 1980). However, most AI operates in closed fields as narrow intelligence, such as in the games of chess and Go. AI is good at searching massive databases and arriving at decisions from patterns, giving rise to capability-based classifications of AI (Dwivedi et al. 2019) revolving around AI doing things that humans are not good at (decisions from masses of data), while humans remain better at evaluative judgements and exercising wisdom, which AI, in turn, is not good at. In terms of technological conceptualization, AI is an umbrella term for a diverse range of computational techniques and technologies – ranging from rule-based systems to deep learning systems – and functionalities – ranging from machine learning to robotics and decision-support to facial recognition (Stone et al. 2016). The European Commission (AI HLEG 2019) describes AI as either software and hardware systems that through data acquisition reason and process information to decide the most suitable action for achieving a given goal or (in robotics) undertaking programmed actions.

Narrow AI offers four functionalities relevant to the public sector: (1) support for decision-making processes, (2) integrated data governance, (3) interaction and virtual agents, and (4) the automation of administration (see Table 5.1). To solve a specific problem, AI might use one or more technologies (if interoperable and integrated) from the wide domain of AI technologies, such as natural language processing, computer vision, neural networks, robotic process automation, and many more. AI technologies in these areas can provide *descriptive, predictive*, *explorative*, *prescriptive*, or *automated decision-making* (Watson 2014).

Local authorities have adapted successful AI-enabled decision systems (Spieth et al. 2014; Ross 2016) and successfully increased decision speed and accuracy

Table 5.1 AI application areas in public services

Application area in public sector	*Purpose and AI functionality*	*Data reference*
Decision-making support	• Augmenting civil servants • Knowledge management systems: codification • Knowledge flows with neural networks • Predictive and prescriptive analytics	Wirtz and Müller (2019) Gupta (2019) Ross (2016) Spieth et al. (2014)
Interaction / virtual agents	• Computer-based interaction with user • Communication: citizen experience, user involvement in service design • Interaction with civil servants • Conversational AI, such as chatbots, natural language processing, computer vision	Kreps and Neuhauser (2013) Androutsopoulou et al. (2019)
Data governance	• Gathering, storing, and processing data: broader inclusion of data and expanding existing systems • Identifying anomalies and patterns: e.g., detecting service needs, identifying potential dangers • Cognitive surveillance and security systems • Diagnostic and predictive analytics	Ahokangas et al. (2012) Schorr and Rappaport (1989) Kankanhalli et al. (2019) Karvinen et al. (2017)
Automatization of practises	• Automation of standard tasks • Document reading and validation, intelligent case management • Higher-level autonomous systems • Knowledge-based systems: expert systems	Kuziemski and Misuraca (2020) Chun (2007) Collier et al. (2017)

(Gupta 2019; Wirtz & Müller 2019). The development of data governance has been supported by the broader inclusion of data in existing systems (Ahokangas et al. 2012) and the expansion of systems from the internet of things (IoT; Schorr & Rappaport 1989). The IoT can successfully expand the breadth of services offered in technologically assisted independent living, linking the inside to the outside of the home, for example with security, tracking, and transport services (Kankanhalli et al. 2019). There are examples of new service models often based on integration, for example, in health and social care integration and children at risk (The Guardian 2019), and in digital phenotyping for personalized medicine (Onnela, 2017). In terms of AI assisting the public sector in communication, digitalization already increases opportunities for communication and the use of conversational AI – for example, using AI-guided chatbots (Androutsopoulou et al. 2019).

Ideally, citizens should participate in critical decisions at all stages of new service development. The public sector is speedily automating its administration. Examples include faster and higher-quality request processing for immigration application forms (Chun 2008; Kuziemski & Misuraca 2020), automated image diagnoses (Collier et al. 2017), and analyzing and supporting the development of the labour market (Kuziemski & Misuraca 2020). AI-enabled innovations in the public sector potentially benefit the efficiency and/or effectiveness of service delivery to businesses and citizens, answering needs and ultimately supporting the level of satisfaction and trust in the quality of governance and public service.

Simultaneously, however, research shows that the results from AI are mixed for citizens (Greene et al. 2019; Coeckelbergh 2020; Dignum 2019). AI innovations pose issues and dilemmas across policy areas, including social, technological, data, economic, political, legal and policy, organizational and managerial, and ethical dilemmas (Dwivedi et al. 2019). The negatives of AI use have been identified, such as issues concerning access and control, data choice bias, and the difficulty of redress (Kinder et al. 2021). To address these issues, numerous expert groups and public and civil organizations have introduced guidelines for designing ethical AI. These include the guidelines of the European Group on Ethics in Science and New Technologies (EGE 2018), AI4People (Floridi et al. 2018), and the European Commission's High-Level Expert Group on Artificial Intelligence (AI HLEG 2019). Overcoming these challenges requires answering the question *by whom, how, where, and when will this positive or negative impact be felt?* (Floridi et al. 2018) What is technically possible may not be desirable or useful: how then do we evaluate the usefulness and ethical desirability of AI innovation?

Since AI is complicated and opaque, information asymmetries arise between stakeholders (consumers and policymakers) and AI experts. This brings out issues of understandability (Gasser & Almeida 2017), what the European Commission calls *explainable AI* (AI HLEG 2019). We prefer the term understandability since instead of presuming the issues are simply one of an AI expert explaining the technology, our view is that also users and providers need to explain emotional touchpoints and user experiences to the AI expert: understandability is a two-way street. Without understanding the basics of *how* and *why*, AI innovation team members lack the ability to justify design decisions to gain the user's informed consent and the ability to puzzle through their implications, always bearing in mind unintended implications that occur anyway in most innovations.

These issues resonate strongly in Finland, the focus of this study, where the Ministry of Economic Affairs and Employment (SAIP 2019) announced "we want Finland to become a leader in applying artificial intelligence and robotics to the benefit of societies and enterprises". Finland is already ranked fifth in global AI-readiness by Oxford Insight, and gross domestic product growth predictions up to the year 2030 are 0.8 per cent without full utilizing AI and 3 per cent with full utilization. Inevitably, AI companies are drawn to the public sector because it has the largest databases and large numbers of intractable problems needing innovative new solutions. Many public agencies lack the resources to employ AI experts and need public–private financing to implement new solutions (Kinder et al. 2020). It is to the issues of AI innovation that we now turn.

Innovations and AI

In a market economy, companies and organizations either *innovate or die* (Freeman 1991). Other issues facing the public sector are austerity, rising demand, and/or quality improvement. Innovation reduces cost by efficiency, a more effective service design, or a new business model. Although the *inevitability of progress* was proposed by the Frankfurt School (Horkheimer and Adorno 1972; Allen 2016), more negative views of technological innovations are also advanced by researchers (Foucault 1997; Sennett 2003; Sandel 2020). Metaphors for innovation include *creative destruction* (Schumpeter 1939), the biological metaphor in evolutionary economics (Witt 1993), and the increasingly popular systems or physics metaphor (Arthur 2015) often related to complexity and ecosystems. Freeman and Soete's idea of the socio-technical paradigms of technological change remains influential (Dosi et al. 1988).

Public services are systemic by nature and do not look to the innovation of autonomous technologies but instead to integrative technologies and service models contrived as ecosystems. The ecosystemic view discusses the systemic nature of innovations and favours a future-oriented, systemic, and multi-agent approach for supporting service innovation: the futures view, systems view, and multi-actor view (Hyytinen 2017). Technologically enabled innovation is future-oriented and therefore often constrained by heritage structures, cultures, and ways of working. Multi-agent approaches often feature stakeholder analysis and prefer long-term visionary targets, though the weighting attached to each stakeholder's interests can cause conflict. The systems perspective focuses on interlinking sub-systems and broadening boundaries.

Technological innovations

Research on technological innovation has established its non-linearity, spill-over effects, unintended consequences, radical or incremental nature (Freeman 1991), closed or open innovation processes (Chesbrough 2011), and adaptation to new contexts and cultures (Wartofsky 1979; Bernstein 2000; Daniels 2016). Learning, sense-making, and recontextualization are essential to all successful technology innovations (Nonaka & Takeuchi 1995). Service innovations have emphasized user involvement in addition to technical interoperability, complementarities, and the coupling between technology-push and pull (Von Hippel 1982). Additionally, innovation research highlights the usefulness of tools such as contextual usability and the importance of human agency in open innovation processes (Kinder 2000). Especially in public services, services-as-a-system "pull" personalized services to citizens that are often organized across organizational boundaries (Laitinen et al. 2018b). When technology innovation brings decision-taking closer to the point of customer contact, it disrupts existing hierarchies and power relations, resulting in new governance arrangements, especially if using hybrid delivery projects, such as PPPs. We note that incentives and motivations for technology innovation are diverse, often in its early adoption stages focusing on cost reductions rather than new business models, i.e., efficiency rather than (more complex) effectiveness. Involving the service user and encouraging learning asks new questions in innovation processes, such as "how do I feel about it?" instead of simply "does it work, is it faster?"

All technological innovation is accompanied by technical and market risk, and for the public sector, there are additional risks in providing services for vulnerable people (Flemig et al. 2016). Evaluation of success, therefore, includes ethical and subjective factors in addition to cost-benefit analyses and return on investment. Ethical issues are contextual by nature and are always case-specific (e.g., Bowles 2018). The impact of technology concerns not only the direct usage situation but also the many different stakeholders who may have conflicting interests. Risks arise where technologies are *black-box* (Rosenberg 1982; Beck 1992; Adleretal 2018), meaning the inputs and outputs are discernible, but the transformation processes are opaque – often an AI characteristic. In design processes, service walk-throughs and emotional touchpoint evaluations (Radnor et al. 2014) add complexity and potential AI expert misunderstandings.

A central issue then for AI innovation is mutuality and understandability – that is, the preparedness of agents involved in innovation (such as developers, users, and service providers) to give the time and commitment necessary to understand each stage of the new service solution (such as the algorithm, choice of databases, and embedded machine learned patterning) and the user explaining to the AI experts the unacceptability of some algorithm designs or database referencing. For governance arrangements, a key issue is whether the market or non-market dominate, making mutuality a critical point.

In summary, both understandability and mutuality are essential features of technological innovations in the public sector, each of which is influenced by the particular context and culture in which the innovation occurs. Each of these points will feature in ethics decision-making and the wider social evaluation of the innovation's acceptability.

AI in public services

Extensive public-sector digitalization has accrued a vast reservoir of big data: fertile soil in which AI can flourish in dealing with important issues.

These issues include framing AI-enabled innovation to avoid technology-push and instead adopting a human-centred and problem-centred approach (Floridi et al. 2018; AI HLEG 2019). Machine learning AI raises the possibility of the *invention of a method of invention*, a prospect underscoring the need to control AI's rate and direction of diffusion (Griliches 1957). For example, the City of Oulu has developed a system of using the public sector as a testbed for privately launched products, such as a health app, a secure mobile phone, and wearable health data signalling. Is this an advantageous circular economy or alternatively a negative development? We note that Bluetooth signalling from IoT devices is important to AI-related innovations – for example, supporting technologically assisted independent living. What does this mean for 5G infrastructure rollout, and who will bear the cost? AI innovations attract calls for public accountability from a wider democratic footprint (Laitinen et al. 2018a), so what level of public understanding of AI is needed?

Researchers have catalogued AI-related problems in US public services, such as the wrongful denial of benefits (O'Neil, 2016; Eubanks 2017). Some are also evident in the United Kingdom, including contract cancellations (The Guardian 2019). Monopoly exploitation of historic intellectual property (IP) and trolling for IP breaches have become a major problem (Standing 2016). These cases highlight the importance of IP and General Data Protection Regulation (GDPR c)ompliance and the careful protection of new IP, especially of basic research in university commercialization. While AI-enabled robots are likely to feature more in manufacturing than public services (Angwin et al. 2016), we note their use in delivery, surgery, and driverless transport, not to mention the existence of Japanese robot companions. Already, AI is criticized for misreading the faces of people of colour in facial recognition (Eubanks 2017), bias-confirmation in predictive policing (Asaro 2019), and gender-biased classification (Bouolamwini & Gebru 2018). Agents ask *can I sue an algorithm* if it is shown to be biased (Brown et al. 2019)?

It is argued that AI adoption in local authority areas should be part of employment and skills planning and not simply seen as an opportunity for cost reductions (Allam & Dhunny, 2019). Perversely, better public services result in an increase in demand and costs, unlike in the private sector, where additional demand results in raised revenue: AI adoption poses unique issues for the public sector. One such issue is the wider public accountability for AI-related services and the upending of hierarchies and power distribution, creating new inter- and intra-organizational governance arrangements (Cath 2018). Final users in the public sector are often vulnerable, highlighting the need for transparency and careful ethical evaluation.

In summary, AI presents the public sector with new service model opportunities and more effective services, and AI innovation comes with the challenges of understandability, mutuality, and ethicality. Both sets of challenges need to be met if AI is to succeed in the public sector, issues we now examine from practice.

The need for mutuality

Mutuality is a type of governance, in this case suggesting agent interdependency featuring trust in relationships as opposed to (for example) purely market governances in which for-profit principles mediate all decisions. Governance here is deployed in a wide sense as rules and norms guiding decisions and actions (Kinder et al. 2020), and it includes mutuality between private and public organizations.

The institutional drivers influence guiding decisions and actions concerning the mutuality of public and private organizations. Market principles guide innovation towards the lowest cost and highest profit margin, whereas mutuality-based innovation is driven more by agent satisfaction with service effectiveness, especially for users. Our research allows the examination of AI innovations in local public services, which are prone to mutuality governances. One important difference between mutuality and market governance in innovation is the role played by service users. Both are likely to list service users as stakeholders since market-oriented services will only achieve success if users endorse their usability. Where mutuality prevails, the role of users is likely to involve user engagement in all design and decision stages, and this entails much more time spent by AI experts explaining and ensuring understandability for the service providers and users. Also, in mutuality governance, the AI experts will spend time listening and learning from providers and service users, especially informal and emotive views on how the new service solution will differ from existing (non-AI) arrangements.

The mutuality-based AI innovation process, therefore, differs markedly from market-driven processes in terms of knowledge flows, levels of trust, and time spent on understandability. From the perspective of the innovation assemblage as an epistemic community (Haas 1992), the type of knowledge flow differs from a market-driven project. The latter is concerned with costs and efficiency, the former with relationalities, contextual usability, and effectiveness. Risk in the market-driven innovation project is not technical but social – that users will reject the project citing usability, access, privacy, etc. Risk in the mutuality-driven innovation project is project-creep (too many functionalities added) and loss of cost and time discipline. The discussion of "open" and "closed" innovation projects debates the advantages/disadvantages of each approach (Chesbrough 2011). Part of the closed nature of top-down projects is that projects may be compelled to use a project management programme, such as Prince-2. This brings focus to the activity on project plan deliverables, milestones, waterfall testing, and outcomes, even if this means rejecting changes to the original plan that the stakeholders deemed sensible (Kinder 2010).

Mutuality in innovation processes has a psychological dimension since projects by their nature are time-limited special events, and, in the case of AI, they bring together stakeholders from diverse disciplines and governances. Mutuality can be studied at the level of the individual, envisioning dyadic, triadic relationships (Henson 1997). In our analysis, the members of the project team are the unit of analysis rather than individuals, often with forming-storming-norming-performing being phases of negotiating team governance, language, and ways of working. Most favourably, project teams create a trust that addresses the confidentiality issues Henson (1997) raises. We find analogies, such as parent-child (Tronick et al. 1977) or lover commitments (Drigotas et al. 1999) limited since innovation team members bond around the purposive intent of creating the new service solution, and where mutuality prevails, they put aside dyadic relationalities and play for the team. In the team context, the discourse on mutuality ties it to values, principles, and practices as part of meaningfulness (Yeoman 2019). Understanding meaningfulness and values can be helpful in conceptualizing relationships in innovation work, especially trust, respect, honour (Nietzsche 1988), and emotional attachment (Vygotsky 1934) between agents.

Part of this coming together addresses some of the issues raised about mutuality in organizational studies research (Dabos & Rousseau 2004). Our approach is that exploring organizing is more revealing than studying organizations (Weick 1995) and especially so for innovation. The reason for this is that where projects such as AI-enabled local public service innovation integrate services, they necessarily disturb existing hierarchies and existing power distributions – in short, all existing inter- and intra-organizational structures. For example, the new AI solution may empower the nurse's decision-making vis-à-vis the doctor or redistribute functions from the social worker to the home care assistant. Whereas psychological exchange is related to old command-and-control hierarchies, integrated service solutions may lead to messy and multiple upwards and horizontal accountabilities for staff (Dabos & Rousseau 2004). We find social exchange theory more helpful in understanding the formation of mutuality, as it seeks to understand trust and acknowledge the boundaries of power and social dominance (Blau 1964). Mutuality in innovative projects often changes old identities, roles, relationships, and responsibilities: we envisage mutuality in AI-enabled projects as dynamic and upsetting previous arrangements. Yeoman's (2019) emphasis on mutuality in innovation projects sharply poses the issues of roles and values in terms of how new arrangements can achieve better service solutions than the old ones. The new "whole" achieves more than the sum of its parts – often described as more from less. The new services-as-a-system is "pulled" by the needs of the user, irrespective of the organizational boundaries.

As we have noted, AI processes of this sort are best envisaged as dynamic ecosystems and not fixed inter-organizational networks. Often this simply acknowledges the cooperative working that local government service professionals have already been practising. Interdependency is best based on trust and mutual respect (Thibaut & Kelley, 1959); without them, service professionals are unlikely to depend upon the behaviour of others, especially in caring for vulnerable clients. In bringing together multiple databases, decision systems, and information flows, AI-enabled innovation can easily not only create mutuality but also conflict (Rossi & Tuurnas 2021), especially if the inter-working between diverse governance arrangements (e.g., market vs. free public services) has not been resolved. An effective innovation project will recognize such problems and take action to resolve them. Often interdisciplinary team meetings that discuss cases and apportion responsibilities are a good forum to identify and resolve problems, remembering that service professions frequently have occupational cultures which place the needs of the client first.

AI innovation processes impact the wider citizenry, either because they use the services (transport, waste disposal) or because they form part of the community's social identity (elderly care, children's education). The accountability of social innovation is tied to the citizenry as a whole (Behn 2001), and similarly, information communication technology (ICT) innovation in public services reveals the importance of social acceptability (Parker & Parker 2007). Research on services-as-a-system in Finland showed that radical alterations in social care, where democratic participation is high and services are localized, require innovations to find acceptability in a wider democratic footprint (Laitinen et al. 2018a). For black-box technologies such as AI, it seems especially important to secure public acceptance of innovative new systems – a wider view of mutuality.

Mutuality then is an important conceptual tool and practice guide for AI-enabled local public service innovations. Mutuality is a way of working (trust, shared knowledge, and emotional attachments), a way of implementing new service models (ecosystems, multiple and messy accountabilities), and (most importantly) a new way for service users to help create public services that meet their needs.

AI and public innovation in practice

The City of Tampere and the City of Oulu have a heritage of being world-leading software clusters, previously supporting Nokia and now supporting advanced software sectors. The cities were chosen because, atypically, they have explicitly decided to re-envision their services through the lens of AI.

The subject of this case study is mutuality between public and private organizations in the development of AI innovations at the city level. The research draws on 20 interviews with AI practitioners, local public service providers, and service co-designers from Oulu and Tampere, Finland. These interviews were conducted by Author 2 in May 2019 and enquired about their ongoing thinking on AI in local public services and the intended future of AI use and ethics attitudes. We used a cognitive conversation method (Geiselman et al. 1985), allowing interviewees to narrate terminology, process inter-relating agents, and sequence cogent stories, linking evidence and interpretation.

All interviewees gave their written consent prior to the interviews, which were subject to guaranteed confidentiality. All interviews were conducted in English, and the results were transcribed.

Table 5.2 Interviewees: gender, designation, position, and organization

City of Tampere, Finland		
Male	CEO	Development agency
Male	Development Manager	Private-sector incubator
Female	Project Manager	The City of Tampere
Female	Project Manager	Tampere region
Male	Development Manager	The City of Tampere
Male	Director	The City of Tampere
Male	Development Manager	Tampere University
Female	Development Manager	Tampere University of Applied Sciences
Male	Development Manager	Tampere University Hospital
Male	CEO	Software company
Male	CEO/Technical Director	AI development company
City of Oulu, Finland		
Male	Member of Council	Youth Council, The City of Oulu
Male	Member of Council	The City Council, The City of Oulu
Female	Manager	Voluntary Organization
Male	Managing Director	Voluntary Organization
Female	Director	The City of Oulu
Male	Director	The City of Oulu
Male	Director	The City of Oulu
Male	Director	The City of Oulu
Male	AI Professional	Oulu City Council

Generalization from the results was needed to follow recontextualization carefully. Awareness of AI-enabled services varied among the informants. Some had a clear picture of how cities develop AI-enabled innovations. Some informants only recognized AI-based practices and tools, like second-generation chatbots, service robots, smart rings, MyData, and data-based decision-making. In the case study, we interpreted the data to create an overall picture of the AI innovation ecosystem. In the analysis, we triangulated between the interview evidence, previous research findings, and our own sense-making.

The dataset does not include the cases of individual AI innovations, but it gives information on a complex environment in which AI-enabled innovations are developed between private and public organizations. For this reason, the dataset is relevant for answering the research question. The informants have an interest in developing services, and many are active in innovation ecosystems at the city level. This also means that many informants look at national AI innovation policy from the perspective of how it helps to develop local practices and services. This has affected the outcomes of the case study.

Innovation initiatives

We begin by specifying the levels of innovation initiatives in the public sector revealed by the data. Innovation operations on the city level – the focus of this chapter – are tied to regional ecosystems and national initiatives that form a complex interdependent environment.

One official explained that the city envisages mutuality as a multilevel and complex environment from which "order" emerges, sometimes in unforeseen ways, and agents in innovation collaboration are nested (Figure 5.1). The analysis of this chapter focuses on the meso-level, where teams operate in city level or regional ecosystems. These are influenced by individual values (Yeoman 2019) and barriers of power and control on the institutional level. For example, a local company might develop an AI innovation that (even unknowingly) aligns with national strategies and occurs because of mutual interdependency between the public and private sectors.

City-level innovation

The interviewees understood the need for mutuality governance between the public and private sectors and the dynamic environment facing AI innovation. The interviewees felt close cooperation was essential and best achieved in long-term relations characterized by trust, which is typical in Finnish local government. At the same time, public agencies need to avoid treating some AI partners unfairly, particularly in competition for innovation project selection. Finland also has traditions of cooperation in the public and private sectors regarding the development of technological innovations, and agents in both Oulu and Tampere cited close working relations between the public and private sectors over the decades with Nokia's research teams.

The City of Oulu and City of Tampere point to successful AI-enabled service innovation projects. In Tampere, these include a MyHealth app, which signals the

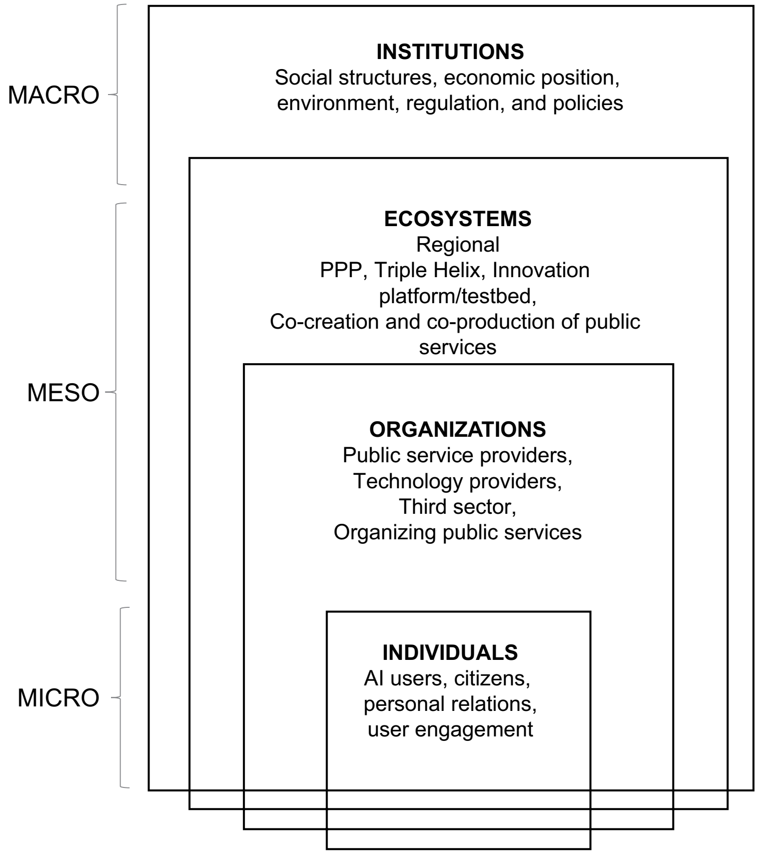

Figure 5.1 Nested operators in the AI innovation process.

need for a doctor's attention, and the extension of technologically enabled independent living supported by the IoT's data-gathering and signalling to ambient service providers. Transport integration and identifying isolated elderly citizens are other successful AI-based projects in Tampere, each of which involves companies and the public sector.

In Oulu, the Oura ring signals health data to doctors, and the second-generation Oulubot chatbot is widely used. The climate (50 km from the Arctic Circle) is important in Oulu, and an AI-enabled prediction centre helps organize local transport and company logistics planning. The IoT is widely used in elderly care systems. We were told that three billion users per day access AI systems developed by small and medium size enterprises (SMEs) in Oulu. The city's procurement system is AI-enabled, combining with adjacent public agencies to reduce costs.

AI regional ecosystems

The Cities of Oulu and Tampere each have the strategic aim of building AI regional ecosystems across the public and private sectors and, in each case, a matrix of problem-centric and technology-centric self-governing ecosystems. In both cases, the problem-centric ecosystem addresses the integration of health and social care based around city hospitals, which are regional centres. Described as cross-cutting and supporting the *bounce-back* of the local economy (in Oulu), other ecosystems are technology-centred. In Tampere's case, the focal point is the newly merged university, which has AI as one of its strongest research fields. In Oulu, the university is also important, with the Chamber of Commerce playing an important role in informal networking between AI SMEs and public agencies. Since the City of Oulu is geographically situated in an adverse northern environment, the City Council is particularly concerned about expanding companies and encouraging AI start-ups, aiming to continue the high standard of living that prevents population decline. Tax revenues from successful companies are an important revenue source for both cities.

Tampere's ecosystem features city-led networks in transport integration, environmental quality, waste disposal, and social care issues, while in Oulu the city's role is more enabling – for example, as a conduit for ideas, promoting informal information exchange events, and holding impromptu events based on ideas for new services. In Oulu, it is noteworthy that Trade Unions and voluntary organizations are often the source of new ideas, which the city's top policymakers then organize around, offering support and data access to interested companies.

National AI initiatives

The interviews revealed the important role of national initiatives for innovation. From the perspective of cities, the most significant AI-related programme would be the AuroraAI programme. The programme encourages AI innovation based on important transitional life events (family circumstances, educational progression) using multi-stakeholder ecosystems that flexibly interact (SAIP 2019), building new service chains that automatically support life-event transitions. In doing so, service costs can be reduced, and opportunities arise to integrate public and private services. A government policy summarizes the objectives: "Success in reaching the target of public services calls for interconnecting public organizations (AuroraAI network) to interact with the services of other sectors with the help of AI". The AuroraAI programme is leading to a service network that interconnects services so that they can support and interact with each other (SAIP 2019).

Officials from the City of Oulu frame their AI activity within the AuroraAI programme using funding to support service development work. One company representative reported using funding for a nationwide experimental service. AuroraAI encourages the commercialization of new products and services by companies. Ethical evaluation by users and service providers is embedded in the AuroraAI projects.

Mutual governance of AI innovations

In addition to the innovation environment, the interviews introduce several arenas where mutuality governance between public and private organizations is taking place in the development of innovations concerning cities and their services.

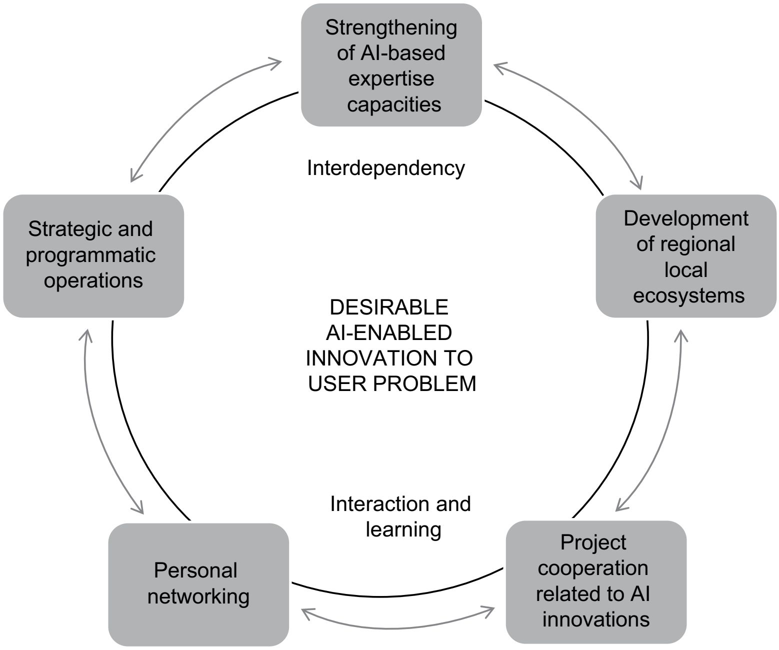

Figure 5.2 Arenas of mutuality in AI-enabled innovation.

These include (1) strategic and programmatic operations, (2) the strengthening of AI-based expertise capacities, (3) the development of regional and local ecosystems, (4) project cooperation related to AI innovations, and (5) personal networking. Some of this is captured in Figure 5.2.

Strategic and programmatic operations

Finland has a very strongly top-down and design-centred tradition in the development of technological innovations (Koskimies & Kinder 2021). This means, for instance, that a new kind of development cooperation and related target settings are typically advanced utilizing national programmes. As mentioned, the City of Oulu is closely involved in the AuroraAI operation. In practice, programmes like AuroraAI can imply that locally developed innovations may turn out to be trendsetters. Programmes are also aimed at generating nationwide benefits from cooperation in innovation development. This calls for open innovation development work that enables different public organizations to utilize innovations in the way they consider practicable. This includes the mutual sharing of information, compatibility protocols, and platforms to build common working spaces in which (cross-governance) development teams operate.

Few public agencies employ AI experts or units dedicated to AI-based research. Instead, city administrations operate using projects constituted to exploit public-sector databases and to address problems. In the City of Oulu, suggestions for projects come from the voluntary sector, the Youth Council, and Trade Unions in addition to projects framed by the City Council. AI programmes in the city's university are encouraged to create projects jointly with the city. Finland's culture of easy movement between the public and private sectors means that problem-centred project work is quite normal and addresses the AI expertise deficit in the public sector while providing data and expertise from service models lacking in the private sector. The cities' top policymakers are important in Finland: in both Oulu and Tampere, the policymakers are a direct conduit for companies with AI application ideas to approach the City Council. The advantage to City Councils of capacity-building using problem-centred projects is that new service solutions directly address issues in the context and culture of the city, reducing the risk of technology-push by providing user testbeds at the trial, test, and implementation phases. Representatives of each city's universities report that AI projects – jointly framed, scoped, and designed with the City Council – are an ideal learning environment for AI students.

Strengthening of AI-based expertise capacities

Finland already has significant AI capabilities and capacity. In the Cities of Oulu and Tampere, most schools teach AI, encourage AI projects by students, and feature presentations by AI-related businesses in the curriculum. At the university level also, AI features across the curriculum. Finnish universities encourage interdisciplinary undergraduate programmes, including internships and business-linked projects. Nokia's retrenchment into a software company has created a pool of AI programmers in Finland (some estimate 10,000); some work independently, while others work in the plethora of AI-related SMEs now forming half of the company start-ups estimated by the Tampere Chamber of Commerce. In short, Finland has significant human capital in terms of AI expertise.

People working in the enterprise sector, as well as those representing the public sector, strongly emphasize that expertise in the public sector has a significant effect on AI innovations and the related cooperation between the public sector and companies. A deficiency in expertise affects, for instance, the ability to work with AI-based practices. The significance of AI is not necessarily understood well enough in public services. A similar lack of expertise can generally be seen regarding the possibilities of AI in the development of services.

Expertise has several practical implications. It is possible that due to deficient expertise, the public sector is not able to detect the AI-enabled innovations developed by companies that would affect their operations. This is why the public sector is unable to adapt its operations to the companies' innovation operations and to direct purchases to this end. It is also possible that companies capitalize on the deficient expertise of the public sector. They are possibly selling innovations at high prices or when not yet completed. In the latter case, extensive amounts of AI innovation development work would need to be carried out during the implementation phase in service operations.

Most AI project participants recognized the importance of ethical understanding and insist that users and providers judge ethicality at each phase of the project, knowing this requires minds-on commitment, time extensions, and patient, two-way communications. Ethical assessment begins at the project framing stage, as the project team builds a picture by layering pieces of information, for example, what decisions algorithms might make and which databases are appropriate to reference in the context and culture of the public service. In an agriculture project, the first overall assessment began by referencing general ethical principles (consent, privacy, etc.) and then proceeded to a user evaluation of each emotional touchpoint in the service walk-throughs. As a university development manager commented, "Open discussion of how we use the data is the best way to avoid criticism of unethical uses of AI". The team members felt that applying high ethical standards and using the voice of the customer gave the AI services *brand integrity*: acceptability in Finnish cities would help in the international commercialization of the products. We found projects involving service users at each decision stage, with considerable effort made in educating AI experts of users' ethical sensitivities and the experts ensuring sufficient understandability by users to approve new service designs.

At the city level, the lack of expertise is generally seen in the implementation of AI-based innovations. Both of the cities involved in this study are therefore working in cooperation with companies in order to advance the better practical implementation of AI innovations. Deficiency of expertise is also tackled in Tampere and Oulu through cooperation in training. Companies may also share the view that the more expertise there is, the more willingness there is to adopt their AI innovations.

Development of regional and local ecosystems

Both Tampere and Oulu see ecosystems as solutions in that in AI-enabled innovation operations, mutual adjustments take place between the public and private sectors. Ecosystems are built up with two objectives.

The first objective may be to accomplish an ecosystem around a certain public service operation – such as health care services. In this case, local and regional ecosystems are also producing innovations that would serve the operations of cities or public organizations (e.g., university hospitals) in the area. A second objective may be to generally establish a local and regional business ecosystem for the development of AI innovations. For instance, the City of Oulu has invested particularly in the development of start-ups. The aim of the city may be to enhance the ability of regionally operating companies to jointly develop innovations. One of the tasks of cities is to generate local and regional vitality. This will also have an effect on cities' tax revenues.

There are, however, differing views at the city level on what would be the best way for ecosystems to work in order to promote innovation operations. In many cases, the ecosystems of cities or regions are networks of operators compiled and managed by them. Alongside this, especially the City of Oulu has invested in services answering the needs of companies. Leadership of the ecosystem is complex since as self-organizing entities there is no command and control: leadership is the result of collective consciousness. For Oulu, this is centred on the mayor's office as the source of new ideas and a conduit linking potential partners. In Tampere, the Chamber of Commerce plays an important role with the City Council in agenda-setting. Each city has a distinctive approach to ecosystem building; from our interviews, both approaches were working well and suited the local context and culture. Overall, ecosystems are creating arenas at the local and regional levels for mutual connections between companies and the public sector. However, it is still unclear what kinds of ecosystems work best.

Project cooperation related to AI innovations

Both Tampere and Oulu have city-level projects where companies and city operators are jointly developing AI innovations. In general, AI companies are drawn to the city's public services because they are the source of the large databases AI requires, and their services reveal a multitude of problems that can be resolved by applying AI to life-as-lived problems. In project cooperation related to AI-enabled innovations, the operations of cities and companies mesh very variedly, case by case. The construction of different entities may be jointly planned by companies and the public sector, which means a joint project application has been made and funding has been sought. Similarly, purchaser-provider cooperation is possible. In this case, the city purchases from companies such innovations that the city expects to need. There may also be so-called innovative purchases. Companies are involved in developing innovations related to a certain entity. This has been the case with Oulubot. The objective of the project cooperation is clearly to create local and regional companionships for the development of AI innovations. Operations made in this way are practicable because cities do not themselves necessarily possess the capacity to produce AI innovations.

Personal networking

Finns build trust in personal relationships, and AI innovation is no exception. The interviewees emphasized how personal relationships are more important than organizational partnerships, especially in a small country in which weather conditions encourage mutual support. At the centre of regional ecosystems is a culture of personal relations built on trust and learning from practice. Although not often articulated, as an interviewee from Tampere said, "[W]ithout personal relationships, there would be no innovation".

Discussion and conclusions

Envisioning AI as a general-purpose technology (Freeman 1991) appears justified given the breadth of applications shown in Table 5.1, with evidence for many found in the case study. This justifies capability-based classifications of AI (Dwivedi et al. 2019), perhaps especially so since we found little evidence of AI experts searching for singularity (Kurzweil 2005) and instead adopting a problem-centric approach to using AI. Our case supports the claim that the IoT will be central to AI innovation, providing appropriate 5G and Bluetooth is available (an issue for remote and rural areas; Kankanhalli et al. 2019). We see this in health apps, health data signalling, transport and logistic integration, and IoT use in technologically assisted independent living. Apart from these areas, an initial wave of AI innovation is targeting cost reductions (including accelerating and enhancing digital accuracy; Kuziemski & Misuraca 2020). There is no evidence at this stage of radical or transformative AI innovations in the Finnish public sector, though these may come especially as city-regions develop their AI capacity.

Our research question refers to AI altering governance arrangements and mutuality in the innovation process. While trust appears high among innovation stakeholders, a degree of mistrust or wariness about AI exists among some users and service providers. Our study confirms that social and community acceptance of innovative public service change is important in Finland (Laitinen et al. 2018b). This is especially so in services-as-a-system, where introducing AI at any point affects the entire service system. Finnish local government and public services are close to citizens (the average local government unit covers 16,000 citizens who pay high taxes; Finns expect high-quality public services; Laitinen et al. 2018a). There is no evidence from our interviews of AI acting as the *invention of a method of invention* (Griliches 1957). As machine learning expands, this may yet occur. Our view is that radical innovations are likely to involve the IoT and robotics (including surgery, home care, delivery, and autonomous vehicles). The view that deep technological change is always accompanied by hierarchic restructuring and power shifts (Cath 2018) is confirmed by our study in the sense that unpreparedness for these organizational changes may be one reason why more radical innovations have not yet been attempted.

There are exceptional elements in the Finnish case, such as the large number of AI programmers working in consultancy or starting SMEs – a consequence of Nokia's downsizing. Also, Finland's close connections with US venture capital mean there is no shortage of risk capital for profitable ventures. The cases mention Finland's technophilic culture, work-based learning in schools and universities, and the importance of personal relationships based on trust and mutual dependency.

We found little danger of technology-push (Leslie 2020), in that all innovation teams to some degree were problem-centred and sought user feedback. We found evidence of psychological-level (*meaningfulness*) mutuality in the innovation teams of the sort portrayed by Yeoman (2019). Deeper mutuality (Koskimies & Kinder 2021), meaning clearly retaining boundaries between the market and social governance, was less clear. In some projects, public databases were used as a test bed for private-sector product launches, clear examples of market incursions into what had been public domains. However, the interviewees appeared sanguine about these results, perhaps feeling that in other fields of activity (independent living, health signalling, transport) the public–private boundary had shifted towards the public sector. Importantly, mutuality can be interpreted in Yeoman's psychology fashion or from an economic (market-social) perspective. In the case of Finland, neither interpretation posed difficulties for interviewees in the two cities cited.

The city-based AI-enabled innovation development teams in the Cities of Oulu and Tampere take ethics seriously. They all experienced useful and two-way learning from service walk-throughs by users. The close involvement of providers and users provided the AI experts with a clear grasp of the context and culture (*institutional assemblage*; Best 2018) in which the new service would operate. Also, *black-boxing* was avoided as the users understood design decisions, building trust among team members. This is especially important when evaluating risks attached to AI projects operating with vulnerable people (Flemig et al. 2016). If AI projects are to be conceptualized as a race between technology and education as Goldin and Katz (2008) propose, it seems fair to suggest that in these cases, education won.

Although research literature catalogues both the positive and negative outcomes of AI use in public services (Eubanks 2017; Kinder et al. 2021), our evidence finds few negatives. We had an indirect report of elders wary that AI might result in fewer face-to-face visits and some concerns that staff training fell behind new system needs. Overall, however, our interviewees reported positive impacts from AI. Perhaps a study more directly and deeply engaged with service users may produce different results. We found that the cities' top policymakers played an important role in instigating and filtering AI projects. It may be that their mediation reduced those AI projects likely to cause a negative impact. Finland is currently building its AI innovation capacity, and from our evidence, it is doing so without negatively impacting individual citizens or communities.

To directly address our research question: *Is AI altering mutuality governance in innovations between the private and public sectors?* We did not study the mutuality governance using technologies other than AI or indeed innovations not using any new technology. All the projects we investigated are PPPs. They differ from some other innovation projects in that user, provider, and AI expert involvement at *every* design stage proved essential, and the amount of learning from users by the technical experts proved profoundly important. Only this high degree of psychological mutuality avoided black-boxing since "inside" the algorithms and databases, linkages remain technically specialist despite the high level of effort put into understandability. Each project was problem-centric, addressing sub-system issues rather than a holistic new system, and this limited ambition enabled success: if AI becomes a technology looking for a problem rather than AI helping to provide a solution, then the success rate is likely to reduce.

The projects aim to brand ethical AI service products seeking internationalization. We note that since each new target use of the technology is likely to have a quite different context and culture from Finnish cities, additional serious learning will be required by AI experts to support product internationalization. We also note that Finland has unitary local authorities – for example, cities provide health and social care – so such contiguous service boundaries may not apply elsewhere and may introduce different governance issues. Recontextualization of the Finnish experience can only occur with a similar commitment to understandability and mutuality. Off-the-shelf AI solutions may work, or they may introduce unfairness and bias.

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References

Adleretal, P. (2018). Auditing black-box models for indirect influence. *Knowledge and Information System*, 54 (1), 95–122.

Ahokangas, P., Matinmikko, M., Myllykoski, J. & Okkonen, H. (2012). Future scenarios, ecosystems and business models for cognitive radio systems. *Future*, 5(5).

Allam, Z. & Dhunny, Z.A. (2019). On big data, artificial intelligence and smart cities. *Cities*, 89, 80–91.

Allen, A. (2016). *The End of Progress. Decolonizing the Normative Foundations of Critical Theory*, Columbia University Press, New York.

Angwin, J., Larson, J., Mattu, S. & Kirchner, R. (2016). Machine Bias. There is a software that is used across the country to predict the future of criminals. And its biased against blacks. [accessed 05.10.2019] https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing

Arthur, W.B. (2015). *Complexity and the Economy*, OUP, Oxford.

Asaro, P.M. (2019). AI ethics in predictive policing: From models of threat to an ethics of care. *IEEE Technology & Society Magazine*, *38(*2), 40–53.

Androutsopoulou, A., Karacapilidis, N., Loukis, E. & Charalabidis, Y. (2019). Transforming the communication between citizens and government through AI-guided chatbots. *Government Information Quarterly*, *36*(2), 358–367.

AI HLEG. (2019). Ethics guidelines for trustworthy AI. High-Level Expert Group on Artificial Intelligence. European Commission, April 2019. [accessed 9.7.2021] https://ec.europa.eu/digital-single-market/en/news/ethics-guidelines-trustworthy-ai

Barrett, M. & Baum, D. (2017). A model of pathways to artificial superintelligence catastrophe for risk and decision analysis. *Journal of Experimental & Theoretical Artificial Intelligence* 29:2, 397–414. http://dx.doi.org/10.1080/0952813X.2016.1186228

Beck, U. (1992). *Risk Society*. Sage, London.

Behn, R.D. (2001). *Rethinking Democratic Accountability*. Brookings Institution Press, Washington DC.

Bernstein, B. (2000). *Pedagogy, Symbolic Control and Identity: Theory, Research Critique*, Rowman and Littlefield Publishers, Lanham.

Best, M.H. (2018). *How Growth Really Happens – The Making of Economic Miracles through Production, Governance and Skills*, Princeton University Press, NJ.

Blau, P. (1964). *Exchange and Power in Social Life*. Wiley, New York.

Bouolamwini, J. & Gebru, T. (2018). Gender Shades: Intersectional accuracy disparities in commercial gender classification. *Proceedings of Machine Learning Research*, 81, 1–15.

Bowles, C. (2018). *Future Ethics*. NowNext Press, East Sussex.

Brown, A., Chouldechova, A., Putnam-Hornstein, E., Tobin, A. & Vaithianathan, R. (2019). Toward algorithmic accountability in public services: A qualitative study of affected community perspectives on algorithmic decision-making in child welfare services. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (1–12). May 4–9, 2019, Glasgow, Scotland UK.

Cath, C. (2018). Governing artificial intelligence: ethical, legal and technical opportunities and challenges. *Philosophical Transactions of the Royal Society A* 376: 20180080. http://dx.doi.org/10.1098/rsta.2018.0080

Chesbrough, H. (2011). *Open Services Innovation*, Wiley, San Francisco, CA.

Chun, A.H.W. (2008). An AI framework for the automatic assessment of e-government forms. *AI Magazine*, *29*(1), 52–64.

Coeckelbergh, M. (2020). *AI Ethics*. The MIT Press, Cambridge, MA.

Collier, M., Fu, R. & Yin, L. (2017). Artificial intelligence: Healthcare's new nervous system. Edited by Accenture. [accessed 2.4.2021] https://www.accenture.com/t20170418T023052Z__w__/au-en/_acnmedia/PDF-49/Accenture-Health-Artificial-Intelligence.pdf

Dabos, G.E. & Rousseau, D.M. (2004). Mutuality and reciprocity in the psychological contracts of employees and employers. *Journal of applied Psychology*, 89(1), 52. https://doi.org/10.1037/0021-9010.89.1.5252

Daniels, H. (2016). *Vygotsky and Pedagogy*, Routledge, London.

Dignum, V. (2019). *Responsible Artificial Intelligence: How to Develop and Use AI in a Responsible Way*. Springer Nature, Switzerland, Cham.

Dosi, G., Freeman, C., Nelson, R., Silverberg, G. & Soete, L. (Eds.) (1988). *Technical Change and Economic Theory*. Pinter, London, 67–94.

Drigotas, S.M., Rusbult, C.E. & Verette, J. (1999). Level of commitment, mutuality of commitment, and couple well-being. *Personal Relationships*, 6(3), 389–409. https://doi.org/10.1111/j.1475-6811.1999.tb00199.x

Dwivedi, Y.K., Hughes, L., Ismagilova, E, Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, V., Janssen, M., Jones, P., Kar, A.K., Kizgin, H., Kronemann, B., Lal, B. & Williams, M.D. (2019). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, 101994.

EGE. (2018). European Group on Ethics in Science and New Technologies. Artificial Intelligence, Robotics and 'Autonomous' Systems. [accessed 22.4.2021] https://ec.europa.eu/research/ege/pdf/ege_ai_statement_2018.pdf

Eubanks, V. (2017). *Automating Inequality: How High-Tech Tools Profile, Police and Punish the Poor*. St Martin's Press, New York.

Flemig, S., Osborne, S.P. & Kinder, T. (2016). Risky business – reconceptualising risk and innovation in public services. *Public Money & Management*, 36(6), 425–432.

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V. et al. (2018). AI4People – An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and Machines*, 28, 689–707. [accessed 22.4.2021] https://link.springer.com/article/10.1007/s11023-018-9482-5

Foucault, M. (1997). *Discipline and Punish: The Birth of the Prison*. Tavistock, London.

Freeman, C. (1991). Innovation, changes of techno-economic paradigm and biological analogies in economics. *The Economics of Hope*, Pinter, London, 120–142.

Gasser, U. & Almeida, V.A. (2017). A layered model for AI governance. *IEEE Internet Computing*, *21*(6), 58–62. https://doi.org/10.1109/MIC.2017.4180835

Geiselman, R.E., Fisher, R.P., MacKinnon, D.P. & Holland, H.L. (1985). Eyewitness memory enhancement in the police interview: Cognitive retrieval mnemonics versus hypnosis. *Journal of Applied Psychology*, 70:2, 385–401.

Goldin, C. & Katz, L.F. (2008). *The Race between Education and Technology*, Harvard University Press, Cambridge, MA.

Greene, D., Hoffmann, A.L. & Stark, L. (2019). Better, Nicer, Clearer, Fairer: A Critical Assessment of the Movement for Ethical Artificial Intelligence and Machine Learning. In *Proceedings of the 52nd Hawaii international conference on system sciences*, January 8–11, 2019, Grand Wailea, Hawaii.

Griliches, Z. (1957). Specification bias in estimates of production function. *Journal of Farm Economics*, 39(1), 8–20.

Guardian (2019). One in three councils using algorithms to make welfare decisions. (15.10.2019 Sample, Science Editor). [accessed 26.3.2021] https://www.theguardian.com/society/2019/oct/15/councils-using-algorithms-make-welfare-decisions-benefits

Gupta, K.P. (2019). Artificial intelligence for governance in India: Prioritizing the challenges using analytic hierarchy process. *International Journal of Recent Technology and Engineering*, 8(2), 3756–3762.

Haas, P.M. (1992). Introduction: Epistemic communities and international policy coordination. *International Organization*, 46(1), 1–35.

Henson, R.H. (1997). Analysis of the concept of mutuality. *Image--The Journal of Nursing Scholarship*, 29(1): 77–81. https://doi.org/10.1111/j.1547-5069.1997.tb01144.x

Horkheimer, M. & Adorno, T.W. (1972). *Dialectic of Enlightenment*. J. Cumming, Trans. New York: Herder and Herder.

Hyytinen, K. (2017). Supporting service innovation via evaluation: A future oriented, systemic and multi-actor approach. *Doctoral dissertations* 14/2017, Aalto University.

Kankanhalli, A., Charalabidis, Y. & Mellouli, S. (2019). IoT and AI for smart government: A research agenda. *Government Information Quarterly*, 36(2), 304–309.

Kinder, T. (2000). A sociotechnical approach to the innovation of a network technology in the public sector – the introduction of smart homes in West Lothian. *European Journal of Innovation Management*, 3(2), 72–90.

Kinder, T. (2010). e-Government service innovation in the Scottish criminal justice information system. *Financial Accountability & Management*, 26(1), 21–41.

Kinder, T., Six, F., Stenvall, J., & Memon, A. (2020). Governance-as-legitimacy: are ecosystems replacing networks? *Public Management Review*, 1–26.

Kinder T., Stenvall, J., Koskimies, E., Webb, H. & Janeova, S. (2021). Local public services and the ethical deployment of artificial intelligence, *forthcoming Government Information Quarterly*.

Koskimies, E. & Kinder, T. (2021). Mutuality in AI-enabled new local public service solutions. *Forthcoming Public Management Review*.

Kuziemski, M. & Misuraca, G. (2020). AI governance in the public sector: Three tales from the frontiers of automated decision-making in democratic settings. *Telecommunications Policy*, 44(6), 101976.

Kurzweil, R. (2005). *The Singularity Is Near: When Humans Transcend Biology*. Viking Penguin. New York.

Leslie, D. (2020). Tackling COVID-19 through responsible AI innovation: Five steps in the right direction. *Harvard Data Science Review*. [accessed 24.03.2021] https://hdsr.mitpress.mit.edu/pub/as1p81um/release/3

Laitinen, I., Stenvall, J. & Kinder, T. (2018a). Co-design and action learning in local public services. *Journal of Adult & Continuing Education*, 24(1), 1–26, August.

Laitinen, I., Stenvall, J. & Kinder, T. (2018b). Street-level new public governances in integrated services-as-a-system. *Public Management Review*, 20(6), 845–872.

Mikhaylov, S.J., Esteve, M. & Campion, A. (2018). Artificial intelligence for the public sector: opportunities and challenges of cross-sector collaboration. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 376(2128), 21.

Minsky, M. (1986). *The Society of Mind*, Touchstone, NY.

Newell, A. & Simon, H. (1972). *Human Problem Solving*. Oxford, England: Prentice-Hall.

Nietzsche, F. (1988). *On the Genealogy of Morality*, Hackett, Indianapolis (Trans M. Clark & A. Swensen).

Nonaka, I. & Takeuchi, H. (1995). *The Knowledge-Creating Company*, OUP, Oxford.

O'Neil, K. (2016). *Weapons of Math Destruction: How Big Data Increases Inequalities and Threatens Democracy*. Penguin, London.

Onnela, J.P. (2017). Smartphone-based digital phenotyping. (p. 22) in Karvinen, J., Koivisto, J., Tuukkanen, S. & Viik, J. (Ed.) 2017. *Proceedings of European Medical and Biological Engineering Conference*, Tampere, Finland. [accessed 30.12.2019] https://embec2017.fi/wpcontent/uploads/2020/10/EMBEC_NBC_2017_Abstract_Book_Final.pdf

Papert, S. (1993). *The Children's Machine: Re-thinking School in the Age of the Computer*, Basic Books, NY.

Parker, S. & Parker, S. (2007). *Unlocking Innovation. Why Citizens Hold the Key to Public Service Reform*, Demos, London.

Radnor, Z., Osborne, S.P., Kinder, T. & Baranova, P. (2014). Operationalizing co-production in public services delivery: The contribution of service blueprinting. *Public Management Review*, 16(3), 402–423.

Rosenberg, N. (1982). *Inside the Black Box - Technology and Economics*, Cambridge University Press, New York.

Rossi, P. & Tuurnas, S. (2021). Conflicts fostering understanding of value co-creation and service systems transformation in complex public service systems. *Public Management Review*, *23*(2), 254–275.

Ross, A. (2016). *The Industries of the Future*. Simon and Schuster, London.

Russell, S. (2019). *Human Compatible – AI and the Problem of Control*. Allen Lane, London.

SAIP (2019). Leading the way into the era of artificial intelligence: Final report of Finland's Artificial Intelligence Programme 2019. Steering group and secretariat of the Artificial Intelligence Program. Publications of the Ministry of Economic Affairs and Employment 2019:41 Helsinki. [accessed 26.03.2021] http://urn.fi/URN:ISBN:978-952-327-437-2

Sandel, M.J. (2020). *The Tyranny of Merit – What's Become of the Common Good?* Allen Lane, London.

Schorr, H. & Rappaport, A. (1989). *Innovative Applications of Artificial Intelligence*. AAAI Press, Cambridge.

Schumpeter, J.A. (1939). *Business Cycles*. Vol. 1. McGraw-Hill, New York.

Searle, J.R. (1980). Minds, Brainrs, and Programs. *The Turing Test: Verbal Behaviour as the Hallmark of Intelligence*. 201–224.

Sennett, R. 2003. *Respect – The Formation of Character in a World of Inequality*. Penguin, London.

Spieth, P., Schneckenberg, D. & Ricart, J.E. (2014). Business model innovation–state of the art and future challenges for the field. *R&D Management*, 44(3), 237–247.

Standing, G. (2016). *The Corruption of Capitalism – Why Rentiers Thrive and Work Does Not Pay*, Biteback Publishing, London.

Stone, P., Brooks, R., Brynjolfsson, E., Calo, R., Etzioni, O., Hager, G., Hirschberg, J., Kalyanakrishnan, S., Kamar, E., Kraus, S., Leyton-Brown, K., Parkes, D., Press, W., Saxenian, A., Shah, J., Tambe, M. & Teller, A. (2016). Artificial Intelligence and Life in 2030. One hundred year study on artificial intelligence: Report of the 2015–2016 Study Panel. Stanford University, Stanford, CA, http://ai100.Stanford.Edu/2016-report. [accessed 04.12.2020] https://ai100.stanford.edu/sites/g/files/sbiybj18871/files/media/file/ai100report10032016fnl_singles.pdf

Thibaut, J.W. & Kelley, H.H. (1959). *The Social Psychology of Groups*. Wiley, New York.

Tronick, E.D., Als, H. & Brazelton, T.B. (1977). Mutuality in mother-infant interaction. *Journal of Communication*, 27(2), 74–79.

Von Hippel, E. (1982). Appropriability of innovation benefit as a predictor of the source of innovation. *Research Policy*, 11(2), 95–115.

Vygotsky, L.S. (1934 1987). *The Collected Works of LS Vygotsky: Vol. 1, Problems of General Psychology*, Rieber, R.W. & Carton, A.S. (Eds.), Plenum, New York.

Vygotskij, R.W. & Carton, A.S. (1987). *The Collected Works of L.S. Vygotsky. Vol. 1, Problems of General Psychology including the Volume Thinking and Speech*. Plenum, New York.

Wartofsky, M. (1979). *Models, Representation and Scientific Understanding*. Reidel, Dordrecht.

Watson, H.J. (2014). Tutorial: Big Data Analytics: Concepts, Technologies, and Applications. *Communications of the Association for Information Systems* 34(65). [accessed 5.5.2021] http://aisel.aisnet.org/cais/vol34/iss1/65

Weick, K.E. (1995). *Sensemaking in Organizations*, (Vol. 3). Sage, Thousand Oaks, CA.

Witt, U. (Ed.) (1993). *Evolutionary Economics*, Elgar, Aldershot.

Wirtz, B.W., Weyerer, J.C. & Geyer, C. (2019). Artificial intelligence and the public sector—Applications and challenges. *International Journal of Public Administration*, 42(7), 596–615.

Wirtz, B.W. & Müller, W.M. (2019). An integrated artificial intelligence framework for public management. *Public Management Review*, 21 (7): 1076–1100. https://doi.org/10.1080/14719037.2018.1549268

Yeoman, R. (2019). *Ethics, Meaningfulness, and Mutuality*. Routledge, New York.