Hovedoppgave

NTNU
Norges teknisk-naturvitenskapelige universitet
Fakultet for samfunns- og utdanningsvitenskap
Institutt for industriell økonomi og teknologiledelse

Einar Aaland

The role of Machine Learning in Smart Wearable Sensors in an emerging Paradigm Shift for IoT services.

How business model innovation, the technological evolution into true wearable sensors, and enabling Machine Learning may combine to provide smarter IoT based services.

Hovedoppgave i Business Administration
Veileder: Per Jonny Nesse
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Abstract

In the years ahead, we are faced with several complex challenges, such as a human welfare, the elderly wave, food production, animal welfare, wildlife preservation, health care, general population obesity, kids safety, and much more. Within almost all of these, there are living creatures such as humans, animals, fish and birds that are somehow serviced today, either directly through feeding, caring, nursing or watching, or indirectly in the form of planning for, preparing for, or facilitating for. Most of such efforts up until now has involved human jobs and services.

Technology seems to be entering the body of humans and animals, sold as wearable sensors and trackers, but there are hurdles to overcome and in most cases it isn't very usable. This research will investigate the state of relevant technologies for such wearable sensors, and seek to understand if we can make these sensors truly wearable, so they can work everywhere without the limitations we experience today. I will investigate what is likely to happen if adding artificial intelligence to these sensors, if we can create smarter and more useful services to use when caring for humans, animals, birds and fish. My aim is to contribute with research so the algorithms may provide better and faster data to more efficiently decide on a relevant cause of action, minimising the effort for the human agent in data collection, and leaving more time for the exclusively human perspectives, e.g. those requiring sociability and empathy.

This thesis will also look at the conditions for business model innovations. If we shall succeed in establishing better, more efficient and smarter technology for our future care services, there must be interesting business to drive the innovation ahead.

Narrative inquiry was used as the research strategy, when collecting information from leading experts, as well as a wide literature study, to triangulate knowledge about relevant technology and their research fronts. The Stepwise-deductive Inductive (SDI) method was used when analysing towards my narrative portrait, concluding on a paradigm shift for wearable IoT sensors services, and that conditions are good for business model innovation, maybe even a business model shift to smarter care services.

There are need for further research in energy efficient microcontrollers, energy harvesting, more optimized machine learning, but the biggest need as it seems right now, it how to train the machine learning models, in the field with little available training and verification data, in order to achieve personalised models, and how to share so all sensors can participate in the training. Another very important subject is ethics, and how to handle to personalised machine learning models in ethical ways.

Sammendrag

I årene som kommer vil vi få utfordringer innen velferd, eldrebølgen, matproduksjon, dyre velferd, bevare arter og mangfold, helsetjenester, generell problematikk rundt overvekt, sikkerhet for barn og mye annet. Alle disse kategoriene involverer mennesker, dyr, fugler og fisker, som på en eller annen måte er betjent, enten via mating, beskyttelse, stell og pass, eller indirekte i form av planlegging for, forberede for, eller å bli fasilitet for. Det meste av slike tjenester har så langt blitt utført av menneskelige jobber og tjenester.

Teknologien ser ut til å innta kroppene til både dyr og mennesker, og blir solgt som bærbare sensorer og sporingsenheter, selv om det finnes store mangler ved dem, og de ikke er veldig brukbare. Denne oppgaven vil undersøke hva som er status for relevante teknologier for slike bærbare sensorer, og forsøke å finne ut om det er mulig å gjøre disse ekte bærbare, slik at det fungerer overalt uten begrensningene vi opplever idag. Jeg vil også undersøke hva som kan skje dersom vi tilfører kunstig intelligens til disse sensorene, om det blir mulig å gjøre dem smartere og mer brukbare i omsorgs-tjenester for mennesker, dyr, fugler og fisker. Jeg ønsker å bidra med forskning slik at algoritmene kan utføre maskinarbeidet, så kan omsorgspersonene fokusere på den menneskelige delen av omsorgen.

Denne masteroppgaven vil også undersøke hvilke forhold som er tilstede for å innovere i forretningsmodell. Dersom vi skal lykkes med å etablere bedre og mer effektiv teknologi for våre fremtidige omsorgstjenester, så må det også være forretningsmuligheter som tiltrekker innovasjon.

Forskningsstrategien har har vært intervjuer for å samle narrative historier fra eksperter om forskningsfronter, en bred litteratur studie, og SDI metoden for å analysere og sette sammen til min narrative versjon. Denne masteroppgaven konkluderer med et paradigmeskifte for bærbare IoT sensor tjenester, og viser til optimale forhold for innovasjon i forretningsmodeller, kanskje til og med et shift i forretningsmodell til smarte omsorgstjenester.

Det er behov for videre forskning innen energieffektive mikrokontrollere, løsninger for energi høsting, enda mer optimalisert maskinlæring, og der hvor det tilsynelatende er størst behov for videre forskning akkurat nå er i hvordan man skal trene opp maskinlærings modellene, ute i feltet med tilgang på lite trenings- og verifiserings-data, med mål om personaliserte modeller. Videre hvordan sensorene skal dele det de har lært, slik at alle kan delta i treningen. Et annet veldig viktig tema er etikk, og hvordan de personaliserte modellene skal håndteres på etisk og forsvarlig vis.

Acknowledgement

This thesis is submitted as the final part of my master's degree at the Department of Economics and Technology Management at the Norwegian University of Science and Technology.

I would like to thank my supervisor, associate professor Per Jonny Nesse for guidance and support throughout this final semester. We have had interesting dialogues about technologies, IoT and business model innovation, and I have gotten valuable feedback from forming my research topic and research questions, to thoughts and advice on the way to completing this thesis.

Thanks to Svein Egil Nilsen (CTO, Nordic Semiconductor) and Zach Shelby (CEO, Edge Impulse) for sharing expert insights and opinions in microcontrollers, sensors, energy management, machine learning, ethics and business valuables, and bringing me to the research fronts, and the use of state-of-the-art technology around the world. This could not have been possible without your stories.

Thanks to professor Kristin Melum Eide for guidance and support, and for helping me structure the work and writing.

I have now been working on this master's program for the last 5 years. It has been hectic at times, both being an employee, local politician, sports coach, father of three, and a master student. The subjects in the study program at NTNU Videre has been very interesting, and with good supervisors and courses, it has been a very interesting program.

But this could definitely not have been done without the continuous support from my love Unn-Kristin Sundet. A very special thanks to you.

Trondheim,

30th of September, 2022

Einar Aaland

Terms and Acronyms

4G	4th generation wide area wireless technology *(current main standard)*
5G	5th generation wide area wireless technology *(trials)*
6G	6th generation wide area wireless technology *(in development)*
AI	Artificial Intelligence. *(See note, fig.10, p.23)*
ASIC	Application-specific Integrated Circuit
AWS	Amazon Web Service
B2B	Business to Business
B2B2C	Business to Business to Consumer
BDT	Binary Decision Tree
BIS	Bioimpedance Spectroscopy
BLE	Bluetooth Low Energy
BOM	Bill of Material
CAGR	Compounded Annual Growth Rate
CC	Cognitive Computing
CE	Conformité Européenne *(Europe Approval)*
CPU	Central Processing Unit
DNN	Deep Neural Network
ECG	Electrocardiography
EDA	Electrodermal Activity
eDRX	extended Discontinuous Reception
EEG	Electroencephalography
EMG	Electromyography
EOG	Electrooculography
ex-situ	Outside the original place
FDA	US Food and Drug Administration
Fog	Decentralised computing and storage
FP8	8-bit floating point
FPGA	Field Programmable Gate Array
GDPR	General Data Protection Regulation

GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GPU	Graphics Processing Unit
HITL	Human in the Loop
IMU	Inertial Measurement Unit
in-situ	In the original place
IoT	Internet of Things
LAN	Local Area Network
LED	Light Emitting Diode
LoRa	Long Range *(proprietary radio communication)*
LPWAN	Low Power Wide Area Network
LTE Cat-M1	Long Term Evolution category M1 *(4G narrowband)*
LTM	*short form for LTE Cat-M1*
M2M	Machine to Machine
MCU	Micro Controller Unit
ML	Machine Learning *(See note, fig.10, p.23)*
MPU	Micro Processor Unit
NB-IoT	Narrowband IoT *(4G narrowband)*
NPU	Neural Processing Unit
NSD	Norwegian Centre for Research Data
PFLOPS	Peta Floating Point Operations per Second *(computing speed)*
PMU	Power Management Unit
PPG	Photoplethysmography
PSM	Power Save Mode
REM	Rapid Eye Movement
RF	Radio Frequency
SDI	Stepwise-deductive Induction
SpO2	Blood Oxygen Saturation Level
SUDEP	Sudden Unexpected Death in Epilepsy
UDP	User Datagram Protocol

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1. Introduction

This thesis addresses wearable sensors for Internet of Things (IoT), and a range of their current limitations in terms of battery life, processing capabilities, physical size, network coverage, privacy and security concerns. These limitations impact features and capabilities of such wearable sensors, their value to the users, and for the services using them. In effect, these limitations affects the business models of the service providers, in terms of value proposition, mode of service delivery, service content creation, costs and revenues. This thesis aims to describe the research front of relevant and related technologies, and subsequently proceed to discuss the introduction of machine learning to the wearable sensors, to investigate whether these perspectives unlock new opportunities in business models for wearable IoT services.

A range of wearable sensors exist in the market today, such as fitness trackers, animal trackers, elderly care sensors, wildlife trackers, kids watches, pre-operative sensors, post-operative sensors, electronic tagging and many more. But are they really *true* wearable? Can they be used anywhere, without having to be charged regularly, in areas of limited network coverage, indoor and outdoors, or without being perceived as too big and clumsy?

In 1991, even before the Internet as we know it, with the World Wide Web, Mark Weiser presented his vision for interacting with 21st-century computers as «computing everywhere, for everyone» (Schmidt et al., 2012), and 7 years later at the first International Conference for Wearable Computing (ICWC-98) Steve Mann defined wearable computing as something we wear, which is constantly on, and active, but <u>not</u> being the primary task, but instead blending into the user's environment (Mann, 1998b).

The Apple iWatch is a fantastic smartwatch, and a wearable sensor, capable of detecting many things. Some people even claim that it has saved their lives (Orellana, 2020) which, according to Apple, is confirmed to be possible (Apple, 2022). The iWatch is being marketed and sold as one of the most successful wearable devices of today, but is it really a true wearable device in all respects?

According to Mann's definition, there are six attributes to wearable computing, from the human's point of view. It has to be unrestrictive to the user, unmonopolising of the user's attention, observable by the user, controllable by the user, attentive to the environment, and communicative to others. The definition proceeds to include two more important properties. It has to be constant and always ready, as well as being personal, in other words the user should actually be able to forget that he is wearing it, and it should not in any situations have to be removed from the user. The definition also states that, as long as the wearable device sustains its application, it can augment or synthesise one or more of the attributes, and still provide the same experience to the user.

In that case, even the high-end and accomplished iWatch restricts the user. The most significant issue is the short battery life, forcing the user to charge very often. In practical terms, this means that the iWatch is of restricted use to an agent when for instance hiking in the wilderness for longer than 1-2 days, since it will run out of battery. Another issue, is that it has to be removed from the arm while charging. This interrupts many of the sensing functions of the smartwatch. So, even though it is still a very good wearable device, it is not a ***true wearable*** sensor by Steve Mann's definition (Mann, 1998a). But is that a problem?

A study (Nascimento et al., 2018) shows that many users report their reluctance in using wearable sensors, such as smartwatches. Their research studied several aspects of smartwatch use, such as confirmation, perceived usefulness, satisfaction, habits, perceived usability, perceived enjoyment, and continuance intentions. They found that achieved level of customers expectation, decided if the wearable sensor would be accepted or not. They also found that habit was the most important feature for deciding on continuance intention of wearing a smartwatch. Another study by (Bhattacharyya & Dash, 2021) investigated reasons for customer churn from services, and found that customers got dissatisfied and resigned from services when their expectations was not met.

With the emergence of low power narrowband communication for IoT the last years, with various communication protocols, short range, such as BLE or Zigbee, and long range, with NB-IoT, LTE Cat-M1, Sigfox, or LoRa (S.-Y. Wang et al., 2021), or the 6G standard (Laghari et al., 2021), wearable sensors have become more and more integrated to services, an emerging effort to make them become wearable IoT sensors. These new developments in communication helps tackle some of the limitations, while simultaneously introducing new ones. A study (Alraja et al., 2019) shows how trust in IoT services in healthcare can be affected, both for the user consuming the service, and for the caregiver having to be responsible for it. This becomes particularly evident when the service is in healthcare, where life depends on it.

The business model is another important factor. When using wearable sensors, the whole service with its content, infrastructure, equipment and total offering gets evaluated by the customer. The willingness of users and stakeholders to invest in and continue to subscribe to a paid service depends on the perceived value provided, its perceived quality, and the continuing fulfilment of the customers original expectations. A wearable sensor service, unable to meet the expectations as defined (Mann, 1998a), probably has to compensate by lowering its price, heavily affecting the business model. One study (Saygili & Yalcintekin, 2021) shows the relationship between hedonic value, utilitarian value and customer satisfaction, as factors for repurchasing and willingness to pay for smartwatch brands.

Based on a defined research topic, further refined by a number of research questions, I will discuss a possible solution path for reducing these limitations by adding Machine Learning (ML) to wearable sensors, in order to upgrade them to ***true wearable.*** The concept flips the paradigm, from computing raw sensor data off-sensor in a cloud centric setup, to inferencing on the sensor data directly, as it is captured from the cognitive object (human, animal, fish or bird), only sharing necessary event data or detected pattern in an ***object-centric*** way. My research will propose a new paradigm to provide *Cognitive Care IoT*, for *Cognitive Objects*, using *Cognitive IoT Sensors* in a *Cognitive IoT Service*.

Finally, the thesis explores how the new true wearable IoT sensors, with ML, might impact the *value propositions* in business models, and how ML might impact *value creation*, *value delivery* and *value capture.*

1.1. Motivation

We have started to realise that many of the complex challenges the future is bound to hold when providing care for humans, animals, birds and fish, will be difficult to cover with the same service levels as currently provided. For example within elderly care, as a consequence of the increased life expectancy of current and future generations, results in increased pressure on the workforce sustaining the provided welfare for elders in a incrementally skewed ratio between workforce and welfare recipients. Additionally, the nursing situations will get more complex with more dementia, more chronic conditions, more loneliness, and more advanced illness and end-of-life care, so it is necessary to improve the way we do elderly care (Rowe et al., 2016). Another example is food production with smart farming of animals, where machines, robots and automation is taking over, and for the sake of animal welfare, disease control, and production quality monitoring, there are needs to monitor individuals and herds both at the farm, in the wild, in transport and at the slaughter house (CornellUniversity, 2022). Another part of food production is fish farming, where emerging research develops fish-wearable sensors to monitor fish health (X. Wang et al., 2022). Or in pet care, revealing the location of the cat or dog, but also a need to monitor the health of pets, by facilitating the development of wearable sensors to establish IoT services for pets (Jinah & Nammee, 2022). In all of these IoT services, wearable sensors basically cannot be allowed to fail, since they all are involved in care for other living creatures, either human welfare, or animal welfare, and therefore the services imply severe responsibilities. This translates back to the definition of wearable devices (Mann, 1998a). There are presumably many more limitations still, which we currently experience, that can be fixed by using the latest and greatest of technology. In my view, the necessary ingredients already exist to improve wearable sensors, and make them ***true wearable.***

My main motivation with this thesis is to help further development of an ***object-centric*** services paradigm, where the objects, such as humans, animals, birds and fish are in centrum. In my opinion the introduction of AI, in the form of machine learning or deep learning, to the wearable sensor will be key to turn the paradigm towards an object-centric architecture. This avoids spending energy for sending raw data, rather only sending classified results, or events, from the sensor. The wearable sensors performing the classification will belong to the object-centric paradigm, a paradigm which can accept low throughput, long latency and poor network coverage. My motivation is to raise awareness about ***true wearable*** IoT sensors, and help accelerate the paradigm shift from cloud-centric IoT service to ***object-centric***. I believe this will also allow for better services, with a lot less privacy issues since raw sensor data is not sent to the networks anymore, longer battery lifetime, and smaller wearable sensors, where they are capable of detaching from infrastructure for periods at the time. Even being fully offline, and maybe someday becoming self-contained and autonomous wearable IoT sensors. This way, the IoT sensors can be significantly improved, more robust and safer for service, and trusted, both by the user and the caregiver. My motivation is to raise focus on quality and ethics, as I believe that is key to any successful business model using such true wearable IoT sensor. My objective is to investigate whether ***true wearable*** sensors in an ***object-centric*** IoT service impact on business models and open up new possibilities, enabling smarter services with better *value proposition* to the users, but also better *value creation*, *value delivery* and *values capture* for the service provider.

1.2. Research topic

A smartwatch is a wearable IoT sensor, since it is worn, and it has the capabilities to capture various data feeding the application, and it can communicate to a service. Still, IoT services using wearable sensors are more likely to be purpose-made, specifically for a particular service, in order to remove everything unnecessary, and to get size, cost and features down to the minimum. Wearable sensors are being developed, tested and set up, for IoT services for both animals, fishes, and humans, all over the world. As shown by a project to monitor chronic diseases with children (Aldujaili et al., 2021), wearable IoT sensors can be utilised to provide a more active life for these children, but also to reduce concerns for parents by providing monitoring and tracking of the children's health conditions. But the research also invokes relevant limitations, since it requires internet coverage in order to function properly. Internet coverage is a common problem for all cloud centric IoT services, for transmitting the sensors raw data to a computational point in the network for processing. In other cases, wearable sensors get physically too big, usually triggered by battery capacity requirements for all the transmissions it has to do for the use cases. Or in an opposite way, if the wearable device has to be physically small, it has to trade-off, either by frequent charging requirements, or to reduce its functionality. Large physical size might lead to new challenges, such as weight (too heavy), or size compared to the human or animal that has to wear it (too large). Physical size, as result of larger battery, might impact on radio quality, since batteries shield for radio antennas. Quality, water resistance and robustness also affect the level of successful IoT service adoption by the users. For services to become profitable, the wearable IoT sensors must gain its trust, and get used by the users.

In order to study wearable sensors in IoT services, and how their capabilities, features and performance will affect the way a user experience a service, and its impact on the business model, I have identified and restricted the research topic, and established three research questions to further refine this topic. As my knowledge and comprehension of the research topic increased during the research period, the research topic correspondingly underwent several modifications and refinements.

The research topic:

> *"Can the evolution of technologies upgrade wearable sensors, to become true wearables, and can Machine Learning enable smart IoT sensor based services, and if so, how?»*

1.3. Research Limitation

It is likely that wearable IoT sensors will have to be very tailored to the use cases in the services they will operate in, because of strict constraints in order to meet the definition of wearable computing (Mann, 1998a). «Nice-to-have» features and functions are, in my research, considered to either consume power, add cost, or add size, and will therefore give a negative impact compared to the definition of wearable computing, and is likely to obstruct the effort to make ***true wearable*** IoT sensors and services. «Nice-to-have» features is likely to impact positively on business models, but that is <u>not</u> required as fundamental to the present investigation. Instead, this research will focus on «Must-have» features and functions in order to meet the definition of wearable computing, in other words understanding how to detach from the infrastructures of power and communication networks, while still being part of a service. Assuming that wearable IoT sensors will be uniquely tailored to match exactly the service they are intended for, this research is limited to focus on wearable IoT sensors for cognitive objects, such as humans, animals, fish or birds. This limitation will, as a consequence of that, add an extra challenge, since it limits the environment the wearable IoT sensors can operate in. The wearable IoT sensors cannot expect computing assistance from the cloud or edge devices, or to have unlimited amount of energy, which it would have if connected to mains power. Sensors for cognitive objects are much more challenging than sensors for a non-cognitive object, due to the fact that they are all sensing on unique and individual objects. Cognitive objects, such as humans, animals or birds are controlled by emotions and affected by internal and external environmental factors (Hoemann et al., 2020). Each individual object develop their cognitive capabilities and emotions all the way from their infancy, based on a large combination of factors from their environment, learned knowledge and experiences, and as a result idiosyncrasies increase. Therefore, all cognitive objects needs to be considered unique, and capable of acting and behaving on impulse. The output from the sensors cannot easily compare to sensors on any other cognitive object, even if classified in the same demographic, age, sex or other grouping parameters. This research will not study the actual sensing, inferencing or training on the cognitive object, only the wearable IoT sensors role in an ***object-centric*** IoT architecture. The thesis will not propose concrete solutions using ***true wearable*** sensors in ***object-centric*** IoT services, but only investigate whether adding machine learning can help overcome limitations currently obstructing wearable computing as described in the research topic, and propose a concept. The research will not propose any concrete business solutions, but will discuss new opportunities for services using such wearable IoT sensors, in general terms, in order to show possible effects as a result of adding machine learning to the wearable IoT sensors on ***Value Propositions***, ***Value Creations***, ***Value Delivery*** or ***Value Capture*** in the business models.

1.4. Research Questions

From the research topic, I derived three further research questions, to focus our attention on the most relevant trajectories for diving deeper into wearable sensors and IoT services they are part of. I want to find out if technical conditions exist for adding machine learning to wearable IoT sensors, with the purpose of upgrading them to true wearable IoT sensors, and to exploit wearable computing to create smarter IoT services, with new added value to both users and service providers.

1.4.1. Research question 1: Wireless IoT Sensor hardware

> *How is the current state of relevant technologies for battery operated sensors in terms of capabilities, performance, cost and size?*

The first research question is directed at the research front, and the current state of various technologies related to and relevant for wireless IoT sensors, to review the current potential of these technologies.

Wired IoT sensors have almost endless possibilities compared to sensors operating on battery. They can afford much more power for sensing, computing and transmitting data to the cloud services. This relegates battery operated sensor services to the realm of a paradox, since they either have to assume a sleeping mode (or very low power mode), or to compensate by requiring recharge very often. In the sleeping scenario, it contradicts the purpose of being a sensor (since it is not sensing, or sending data to the service), and in the recharge scenario, it contradicts the purpose of a wireless existence (since it has to be brought back to a power source often). I will describe a conceptual model of cognitive objects, in order to discuss limitations resulting from such cognitive objects, in comparison with the definition of wearable computing (Mann, 1998a). I will also describe a conceptual model for true wireless IoT sensors in order to explore the current state and potential exploitation of relevant technologies for wearable sensors, before trying to uncover the current capability of various technologies, and to get a grasp on their current performance potential and the limitations inherent in these potentials. For wearable sensors, cost is also crucial. Such sensors deploy in large numbers, and are at the same time likely to be part of low cost services. Another important feature is size, since they will be worn by cognitive creatures such as humans, animals (both in captivity and in the wild), birds, fish and similar. The combination of performance, cost and size will define the inherent limitations on the potential versatility and performance yielded by wearable IoT sensors.

1.4.2. Research question 2: Machine learning to the wireless IoT sensor

> *How may the inclusion of recent innovations in machine learning affect the potential versatility and performance of wearable IoT sensors?*

A wireless device needs to transmit its data via some type of radio transmission to provide any kind of sensory data usable to a service. A well-known limitation on radio transmission is the high consumption of battery power, especially in poor network coverage. The second research question addresses the introduction of Machine Learning (ML) and explores the classification of sensor data, to investigate the degree to which radio transmission can be severely reduced. This research question opens up a discussion on the potential to drastically limit and decrease the amount of data transmitted by the sensor to a computational reading point in the service. The path towards this goal involves including machine learning innovations into the wearable device itself, to distil and refine raw data in real time, and simply send the inferences of this process instead of transmitting the much larger set of raw data. This would imply sending only relevant results from classification of the data (as required by the IoT service), thus avoiding sending any redundant data, resulting in not draining the batteries, especially under bad network conditions, and the opportunity for the sensor to operate without network, and to become self-contained or autonomous.

This discussion addresses the crucial question whether moving machine learning to the wearable sensor, can change the role of the wearable sensor from a raw data collector, to a sensor communicating the relevant states of the cognitive object, regarding position, environment, behaviour or emotion. Can the wearable IoT sensors go from only sensing and blindly transmitting raw data (sensor input), to the next level and instead sense states of the host it sits on (sensed condition), and become smart, true wearable IoT sensors?

1.4.3. Research question 3: Machine Learnings effect on business models

> *How can recently developed technologies and innovations, including the addition of machine learning to the IoT sensor, enable business model innovations and smarter IoT services?*

Assuming that research questions 1 and 2 can predict positive outcomes, how might this affect the possible business models in terms of *Value Proposition* for the wearer. Can it provide better service in poor coverage situations, longer time-spans of battery operation, more useful features, new use cases, or lower subscription costs.

And how will machine learning in wireless IoT sensors affect *Value Creation*, *Value Delivery* or *Value Caption* in the business model for the service provider. Will it enable new ways of delivering the service, reduce costs, increase the quality and thereby reduce churn, open up new ways to create content, or maybe new revenue streams in the service. To facilitate a discussion of this topic, I provide a description of a conceptual model for an object-centric IoT service.

1.5. Research Objectives

The aims of this thesis is to produce contributions of special interest as described in this chapter. The research is limited to only include wearable IoT sensors, in particular sensors for cognitive objects, and wearable computing as defined by Steve Mann (Mann, 1998a). His definition describes tree modes of operation, stating that the wearable computing device shall always be on, and ready, it shall operate in the background without interfering the user wearing it, and it shall prevent unnecessary exposure of data leaving the environment surrounding the user wearing it. The objective of this thesis is to contribute to a raised awareness on some particular topics, and to point out new opportunities with machine learning in the sensors to help overcome some of the current limitations of such devices.

1.5.1. True wearable sensors

Device manufacturers have, for a long time, been marketing small sensors as wearable, but without really meeting the definition of wearable computing (Mann, 1998a). Actually, most such devices are at best portable sensors, since they can be carried around, but cannot really be worn without having limitations, either on battery time, network or infrastructure coverage, size, weight or price. One major contribution of this thesis is to raise the level of ambition to meet the requirements of *true* wearable sensors, where the aforementioned limitations are removed or reduced at such an extent that it does not affect the wearer of the sensor.

1.5.2. Object-centric IoT architecture

The common understanding of IoT is that there are devices placed around the Internet, communicating with a service in the cloud. There are different types, either with sensors harvesting for Big Data computing, such as a weather forecasting service, or data is collected to compare with the population of sensors, also typically done in the cloud (Calihman, 2019). Another way of computing can be done in a domain, also called Fog (Dar & Ravindran, 2019), or all the way at the Edge of the network (Lombardi et al., 2021). A general overview of IoT architectures also defines various ways of connecting wirelessly to the network (Alshouiliy & Agrawal, 2021) but there are many aspects to consider such as latency, coverage, domain access, security, networking and radio standards. As a common denominator for all of these we may identify the feature of raw data flows inwards in the architecture, from the sensor or application, to the cloud service or domain, for subsequent inferencing, comparison, computing or storage. Computing power is almost unlimited in the cloud, while the sensors are limited.

Object-centric IoT architecture flips this around, since inferencing happens in the sensor, where raw data is captured, removing the need of massive data transmissions. By moving the machine learning algorithms to the actual sensor, it might also in the future be possible to «personalise» classification, so the algorithm gets re-trained on the objects behaviour, and not just in a general sense on a training dataset from the whole population of sensors. This is likely to become important for sensors on cognitive objects. In healthcare there are examples of moving machine learning to the edge (Greco et al., 2020). Object-centric IoT architectures might solve many of the limitations compared to the definition of wearable computing (Mann, 1998a), and maybe introduce new ones. This contributes to highlighting object-centric IoT architectures, and hopefully spark more discussions regarding such architecture.

1.5.3. Reduce dependency on network coverage

By moving machine learning to the wearable IoT sensors, the sensors can be made to operate more independently, since they do not need to transmit raw data to a service in order to function. This way the wearable IoT sensors can report to the service solely when sufficient network is available. Removing dependency on network might also reduce a lot on the energy usage, since it can choose to send when the coverage is good, and in batches, instead of lots of retransmissions (of raw data) with radios boosted to max output when conditions are bad. This contributes to the discussion on network dependency, and at what level the wearable IoT sensor needs to respond.

1.5.4. Long or short range radio technology

By moving machine learning to the wearable IoT sensor, the sensor will get capable of «interpreting» directly without having to send any raw data to a computational point. Since the wearable IoT sensor might get self-contained, it will not be so sensitive to network latency or packet loss either. This means narrowband mobile technology (LTM or NB-IoT), low bitrate (SigFox or LoRa) or short-range (BLE or Zigbee) radios may be sufficient for the small amount of event data. This contributes to reduce the focus on 5G and 6G, and creates awareness for operations with wearable IoT sensors on slow data rate networks. This might also offload slow and non-responsive data traffic from the 5G and 6G networks (which is intended for higher throughput, low latency data transfers).

1.5.5. Reduce privacy issues

Reducing the need for transmission of raw data to the cloud service, correspondingly reduces the risk of privacy issues, simply because the raw data never leaves the wireless IoT sensor and neither will be stored. Instead, only the result of the local computing gets transmitted, but at another extracted level. This contributes to the discussion of what data actually needs to be transmitted from the wireless IoT sensor, and to raise the awareness for ethics on how to handle information about what was inferenced at the sensor, and knowledge about personalisation of the local machine learning models in the sensors.

1.5.6. Business model innovation

Machine learning in wearable IoT sensors enables detecting events, abnormalities, patterns and situations rather than just capturing raw sensor data. This enables reasoning and detection of symptoms and behaviours which can be used for predicting future issues, calculating risks, or help diagnosing health issues, finding parameters for feeding adjustments, or detecting emotions. This implies huge opportunities to innovate in business models, to make more efficient operation models, and create more value for the caregivers providing the care to humans or animals. New features and functions become available, and others improve, which might raise the V*alue Proposition* to the end users. Additionally, the service providers may get new opportunities with Business Model innovation, with improvements to *Value Creation*, *Value Delivery* and *Value Capture*, cf. e.g. (Burström et al., 2021). This contributes to the awareness of new business possibilities as a result of machine learning in the wearable sensors. Machine learning in the wearable sensors brings AI into the business model, which can be further used in the business logic, and my objective is to show the business potential residing in this innovation evolution.

2. Theory

My research is focused in the intersection between relevant technologies for wearable IoT sensors, the cognitive objects they sense on, and business models potentially harvesting these innovations. My research rests on recognised theories, described closer below.

The research topic concerns whether wearable IoT sensors can become true wearable, therefore I will first describe the theory about wearable computing.

Wearable sensors can be worn by humans, animals, birds or fish, which all are unique beings with own thoughts, emotions and behaviour. In what follows relevant theories related to cognitive behaviour will be described.

My research will mainly use the *Business Model Canvas*, backed by three relevant theories which brings in the perspectives of new startup with *Lean Canvas*, new technology with *Crossing the Chasm* and new markets with *Blue Ocean Strategy*. The theories will be briefly described.

Artificial intelligence provides results for the wearable sensors in the perspective of the what it can achieve, and the ecosystem around it will be covered by theories from key experts. Similarly, the presence of AI, creates some relevant effects within the business perspective.

2.1. Steve Mann

Steve Mann defined wearable computing at First Conference on Wearable Computing as something we wear, as a new form of human-computer interaction comprising a small body-worn computer, that is always on, always accessible, but <u>not</u> being the primary task, and to blend into the environment of the user (Mann, 1998b). Steve Mann is often referred to as the «Father of wearable computing».

2.1.1. Wearable Computing

His definition had three operational modes, with six attributes, and two additional properties. The three operational modes say something about the roles between the human and the wearable computer. It can encapsulate the human body, completely or only parts, with the additional intention to protect us, and act as a filter. This could be clothes where the wearable computer is embedded in the clothing, while it covers our body at the same time, or the wearable computer can protect data privacy, so instead of sending raw data, it can compute directly on the data, and rather send results of such computational tasks, and this way change the information before it leaves the encapsulated space. In addition to the potential ability to encapsulate us, for instance as clothing, wearable sensors can be sensors with direct contact with our flesh, and take measurements of various physiological quantities and biometrics.

Mann defined wearable computing with six attributes, to describe how it should function, and the main features of it. His conceptual model (fig.1) illustrates the inputs to the wearable computer, the outputs, and the relationship between the human and the wearable computer.

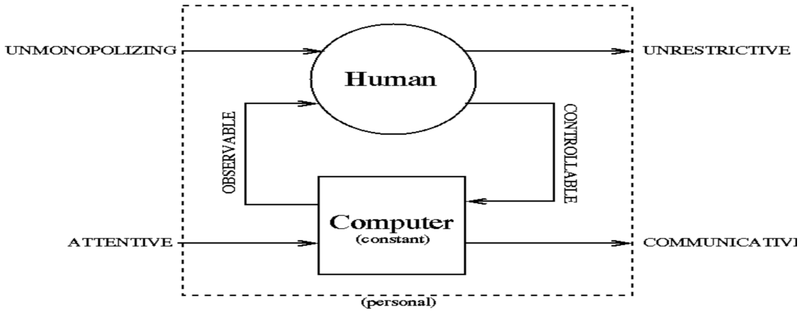


Figure 1. Wearable computer attributes

The wearable computer cannot distract the wearer, and it cannot affect the user in any way, since the wearable computer should be considered as the secondary activity, and therefore only be observing the human. It must not restrict the wearer in any way, or any of the activities he is doing. The wearable computer should be protected from misuse, and could act as an information filter towards the outside world. The wearable computer should not be affected by its surrounding environment, such as network conditions, and it should be capable of handling any new conditions, such as missing network, or slow or missing responses from external factors.

In Mann's definition, the wearable computer had to be always on, it could have sleep modes, but it could not be dead. Basically it had to react immediately. After some time, the wearer would forget that he is wearing it, so it would become a true extension of the mind and body of the wearer, similar to a wrist watch, or a wedding ring.

Mann suggested that wearable computing would result in a paradigm shift for personal empowerment, but he also alerted about surveillance and privacy. Mann reflected into the use of Artificial Intelligence (AI) in wearable computers and humans, so the human could perform tasks that *it* is better at, while the computer will perform tasks that *it* is better at. This would be a synergy that would complement each other. At the time of Mann's definition of wearable computers, the internet was still in its infancy, and Internet of Things and smartphones was still many years away.

2.1.2. Sousveillance

Mann made an interesting point about Sousveillance, as the opposite of Surveillance. Many companies, law enforcements, public buildings or retail stores are using surveillance. Data from sensors and cameras is recorded to protect their property or society, and recordings of such surveillances is usually kept secret. Mann argued how surveillance could invite corruption and misuse of power, which could result in political crisis, innocents being prosecuted, or even killed.

Sousveillance would be able to sense and record the same situations, and empower humans to protect themselves. Mann defined sousveillance as «surveilling the surveillers» by using wearable computers for data collection in surveilled environments (Mann, 2002). For this reason, Mann proposed a Veillance Contract stating that everyone using Surveillance, also must accept Sousveillance, in order to use the recorded data in the court of law (Mann, 2013). There are many examples of surveillance recordings, that was not released to the public, which got altered, or even deleted, in order to protect corruption, misuse of political power, or police brutality. But there are also examples of sousveillance where courts refuse to use police testimony as evidence if video recordings are not released (Segal, 2016). An example is private recordings of telephone conversations, which is another form of sousveillance.

2.2. Robert Plutchik

Over the past century, more than 90 definitions on the nature of emotions have been offered, and there have been almost as many theories. Robert Plutchik (Plutchik, 2001) offered his theory based on evolutionary principles, and claimed that emotions are an essential part of who we are, and how we have survived. Emotions are adaptive, and gets infused as states of feelings. The feeling state is part of a process involving both cognition and behaviour, and contains several feedback loops, potentially altering the emotions, to change the expressions of feelings (fig.2).

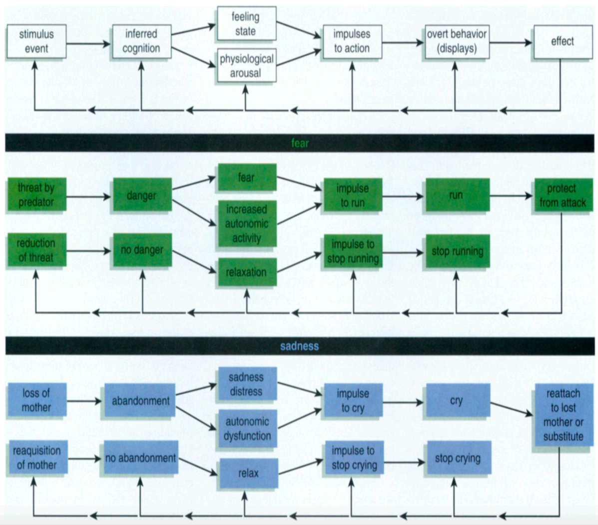


Figure 2: Plutchik model of cognitive general emotional responses

2.2.1. Plutchik Wheel of Emotion

The Plutchik Wheel of Emotion (fig.3) was proposed in 1958 with eight basic bipolar emotions, or states of feeling, arranged as four pairs. *Joy* versus *sorrow*, *anger* versus *fear*, *acceptance* versus *disgust*, and *surprise* versus *expectancy*.

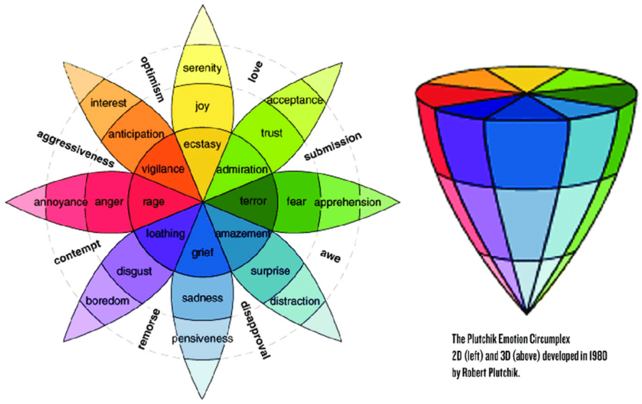


Figure 3: Plutchik Wheel of Emotion

2.2.2. Psychoevolutionary Theory of Emotion

Plutchik defined ten postulates in his Psychoevolutionary Theory of Emotion. Through his research, he studied animals as well as humans, and found that the theory applied equally to all cognitive beings, but to different degrees, based on evolution. In general, animals are more controlled by emotions and feelings, while humans are typically more cognitively controlled. By combining the eight primary emotions, many more concrete and specific emotions will be defined, but as derivatives. All emotions vary in degree of intensity, or levels of arousal.

Plutchik's Theory of Emotion defined that emotions, or feelings, are likely to produce behaviours, in order to respond to the trigging event that caused the feeling. His model also included cognition, to capture the trigging event (fig.4).

Stimulus event	Inferred cognition	Feeling	Behavior	Effect
Threat	"Danger"	Fear, terror	Running, or flying away	Protection
Obstacle	"Enemy"	Anger, rage	Biting, hitting	Destruction
Potential mate	"Possess"	Joy, ecstasy	Courting, mating	Reproduction
Loss of valued person	"Isolation"	Sadness, grief	Crying for help	Reintegration
Group member	"Friend"	Acceptance, trust	Grooming, sharing	Affiliation
Gruesome object	"Poison"	Disgust, Loathing	Vomiting, pushing away	Rejection
New territory	"What's out there?"	Anticipation	Examining, mapping	Exploration
Sudden novel object	"What is it?"	Surprise	Stopping, alerting	Orientation

Figure 4: Cognition - Emotion - Behaviour

There are many other theories, or wheels of emotions, such as Junto's Wheel, the Geneva Wheel, or the Feelings Wheel, they work with the same principles, except they have different definitions of feelings, and how they combine, but common for all of them is that emotions generate and maintain behaviours.

A finish study from the university of Turku from 2014 (Nummenmaa et al., 2014) maps emotions to the human body, showing how the body reacts to feelings of six basic and seven non-basic emotions, as an indication to where in the body the reaction is located (fig.5)

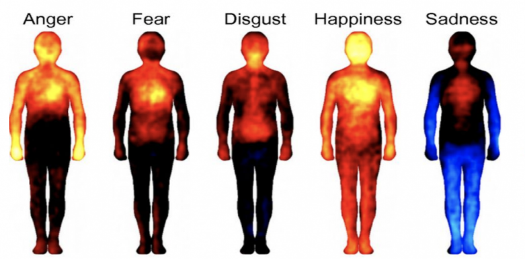


Figure 5: Emotion - Body response

2.3. Alexander Osterwalder

Business plans are complex and contain goals, methods, strategies and timeframe for a business. They also describe financial projections, background information on the business, and a plan to achieve the targets that the business plan sets forth. Usually external focus is utilised to establish loans, capital and attract customers, while the internal focus is directed towards employees, owners and partners. Business plans are decision-making tools, and cover a wide range of different business disciplines, with financing plans, human resource plans, supply chain management, product roadmap, marketing plan, and many more sub-plans. A simplified description of a business plan, the business model, shows the key principles and core dynamics in a very simple and visual way.

2.3.1. Business Model Canvas

Alexander Osterwalder simplified business planning when working on his PhD thesis (Osterwalder, 2004), which later became the his Business Model Canvas (Osterwalder & Pigneur, 2010). The Business Model Canvas is a simple and easy tool to capture the essential parts of a business plan, expressed in one page consisting of nine specific building blocks, providing a quick overview, and indicate the direction for further development of the plan. It will provide a simple and structured platform for conversations, to evaluate existing and new projects, and how to get to market. The Business Model Canvas (fig.6) is useful for mapping existing business models to visualise and the course of events, or to understand competitors, in order to identify new opportunities. It is also used to design new business models, or to innovate in the current business plan. It provides clarity and a clear picture in current or new business models, and is a simple platform for communication and collaboration with stakeholders. It is simple to work with, yet not simplistic, and has become popular since it is quick to use. The nine sections of the Business Model Canvas are best understood by looking at three main categories; how desirable the business offering is, how feasible it is to put into existence, and how viable the business is. The first two categories consist of four building blocks; describing the *value proposition*, offered to *customer segments*, via which *customer relationship* and *channels*. By mapping these, it will become clear who the customers are, what to deliver to them and how to reach them. This category will also express if there

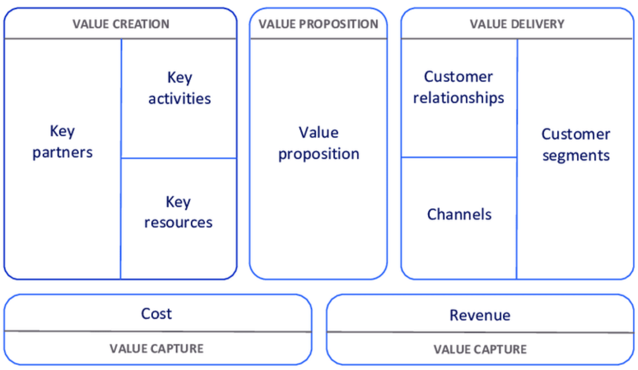


Figure 6: Osterwalder - Business Model Canvas

is a product-market fit between what the company is offering, and what the customers are willing to pay for, and indications of how much the customers might be willing to pay for the product or service. The value proposition can either remove a pain for a customer, remove or reduce a job they otherwise would have to do, or add a new gain. The customers will be grouped into segments, based on shared parameters such as age, location, interests, or pains, gains or jobs. These factors, together with the physical and emotional connection with the customer, decide the desirability in the business plan. This section of the canvas will explain how the company should operate towards the customers, and the pathways related to sales and marketing. The third category consist of the three building blocks describing the keys for business plan feasibility, with key partners, key resources and key activities. This description makes explicit the modes and means of the plan's execution, and the selected agents performing different work packages. This part is about resources and activities, internal and external, to successfully deliver the value proposition to the customer segments. It also describes outlines the future development trajectory of the company, as well as product and service, innovation and development. The fourth category consist of the two building blocks describing the financials; the cost structure outlining all fixed or variable costs, and the revenue streams describing how the segments will pay for investments, operations or values delivered. Revenues can be one-off transactions, or recurring subscriptions. Costs and revenues do not have to come from the same category or building block, but a business plan is not viable if the revenues do not cover the costs, unless the plan explains how to recapture loss over a given time period. This is quite normal for startups before they become profitable, and this is usually covered with shareholders equity, or subsidies.The Business Model Canvas can help identify resources needed for the creation of the product, service or operations, or to spot opportunities in the market. It can also be used to analyse competition, and find uncovered gaps in the market. The canvas may provide new perspectives and help communicate the vision of the company, which is crucial to elaborate on any financing of the business plan. The Business Model Canvas have several techniques for improving the different aspects of the plan. Zoom out allows for researching the environment around, industry forces, market trends, technology landscape, or value chain actors. It becomes simple to describe the business model «as is» in order to improve on it, and to zoom in to improve on the value proposition and product-market fit, or to consider innovations, and experimenting on improvements.

The Business Model Canvas has been criticised for not considering the environmental forces shaping a sector and therefore your business. Such forces can be competitors, technologies, or legal or political changes, trends or macro-economic factors. The Business Model Canvas has also been criticised regards agile companies and start-ups, for being too rigorous and to little flexible. The Lean Canvas, another business model approach, addresses this, cf. below. Osterwalder has continued to develop the Business Model Canvas, to elaborate more on how to innovate in the business model, and to create new business opportunities. The last book (Osterwalder et al., 2020) focuses on continuously reinventing the business model, and business model shifts.

2.3.2. Business Model Shifts

A business model shift describes an organisation's shift from a declining business model to a more competitive one. Osterwalder organises the business model shift in four groups. The first group is Value Proposition Shifts, and includes a radical shift in the offering to the customers from Product to Service, from Sales to Platform, or Low Tech to High Tech. The second group is called Frontstage Driven Shifts, and includes a radical shift of market segment and how the product or service is delivered from Niche Market to Mass Market, or from B2B to B2B2C. The third group is the Backstage Driven Shifts, and includes a radical shift of how value is created from Closed to Open Innovation. The fourth group is the Profit Formula Driven Shifts, and includes a radical change of how profits are made from High Cost to Low Cost, or from Transactional to Recurring Revenue.

A similar way to describe shifts in business models is provided in the book «Business model shift - six ways to create new values for customers» (Pijl et al., 2021) Patrick van der Pijl, being one of the co-writers of Osterwalder's «Business Model Generation» (Osterwalder & Pigneur, 2010). They focus on six concrete shifts of greater significance, almost as paradigm shifts. They describe The Service Shift (to deliver as a service instead of delivering products), The Stakeholder Shift (to generate values for stakeholders, instead of making profit for shareholders), The Digital Shift (to provide our offering all the time and everywhere, instead of physical, or at a given time and place), The Platform Shift (to create pull by connecting people who have something with people who needs it, instead of pushing the value in a pipeline where everyone is locked in), The Exponential Shift (to enable exponential scale by removing incremental limitations, using artificial intelligence and focus on automatic learning and adapting), and The Circular Shift (to make sure all waste becomes new resources as recycled or as new supply to other vale chains). They also described a seventh Business Model Shift, which was to create and innovate your own business model.

2.4. Ash Maurya

Ash Maurya adapted Osterwalder's Business Model Canvas to suit the needs of startups and lean organisations, and introduced the Lean Canvas (Maurya, 2022), a simpler and more practical canvas for entrepreneurs and startups (fig.7).

2.4.1. Lean Canvas

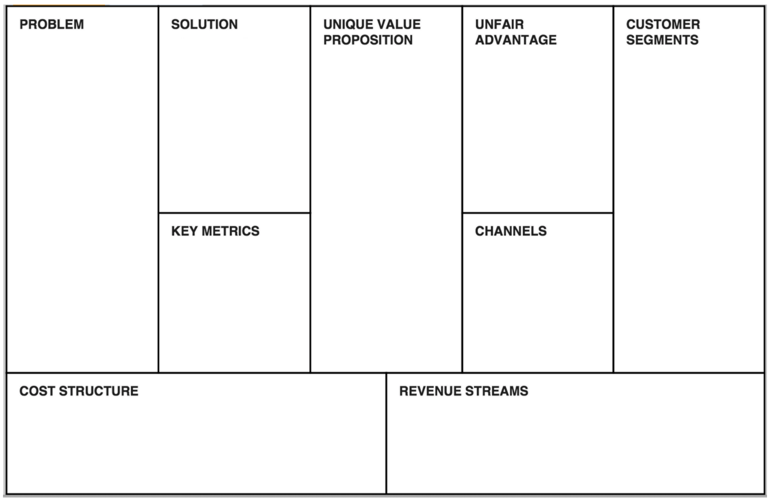


Figure 7: Maurya - Lean Canvas

Maurya wanted to meet the primary need for startups and agile practises, which was to make the canvas as actionable as possible, and to keep the focus on identifying the most uncertain and most risky parts, and to focus heavily on the most accurate understanding on the customer needs and problems. So he removed some of the blocks of the original Business Model Canvas (Osterwalder & Pigneur, 2010) which he considered too «outside-in» and maintaining too little entrepreneurial focus, and replaced them with blocks to tune in to the customer problem and solution. The Lean Canvas describes the *Problem*, since many startups fail to focus on this, and instead build the wrong product, as well as a simple description of a possible *Solution*. The Business Model Canvas is using another Value Proposition Canvas in order to map out and test product-market fit, but the Lean Canvas keep it in the same canvas.

The Lean Canvas is criticised by some, since they think it is too focused on the customer and their concerns, and that this will take away the attention to developing your own business, as the business grows and scales, and it does not encourage bold actions aimed at creating radical innovations. Also removing the focus on key partnerships is criticised, since in many cases partners are a crucial part of delivering a complete solution in the early days as a startup.

2.5. W. Chan Kim & Renée Mauborgne

Markets tend to stabilise and over time and homogenise in their offerings, eventually only differentiating on price and feature list. Price usually only go down, and new value and functionality only gets added to the bottom of the feature list. To compete in such markets, usually means lowering your margins and spending more time and resources developing less and less important features. This describes a high competitive market, with lots of rivals, *a red ocean*.

2.5.1. Blue Ocean Strategy

According to Kim and Mauborgne, crowded markets and red ocean strategies tend to produce minimal profit margins, while *blue oceans strategies* lead to more profitable growth. The Blue Ocean Strategy (Kim & Mauborgne, 2015) main principles is to avoid the head-to-head battle against competitors by reconstructing the offering to be standing out from the rest of the competition with a compelling value, at a low entry point, easy onboarding and attractive price. This way the blue ocean strategy decomposes the market boundaries, and creates a new market without direct competition. The strategy is focusing on innovating in the business model to strengthen important parts for going forward, while also stop spending resources on factors that should go into history. The strategy's first step is to analyse the market, and the competition, to figure out what factors the market requests «today», and what value the competitors offers in those factors. Then figure out what factors will be necessary in «tomorrows» market. Some new factors will be needed, some will become more important than today, some will become less important, and some will no longer be needed. The competition's offering should be placed in the Strategy Canvas (fig.8) to illustrate the value they offer in the various competing factors of «today», and should be compared to your own offering which should be based on what you intent to offer «tomorrow». The Strategy Canvas should be organised to display the factors in this order: Eliminate, Reduce, Raise, Create. This will create a strategy which leads to an uncontested blue ocean, which you can dominate. The blue Ocean Strategy is much about first mover advantage, which can be strengthened by AI in the business model from *network effect* and *learning effect*, both to establish competitive advantage and to stay competitive.

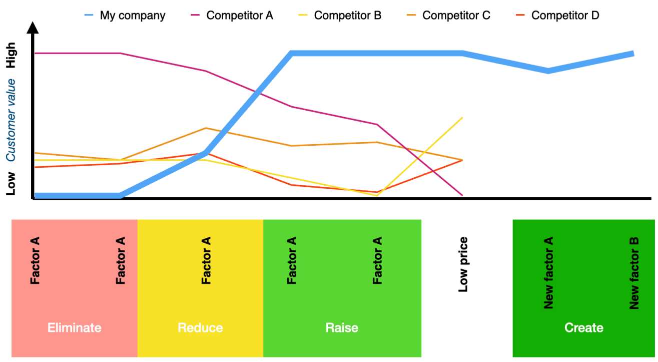


Figure 8: Blue Ocean Strategy Canvas

2.6. Geoffrey A. Moore

All innovative technological products take time to be absorbed by any community. It takes time and effort to understand the value that the new technology brings. Not all persons, companies or markets catch the essentials at the same pace, or they are not in the position to get involved. Due to differences in attitudes to new technology, this adoption process tends to happen in stages, one group of people at a time, according to the aptly named *Technology Adoption Life Cycle*.

2.6.1. Crossing the Chasm

The life cycle represents how different people, based on age, income, and other demographic and psychological characteristics, begin adopting a new piece of technology. In time, such new technology reaches its potential, diffusing among all society members until it becomes second nature.

There are five stages of new technology customer engagement, called the **five adopter groups**. These five adopter categories are innovators, early adopters, early majority, late majority, and laggards. The first two groups represents the early market, where new technology comes in, to get the solutions tested, to get feedback, to improve the products, to get familiarised and to get reputation. The last three groups are the mainstream market, where the big volumes and money are, and the return on investments.

Between the early market and the mainstream market is a chasm, or «a gap», in the market which needs to be crossed, in order for the new technology to prove its right to go into the mainstream market. The chasm is like the «exam» for the technology, to test that it has fixed the critical problems, established the right support for it, found a sustainable business and operation model, and gotten enough adopters to state their opinion regards value and maturity. Crossing the Chasm is to prepare to go mainstream.

Geoffrey Moore describes this in the book «Crossing the Chasm» (Moore, 2002). When introducing new technology and innovating in business and operation model, the two key groups are the Innovator and the Early Adopters, which I will focus on.

The first and smallest group, are the innovators. They are in close contact with scientific resources, giving them the insight to knowledge and understanding of new technologies. Crucially, innovators also have a high tolerance to risk, which means they are likely to purchase an item despite knowing it may not become successful. The innovators wants to help troubleshoot, only for the sake of getting the technology to work.

Early adopters come next, making them the second to adopt new technologies. They tend to look towards innovators to seek smart ideas they can use when being visionaries, when informing their opinions of others around them. They are opinion leaders because they are the most sociable of all the groups and communicate their opinions and ideas more effectively, frequently, and to larger audiences.

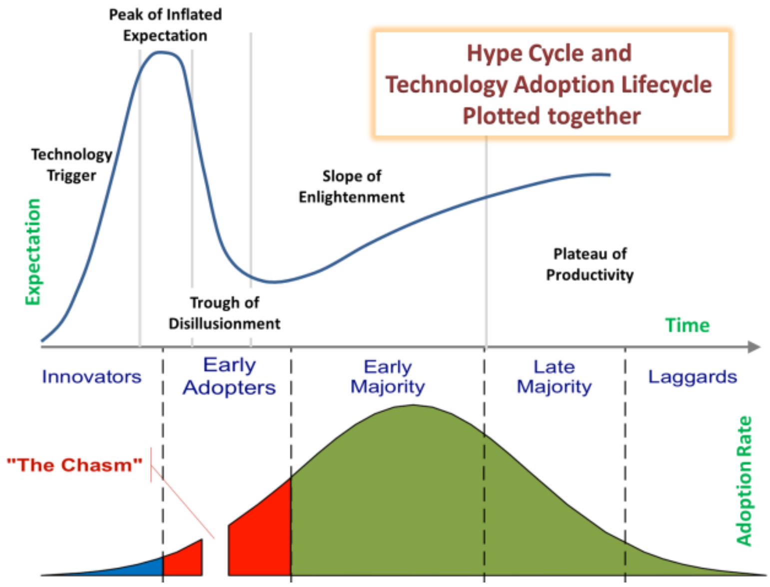


Figure 9: Gartner's Hype Cycle and Moore's Technology Adaption Life Cycle

An illustration (fig.9) shows the Technology Adoption Life Cycle in contrast to the Hype Curve (Gartner, 2018), the Innovator phase overlaps the Technology trigger phase, before the Early Adopter phase brings the new technology from the hype and back to realism. In this phase there are naturally lots of bad press since many find out that the hype isn't ready for mainstream yet. The early adopters can see through this, and can, based on knowledge and experience, still be visionaries. Their role is important for pointing out what needs to be fixed and improved. When prepared and ready, the new technology have to «jump» over by *Crossing the Chasm* to establish in the mainstream market. Those who are not prepared enough, will simply not make it. They will fail with bad technology reputation or run out of cash. It takes time and effort to cross the Chasm.

Crossing the Chasm is a strategy for new technology to enter the market, which can be strengthened by AI in the business model from *the network, the learning* and *the long tail effect*, to establish adoption for the new technology and to generate more value and business from the growing use.

Crossing the Chasm can also be valuable for startups which are entering the market with their new technology, since the main principle is to offer to the market a complete offering, including supporting infrastructure. The strategy suggests to use partnerships to make the market offering complete, but also explains the importance of altering the partnerships as adoption of the new technology as it moves through the phases. In terms of the offering, the customer needs the complete solution including infrastructure and support, and the company needs to be dynamic in order to maximising operations and market position.

2.7. Pete Warden & Daniel Situnayake

A simplified description (Agrawal, 2018) of Artificial Intelligence, with its subdomains Machine Learning, Neural Networks and Deep Learning, explains AI as human intelligence exhibited by machines. Compared to a regular computer program, which takes an input through the program to provide an output, Machine Learning will use both the input and output to create a model, and a new program, which can be used to classify new inputs according to that same model. In machine learning (ML), data is analysed statistically using analytical or mathematical models that identify patterns in the data. The ML algorithms are trained using sample data, and can then be used to make predictions or decisions without explicit programming.

The general trend has been to collect large amount of data and transmit it inwards to a computational point in the cloud, in a cloud centric model. The data has been used to train the machine learning model, using various techniques, in order to continue to expand the large centralised model. This model has then been used for interpreting new data, also called inferencing. This is also referred to as model centric, since focus on how accurate, the model can get.

Note: The expressions AI and ML are both used in this thesis, and it might seem unstructured, but there are reasons. These expressions overlap as shown in the illustration (fig.10) , and which expression is used depends on who is referenced, and how they use it. The second reason is that the different algorithms represent different nuances to training and use, and sometimes it is necessary to be more specific, while other times it is ok to use a wider expression.

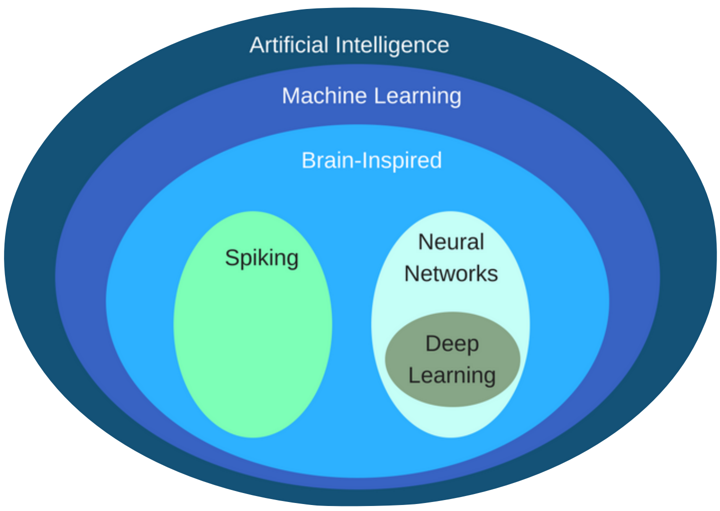


Figure 10: Artificial Intelligence, Machine Learning and Brain-Inspired machine intelligence

2.7.1. TinyML

The book TinyML (Warden & Situnayake, 2019), is about Artificial Intelligence (AI) in the form of Machine Learning and Deep Learning running on constrained devices in challenging environment, such as a microcontroller only powered by a battery or similar. Tiny machine learning (TinyML) is broadly defined as a fast growing field of machine learning technologies and applications including hardware (dedicated integrated circuits), algorithms and software capable of performing on-device sensor (vision, audio, IMU, biomedical, etc.) data analytics at extremely low power, typically in the mW range and below, and hence enabling a variety of always-on use-cases and targeting battery devices (TinyML, 2022).

Microcontrollers have become more powerful, while energy consumption has gone down. This has enabled a huge demand for applications to become wireless and wearable. This is one of the areas where TinyML comes in, since instead of spending energy to transmit large amount of raw data to the cloud to be inferenced, the machine learning model gets optimised and trained before being moved out on the edge, having many small local machine learning models in many edge devices such as wireless and wearable sensors in an distributed model.

In the beginning, training will happen centrally, or ex-situ, but there are already examples of models being trained in the device, or in-situ. Small local machine learning models, allows for re-training, which can adapt the model to the object it is placed on, and personalise the model. This is important in order to make sure the data captures is as good as possible, removing noice and distortion. This is often referred to as the data centric approach, which focuses on quality of data, instead of a massive machine learning model in the cloud.

Machine learning has been used to classify events, things, patterns and sort between objects or actions. It has also been used to detect abnormalities or something changing over time, and by this being able to predict and prevent. Even detection of emotion can be done from video images (Khan, 2013), or recognising emotions from speech (Dorota & Adam, 2012). Small wearable sensors attached to humans or animals also can detect both behaviour and emotions (Aich et al., 2019).

2.7.2. AI at the edge

The TinyML movement has optimised algorithms, techniques and tools in order to run more efficiently, use less memory, inference based on less features, get trained based on less data and made platforms for the general industry to embed in their products. A very comprehensive overview (Capra et al., 2020, p. 225169) lists «AI at the edge» as one of the top trends for 2020.

2.8. Marco Iansiti & Karim R. Lakhani

From a book summary (Dahunsi, 2021) a value of a firm is shaped by two concepts. The first is the firm's business model, defined as the way the firm promises to create and capture value. The second is the firm's operating model, defined as the way the firm delivers the value to its customers. The authors of the book «Competing in the Age of AI» are suggesting an AI business and operating model in order to scale, scope and learn, in order to solve the constraints with current products and services, and to tackle threats from the market and to turn them into new opportunities.

2.8.1. Competing in the Age of AI

In the book (Iansiti & Lakhani, 2020) the authors argue that reinventing a firm around data, analytics, and artificial intelligence (AI) removes traditional constraints on the scale, scope, and learning that have restricted business growth for hundreds of years. From Airbnb to Uber, Microsoft to Amazon, research shows how AI-driven processes are vastly more scalable than traditional processes, allow massive scope increase, enabling companies to straddle industry boundaries, and create powerful opportunities for learning—to drive ever more accurate, complex, and sophisticated predictions. The broad deployment of AI could threaten millions of jobs in the United States alone. And beyond the erosion of capability, threats to traditional skills, and other direct economic and social impact, we are increasingly vulnerable as an increasing portion of our economy and our very lives become embedded in digital networks.

The authors describe «The AI Factory» as a scalable decision engine that powers the digital operating models of future firms and organisations, where decisions are increasingly embedded in software, which digitises many processes that have traditionally been carried out by people.

2.8.1.1.Network effect

Network effects describe the value added by increasing the number of connections within and across networks, such as the value to a Facebook user of having connections with a large number of friends, or access to a broad variety of developer applications. The most important value creation dynamic of a digital operating model is its network effects. The basic definition of a network effect is that the underlying value or utility of a product or service increases as the number of users utilising the service increases.

2.8.1.2.Learning Effect

Learning effects capture the value added by increasing the amount of data flowing through the same networks—for example, data that may be used to power AI to learn about and improve the user experience or to better target advertisers. Learning has two outcomes, either it is for sharing with others, which generates value for the network, or learning is for personalising, which generates value for self.

2.8.1.3.Long Tail Effect

Chris Anderson popularised a theory about the long tail effect (Anderson, 2006) which suggests that, as the Internet makes distribution easier, by using AI and state-of-the-art recommendation systems that allows consumers to become aware of more obscure products, the demand will shift from the most popular products at the "head" of a demand curve to the aggregated power of a long "tail" made up of demand for many different niche products. This means consumers can buy products based on suggestions, which are somehow tied up in another relevant topic. To exemplify if a customer is buying a book about how to train and raise a puppy, the long tail can also suggest to the same customer a dog collar, or to go to the vet for a vaccination for puppies. The likelihood of buying goes up since both of these things are relevant for new dog owners.

2.8.2. AI driven business and operation model

The network and learning effects, together with a digital operation model enables scalable and growing business models, since value automatically grows for everyone in the network with the increase in numbers of users in the related network, number of providers, or both, since there will be more to sell to, or to buy from. Similarly, the learning effect results in increased value by becoming better at delivery, learning more about needs, and learning which new values to add to the network. Digital operating model enables scale, scope and learning, while the AI business model enables new value creation and new ways of value capture and sharing. The AI Factory implements algorithms in their core to operate the business, and they makes algorithms such as machine learning and deep learning to expand knowledge, either in a model centric model with large centralised ML models, or in a data centric model with optimised local models. The authors emphasise the importance of building with ethics from the start. And, to make sure biasing of the algorithms are under control and manageable. They are not very clear on the subject of privacy and the effect from GDPR. They are curious on who will be affected by regulation.

3. Method

This chapter describes how I consider my own scientific standing, my choice of research methods, how I decided to approach theory, my approach for data collection, and how I analysed the data material. I am also discussing the method quality in terms of credibility and trustworthiness, narrative restorying and ethics. My work is much based on the methods of Tor Busch's «Akademisk skriving for bachelor- og masterstudenter» (Busch & Busch, 2021) for structuring the thesis, and the research methods from Aksel Tjora's «Kvalitative forskningsmetoder i praksis» (Tjora & Tjora, 2021), as well as some from Tor Grennes's «Innføring i vitenskapsteori» (Grenness, 2001).

Through time, there have been many definitions of technology, depending on field of knowledge, whether it is biology, physics, electronics, information, or social. According to Collins Dictionary (Collins, 2022), technology refers to methods, systems, and devices, which are the result of scientific knowledge being used for practical purposes. This study aims to understand where the research fronts of relevant technologies for wireless IoT sensors are, and in order to do so, it is important to consider where it is most likely to find them.

According to Simplilearn and Nikita Duggal (Duggal, 2022), machine learning, edge computing, IoT and 5G ranks amongst the top 9 technology trends for 2022. Similarly, Forbes and Bernard Marr (Marr, 2022) ranks IoT, sensor generated data, AI and machine learning, tiny computer chips, material science, and new energy solutions, as major trends for 2022 that will forever alter how we do business, and live our lives. My research, on wearable IoT sensors, are related to several of these technologies which are projected to be in rapid advancements for 2022. Therefore I assume investments and innovation to be high, and many new solutions and technologies will be added in the near future.

This study aims to understand if evolution of technologies, with the addition of machine learning, can play a role in upgrading wearable IoT sensors, to become *true* wearable IoT sensor, and if that could enable new explorations of business models for such IoT services. In order to do so, it will be necessary to find, and understand, state-of-the-art for relevant technologies, in terms of capabilities, size and cost, before trying to understand how machine learning can enable new values for smart IoT services. According to researchers (Jin & Ji, 2018), information networking, especially wireless communication, changed the information flow and decision-making mechanism of traditional business models. Wireless networking in IoT has the same characteristics and therefore also likely to have a large potential of doing the same if true wireless IoT sensors emerges. But their study of *research hotspots* and *trends* within business model developments came to the conclusion that business model innovation of IoT had been very scarce. I will seek to understand if machine learning into wireless IoT sensors can make an impact on such business models.

In order to establish my preferred research design, a set of interlinked subjects, as described by the research onion had to be considered (Busch & Busch, 2021). The research onion (fig.11) consists of six main layers (Saunders, 2016). My research aims at gaining new knowledge for the society, by providing new perspectives and opportunities, therefore I will define my master thesis as basic research. If reasoning for my research methods is not necessary, chapter 3.9 provides a research design summary.

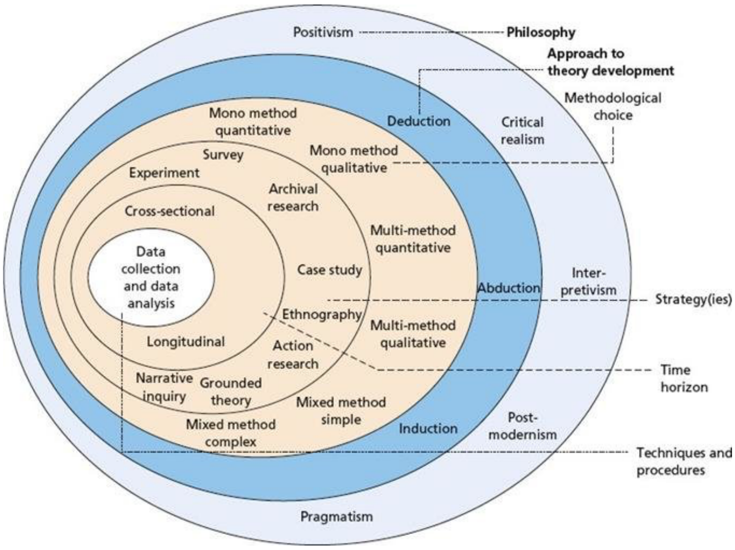


Figure 11: The research onion

3.1. Research Philosophy

When pealing the research onion, I first had to consider my own worldview from which the research should be conducted, usually studied in terms of ontology, epistemology, methodology and methods. Ontology refers to the authenticity of the information and how one understands its existence, epistemology is about where to find valid information required for the research and how to obtain it, methodology is how to best collect the information, and methods refers to the actual data collection. By discussing this, it will get clearer what this research is actually studying.

3.1.1. Where to find valid information

In general, research is divided into two main types, basic and applied, but as described (Solheim et al., 2007), these can also be viewed in a slightly different way, as classical and technology research. The definition of technology research is creation of new, better, quicker or more useful artefacts, than what already exist. Classical research on the other hand is research focusing on the world around us, seeking new knowledge about nature, space, the human body, the society, etc. In the more traditional definitions, basic research is mainly concerned with the improvement of scientific knowledge and to obtain new knowledge, while applied research is focusing more on certain real-world problems and how to solve them. As described by researchers (Lomnitz & Chazaro, 1999), basic research is driven by curiosity, typically funded by the public and aims to provide general theories and knowledge, where findings usually are made public, often motivated by a research degree and recognition. Applied research tend to be more practical, and driven by the need to find solutions to actual problems and issues, typically funded by private organisations, and aims to achieve commercial results and economical pursuit, where findings usually are kept private, often motivated by economic value and return on investments. Another important distinction, is that business models is a key part of applied research, with economic return on investments as a primary goal, while basic research is more driven by gains for society. From this, we can say that classical research is heavily rooted in basic research, while technology research is more used within applied research (even though some classical research will be in applied, and some technology research will be in basic). As pointed out by Lomnitz and Chazaro, less funding will have negative affect on available resources, reduce options to hire more people, less investments and less upgrades of labs. Researchers (Gulbrandsen & Smeby, 2005) pointed out that university research, which traditionally would mean basic research, had to an increasing extent, become funded by industry, since the share of public funding of basic research was decreasing. Their findings showed that from 1980 to 1999 external funding grew from 20,5% to 38,4%. It was also shown that there was a higher amount of patents, new products and new firms coming out of industry funded university research, and that almost 60% of the non-external researchers viewed their work as basic research, compared to only 40% if they where funded externally. In other words, externally funded, would more likely be applied research, even in universities. Externally funded researchers also produced more output, and they organised their work differently. Applied research also had advantage of direct access to the issues to be solved, in a different way, then basic research. A study (Kjelstrup, 2001) pointed out that researching only for the sake of just gaining more knowledge almost certainly would lead to greatly reduced funds for basic research, and she pointed out that there was a building gap towards applied research. Funding is both a motivation and a need for researchers. A more resent study (Stenbacka & Tombak, 2020) estimated that only 20% of the R&D budgets for the developed countries was spent on basic research. But their study also claimed that governments now had influence mechanisms in place in the forms of tax deduction, or stimulus, and they found that firms kept investing in basic research, despite the opportunities for free riding, and they even presented conditions under which firms even had incentives to augment the public funding to the university.

3.1.2. Research front

This study aims to investigate research fronts of technologies for wireless IoT sensors, many of them closely related to technologies of rapid advancements. Or, to be more accurate, the research will not be about finding the research fronts, but to seek out what the newest and best of related technologies can do and achieve today. Therefore it is important to study, and to get a good impression of the capabilities, in the near vicinity of the research fronts. Technologies such as IoT, 5G, machine learning, tiny computer chips, and new energy solutions are likely to be driven by commercial firms. Such companies would probably have a higher interest to keep information internally, when making the technologies commercially exploitable, in order to generate return on already invested capital, instead of producing more for public knowledge. Many of these technologies are being used for tailor made solutions for solving specific issues, and service models are being created for them. They are involved in creating new, better, faster and more useful artefacts, than before, as technology research. Based on the problem descriptions complexity and wide range, I have decided to do an intensive research, particularly looking for the research fronts within applied research, and to seek out domain experts to help me create an understanding of capabilities of technology and business opportunities.

3.1.3. Seeking conditions for a new paradigm

My research is seeking to interpret and understand if conditions with emerging technologies are present for a possible paradigm shift in architecture and service for wearable IoT services, and to understand if the wearable IoT sensors can be made true wearable according to the definition for wearable computing (Mann, 1998a). My own background with telecom, internet endpoints, wireless products, IoT products, and low power narrowband sensors makes me, as a researcher, subjective in terms of already being biased with some knowledge in this field. The interview guides were developed by me, where focus areas and questions in the guide was selected on purpose, in order to lead the interview towards the state-of-the-art in the various technologies. On the positive side, I might be capable of asking better followup questions, and get the interviewees to elaborate, or challenge their world view for a deeper understanding. As a researcher, I believe that new technology gets created in the cross section of science, physical laws and phenomenas, affected by social and cultural factors, and driven by peoples thought and ideas. For these reasons, my research philosophy belongs to interpretivism similar to Geoff Walsham's description (Walsham, 2006).

3.2. Research Approach

Another dimension which needs to be considered is what type of reasoning to use. Deductive reasoning will be found in the chain of:

theory →hypothesis →observation →confirmation

Usually deductive research is done with a quantitative approach. In my field of research, where I will try to uncover the research front of rapid developing technologies, it will be hard to succeed by using deductive reasoning. I will also challenge the most common IoT architectures and data communication, by proposing a new paradigm where sensor data gets inferenced directly in an object-centric way.

Inductive reasoning can be simplified through the chain of:

few observations →seeking patterns →forming hypothesis →likely theory

Inductive research where there are small amount of observations, are best done with a qualitative approach. By interviewing representatives for the leading technology companies, going in-dept to gain detailed knowledge, I have tried to collect the stories from leading technology vendors to locate significant patterns, and make concepts of them. I have also collected information from journals, other research, and news, in a literature study, in order to supplement and generalise to new paradigms. In my research, I have tried to collect an overview on how these new technologies creates new possibilities.

One methodology of conducting such qualitative research is the Stepwise-Deductive Induction (SDI) (Tjora & Tjora, 2021), which my research is based upon. The research was done based on interviews that generated stories as empirical data material. The SDI method works in steps (fig.12), from raw data, to concepts and theories. The «upwards» going process is inductive, while the «downwards» loopback should be considered deductive, since they check validity from the more theoretical to the more empirical. The SDI method is inductive

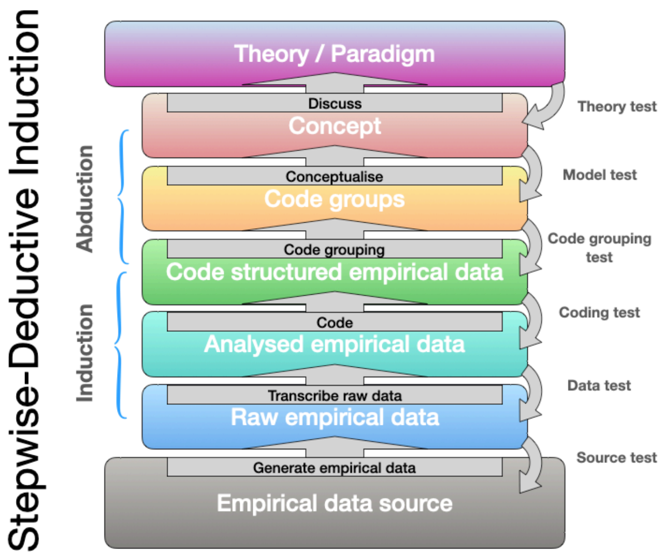


Figure 12: Stepwise-Deductive Induction (SDI)

at first, since there are no theory to start from, only the stories which in my case was collected through interviews, but became abductive when conceptualising and generalising to paradigms (or theory). Researchers (X. Wang et al., 2021) claims: *«Generally, there are two approaches for discovering research front. One straightforward manner is the qualitative method, e.g., Delphi, expert interview, scenario planning, which relies on the knowledge of domain experts. This method is time-consuming and subjective and becoming more so on both counts in the current information-flooded era. Another is the quantitative method, e.g., bibliometrics analysis or patent citation analysis, which is more time- and cost-efficient.»*

Domain experts within applied research are likely to possess relevant information about technologies for wearable IoT sensors. I conducted qualitative research based on semi-structured interviews in order to capture their stories. The stories were then transcribed and coded in an inductive way, and conceptualised or restoried to new paradigms in an abductive way. Before conceptualising, a review of grounded research was conducted, and put together with findings from literature studies to develop my new concepts. My research design is qualitative with stepwise-deductive inductive reasoning.

3.3. Research Strategy

In order to answer the research questions and objectives, I used narrative inquiry research, which in some way is close to case studies, where the intention is to understand human experience from a holistic approach through time. The idea of narrative inquiry is that stories are collected as means of understanding experiences as lived and told, through both research and literature. The narrative inquiry approach focuses on the use of stories as data. According to researchers (Savin-Baden & Niekerk, 2007), the advantage of this approach is that it is relatively easy the get people to tell stories, and gaining in-dept data is possible. On the other side there are cons of narrative inquire as well, such as the relationship between the narrative account, the interpretation or story being told, and the retold story. In this type of research strategy the reliability, validity and generalisation, is focused more on the credibility of the storyteller, and the validity or the trustworthiness, in order to consider the honesty in the narrative inquiries. There is a sense that what gets presented is based on shared truths and shared values, and peoples norms and values, including my own, are important factors. Narrative inquiry can reveal unique perspectives and deeper understanding, and is a very powerful tool to transmit and construct new knowledge in the post modern era, and according to Robert Atkinson *«we think in story form, speak in story form, and bring meaning to our life through story»* (Atkinson, 1998). Narrative inquiry records the experience of an individual, reveals the lived experience and particular perspectives usually through interviews. We are all a part of the big meta narrative which includes everything. I used the interview guide to set a scope for the interviews in line with my research limitations, in order to set the micro narrative to wearable computing and true wearable IoT sensors, and from there ask open-ended questions. I brought machine learning into the narrative. There are different types of approaches to narrative inquiry. My research follows the pragmatical-relational approach (Damsa, 2014). The distinctive features of narrative inquiry is first of all that a respondent shares a story about the lived experience, and their opinion and views according to the problem description, research questions and interview guide. These stories will express their understanding of the various research fronts, as seen from them, as members of the industry. The second feature, is that the researcher must do restorying, or re-tell the narrative after analysing it. In my case this will be after using the SDI method (Tjora & Tjora, 2021) for coding, grouping and conceptualising. The last feature, is that the researcher must create a narrative portrait as the output from this process. This will compare to generalising to a new paradigm. One of the weaknesses, or limitations, of narrative inquiry, is that the method is very subjective, therefore I will triangulate between the respondents and findings from studies of literature, other research, product reviews, industry events, reports and publications.

3.4. Choice of Methods

Since my problem description is very wide, where one part of it seeks to understand the current state of certain technologies, while the other part seeks more understanding of something that is not present today, but can become depending on conditions and outcome from the first part. The second part also seeks to explore opportunity in business models, which might initiate new perspectives and serve as motivation to invest more research into the proposed paradigm. This is also exemplified by the three research questions. Because of the wide problem description, I used a multi method design approach.To illustrate my multi method design roles according a definition (Driessnack et al., 2007), the first section is the projects primary theoretical drive, which is qualitative (inductive) and forms the analytical core of the study (denoted as QUAL). The second section which adds the new dimension is to illustrate future opportunities, is also qualitative (abductive) but is the supplementary part of the research (denoted as qual). The relationship between them is sequential and illustrated by →. From this I can illustrate my multi method research design as:

[QUAL → qual]

My purposes for mixed methods; Triangulation, Complementary, Development and Initiation. *Triangulation* when analysing the stories against research and other documentation, in order to interpret the truth in the information, before restoring or re-telling the stories. *Complementary* since I wanted to provide a greater range of insights and perspectives. *Development* since I wanted to use the findings from the descriptive research on wearable IoT sensors, to study the possibility for a new paradigm. And *Initiation* since it involves intentional analysis of new perspectives towards an object-centric paradigm.

3.5. Time Horizon

This research is cross sectional, in the sense that it is conducted at one point in time, and will represent an understanding of the research fronts at the time of researching. Similarly, discussing if machine learning can upgrade wearable IoT sensors to cause a shift in paradigm to change architecture and new possibilities in business models, is a cross sectional view at the time of research. On the other side, my research strategy is to conduct a narrative inquiry, seeking the respondents story, which represents their interpretation of lived stories about technologies and capabilities, based on knowledge and experience over time. Therefore, the stories they tell represent longitudinal data, but not in a very structured way.

3.6. Research Techniques and Procedures

I planned to collect qualitative data using semi-structured interviews, with open-ended questions in order to get the respondents to share their stories. The interviews are the primary data, but I also conducted literature studies as secondary data in order to support the narrative restorying, or re-telling to construct my narrative portrait, when suggesting the new paradigm.

3.6.1. Collecting domain expert stories by interviews

I used semi-structured interviews according to Tjoras (Tjora & Tjora, 2021) recommendations, with open ended questions, to capture domain experts view on technology and business opportunities for wireless IoT sensors. Due to the pandemic restrictions it was done as video interviews using Zoom.

3.6.1.1.Simplified models

In order to direct the focus of the narrative storytelling towards machine learning in wearable IoT sensors, and the research limitation of cognitive objects, I created three simplified models. This made it easier for the respondents to elaborate towards these models. These simplified models were also used as a foundation when conceptualising.

3.6.1.1.1. Object-centric IoT Service

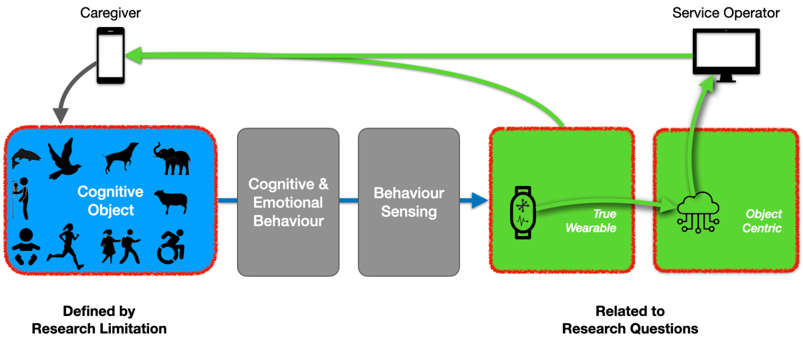


Figure 13: Simplified model of Object-centric IoT Service

The first simplified model describes an *object-centric IoT service* architecture (fig.13). Captured sensor data gets inferenced directly in the sensor, and only patterns and events is sent inwards in the architecture. This is opposite to traditional cloud centric IoT architectures such as cloud computing, fog or edge computing, where large amount of raw sensor data gets sent wireless to the computational point for being classified. Cloud centric architectures trains the machine learning models based on large datasets, which represents a huge number of examples from multiple sources. The simplified model of the object-centric IoT service rather move machine learning and reasoning to the raw data at the sensor. The model does not at this point describe where, and how, the training of the machine learning model takes place, but makes a point that training at some point must be personalised to the particular object it gets placed on.

Early on in my research, I used the expression Object-centric IoT Service as a simplified model, but I felt the expression did not give the correct meaning. I was too focused on the technical side of it, on the IoT architectures, on where machine learning and inferencing would take place, and that the expression should reflect that learning and sensing would be only on one object, instead of a larger group, or population, like in cloud centric. I felt that my expression missed an important factor; that the sensor was attached to Cognitive Objects, and not non-cognitive object. For this reason, I changed my conceptual model to Cognitive IoT Service. The respondents were introduced to the concept of *object-centric IoT service*, since renaming came later.

3.6.1.1.2. True Wearable IoT Sensor

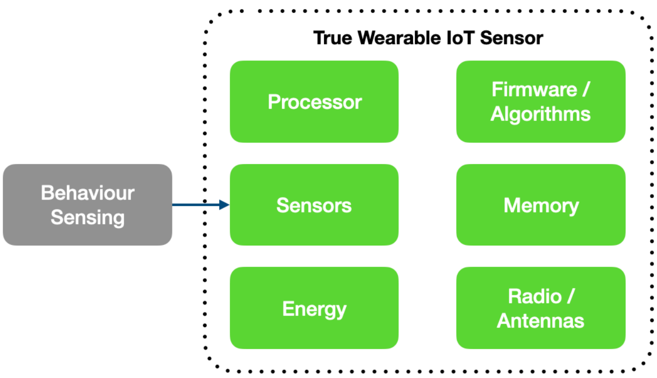


Figure 14: Simplified model of True Wearable IoT Sensor

The second simplified model describes a wearable sensor system (fig.14) in terms of function blocks such as processor, sensors, energy source, radio, antennas, memory, firmware with operating system and algorithms. Of course, architectures of such systems will be very dependent on application, and especially as a consequence of the object-centric IoT service concept. The simplified model of a true wearable IoT sensor would only serve as a generic system to ease and focus the interview. The main principle in true wearable IoT sensors is to avoid spending energy on sending raw sensor data, but instead move the machine learning algorithms to the sensor and do the inferencing there instead. As described in the simplified model of object-centric IoT service, the true wearable IoT sensor will get trained on the particular object it gets placed on, to become personalised, but this simplified model does not describe this. The goal for true wearable IoT sensors is to meet the definition for wearable computing by Steve Mann (Mann, 1998a).

In the early days of my research, I used to describe such sensors as true wearable IoT sensors, but I didn't get the correct feeling with that expression. I felt it gave a false impression of the condition the sensor would be placed under, and that it would only imply a need for improvement on the limitations of wearing it, such as size, weight, shape and durability. I felt the expression only said something about how the sensors needed to be, by becoming truly wearable. I also felt that it did not express what the sensors should detect, and where it should detect it. I needed my concept to express that the sensor should detect behaviour from cognitive creatures everywhere they where. For this reason, I changed the name of my conceptual model to Cognitive IoT Sensor. The respondents were introduced to the concept of *true wearable IoT sensor*, since renaming came later.

3.6.1.1.3. Cognitive Objects

An article overview from VerywellMind (Cherry, 2022) explains cognition to be the mental process involved in gaining knowledge and comprehension, including thinking, knowing, remembering, judging, and problem-solving. They explain the emergence of cognitive psychology back to the earliest definition by Ulric Neisser's quote *«The term cognition refers to all processes by which the sensory input is transformed, reduced, elaborated, stored, recovered, and used…» (Neisser, 1967)*.

Another simplified illustration by Braingymmer (Jasper, 2020) shows how cognitive skills such as perception, attention, logical reasoning, thinking speed and memory influences the cognitive processes of information retrieval, memory recollection and decision making. During a day, all kinds of stimuli and information passes through any brain, building experiences, and training different skills, in different ways, resulting in all cognitive objects becoming unique. Even identical twins are different (Deater-Deckard et al., 2001). The behaviour from a cognitive object can additionally be affected by ageing, inactivity, injuries, illness, drugs, environmental poisoning. All these sources can influence the behaviour individually, or in combinations, and is different from humans, to animals, fish or birds, and

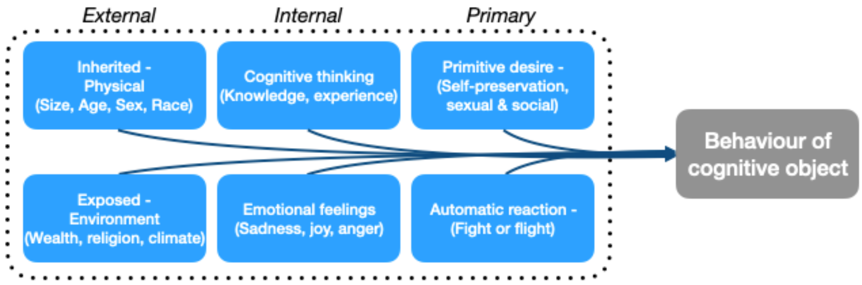


Figure 15: Simplified model of Cognitive Object

depends on external influence or primitive needs. A simplified conceptual (fig.15) model of a Cognitive Object based on Plutchik Psychoevolutionary Theory of Emotion (Plutchik, 2001) shows the influential factors which leads to behaviour, which can be measured as biometrics or motions, either as quick changes, or gradual development over time. The biometrics to use, will depend on the cognitive object, and needs from the service and caregiver.

3.6.1.2.Interview guide

My research strategy is a narrative inquiry approach for capturing stories from the respondents, and in order to put the focus in line with the problem description and the research questions, I created an interview guide (fig.16) to narrow the scope by introducing my three conceptual models to the respondents. The interview guides were developed in order to create the correct atmosphere for the respondents to share the story as seen from their perspectives, regards current state of various technologies, possibilities, and to talk about machine learning in wearable IoT sensors. The interview guide intended to only lead the respondents into the topic of the research, without affecting their story. All the questions was open-ended questions, and the respondent was asked to elaborate on several occasions. The warm-up section was for establishing background of both the researcher and the respondent, to build confidence and trust, and allowing the respondent to get familiar with me, my experience with technology, introducing this research and my motivation for this study, and for me to get more familiar with the respondent. The setting scope (models) section, was a dialog to introduce the three models, while setting it in relation to the respondents technology. Then the interview guide led into dept, in

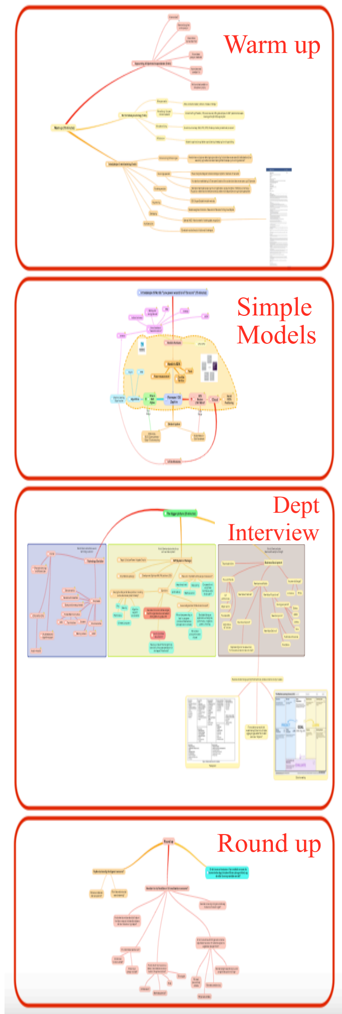


Figure 16. Structure, interview guide

technology for wearable sensors, in the perspective of the models, and lastly it led into dialogue about business model. The interview guides were structurally similar for the respondents, but still different since one of the respondents works for a hardware platform vendor, while the other works for an algorithm platform vendor. All interviews was done in the respondents spoken language. Misinterpretations could have occurred when translating and transcribing the first two interviews (done in Norwegian), so the respondent was asked to check the transcripts and translation afterwards. Conducting the interview in the spoken language should be considered positive for storytelling, since this reduced language barriers in the interview. The interview guides for the first two interviews were written in bullets, providing interview themes, as well as elaboration topics, while the interview guide for the third interview was written with complete questions. See copy of the interview guides in appendix B and C. The interview guides differed from the interview transcripts. During the interviews, the dialogues sometimes sidetracked as new ideas was brought up, and the respondent was encouraged to continue his story. Sidetracks were after some elaboration guided back to topic.

3.6.1.3. Interview candidates

Through previous work experience, I happened to have access to domain experts with key roles at market leading vendors within the two of the most significant technologies for wearable IoT sensors; the first vendor is with ultra-low power processing and communication, and the second offers small footprint machine learning platform and tools. Their world-view is likely to represent the direction the technology is moving. In some situations, market leading companies even sets the standards as de-facto, as industry leaders, only based on their market position, while in other situation they move with the standards and trends, as industry followers. Both these domain experts would represent market leading technologies, and based on their track record, and long experience in their domains, I consider their credibility and trustworthiness as high. They both agreed to participate in my research. Some will say that only two respondents in my research is too few, therefore have a few considerations on this. My research is trying to locate research fronts, which was described earlier in this chapter. Much of this is subjective and depend on who you ask. Some of the research fronts are also heading in radical directions, and some is only hype, as shown in Gartner Hype Cycle (Gartner, 2018). My research is not trying to discover the hypes or radical research, but rather technology which are starting to become real opportunity and on the edge to market. I asked two interview candidates from two market leading vendors of significant technologies for wearable IoT sensors. The respondents have knowledge about trends and capabilities of their many thousand commercial customers, and what they are researching.

My research is also trying to establish knowledge about a new paradigm, by proposing a concept based on new innovation from several technologies which can be relevant for wearable IoT sensors. Currently the majority of R&D in product and services are aimed towards markets where there are business to make. Most of this are related to existing IoT topologies, equipment and services, meaning established ecosystems and environments, which is well established. The two respondents I have interviewed are both technology vendors, one in wireless microcontrollers and hardware, and the other in machine learning and algorithms, which I consider to be agnostic to market dynamics. I rather consider both of them to be interested in trying to be included in the next market trends, and therefore will share their true beliefs on what that is. Therefore, I doubt that the research in this situation will become better by interviewing many respondents, it is more important with depth research towards the significant focus areas, and then checking this against reality in the market. I believe the domain experts participating in this research represents a neutral standpoint which is not biased in their current business and revenue. The depth of the interviews was focused toward the simplified models, and therefore not affected by the respondents, but instead guided by the problem description and research questions.

3.6.1.3.1. Respondent A: Leading fabless semi-conductor vendor for wireless appliances

The first respondent, represents a leader in ultra-low power wireless microcontrollers. The assumption is that they, based on being leader for decades, have a general understanding on the research front of hardware and firmware for such wireless sensor systems, both by innovating new chip solutions which the market continue to consume, and by learning from their customers what they do, and wants to do next. The interview guide was developed with a purpose of narrowing in to a wireless IoT system, in order to understand the microcontrollers capabilities for processing sensor data, need for power and source of power, the vendors development tools and support for infrastructures, and how capable their ultra low power microcontroller would be for computing machine learning algorithms. The interview guide was also developed to cover topics of service architecture, privacy and ethics, as well as uncovering possible opportunities in business models for such IoT services.

3.6.1.3.2. Respondent B: Leading platform vendor for machine learning on edge devices and sensors

The second respondent, represents a leading platform vendor for small footprint machine learning and deep learning, and tools for tuning and training the models for constrained devices at the edge of the IoT networks. The assumption is that they, based on their platform being used in a large number of tiny sensors and small appliances, have a quite good understanding of the current capabilities of machine learning and deep learning algorithms, how common they are on small wireless sensors, how they can impact on the operation and functionality of the sensors, and how these can improve the IoT services.

Since they are one of the leading provider of such tiny and compact machine learning algorithms, it is assumed that they have a general understanding on the research front of such algorithms. The interview guide was developed with a purpose of narrowing in to a wireless IoT system, in order to understand what possibilities there are for computing and inferencing on the raw sensor data, where it is captured, if that solves any current issues, and if it adds any new values or features. The interview guide is also designed to cover topics such as tools for development, tuning, algorithm training, and optimisations for low power computing, but also to understand data privacy and ethics, as well as trying to understand if there are any impacts to the business models of IoT services.

3.6.1.4.The interviews

Both respondents were asked to set a side one hour for the interviews. They selected the best time themselves, at any time a day, and I sent a short summary of the interview guide so they could prepare and get their mindset into telling their story and experiences. They were informed that I was seeking the research front, in order to move to focus towards wireless IoT sensors, and *true wireless* IoT sensors, as well as to hear their opinion on IoT architectures and *object-centric* services. The interviews were conducted according Aksel Tjoras (Tjora & Tjora, 2021). In the interview with the first respondent, representing the low power wireless chip vendor, one hour proved too short. We had a very interesting dialogue, so we agreed on a followup interview to cover what we did not manage in the first interview. This also gave the respondent an opportunity to prepare, so we did a second interview for another 30 minutes. The interview with the second respondent, representing the machine learning algorithm platform vendor, we also got into interesting conversation, which I had not foreseen, about ethics, in particular *being* ethical. Therefore the round up part of the interview did not complete, so we agreed on a second interview to cover this part. But time passed, it was Christmas time, the company got very busy raising their second round of financing, and there were corona closedowns, so we did not manage to do this interview. Still the first interview provided their story to a satisfactory degree.

My impression of the interviews is that we managed to get a relaxed setting. I already knew one of the respondents, so the focus with him was to get into the setting, and limitation, of my research. With the second respondent, the warmup section also gave a brief introduction of my experience. My intention was that the respondent, and storyteller, should try to remove barriers of free speech, or the feeling of having to simplify the story for the sake of getting understood. I felt that both respondent took the lead in telling their story, sharing their view, by reflecting back on their experience so far, how they perceived the current state of technology, and how they foresee possible opportunities for the future.

They brought up things I had not prepared in the interview guide, for instance of how to *be* ethical, and not just ethical with the data. The interviews were recorded in Zoom and stored as required by NSD.

3.6.1.5.Transcribing

The interviews were transcribed using the HyperTranscribe 2.0.0. The tool provided an effective way of playback, and linking that to the transcribed text. All interviews was sent for review and feedback, without any comments. The first interview was done in Norwegian, so it had to be transcribed and translated into English. Translation was done while transcribing. The second interview was conducted in English, so only transcribing was necessary. The actual transcription was actually done by Google Docs and its dictate function, which can convert voice to text. Before transcribing, I installed an audio driver to my computer called VB Cable, which made it possible for me to transcribe the interview, by playing the recorded interview through VB Cable to a Google Docs document using the «Voice typing» function in Google Docs. The function of the VB Cable was to virtually feed the audio playback from the video internally in the computer from the speaker output to the microphone input. This way, the video recording automatically got transcribed to a raw text document, using the Speech-to-text function in Google Docs. I still had to go through the generated raw text and fix punctuations, mis-interpretations, and establish the sentences and sections of who said what during the interviews.

3.6.2.Literature study

In the case of fast evolving technologies, like machine learning, the number of publications and articles are growing exponentially, which I felt was a challenge for literature and document studies. Some of the publications referenced in my thesis have actually been published during the period of performing the research. The literature studies complements the stories told by the respondents. Since I was looking for the research front of new technology, where much of the information was likely to be kept internally under non-disclosure in the technology companies, which could be difficult to get access to. Still companies doing Applied Research have to promote and sell their technology. This can be published through their platforms, or as presentations in industry forum, news articles or journals. Alternatively they will do marketing of their functionalities in their own products. Therefore I cannot ignore product and platform introductions, industry conferences, news, press releases or journals.

3.6.2.1.Literature search

I conducted searches in the Oria database, at Google Scholar, and in Goggle as open searches. I searched for articles, thesis and books, and found interesting information based on my search key words. I split the key words in four lists, in order to find relevant literature for the three research questions, the research limitation, and to cover my problem description. When finding relevant literature, I studied their key words and picked up some new ones which I used for further searching. I also followed citation of interest, to other related research. Some of the sources for the literature is commercial company websites, and podcasts, and some can always claim that something is wrong or misleading, but since my research is a narrative inquiry, the primary data is the narrative stories from the respondents, which I triangulated towards the secondary data, the literature. I used EndNote 2.0 to organise my references, which also generated the bibliography according to the APA standard.

3.6.2.2.Key words

The first list contained key words that would guide me towards wearable sensors, and the research fronts for the related technologies, such as *IoT sensor*, *machine learning*, *research front*, *battery operated sensors*, *low power microcontrollers*, *battery*, *energy harvesting*, *edge computing* and *constrained devices*.

The second list contained key words that would guide me towards the limitation on cognitive objects which was my initial target for such new IoT sensors, such as *animal sensor*, *welfare sensor*, *dog trackers*, *sheep trackers*, *bird tracking*, *fish tracking*, *home prisoner foot tag*, *behaviour classification*, *emotion classification*, *fall sensor*, *sleep tracking* and *fitness tracker*.

The third list contained key words for understanding the IoT architectures and the current paradigm with IoT data flowing inwards in the architecture, such as *cloud centric, IoT architecture, smart IoT, edge computing, object-centric, narrowband* and *IoT service*.

The fourth list contained key words for understanding innovation in business models, from the traditional models, to new models including smarter equipment and services. Key words such as *software as a service, hardware as a service, AI business model, AI value proposition, ecosystem innovation, lean canvas, osterwalder, network effect, learning effect* or *circular business model*.

3.6.3. Analysing using Stepwise-Deductive Induction

To analyse my interviews, I have used SDI analysis (Tjora & Tjora, 2021). I used HyperResearch version 4.5.3 to code the transcribed interviews. Non of the codes was created in advance, rather created dynamically during coding. This way, the actual content was kept as part of the code in an empirical-close coding method. Both interviews were coded in the same project in HyperResearch, but as different cases. This way they shared the same code book, but could still be filtered as cases. During the first round of grouping, I organised codes with similar meaning together. Before grouping, I had no idea about which groups that would form, but as the codes where sorted, it became clearer how to name the groups. When all of the codes had been grouped a first time, I went through and grouped a second time, and created subgroups. This time the subgroups was organised and named closer to the research questions and the problem description. This grouping, the code book, the empirical close codes and the transcribed interview, was then stored as an interview coding report, generated by HyperResearch.

3.6.4. Conceptualising to a new paradigm

After empirical close coding, and grouping of the codes in two steps, I started analysing by going through each subgroup to seek knowledge from the two respondents stories. They represent technology on two different levels; one at the bottom, in hardware, and the second one at the top, in algorithms. Even though it might be easy to think that they are involved in nearly the same thing, there are quite a distinction; Respondent A, a wireless microcontroller vendor, are very different from Respondent B, a machine learning platform vendor. First of all their effort, timeline, investments and resources from doing their business development and deciding to develop what they have, is very different. It takes much longer time from deciding to do something in hardware, till their customers are in manufacturing and they get return on their investments. Same thing, it is very different for the machine learning platform vendor to support many hardwares. On the other side, they are being integrated to the same products, in a wearable IoT sensor market. Therefore it is exiting to learn from them, their perspective, on what is becoming the same product in the market. When working through the subgroups one by one, I got to learn about the same topic from two perspectives. Many times this were the same, but some times their view were different. In some of the topics, one of the respondent had deeper insight than the other, which was natural since they provided different tings. In order to answer my research questions and develop my concepts, I merged the analysis of the interviews, and the literature studies (fig.17).

Data Sources	# 1	# 2	# 3
How	Semi structured interview	Semi structured interview	Literature Studies
Who	Participant 1	Participant 2	Journals, News articles, Press releases, Industry reports, Publications, Product reviews, Websites
What	Platform	Platform	Products and research
Position	Market Leader	Market Leader	New entrants, researchers, writers, experts
Product	Hardware	Firmware, algorithms	Techniques, products, solutions, concepts, models

Figure 17: Research Data sources

My research was done as a narrative inquiry research, where I triangulated between the analysis of the two narrative stories, and the analysis of the document studies. Based on the triangulated analysis, the discussion reflected towards the research questions, before conceptualising, into a new paradigm, which I then evaluated in terms of business development. This was also a part of the problem description and one of the research questions. As a final step, I restoried my the research into my Narrative Portrait, before concluding and summarising.

3.7. Research Quality

Searching for the research front in rapid moving technologies, means it will be moving while this research is being conducted, in other words «chasing a moving target». Looking for what gets defined as state-of-the-art in the various technologies, also has a degree of subjectivity, since it will depend on who you ask. With this in mind, I selected narrative inquiry to be the most adequate way of considering capabilities with current technologies, and possibilities going into the future, maybe creating enough interest to see a new paradigm. Seeking the research fronts, or understanding what different technologies can do, cannot be answered very accurate anyway, so using terms such as *reliably* and *validity* is problematic. It is more correct to use the terms *credibility* and *trustworthiness* instead. A study (Loh, 2013) argues that for some research, the traditional way of describing research quality with reliability, validity and generalisability will not be adequate. This is the case for narrative inquiry, since the method captures knowledge through lived and told experience in the form of stories, based on few respondents, which have their unique perspectives, intentions and affections. Narrative inquiry also addresses the perspectives of both the researcher and the respondents. One might say that it becomes a mix of all of this. For that reason it is more important to check the issue of trustworthiness. Loh also speaks for verisimilitude, or believability, and that the study must seem plausible to the consumers of the study. Where credibility relates more to the respondents, verisimilitude would relate more to whether or not the paradigm is relevant for the audience. Since this research, triangulates the told story towards examples from the market which indicates opportunities evolving, the verisimilitude should be there. But that does not mean the suggested paradigm will elapse in full, it only indicates that it can. If the verisimilitude related to the third research question is high enough, and there are good enough opportunity to explore in business models, then the suggested paradigm likely will happen. A research (Wells, 2011) states that the trustworthiness actually is a broader and more relevant concept than the validity for narrative research, but points out that reflexivity and ethics is crucial to the assessment of the trustworthiness. In my study I am seeking the respondents, or domain experts, interpretation of the technology evolution, and how they understand the research fronts, what technology is capable of today, but also trying to understand a future state for true wearable IoT sensors, and services. These domain experts are likely to be the best to share their view on this matter. The respondents role and position as leading companies, establishes credibility. In their position, they cannot make statements that differs much from the market trends, unless trying to set new standards. Being leaders, actually proves their offering to the market has gotten adopted over time. The position as leading, and the respondents roles in this, gives them trustworthiness.

The relationship between me, as a researcher, and one of the respondents started as colleagues approx 20 years ago, and we have been acquaintance since. Potentially, our relationship could have affected the stories being told, in the sense that the response was given as «best suited» to help my research, even though he was reminded to share his story. On the other side, our relationship might also have given me access to more information than others would have gotten, even though the respondents was instructed to withhold any confidential information. With narrative inquiry it is quite important that the relation between researcher and storyteller is based on trust and respect, which in this case is strong.

Before the interview, the scope was limited to wearable IoT sensors. The problem description was discussed, to establish a shared reality. And the research questions was given as a guideline to what the research was trying to answer. The respondents told their stories according to these parameters. This way, I captured their stories, or narratives, to analyse and compare, or triangulate, with other literature or information from the market, before conceptualising and creating my narrative portrait, which I present as a new possible paradigm. The findings from the stories are found in chapter 4, the interview guides are attached in appendix B and C (anonymised copy of the transcripts can be made available). Discussions, conceptualising, and restorying to my narrative portrait can be found in chapter 5.

In terms of research quality, I, as a researcher, was already motivated by the desire to create better sensors for services to humans, animals, birds and fish, as described in chapter 1. I also have 4 years of experience working with wearable IoT sensors already. The risk is that my desire to solve is greater than reality. On the other hand, my experience might have added knowledge when restorying. With narrative inquiry, the researcher is supposed to use the analysed stories, and findings from document studies to restory to the researcher narrative portrait. Since I, as the researcher, already has experience and knowledge within the field, there will be bias when conceptualising to the new paradigm. Therefore it is of importance to consider the researchers credibility and trustworthiness too.

My experience working with wireless IoT sensors so far, has already influenced the research questions and the interview guide, trying to achieve what is described as my motivation and research objectives, and should not be ignored. I feel that the mentioned bias does not affect the trustworthiness negatively, rather contributes positively to the restoried paradigm. The restorying was carried out with reference to other research and documentation, with real examples, in order to contribute to the trustworthiness to the narrative inquiry.

3.8. Research Ethics and Data Privacy

With narrative inquiry, there are some extra ethical considerations to make, as described by Clandinin and Caine (Caine, 2012), since they move beyond institutional requirements of privacy, confidentiality, and informed consent. The researcher must make sure to protect the integrity of the respondents, to keep their desired confidentiality, be trustworthy, be sensitive and avoid harm, keep fidelity and to be clear on the objectives of the narratives, while it is important for the respondents, including the researcher, to show respect, show care and empathy, as well as compassion and truthfulness.

In short, stories are told and retold based on shared values and common beliefs. The stories of the respondents represent their opinion, on how far technology has gotten, and what they think it is capable of. It is important for me to uphold their dignity, and not expose them against their will. At the same time, it is also important for me to credit them the ownership of those narratives.

The respondents were asked to sign a statement of privacy (see Appendix A), which informed them about their responsibility to not disclose confidential information and business secrets, as well as their right to be anonymous. After the interviews, a copy of the transcripts was sent for their review, and they were asked how they would like to be credited for their participation. Their response was to be anonymised in the text.

The recording of the interviews was keep on a USB stick according to NSD guidelines, and deleted after review of transcripts.

3.9. Research Design Summary

I have an impression that Aksel Tjora (Tjora & Tjora, 2021) is critical to a majority of literatures describing the qualitative method, and that the choice of data generation method too often is dept interviews, maybe only because that is the least resistance way. He tries to express a greater methodical openness, and that the choice of research design should have a stronger professional anchoring.

Planning and execution of the selected methods shall be conducted with an academic precision throughout the research. According to Tor Grennes (Grenness, 2001), the choice of methods shall be guided by the problem description. My problem description seeks more knowledge in two directions, which requires different approaches, in line with what Tjora is expressing.

My research philosophy is within interpretivism, where I believe to find most the relevant information within applied research, more accurately within technology research (Solheim et al., 2007). The main research design is a narrative inquiry research, using Aksel Tjoras Stepwise-Deductive Inductive method (Tjora & Tjora, 2021) for working with the stories and data. The first section was conducted as intensive and descriptive research using semi-structured dept interviews to capture stories from the respondents to generate qualitative data, while the second section was conducted as an exploratory research using the stories from the interviews. After analysing and conceptualising, the findings was triangulated with document studies of other research and available documentation. Both sections are qualitative and interpretative, where the interview guide led the respondents to the three research question, as a multi method research design. They where asked to elaborate and share their opinion regards capability of relevant technologies for wireless IoT sensors, as they see it, and how that could potentially impact future use and business models based on their subjective understanding today, or with a cross sectional time horizon. My research goal is to work towards the definition of wearable computing (Mann, 1998a), in order to understand how machine learning will impact wearable IoT sensors and related business models.

The research quality of the narrative inquiry was considered based on credibility and trustworthiness of both the respondents and the researcher, as well as triangulated with other information from document studies.

4. Findings

After generating data by conducting interviews, and having conducted a wide search for relevant literature, I started analysing the data material. This chapter will describe the results of the analysis of the interviews empirical data, as well as a structured summary of literature and information found in journals, press releases, research reports, product reviews and industry reports.

4.1. Interviews

4.1.1. Interview transcripts

I interviewed two respondents; which resulted in at total of 159 minutes of video recording, 95 minutes with the first respondent, during two interview sessions, and 64 minutes with the second respondent. The recordings were transcribed and sent for review. The transcripts contained information from the internal operations of computing, memory usage, clock and radio performance, through firmware, external sensors, power profiling, machine learning algorithms, training of algorithms, IoT architectures, and up to ethical use and business model aspects. It also contained discussions and elaboration about challenging topics, solutions and examples of applied technology. My first impression, was two dedicated respondents, with a high level of expertise in their fields. Both respondents described their companies as world leading in their fields, and dedicated to provide the best technology and tools, and to jumpstart their customers with good evaluation and development projects. I even got some feedback when introducing my research questions.

> Respondent A: *«Seems to be in my field of speciality, sounds great. This is my passion, all of it.»*
>
> Respondent B: *«Cool, you are digging through a very large area, it's interesting. And it's good that you are looking at it from hardware, to machine learning, and then to business value.»*

4.1.2. Coding the transcripts

Both transcriptions were coded empirically close, and resulted in 249 individual codes in the project code book. Many of the codes had similar but different names and content, but none of them was reused. Some of the codes later proved irrelevant, and got organised into a group for such codes. Some codes were only small sentences and statements, while others contained whole descriptions and dialogue between the interviewer and the respondent.

4.1.3. Grouping the codes

After the first grouping, the individual codes organised into 9 main groups (fig.18). The group names started as a narrow describing name, but evolved into a wider description, or categories, as more codes were added. When all codes had been organised once, I grouped the codes again into a sub-group level. In total there were 30 sup-groups, which organised the codes closer to the research questions and problem description. The purpose of this sub-level was to synchronise the information from the narrative stories with the information from the literature study, and to form a structure for the discussion.

SDI Analysis

1st grouping (empire close codes)	2nd grouping (research questions)
Participant focus	
Customer flying start	Jumpstart customer Low barrier to test Making available for everyone
Disadvantages with current technology	Not true wearable Too difficult to use Bad quality or not trusted
Sensor technology research front	Energy Equilibrium Price and Size Processing Sensor Machine Learning
IoT architecture principles	IoT Topology Local ML inferencing Wireless transmission
New values from true wearable IoT sensors	Adding gain points Fixing Pain points Solving Jobs Combo value
Application and design specific considerations	Challenges Optimising for size and cost Optimising sensor for best performance Variety of options and application needs
Careful and needs more research or difficult	Needs more research Needs to meet minimum requirements Needs true and acceptance Needs ethics and regulation discussion
~~**Definitions and ungrouped codes**~~	Research objective and limitations Feedback Other

Figure 18: Main groups and sub-groups

Each of the codes were then marked with the relevant research questions, as shown in the example from the HyperResearch report example (fig.19). The respondents had similar opinions on the same topics, only different in nuances by coming from different perspectives. Only in some cases there where different viewpoints. The next chapters will describe 8 of the 9 main groups. The last main group was skipped since it contained things that I considered outside the scope of this research.

1		Main group code	Sub-group code	RQ # mapping	Code	Content
109		Sensor technology research front	Machine Learning	2	Local inferencing does not have network battery or latency issues	There are many things you simply cannot do if you don't process locally, and instead have to send the raw data to a computing point. On the simple side, the fall sensor, would not be possible if having to send all the raw data to the cloud, since that would be costly, would drain the battery, would introduce network dependency, for instance if grandmother fall when not in present in of the infrastructure. Local processing will still detect it, and can do some alerting by sound or blink for instance. That is the simple application. Let's say grandmother is speaking to a voice command, that amount of raw data cannot be sent of to a computing point to be inferenced. That has to be done where the voice data is. Or let's say it is a position tracker on dementia patient. If that device has to send all of its data to a computational point in the cloud to determine if the patient leaves the home, then the device will be drained for battery quickly. In that case, the wearable device will not get its position and start alerting in case of network unavailable. Next level would be for instance a fitnes tracker, which is much more complicated. So, it is not a question about computing in the cloud for wearable devices, it is opposite, processing in the device, which opens up all the advantages with "True Wearable".
110		Sensor technology research front	Machine Learning	3	Local machine learning works in many places with network issues elevator tunnel mountain underground	And this will be even more so when it comes to cognitive wearable sensors, which will have a personalised type of behaviour to it also. Another example would be for instance sensor used in an ambulance, and the ambulance looses network coverage. Then heartbeat sensor used in the monitoring of the patient fails, if it is not processed and inferenced locally on the cognitive "True Wearable" IoT sensor. And there are lots of places where wearable sensors can might loose coverage to the network, for instance if away from the radio infrastructure, if the power in the area is lost, indoor, under ground, in the mountain, at sea, in tunnels, in elevators and so on. The list is long. And for every place with weakened or no coverage, the battery will drain faster, since the radios likely will try harder to amplify the signals, process it harder, and boost the transmitter. So local processing in the sensor will make it "True Wearable" within your definitions, and it will enable more and new functions and features.
111		Sensor technology research front	Machine Learning	1	Today some applications process locally in device	And in some applications it gets processed locally in the device or at the endpoint.
112		Sensor technology research front	Machine Learning	1	Important for machine learning is very low sleeping modes and super-fast wakeup	I can speak about what matters for machine learning at the moment, its probably the interesting angle here, machine learning is changing some of the game here, with these low-power devices. For a couple reasons. We want to be very low power when nothing is happening, that's important, so microcontrollers are really good at that, because of the way they are designed, we can go to very low sleep power modes, and then we can wake up fast, when something happens, that's important for machine learning. Especially for wearable applications, let's focus there. Super important, that low power sleep mode.
113		Sensor technology research front	Machine Learning	1	Technique is to work on smaller portions of the data at the time	Just to go back a little bit, back to memory footprint, or memory usage. Correct me if I'm wrong, but by faster and more optimized machine learning models, you can work with smaller chunks of captured sensor data, therefore gain reduction of the RAM footprint. But you will also be able to work on shorter time window of sensor sensor data, to detect patterns, is that correct? Is that something you work on, narrowing down the time you need of captured data in order to work? Or maybe more like capturing and analysing on-the-fly instead of looking at bigger samples?
114		Sensor technology research front	Machine Learning	1	We work on small portions as sliding windows	That's true, yeah. I mean, the way machine learning models work, is as they work on typically very short windows. We usually work on 1 sec windows, as long as we can capture the event we are looking for, the pattern, let's say, a motion pattern of walking, or maybe even jumping Jacks. That pattern is pretty fast, we could probably detected it in just a few hundred milliseconds. It could be more complex, maybe you're doing something like such a pattern (showing hand gestures on camera), or you need to cover a whole cycle of events in your pattern, as long as the window size for the captured raw data is big enough, to capture the whole pattern, the whole word, or the whole phrase that you're saying, then the machine learning algorithm will work within that. You might have a sequence of things, and then you want to have a period where there's no speaking, and then there's this word, which you want to detect. Actually, you need to detect it at least three times, because your window is moving, the window is shifting, so you need to detect it in the sliding windows, and then you need to have, again, no speaking. Then it becomes a very clear command, "power on", then silent again. There's also some posterior combination, so you might be doing this over kind of several windows that are sliding, but we are talking about working in a very small window, very concentrated window size.

Figure 19: Extract examples of empirical close codes from respondent response in HyperResearch report

4.1.3.1.Respondents focus

The first group was «Respondents focus» were all codes concerning the respondents, and their companies, was organised. This group would give a description of what they focus on, how they focus, what their business is, and how they view themselves compared to the market, information regards their companies, how they approach market and customers, as well as dedication and interests. This main group, was not grouped into sub-groups, since it was considered irrelevant for the research questions, and to respect anonymity. The only use from this main group was used when describing the respondents as interview candidates, and in some general descriptions in the findings chapter.

4.1.3.2.Customer a flying start

The second group which I called «Customer a flying start» was organised into three sub-groups. In the first sub-group «Jumpstart customer» all the codes which contained how my respondents prepared their products and platforms so their customers could get through to production and into market as fast and easy as possible. Both respondents expressed how they optimised, qualified and certified their offerings so that their customer could keep the focus in their domain, whatever that is.

> *Respondent B: «Our customers are the domain experts, they understand thermodynamics, or human health, or machine vibration. The customers understand the problem they're trying to solve, they're the skilled engineer. They don't need to be machine learning, or data science experts, we enable them to use machine learning as a piece of tooling.»*

Both respondents expressed how important it is to give the customer a «low barrier to test» their solutions. They emphasised on delivering evaluation kits, development kits, example code and reference projects, so it shall be quick to test and get into prototyping of the customers own project.

> *Respondent B: «we make it easy, we make it visual. Our philosophy is 15 minutes from collecting raw sensor data, for example, to having some model working, in testing. A 15 minutes development cycle, that's our philosophy, that's why we started the company, that's why we exist, just to enable those engineers to use the results of the data in their innovative projects».*

The ultra-low power wireless microcontroller from respondent A's company is inside many special evaluation kits for kids and students, or development kits for companies, to control robots and make smart wearables in no time. Both respondent's companies are making tools for tuning quality, for optimising power usage, and to reduce application executions time, and they hold webinars to help the customers to get the most out of the technology in smart wireless appliances. They make state-of-the-art technology as platforms and tools for customers to use and quickly integrate in their products. Machine learning and artificial intelligence have previously been related to big data centres and supercomputing, but machine learning can now solve functions smarter and more efficient than previously, at ultra-low power.

> *Respondent B: «enabling them to work with data, and develop new features in those products, using machine learning. So it's about democratising machine learning, and what we do, we provide all the tooling in the Cloud, for all these engineers».*

This means that not only will it be «available for everyone», but the machine learning models will be running everywhere also, as small models, instead of only large ones in the core of the networks controlled by large corporations such as Facebook and Google.

4.1.3.3.Disadvantages with current technology

The next group was «Disadvantages with current technology» were the codes concerning the respondent's opinion on what holds technology back today. I wanted to understand what is hindering us from leaping forward into true wearable sensors. The codes were split into three subgroups, one where the respondents expressed that not all wearables was actually «not really true wearables», another saying something about «difficulty to use», and the last for statements about «bad quality and trust».

In the beginning of the interviews, both respondents got introduced to my definition about true wearable IoT sensors, which builds on the definition of wearable computing (Mann, 1998a). During the interviews both had confirming statements that wearables wasn't really true wearables, since they either had to be taken off to often for charging, or too big and heavy to wear. In order to achieve a good combination, and to qualify as a true wearable, the total amount of energy spent to execute its functions, had to balance with the total amount of energy available in the wearable.

> *Respondent A: «The issue with an MPU (Microprocessor Unit) application such as the iWatch, is that it is running most of the time, in order to provide rich results of the raw data. Even though it operates with low power cores etc, it will still consume a lot of energy when working on the all the raw data all the time».*

> *Respondent B: «MPU's are powerful, but not very well suited for true wearable. We are not seeing MPU's achieving ultra low power. MPU's tries to achieve more performance on the same power, rather than less power».*

The respondents mentioned three choices. The first one 1) was to reduce energy usage, by switching to an ultra-low power MCU (microcontroller unit), and 2) optimising how you run your application, or 3) choose one of the two drawbacks: a) either add battery which makes the wearable bigger, heavier and more expensive, or b) you have to accept to charge more often.

Respondent A: «There are actually a users acceptance pyramid there too. You have a one day barrier, a one weeks barrier, and then the one year barrier, which applications push for. It is usually these steps.

The big question and ambition is how we can get rid of batteries in our applications, and this is something we are focusing in going forward. In case the wearable device is to big, clumsy or difficult to use, it will end up in the grandmothers drawer.

Products with battery is limited by their access to power infrastructure, either to charge, such as a power grid, or system, or for swapping batteries, with stock of batteries and making sure the stock is good. Then there are another level of complexity, since it also must be in line with the person or animal. So either the object which the sensor is attached to needs to be in vicinity of the charging infrastructure, or the sensor needs to be taken of to get charged. If it is attached to a wild animal, you might have to sedate it, to do it. And to make it even more complicated, in the health sector, you even need nurses to do it».

The next disadvantage with the existing technology and IoT topology is if having to off-load the raw data for inferencing in the network somewhere. On one side the wearable will spend energy just to send data over wireless, which affects the energy budget, but on the other side makes it more difficult to use.

Respondent A: «If processing off-chip, then short range (BLE and Zigbee) radio is better regards energy usage and latency typically, but much more infrastructure dependent, than long range (LTM and NB-IoT)».

In other words the price to pay for becoming less dependent on radio infrastructure is either bigger battery, or more charging, if using long range. Opposite, short range radio uses less energy, but restricts the wearable from moving away from the receiver. Both respondents spoke about privacy as one of the main reasons to do machine learning in the sensor.

Respondent A: «There is also something about privacy, since device computing does not have to send any raw data, it will be safer for customers; the data never leaves the sensor, only the result of the data, and that does not reveal anything about the objects privacy. This is visible in smart homes, where the focus is to not send that data out of the house, since that might reveal privacy issues in the family for instance. What happens in the house, shall stay in the house, is a saying. At the same time it meets the true wearable requirements».

There are also issues regarding the feeling of bad quality or privacy, if the user can't trust the wearable sensor and service.

Respondent A: «A common issue for IoT applications, is latency or lack of service availability, in cases where raw data needs to be sent further into the cloud to be processed and analysed. If the machine learning algorithms, or filter functions are located external to sensor, the raw data somehow needs to be transmitted, either over short range radio or long range radio. We have spoken about the issues regards energy usage, and privacy, but there are also an issue with communication latency and availability»

4.1.3.4.Sensor technology research front

The interview guides, the simplified models, and the research questions, narrowed down the research to focus on relevant technologies for wearable sensors. Therefore it wasn't a big surprise that both respondents elaborated into constrained devices as seen from their perspectives, one from the hardware side, and the other from the algorithms on top. Both respondents expressed about processing; one with the perspective of manufacturing the microcontroller, and the other with the perspective of using it. Therefore it is natural that respondent A had more details to share regards chip related topics, while respondent B elaborated more into machine learning execution.

> *Respondent A: «One part is the energy used when the chip is active, meaning what parts of the chip is powered on, how the clocks are running. The second element is what energy is used when the chip is in sleep and deep sleep, also referred to as the leakage and idle currents. And then it is important how efficient the processor is with the cpu architecture, memory handling, hardware accelerators and so on, to wake up, and to executing the code and algorithms. Both for computing and communication, our key strength is to do all of this at the lowest possible use of energy.»*
>
> *Respondent B: «We work with all of them, across the industry, from MPU's, to MCU's to NPU's. With MCU's, you've got all your peripherals, all your memory, everything integrated, within one controller, which means, and the big difference is, you can go from an ultra low power sleep mode, to fully on, extremely quickly, without losing state. You can keep all of your program state, which means you can go, wake up, sleep, wake up, very fast. Or you can put the machine learning model in an NPU, and the ML can run all the time, at say 100 micro-watts, processing sensor data all the time, or processing audio continuously, and then when it detects a pattern, it wakes-up a larger general-purpose MCU.»*

The fact that microcontrollers are getting very powerful while at the same time being ultra-low power, raise the question on how the available energy in the wearable sensor should be spent. Should it be spent on radio transmitting raw data, or should it be spent on inferencing and making sense of what the data from the sensors are experiencing? Both respondents used fall sensor as an example, since such a sensor would have to send a lot of raw data to the network all the time, causing the sensor to spend energy on transmission, but also not being able to go to sleep. Maybe a fall never happens, or maybe only a few times, that's when the radio should activate.

> *Respondent A: «There are many things you simply cannot do if you don't process locally, and instead send the raw data to a computing point. So, it is not a question about computing in the cloud for wearable devices, it is opposite, processing in the device, which opens up all the advantages with <u>True Wearable</u>.*
>
> *And there are lots of places where wearable sensors might loose network coverage, for instance if away from the radio infrastructure, if the power in the area is lost, indoor, under ground, in the mountain, at sea, in tunnels, in elevators and so on. The list is long. And for every place with*

weakened or no coverage, the battery will drain faster, since the radios likely will try harder to amplify the signals, process it harder, and boost the transmitter. So local processing in the sensor will make it <u>True Wearable</u> within your definitions, and it will enable more and new functions and features.»

Respondent B: «Machine learning models work usually on 1 sec windows, or as long as we can capture the event we are looking for, the pattern, let's say, a motion pattern of walking, or maybe even jumping Jacks. That pattern is typically pretty fast, so we could probably detected it in just a few hundred milliseconds. Machine learning can possibly inference the sensor data on-the-fly, without sending anything to the network»

When the radio transmitters are on, energy gets consumed. Even though there has been an evolution in both the short and the long range standards the last years, the respondents seems to think that the radios should not be used for raw data, but only for short messages and notifications. Short range has gotten Bluetooth Low Energy (BLE), and now the mobile networks deploys long range with new narrowband standards with specific low power functionality. This seems to be in sync with more and more wireless and wearables.

Respondent A: «Our focus was to add support for the protocols which was low power communication, both short range and long range. There are techniques in narrowband which we are particularly good at, such as PSM and eDRX, which are sleep techniques, where our quick and efficient wake-ups, going from low energy usage in Idle mode, to low energy usage at processing.»

Another kind of radio, is GPS reception, a sensor for positioning. Respondent A explained how energy demanding this operation is, and how they have developed cloud assist to speed up the time-to-fix to get hot- and cold-fix, again to help reduce power consumption. But there are multiple other techniques to do positioning, which are low lower, which can help reduce the use of energy.

Respondent A: «GPS is the heaviest, so if we can assist in order to reduce time the GPS receiver is computing we reduce the energy usage dramatically. That is the first. But to reduce energy usage the most, we should not use GPS at all, we should triangulate the cell towers instead, which also have an advantage indoor or under ground, both since narrowband works there, then it will take away the time the GPS receiver is scanning, when there are now satellites to see, which consumes a lot of power. Positioning can also be done by BLE access points, or positioning in its simplest form with dead reckoning using an accelerometer. The best is if combining, by trying the most energy-efficient technique first.»

Regards other sensors, there are many. The respondents talk about biosensors, movements, pressure, temperature, light, spectrometers, microphones, camera, and all kinds of sensors. Many of these sensors have also built in support for waking up, and wake-words, patterns or activity, in such a way that this can be used to keep the system in sleep or deep sleep, while waiting for the trigger to wake up.

Respondent A: «There are sensor coming which are specifically made for waking up when they are triggered, and then they wake up the next step, before waking up the main processor, in a pyramid like concept. That is similar to the techniques used today elsewhere, such as wake on LAN, wake on movement, wake on activity, wake on RF etc. We know this from the wakeup of the phone or home gateway with "Hey Siri" or "Hey Alexa". Sensors such as accelerometers, microphones, temperature, have built in inferencing so that they can classify and find the "trigger data" in order to wake up the main system.»

Respondent B: «wake commands, or wake pattern, you can do that with motion sensors, with accelerometer, all kinds of things, so if it's something that we can wake-up, and then do some machine learning, and its sensors or audio, we can do it in today's silicone, today's MCUs, without special accelerometers. If it's something that needs to be always on, so we have to run the machine learning all the time, and that is what wakes-up the bigger thing, then we need an NPU probably, something like a Sentient in order to do that.»

One of the major topics has been energy. They both seem to agree that the solution is not to add more battery, but rather finding ways to either become battery-less, or at least spend the available energy as vise as possible.

Respondent A: «make devices that can capture the needed energy within the surroundings, AND it can fix the job at an acceptable cost and size. I believe we are moving away from batteries in general, and over time, totally»

Respondent B: «Energy harvesting, which is still hard to achieve, is a great example of wearable where super-low power is born. I think that heat and motion will have great potential for these small wearables. Cause you do have heat differentials in something like this, and you have definitely a lot of motion potential. But actually fitting that into a silicone package, that you can engineer into the product, thats though. I have not seen energy harvesting as the main power source for wearable IoT quite yet, but it's got potential».

One part of the solution is to extract power from the surroundings, but another is how efficient the hardware and algorithms are. And it is about what needs to be powered, at what duty cycle, for how long, and in which way.

Respondent A: «The leakage currents is very important, and they have to be low. For applications that have to toggle between sleep and active mode, it is very important that the wake up, with clock distribution and acceleration, is quick and power efficient. This way the time and energy to get to active mode is lowest possible. And then it is important how efficient the processor is when executing the code and algorithms»

Respondent B: «another way, by creating the whole processor to be a very specialised math accelerator for machine learning, seen in like very low power wake up application.»

Both respondents expressed their opinion about the balance between capabilities and performance, versus the solution price and size. Since we are talking about wearable sensors, the size of the device is critical, in order to blend into the natural surroundings of the wearer. But it does not matter if it is cheap, or small, if it can't do the job it is supposed to do. In order to reduce the use of radio, it needs to compute the data directly at the sensor, so performance is of the essence, and it must be performance for inferencing. The optimal combination of hardware and algorithms, will also lead to the optimal price and size of the wearable IoT sensor.

> *Respondent A: «The total systems are getting low enough in price, to do it all in the sensor soon, and this will improve operations since there will be no cost of data-com anymore, there will be no energy spent transmitting data, and the sensors will be much quicker without latency.*
>
> *Local computing drives the energy usage down, and from the other side comes energy harvesting. Some wearable sensors are there now, harvesting from sunlight, kinetic or body heat. Energy harvesting becomes more and more relevant, the lower the energy usage gets. There are a breakpoint where energy harvesting can deliver enough power compared to what the application needs, at a reasonable cost. Smart sensors helps the wearable IoT sensor stay the longest in sleep, while tiny machine learning algorithms helps process more on the sensor removing the need for energy demanding communication.»*

We are at a time when it is all coming together, almost like an equilibrium, or a tipping point. From the processing side, the microcontrollers are now high performance *and* ultra-low power at the same time, and they have gotten memory and support for computing smarter algorithms. And from the algorithms side, the machine learning models have been optimised for running on constrained devices *and* using limited amount of energy at the same time. In other words don't have to waste energy to off-load raw data for inferencing. Then sensors have gotten smaller, smarter, and more power efficient, so that the total system is power efficient enough to only run on tiny batteries, and in some cases only by energy harvesting.

> *Respondent A: «We are probably getting to a point for some products and applications, where the technology is energy efficient enough, and evolution on energy harvesting is getting good enough, at the right cost and size, and interest and demand is establishing in the market, in such a way that a market for non-battery products might establish. That point in time is now for some applications already, and with the addition of machine learning at the capture point, there will less and less need for support from computing power on the network, therefore less and less need for communication of raw data, only the result of the analysed data. And as the trends develops, this will become even clearer. And at one point in time, these wireless sensors will be without battery. They will use so little power computing the raw data, analysing it, and acting on it, that it can be done without battery. I believe that we will end up without battery using energy harvesting in more and more applications. That is next step.»*

4.1.3.5.IoT architecture principles

IoT topologies we have today are the result of an evolution from M2M machines in the early days, to connected IoT devices, and lately wireless IoT devices. In the beginning the applications used the internet to send configurations, communicate control signals and read statuses, but rarely as constrained devices. When the IoT devices became wireless, they also became constrained, since they where limited on processing power, energy and communication. And the wireless IoT devices also became sensors in large systems, where the sensor data was used in the cloud or at nodes to compute, and to make sense from that data. Both respondents express that they are convinced that is changing now, and that machine learning is moving to the edge devices, that more and more will be inferenced where the data is captured.

> *Respondent A: «I believe there will be very much that will get pushed all the way to the end device, and by that much of the architecture elements you mentioned will become irrelevant. In general, it is always better to process data local, as long as it is feasible, since it will preserve battery, reduce communication cost, reduce latency, and not be affected by network availability. And, we add more processing at the endpoint, it gets cheaper, the battery technologies gets denser and denser at lower cost, the microcontrollers can do more compute per watt, and the various algorithms such as Machine Learning gets available for such controllers. And we see more and more dedicated AI and ML sensors available, which is meant for low power smart endpoints, so that is obvious for me.»*

> *Respondent B: «Inferencing directly on the data will be a big reduction in power consumption, so now we don't have to move the data somewhere else to be classified on. Bio-sensing, so determining human or animal body functions, based on things like skin temperature, heart rate or heart rate variability, EEG even which is brain signals. Things like sickness that you can detect, or recovering and wellness in sport, that's a huge area. Then the third area that's really interesting is human gestures, so both hand gestures where you can use accelerometers, radars, or cameras, or you can use human speech or animal sounds audio as a sensor, either for gesture commands or for other types of interaction with the wearables is a big area. All of this is possible without sending a single data packet to the network.»*

The respondents seem to be of the same understanding, that the trend for IoT topology is changing. From collecting large amount of sensor data towards the cloud for machine learning and inferencing, to moving machine learning to where the raw sensor data is captured and inference on it there. This way the IoT architectures shifts.

> *Respondent A: Until now, the main reason for transmitting the raw data has been access to computing power, but that is in the change.»*

During the interviews there was also debate about the various communications standards, that there are short range standards using Zigbee or BLE, and that there are long range narrowband standards such as NB-IoT, LTM, LoRa or SigFox. The respondents seem to be convinced that avoiding radio transmissions in general by doing local compute instead saves energy the most. But in some cases data such as events, logs, abnormalities or alarms must be sent. It depends on availability. If short range transmission via an edge gateway or mobile is possible, then that is quicker and requires less energy, if not fall back to long range narrowband, or store the information and send later, if it can wait.

> *Respondent A: «If you really need low power, then it is no chance to wake up a long range modem to send data at for instance 200mW transmit, that will not give you low power applications. It will get even more efficient to process this locally where the data is captured, since processing gets more and more power efficient for processing, but for radio, it will not be so easy to reduce the power usage to much. It is much easier to cut power on the compute side, than the communication side. In terms of short range, it is very relevant to think of the mobile phone as an Edge Device which can assist in Edge Computing, before it sends the result back to the device, or sending it on to the cloud.»*

4.1.3.6.New Values from true wearable IoT sensors

Making the wearable IoT sensors smarter, and shifting the way it operates compared to earlier when all data was sent to the cloud for computing, fixes some pain points, solves some jobs and adds some new gain points. The respondents mentioned the importance of the wearable IoT sensor's price and size, the importance of low operational cost for infrastructure and data plan, as well as one of the key drivers to remove the battery is to be environment friendly. Both respondents made comments about new values for wearable sensor vendors, service operators, and the users. Here are some comments:

> *Respondent A: «machine learning in the sensor will be the lowest cost for communication, longest battery life, maybe even battery-less, with advantage for the environment and the user which does not have to charge, and making the device realtime. But of course, it needs to be defended in business models. Most companies cannot do it just for the sake of environment alone, it must be profitable also, but more focus on the environmental effect when becoming battery-less, will enlighten the consumers, and create market potential.*
>
> *Reducing energy usage and not having battery in the product, can also reduce size and weight of the product. Less charging and administration of that, this can be a real issue. The cost of data communication and cloud computing typically consist of monthly subscription per the user and data plan if using long range, or investments and maintenance in the network topology if using short range, but also for using the cloud service such as AWS. In terms of the telco and data plans, they are very limited, and it does not take much usage before the limits has been reached, and it will become expensive, or the service will get limited by the data plan.*
>
> *Examples of new value and applications, today, dogs are trained typically using clickers, this is well known to work if the dog is trained for it. In a scenario having a dog tracker, and the dog run away, we can use a geofence to detect it, and the tracker can use machine learning detect that the dog is running, then the tracker can automatically call the dog back using a clicking sounds. And of course award the dog automatically for coming back using a snack dispenser.*
>
> *Respondent B: «The value of machine learning in the sensor can be a new level. For instance a fitness tracker, where you might have an accelerometer, skin temperature and combinations of LEDs looking at blood flow, so basically looking at heart rate and heart rate variability. Those combinations of sensors are used to derive lots of stuff. In extreme low-power case running some*

machine learning algorithms as well, off a battery, that fits in the ring. This is a real product today, the Oura ring, which can be active for 6-8 days without charging.

Machine learning in the sensor will make the wearable sensor agnostic to network conditions, for doing the inferencing part. It will of course have to handle to temporarily store events and detected patterns, and share that with the service once the network is available, and there might be situations which needs to be handled, or to notify for, regards responsiveness, but that will depend on the application.

Regards personalisation, machine learning can learn to recognise one specific object, let's use the example of your dog, it is gonna detect how your dog barks. So, let's say you want to detect when your dogs is barking, but your dog might bark different from the general machine learning model. Then we can train better barking recognition. So think of it as the better algorithm that personalised to your dog. That's a next level of things, personalisation.

But then there might be new behaviours, which the sensor haven't seen before, especially in professional application, maybe less so in consumer. In professional applications we see the need to open up the data and machine learning development for the end user, somebody that is solving a very specific problem, so in your case it might be your dog, as a very particular behaviour you're trying to get rid of, or maybe a better example might be in elderly care. We had for example a big health provider come to us with the challenge: "we want to know how elderly people are recovering from this very specific type of surgery", and "why did they have balance problems or not", and so they wanted to collect their own dataset using the wearable, they wanted to develop their own ML algorithms, they wanted to deploy these ML algorithms to the wearables. This shows the endless possibilities as wearables consume less energy, compute more, algorithms gets more efficient, and sensors cooperate even more.

Another thing to mention, is privacy. There are of course issues with misuse, that must be prevented. That's why we have our Responsible AI License. AI and machine learning sound scary, but is not very different from other technology, which also can be misused. If considering the positive side, machine learning can be used to improve privacy, that's a point. Since inferencing happens directly on the raw data in the sensor, it does not have to be sent off to the network, so there are no disclosure of personalised data. Security and ethics are still very important, but local machine learning increased privacy by reducing personalised data from being sent to unknown recipients.»

4.1.3.7.Application and design specific considerations

Wearable IoT sensor services have been using general devices such as iWatch, fitness trackers and smartphone apps so far. Some has been made purpose built already, and many more are underway. The respondents uses examples of general wearable which comes to short, but also gives examples of devices which are becoming true wearable IoT sensors, such as Oura, Whoop, SlateSafety, and others. They shared some considerations to optimise for maximum battery lifetime, smaller size or less network and infrastructure dependency, while still conducting the tasks of the service. Mainly respondent A which discusses the importance to consider things like frequency of scanning, precision with measurements and positioning, accuracy and how the wearable devices works together with the service in terms of communication, configuration and training.

> *Respondent A: «The key for the wearable sensor is to optimise it for smallest size and cost, while still achieving the key objectives for the sensor. To do that, the application and the sensor together needs to be optimised for optimal performance. Optimal does not necessarily mean best performance. For instance, accuracy comes at a cost (or energy). So then it is about finding the optimal combination between good enough i.e. positioning and acceptable use of energy. And then you have to choose what accuracy you need. Do you need 1 meter, 5 meters or 25 meters, that also affects the energy usage. And of course how often the position shall be fixed, once a day, once an hour, or once per minute, or continuously. Optimal also means to find out what you can sacrifice, or wait extra for, in order for letting your system go to deep sleep. Then machine earning in sensors can be used for waking up the main system, and then toggling the application between sleep and active, in the quickest way be energy effective.*

4.1.3.8.More research needed

Machine Learning, or AI, is still very new at the edge. That seems to be clear from both respondents. They also seem determined that the trend is shifting from cloud computing to edge computing. To do necessary research on the wearable hardware, the algorithms, and the network infrastructure to support this, there are a lot research and investments that needs to be made. In the cloud computing paradigm, the machine learning models, both for training them, and for inferencing had lots of resources and power available, while in this new paradigm the sensors are constrained devices. Actually very constrained. In this topic, respondent B had more to share than respondent A. Maybe that actually is an indicator that machine learning still has a long way to go. In specifics, respondent B elaborated on the need for further research in optimising models, new algorithms, how to train them, getting training data and some ideas on how the user can assist training by verifying or dismissing the what the sensor suspect it is. Then there are needs for further work in ethics, privacy, security and building good attitudes in the industry, as well as the need for building trust with the user.

> *Respondent A: "In general, the energy usage gets better as geometry migrates down to smaller transistors, specially on active mode, but on idle and leakage currents it is somewhat more difficult to achieve the same gain with reducing geometry. But of course, it is not always that smaller is better for power usage, since there are technical effects to overcome, such as saturations for instance. This have to continue, to shrink, and optimise, we believe that.*
>
> *Another tricky part today, is to capture training data, since that too requires use of energy, but we believe even that gets easier. Next step at some point will be to train the algorithms individually.»*
>
> *Respondent B: «so the way I see this working is that, first we figure out how to use machine learning to solve a general algorithm, and then the next stage of sophistication, is when we start doing personalisation of the local ML models. Then we have to continue optimising the models.*

The inferencing need to go on fast, but the problem is that machine learning models are really large. We're having to a fit a lot of complex signal processing, the signal processing itself isn't really huge, but it just takes time to execute, so that's one thing. Sensors are simple, audio applications are more complex, and then computer vision are the most complex. If we want to do machine learning on a wearable, like facial recognition, or environmental recognition, that is really complex, so the models get really large.

Then it is about the training data that we need, is long. We need hours of that data, or even tens of hours of that data, with very good labels, what's happening, and exactly when, and thats what allows us to then create an algorithm that works on a single window, or just a group of windows, is because we have a lot of very good training data. We need more research on how to collect it, label it, since this also requires energy and effort.

One way can be to involve the user, or the owner of the dog by asking, "We noticed your dog doing this...", show that on the phone display, and then ask a question to the user if that is correct. Maybe the app on the phone can use the video camera on the phone to capture events, which can be timestamped and used for tagging. So, you start to collect additional, and more specific examples, about your dog, and that's how personalisation works. And then there is a bunch of different machine learning techniques we can use to layer those datasets together, or improve and retrain the machine learning algorithms to do that.

Or in the case on anomaly detection to detect that something is different from what we already know, and just ask the owner: "hey, we just detected that your dog did something new, at this time, could you tell us what that was?" Then the sensor will, together with the user, start to learn new behaviour, which we want to tag, and then we can put that back into our dataset.

Then there is another part of this fantastic technology. It could be misused, absolutely, yes, it has gotten to that point. It's nothing about AI, it's just machine learning as a very specific algorithm. I can be used for ethnic detection, you could use it for illegal surveillance, you could use it for weapons even. There must be an ethics framework, if you're working with AI in general. And we do, as a company, we have a tech-for-good cultural value. And we use a responsible AI licence, an illegal licence in our terms of service, to make sure our users are not applying this technology wrong. This is where some of the ethical responsible AI licences come in, they disallow the use of the technology to do those types of things. You're not allowed to do surveillance, you can't do ethnic profiling, you're not allowed to do anything that would break consumer privacy.

But AI and machine learning can also be used to make an improvement in, for example privacy, thats a choice on how it's used. Since you don't have to move the raw data anywhere, privacy can be improved, and this can be a big thing for user in order to trust that privacy is not tempered.

There are a second side to trust, which is trust in technology and if it works, especially with machine learning. Where trust is a bigger problem, is in industrial applications, it is less so in consumer applications. The difficult trust questions, it is usually around life and death, in health, safety and welfare, and those tend to be regulated, or should be regulated. I'm a big proponent of a definite regulation! Machine learning might have a role there, but should be regulated.

> *And autonomy, we need to be careful with that, with good guidelines, and guardrails, when you are not in control, yeah because, remember that machine learning in particular, is probabilistic in nature, so you may have probabilities of things happening that you have never seen before. We need to make sure there are some rule-based guardrails around the probabilistic algorithms.*

4.2. Literature studies from the community

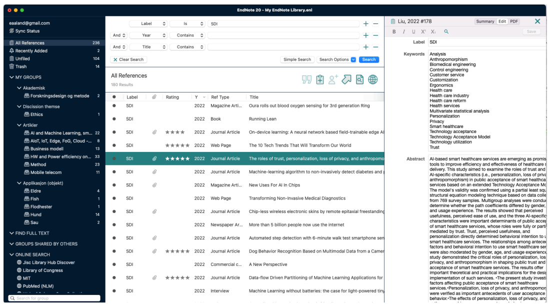


Figure 20: Endnote library of relevant literature

This research have studied 239 literatures, such as thesis, articles, journals, news letters, press releases industry reports and similar, selected based on keyword searches on Oria, Google Scholar or Google web search, or found by looking through bibliographies of related research. Out of the 239 literatures organised in Endnote 2.0 (fig.20), 176 of them was used and referenced in this research, where 114 of them are released after 2020. The selected literature relates to the simplified models, in order to deepen my knowledge and understand how technologies related to wearable IoT sensors are, how IoT network architecture and topologies are, and seek trends in business model innovation based on AI and ML.

4.2.1. Processor Units for wearables

A comprehensive review published in Science (Leiserson et al., 2020), study computing from the bottom till the top, from hardware to software and algorithms. The study claims that semiconductor miniaturisation is running out of steam, and Moores Law is coming to an end, for several reasons, and that both Intel, Samsung and Apple failed to keep up with the predicted pace for shrinking the geometry. But instead of getting the new leaps in performance from the hardware running at the bottom, a new era is underway, where the advancement in performance lies in the algorithms running at the top. In other words, instead of shrinking transistors, the hardware architectures gets optimised for executing algorithms much more efficiently, for instance for neural networks, meaning special processors and controllers which are highly optimised for executing algorithms for machine learning and deep learning, at very low power. Their research shows a development in the trajectory of relative performance for algorithms as well processor clock rate over the last 30 years, and illustrates CPUs going from single core to multicore, in order to keep up the pace, but it also shows that the development of algorithms continues to add new leaps in performance.

Another research (Sun et al., 2019) confirms that both Moore's Law, which predicts the transistor count per die area, and the Dennard Scaling Law, which states that the power usage is proportional with the die area, are struggling to keep its trajectory. A research (Yoo, 2020) about purpose built processors for running deep learning algorithms, also referred to as DNN accelerators, enables faster deep learning neural networks at a lower power, which enables numerous of applications in sensors and mobile devices. This research also compares the processing architectures of CPU, GPU and NPU, and shows difference in programmability, efficiency, flexibility and power usage. Their research also look at training of such DNN accelerators. Other research on trends in processor architecture (González, 2019) also points to a slow down in the geometry development to gain more computing power at lower energy and cost. The laws of Moore and Dennard are not keeping the pace anymore. The research covers single core and multicore, how memory is designed, and concludes with next leap in computing performance at low power will be specialised processing cores, optimised for executing algorithms and neural networks on top.

A group of researchers (Berggren et al., 2020) published a roadmap for emerging hardware and technology for machine learning, where they claim that recent progress in artificial intelligence is largely attributed to the rapid development of machine learning, especially in the algorithm and neural network models. They also claimed that performance of the hardware, in particular the energy efficiency of a computing system, sets the fundamental limit of the capability of machine learning. The aim of their roadmap was to present a snapshot of the emerging hardware technologies that potentially would be beneficial for machine learning. They focused their attention to faster and more efficient non-volatile memory architectures for neural networks, energy conservation and power management, and in the long term challenges with in-situ training of the machine learning models.

Recently, several ultra-low power microcontroller have been launched in the market. One of them (Perceive, 2020) claim that their Ergo AI processor runs datacenter-class neural networks within even the most power-constrained environments. The Ergo is optimised to run machine learning and deep learning, even with the necessary memory integrated for best performance at lowest power. According to Perceive they can inference on 30 fps video feeds at as little as 20mW of compute power, or much lower when inferencing sensor data.

Another study (Chéour et al., 2020) of microcontrollers reviews architectures employed in the context of wireless sensor networks and IoT, and outlines many of the low-power techniques allowing a wide range of applications. They have studied techniques such as variable CPU speed, power mode variation, batched execution, computation level and types of hardware solutions. The paper showed an overview approx 20 microcontrollers being used in IoT applications, where most of them operated below 30mW, and some below 1mW. How they operate and the low numbers they achieve is of course depending on the application they are in, the networks conditions they are under, and how it is configured to run.

Another way to achieve higher processing power, at a lower use of energy, is to make custom hardware architectures, specifically for particular applications, and avoid the loss caused by general purpose processors, (CPU) or even application purpose controllers (GPU and NPU). The Swiss research lab CSEM (CSEM, 2021) have developed an integrated circuit that can carry out complicated artificial-intelligence operations like face, voice and gesture recognition and cardiac monitoring. The CSEM system-on-chip works through an entirely new signal processing architecture that minimises the amount of power needed. It consists of an ASIC chip with a RISC-V processor (also developed at CSEM) and two tightly coupled machine-learning accelerators: one for face detection, for example, and one for classification. The first is a binary decision tree (BDT) engine that can perform simple tasks but cannot carry out recognition operations.

Arm, the market leading processors architecture with more than 100 billion chips sold, recently released their new architecture core ArmV9 (ARM, 2021). This new architecture will provide specialised controller types for a variety of applications, one of those for edge IoT devices. When Arm launched the «Total Solutions for IoT» late 2021 (ARM, 2022), they started offering to the market highly optimised controllers for processing at the edge, with cores for security, neural networks and machine learning execution. They claim this to be a radical shift in the design approach for the IoT and embedded markets, combining hardware IP, platform software, machine learning (ML) models, tools and much more to simplify development and accelerate product design. At the heart of Total Solutions is Arm Corstone (TM), a pre-integrated, pre-verified IP subsystem that frees silicon designers to focus their time and efforts on differentiation.

A research study (Covi et al., 2021) of adaptive extreme edge computing for wearable devices focuses on neuromorphic chips, either with fully digital or analog/digital mixed signal. Common is that these processors are optimised for synaptic computing such as neural networks, at low energy consumption. The study mentioned several neuromorphic processors being used in edge devices, but for wearable sensors only suggestions on future solutions. Then the study discussed memristive devices and computing, which means devices that can remember its resistive state, in other word learn. The study seems to represent the forefront in processing for artificial intelligence and learning for edge devices and soon wearable devices. The study concluded with continual learning would be required for adaptable wearable devices.

Recently, one of the worldwide leaders in edge AI on-chip processing and learning (Brainchip, 2022) introduced the company's first-to-market neuromorphic processor, Akida (TM), mimics the human brain to analyse only essential sensor inputs at the point of acquisition, processing data with unparalleled efficiency, precision, and economy of energy. Keeping machine learning local to the chip, independent of the cloud, also dramatically reduces latency while improving privacy and data security. According to the company, Akida can perform on-chip learning by leveraging the trained model as a feature extractor and adding new classes to the final layer, directly in the field. Brainchip achieves such one-shot learning at the edge, by training their spiking networks to update the deep learning model in the spiking domain. Brainchip Akida is already being used in the Mercedes EQXX concept car. According to Mercedes, the BrainChip solution was 5 to 10 times more efficient compared to other conventional processors (Ward-Foxton, 2022a).

Untether recently unveiled its 2nd gen architecture for AI inference, an architecture for addressing very large neural networks, including transformer networks in natural language processing and beyond, endpoint applications that require power efficiency, and applications that require performance and power efficiency combined with prediction accuracy. According to EE Times (Ward-Foxton, 2022b), the first chip, SpeedAI, targets datacenter inferencing accelerators capable of 2 PFLOPS of FP8 performance (floating point) running at peak power consumption at 66W. This is not relevant for edge computing, but this high performing power efficient AI architecture, is planned with a version at 25W for infrastructure, 5W for autonomous vehicles, and sub 1W for battery operated devices, in particular wearables for law enforcement and military body cameras.

A recent study of the semiconductor market for AI Chips (Koon & ESperling, 2022) describes a large change from cloud computing, where up until now massive machine learning and deep learning models inferenced raw data centrally in large data centres, but now AI is getting deployed across many new applications. The rationale for this is many, such as issues with network latency, network availability or privacy concerns. At the same time this change fosters new issues such as handling power and performance in wireless and constrained devices. According to the study there are many questions to be raised, such as what algorithms to use, what is the power budget, what accuracy is needed and so on.

But at the other side, if you know what you want to achieve, and select the right AI processors, right kind of memory, energy solution and security, the advantages and gains can be high.

We are at a tipping point, where architectures for edge AI are starting to emerge, hardware is getting the right amount of performance at a low power level, to move the inferencing to the edge. According to the study, Precedence Research estimate the AI market to grow from $87 billion in 2021 to $1,6 trillion in 2030. AI has become such a hot topic these day, that every major tech company is making AI chips. This market barely existed five years ago. Traditionally AI has been for the cloud with big models, but now AI is turning small, towards the edge, with optimised and specific processors doing advanced inferencing in the mW range, or even in the uW, it only depends on the application requirement. The market for edge AI will from $7 billion in 2020 to $39 billion in 2030.

4.2.2. Machine Learning and Deep Learning

Moving machine learning to the edge device is also suggested by a group of researchers (Warden et al., 2022), where they claim that machine learning sensors is the start of a paradigm shift. They propose a more data-centric paradigm for embedding sensor intelligence on the edge devices to combat issues such as privacy and security, as a consequence of moving data into the cloud for processing at a central point. In their vision of «sensor 2.0» they entails segregating the input data and inferencing from the wider system at the hardware edge and only provide a thin interface to share the outcome such as events, patterns or abnormalities. Furthermore, they explain various issues with using the "Sensor 1.0» paradigm, such as a domain skew between training data and sensor data, which can either come from difference in sensors and how they are used, or that there are difference between the objects the sensors sits on. The result can be reduced accuracy, while the machine learning models gets bigger. Their definition of the «Sensor 2.0» is *"An ML sensor is a self-contained system that utilises on-device machine learning to extract useful information by observing some complex set of phenomena in the physical world and reports it through a simple interface to a wider system."*

4.2.2.1. Inferencing

According to an article published by ZD Net (Anadiotis, 2021), the TinyML movement, which deploys machine learning directly in the wearable sensor, is getting big. Originally, machine learning was not developed for being deployed at the edge, the primary purpose was in the centre of the network, which was developed to compute for a very big number of sensors, using machine learning models trained on large datasets, with powerful processors. But, as this article argues, 95% of the data could be handled at the edge with simplified models, while 4% could be treated by an edge gateway, and the last 1% could be handled in the cloud. Tiny machine learning (TinyML) is broadly defined as a fast growing field of machine learning technologies and applications including hardware, algorithms and software capable of performing on-device sensor data analytics at extremely low power, typically in the mW range and below, and hence enabling a variety of always-on use-cases and targeting battery operated devices.

Standard microprocessors like CPU's consume between 65 and 85 watts, or GPU's can consume anywhere between 200 and 500 watts. They are made general purpose computing, or number crunching. On the other side typical microcontrollers consumes power in the order of milliwatts or microwatts. That is thousands of times less power consumption. And the microcontrollers come for different application, some is built for wireless applications, some for sensors, and others for audio or video. And they are built with different cores and architectures, in order to suit the target applications as best as possible. These days architectures are being optimised for running machine learning and deep learning. TinyML devices can run unplugged on battery for weeks, months and even years, while running machine learning applications at the edge. According to an article (Arun, 2020), the advantages by using TinyML at the edge is low latency, low power consumption, low bandwidth and privacy, all because raw data does not have to be sent to the network. Typical applications for TinyML is predicative maintenance, healthcare, agriculture and ocean life conservation.

Avoiding the paradigm of a centralised large machine learning model, which involves massive transmission of raw sensor data from the edge where most of it is captured, training of very large models, with all the issues involved, has also motivated the Amazon Alexa team to develop small and decentralised models. Initially the architecture assumed that there was access to the cloud, where the machine learning models that powers Alexa (one of the largest and most comprehensive machine-learning model today, with millions of features) resides. But from now on, and into the future, smaller devices without access to the network needs some of the core functions. By adding some techniques such as «perfect hashing», the Alexa Auto team has managed to reduce the memory footprint of their machine learning models by 94%. In simplified terms, the technique reduces options with the result of simplifying the model and a drastic reduction in the memory footprint (Grant P. Strimel et al., 2018).

In an increasing world population along with increasing average life expectancy (WHO, 2022), healthcare systems are going through a transformation where heart monitoring of people is possible without hospitalisation. E-health is still very new, and IoT architectures being used is mostly using traditional topology with star or clustering, where sensor data gets collected by sensors, and inferenced centrally as proposed for smart healthcare system (Uddin, 2019). The sensors will collect large amounts of data to detect movements and body signals, and transmit to a computational point for inferencing and detection of falls, heart attacks, Parkinson's, or illness. This solution will use GPUs at an edge device to inference the raw data from the sensors, and then notify caregivers once an event, abnormality or pattern is detected.

Falls are a frequent reason for deaths or post-traumatic complications with elderly. Therefore early detection of falls can be crucial for the survival of a person, or for providing necessary support. A project (Mrozek et al., 2020) which compare doing fall detection in two ways; the first in a IoT star topology, by sending raw data to the cloud for machine learning and inferencing, and the second by doing machine learning on the edge device, shows a 10-fold reduction of transmitted data, while achieving the same accuracy. The study used an iOS device, meaning the traffic to the cloud for sharing the results was broadband transmission (4G or WiFi). The study does not say, but if this had been a narrowband sensor, the amount of transmitted data would likely have been decades less. The study claims that machine learning on the sensor will significantly reduce the frequency of data transfers, the amount of data to transfer, and the storage needed centrally. The study does <u>not</u> cover all the other advantages such as latency, network dependency, battery usage and privacy issues.

AI and deep learning was used in another research (Juneau et al., 2022) where the developed algorithms detected and classified steps to analyse the risk for fall. Early identification and intervention for those at elevated risk are critical to prevent falls and prolong well-being. This approach correctly classified over 80% of non-fall risk respondents, though the approach did misclassify more than a manual approach would do, so further work is necessary. The algorithm was running on a smartphone, but could be moved to a wearable sensors when optimised.

Another example of machine learning sensors (Kulkarni et al., 2022) used ECG signal data to accurately detect and predict diabetes type 2, and pre-diabetes, only using non-invasive wearable sensors. The global epidemic of diabetes continues to burger according to the study. Estimate suggests that the world-wide prevalence of diabetes in adults was nearly 10% in 2019, meaning more than 450 million people. The study evaluated accuracy using different techniques with machine learning and deep learning, and demonstrated the potential and shows high accuracy in both the validation set as well as the independent test set. But the study also concluded with limitations since the respondents enrolled in the project already was high-risk individuals, and therefore cannot be considered reflective of a general population prevalence, so further and wider testing will be necessary. But the project can already have high potential in high-risk populations, and since it is non-invasive and a very simple and low cost way of screening population, it can already be interesting for large scale screening.

According to researcher Rosalind Picard (Picard, 2019), every year 50.000 otherwise healthy people with epilepsy suddenly die, a condition known as SUDEP. These deaths may be largely preventable, just by detecting the epileptic seizure as they occur and alerting a caregiver in time to help. Their research in sensing body response from emotional conditions, by a coincidence came across epileptic seizures, from where they developed sensors using machine learning to detect when such seizures occurred. Their research was commercialised into healthcare products (Empatica, 2022), which is the first products to be CE certified and FDA cleared in neurology.

The COVID-19 pandemic has sparked much research and innovation . One such study (Risch et al., 2022) has developed a machine learning algorithm, running on a commercially available CE and FDA approved wearable sensor bracelet, for pre-symptomatic detection of changes in physiological parameters related to COVID-19. The wearable sensor proved to identify 68% of COVID-19 positive respondents up to two days before they showed their first symptoms of infection, at first prototype test. This research will continue to train and tune the machine learning model in the lab.

Smart medical devices and IoT, smart sensors and wearables are already creating a platform enabling remote monitoring and supporting medical conditions of patients in and out of clinics, according to the book «Healthcare Data Analytics and Management» (Dutta Pramanik et al., 2018). The first chapter give a wide overview of IoT in healthcare, smart sensors, pervasive systems and applications of use. The chapter describes healthcare sensors for monitoring blood pressure, body temperature, ECG, EEG, movements, pulse, heart rate, cardiac rhythm, and pill camera (for swallowing), which all communicates over wireless short range. Then there are description of medical care units such as room monitoring, barometric pressure, light and motion and activity tracking. Fitness trackers are describes with wristbands, eye gear, smart shoes, smart bra, smart clothing which can monitor more physical signals. Emotions can be monitored by combining biometrics and motion. The chapter describes advantages and issues of IoT as experienced in 2018, and describes the future of IoT in healthcare with a range of high-tech innovations in wearable and implantable devices. Next generation healthcare will have focal point in quality of patient care, and there will be a high degree of automation and enhanced decision making with IoT healthcare. According to the chapter, pervasive healthcare was relatively new, in other words sensors that could compute and analyse themselves, and they viewed the infrastructure as immature. Security and privacy was a concern then too.

Machine learning and deep learning is also used in sensors for animals, fish and birds. A project studying detection of lameness in sheep (Jamie Barwick, 2018) concluded that an ear tag would detect lameness from different types of walks and gaits. This is a big matter, since manually detecting lameness in sheep by observation at an individual level is very difficult and time consuming. Lame locomotion is one of the most common and persistent health problem for sheep flocks, and has resulted in economic and welfare concerns, since the condition is known to be painful and leads to altered activity, mobility and appetite, and can lead to more severe conditions and infections such as footnote and contagious ovine digital dermatitis (CODD).

Dogs are one of the most popular pets around the world, and dog owners are worried about the animals health condition. A research project (Boteju et al., 2020) used deep learning to detect behavioural conditions such as walking, running, resting, and barking, where the intention is to detect unusual patterns within the dogs ordinary behaviour, and from there diagnose the abnormal condition. Another research (Griffies et al., 2018) used machine learning to detect dogs scratching and head shaking, in order to discover ear infections to be treated. A third research (Wernimont et al., 2018) used wearable sensors and machine in clinical treatment by veterinarians to monitor the effect of treatment by feeding. The dogs where monitored on scratching, head shaking and sleep quality, to discover skin conditions.

Wearable sensors have also been attached to dogs to detect activity, behaviour and emotions. A research study (Aich et al., 2019) based on motion from two sensors on dogs, one as a collar and the other one attached to the tail of the dog, detected six types of activity, and tree types of emotions. Activity was generalised to walk, sit, stay, sideways, eat, jump and nose work, while emotions was generalised into positive, neutral and negative. The study showed good ability to detect emotions, and evaluated 5 different algorithms to do so. The study also pointed out that detection of emotion would likely be improved by adding biometric data such as skin response, respiration and heart rate.

4.2.2.2.Learning

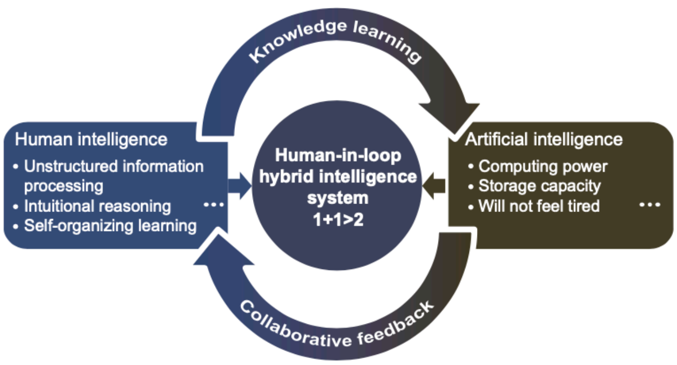
One huge factor of COVID-19 was to detect infected in order to isolate and quarantine, as a mitigation of the pandemic, while waiting for the vaccines. Many of those who got ill from the decease, also got long term effects, such as low energy, sleepiness, exhaustion and was in need of rehabilitation. Rehab mostly had to happen at home in unsupervised environment. In relation to this, researchers (Vourganas et al., 2021) have developed a machine learning model with artificial ambient intelligence with individualisation to support engagement and motivation, two important factors for counteracting the longterm effects of infection. Their research presented a patient-centric individualisation, for adapting the sensor and train the model to the patient it was matched to. As part of this, ethical efforts was made to comply with accountability, responsibility and transparency. They presented a hybrid learning approach for patient-centric individualised home-based rehabilitation support considering unbiased, explainable and interpretable AI. The individualisation approach follows constant re-training of the hybrid model. The re-training element incrementally improves the overall model accuracy, which means that the user continues rehabilitation at home, the device better adapts to the user's specific difficulties area and conditions.

In the non-human world, wearable IoT sensors are found with many species, both for wildlife preservation, agriculture, farming, and pets. Sensors are getting better, smaller, more feature rich, but there are also challenges. For instance with wild species, collecting enough data for training models might be problematic. One technique can be to train on one species and transfer to another, like between dogs and wolfs. A research project (Bence Ferdinandy, 2020) did exactly that, and found it feasible to train and test across species, using data from dogs to train the classifier on 8 behaviours such as lay, sit, stand, walk, trot, run, eat and drink.

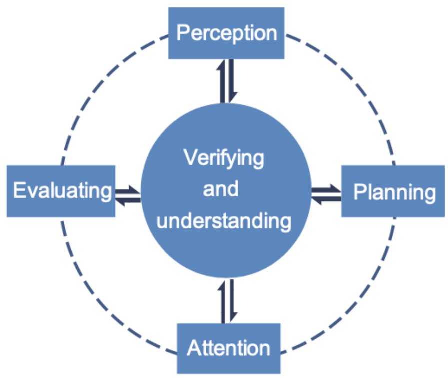
Another comprehensive study of training the machine learning model explains Federated Learning in wearable devices, where they use their local sensed data to train a machine learning model, before updating the server with changes to the model rather than sending raw sensor data. This way all wearable device can train their own separate models, while common base model gets built on the server, which all wearable devices can use as a starting point, before personalising (Lim et al., 2020).

Today, most edge AI models are trained in the cloud, or ex situ, making use of available computing power on high performance processors, and are generally viewed as an edge-cloud cooperative system, mainly because the edge sensors and devices so far have been constrained devices. Classical edge applications usually undertake a responsibility for sensing and sending raw data to the cloud. This is now changing according to a research project (Matsutani et al., 2022). IoT applications are divided into 6 levels, where Level 1 means «cloud-edge cooperation, cloud inference and cloud training», and Level 6 means «all on device». A typical «prediction only» edge AI system is corresponding to Level 3. As the levels goes up, the data transmission latency from the edge device decreases, the data privacy increases, and the network bandwidth decreases, while the computation cost at the edge device goes up. The research project aims at trining the machine learning model on the device at Level 6, or in-situ. The experimental results demonstrate that retraining by the on-device learning significantly improves the accuracy by personalising or adapting the sensor to its environment, while saving the computation and communication costs to become lower power. The project measured increased energy usage at around 110mW for on-device training, while at the same time reducing energy usage for radio transmissions by 170mW, in total reducing the sensor energy usage, by shifting from radio transmission to local retraining and inferencing.

In 2017, a group of researchers (Zheng et al., 2017) proposed a framework for training and learning from cognitive objects via hybrid-augmented intelligence, which can be divided into two basic models (fig.21 and fig.22); The first one is a cooperative model between human and machine called Human-in-the-loop (HITL), and the second is using cognitive computing (CC) in order to achieve an artificial intuition in the machine learning model. The general principles behind this hybrid model is that human and machine can complement each other in the process of learning and executing intelligence. Humans are great in creativity, while machines are great at following rules. Therefore humans learn faster, while machine are more accurate. Humans are great at reasoning in complex information, while machines are great in repeating and does not get tired. Humans are very dynamic, while machines are very logical. The idea behind HITL is to use humans in the process of training the models as decision support, to confirm, or to discriminate machine learning. In this way, it might be possible to personalise models to a specific purpose.



Figur 21: Human-in-the-loop (HITL)



Figur 22: Cognitive computing (CC)

Research in computing architectures and processes has shown advancements in neuromorphology, and architecture which can be constructed to emulate the biological brain in structure and processing. A CC framework will require the machine to mimic the human brain in verifying, understanding, perception, planning, attention and evaluation, in order to best, including to find out what has to happen next, did it produce the right results, or do we need to try again? Such intuition can be divided into selective encoding, selective combining and selective comparison. Selective encoding is about filtering out irrelevant information, selective combining is the actual reason making, while the selective comparing is evaluation of the newly achievement is better than previous results. The machine intuition is needed to mimic human assumption-making, and evaluation of the assumptions.

4.2.3. Sensors

Sensors in wearable devices are designed to collect information in the real world and convert them into electric and digital signals, which can be used for further extraction of information about status or trend, based on single sensor or multiple sensors in more advanced systems. Sensors are implemented in different way in order to capture body signals and biometrics, movements, orientation and position, or other measurable factors such as temperature, colour or frequencies. Some sensors might use energy to sense, while others works on resistance or conductivity. A research review (Covi et al., 2021) discusses wearable sensors currently using machine learning, and provides a comprehensive overview of biometric signals to sense such as electrocardiography (ECG), electroencephalography (EEG), electrooculography (EOG), electromyography (EMG), photoplethysmography (PPG) and bioimpedance spectroscopy (BIS). The study also discusses multi sensory in wearable sensory, as well as challenges towards smart wearable sensors with edge computing, which resides within wearable sensors being constrained devices with limited computing power, size, energy and communication is mentioned.

Sensors come in many shapes using many techniques. A research study (Kim et al., 2022) demonstrates a new chip-less wireless electronic skin (e-skin) by remote epitaxial freestanding compound semiconductors. The surface acoustic wave-based e-skin offers sensitive and energy effective sensing of strain, ultraviolet light and ion concentrations in sweat. The study demonstrated weeklong monitoring of pulse, using a small sticker with e-skin without the use of battery.

Wearable electrochemical biosensor for detecting compounds in human sweat is another type of wearable sensors being tested in the lab in a research project (M. Wang et al., 2022) currently. The sensor can detect common nutrients and biological compound in minutes, in a sticker size sensor. This allows for detecting nutrients and metabolites when we eat, and watch nutrient levels change. And similar for hormones and drugs. According to the research document the biosensor consists of graphene electrodes, that can be repeatedly regenerated in-situ (reconfigured), functionalised with antibody-like substance needed for sensing, as well as signal processing and calibration, and wireless communication. The biosensor can be used for diet, lifestyle and to monitor gut microbiota.

Another self-powered wearable device that records physiological bio-signals are being tested in this research project (Yi et al., 2022). The system contains power-efficient triboelectric nano generators (TENG), highly sensitive pressure sensors, and wireless near field power and communication, enabling radial artery pulse waveform monitoring without external power.

Fraunhofer researchers have with the Pneuma.Vest project (Schwarz, 2022) developed a technology whereby the noises in the lungs are recorded using a textile vest with integrated acoustic sensors. The signals are converted and displayed using software. This is a high-performance addition to the traditional stethoscope. Piezo-ceramic acoustic sensors have been incorporated to the front and the back of the vest to register any noice produced by the lungs in the thorax, and electronically amplified, while the lungs are visually depicted on a display. Additional to the acoustic sensors in the vest, machine learning are being developed to classify complex ambient noice from the thorax, to assist the pneumologist when diagnosing the patient.

A researcher in Nigeria (Africanews, 2022) has developed a smart bra that can detect early signs of breast cancer, which helps detect abnormalities very early and recommend a visit to the hospital to get a health check and diagnosis.

NBA basketball has adopted wearable sensors in sports clothing (Dowset, 2022), with an emphasis on preventing soft tissue injuries and the development of healthy habits in youth basketball. The wearable sensors are sewn into the fabric of the sports clothing, and can measure load and force, in order to help diagnose, recover and prevent injuries. The measurements can detect if athletes are fully recovered, and to find imbalance between each side of the body. It will detect specific forces on distinct foot areas, gait analysis, ankle angle and roll analysis, feet orientation and angle during jumps or walk and more. One of the wearable sewn-in sensors even measure electromyography (EMG) which is electrical signals from the muscles as they move.

Sensors are often measuring various types of energy, such as movements using accelerometers and gyros. In this case there will also be movements to produce kinetic energy. Or in a case of measuring temperature, there might be the right conditions to extract energy from temperature difference, or in the case of sensing light, there might be enough to extract light energy. Activity monitoring for fitness, will have kinetic energy to extract. In this research project (Zhang et al., 2020), a low-cost triboelectric intelligent sock was developed, which harvested waste energy from low-frequency body motions in order to transmit wireless sensory data. Additionally, the sock was used as wearable sensors to deliver information regarding identity, health status, and activity of the user. Lastly, an optimised deep learning model for the gait analysis was proposed. The final application will be a digital human system for sports monitoring, healthcare, identification and smart home applications.

Other sensors for use in wearable IoT sensors is gyros and accelerometers, temperature sensors for skin and ambient, positioning from simple to GNSS, light sensor, gas sensor, blood oxygen, pressure sensing with barometer or altimeter and more. Various sensors are combined to match the need from the object to be monitored, either it is a human, animal, bird or fish.

The sensors are also used to determine if a wearable device should be in sleep, in hibernate state or if it should be woken up to idle or running states. In the simplest way, sensor signals can be compared to reference values, for instance by using a comparator, or digitally loading the sensor with a wake pattern. The more advanced way is a two step approach, such as described in this research article (Yang et al., 2019), where a low power interpolation preprocessor situated in front of the main machine learning inferencing model is. The first step is for filtering out sensor input, in order to keep the main system in sleep and reduce energy consumption.

This two step approach is also used by Swiss researches (CSEM, 2021) when developing an energy efficient AI system-on-chip which runs on solar power. The system consists of a tiny camera for doing face and mask detection, an E-ink display, and powered by a solar cell or a tiny button battery. In this case the camera module is used as a sensor, to detect if a face is present in from of the camera. It uses two tightly coupled machine learning accelerators, the first one is used to simply detect a face, running in a low power mode, and if a face is detected, then the system wakes up to do the second step which is classification. A similar approach is used for voice detection, or in other application, just swap the camera to a microphone, or any other sensor.

4.2.4. Radio Standards and IoT architectures

One of the major issues with wearable sensors is communication of huge amounts of raw sensor data away from the wearable sensors, for many reasons such as privacy, reliability, battery capacity and latency. Because wearable sensors have been constrained devices so far, there hasn't been many other alternatives than to offload the raw sensor data to somewhere at the edge, in the fog or in the cloud to do the inferencing.

The wearable sensor needs to communicate with the service, either as a short range radio connection such as Bluetooth or ZigBee, or as long range communication over LPWAN, such as NB-IoT, LTM, LoRa or SigFox (Borralho et al., 2021, pp. 22-23). This research shows how energy usage goes up and performance gets degraded, when coverage diminishes.

A study (S.-Y. Wang et al., 2021) of the four most common LPWAN narrowband technologies of NB-IoT, LTM, LoRa and Sigfox shows how these technologies are very much better for applications which can accept low data rate communication, than the LTE 4G and 5G broadband standards, in terms of power consumption and cost of use. The study tested the communication in different scenarios such as moving cars at highways and flying drones, and found som packet loss and delay, but not unexpected. Packet loss happens, and since this is UDP packets, it can be fixed by retransmitting, if it is necessary. And LPWAN would probably only be used if short range communication is not possible using Zigbee, Z-wave or BLE. The study found that there was a higher risk of packet loss in the outskirts of the coverage area, in the radio shadow caused by landscape, in the interfering cell overlap, or in the interfering sector overlap areas. In these areas, the transmitter will automatically increase transmit power, and more retransmissions will occur. Another group of researchers also shows how battery gets drained much quicker in cases where that signal strength is poor (Ding et al., 2013).

An analysis (Braten et al., 2021) of current IoT architectures based on 32 relevant cases found that there where three types of IoT system topologies. In all cases but one, the IoT edge nodes sent data from the sensor to a point in the topology where raw data was stored and inferenced. These topologies where *clustered* and *star*. In only one case, the sensor inferenced directly on the data and only transmitted the result. This topology was the *fully distributed*.

4.2.5. Battery and Energy Harvesting

Development in battery technology has intensified over the last decade, for many reasons. The obvious is the environmental transition to clean energy, electric vehicles, and lots of appliances such as mobile phones, cameras and power tools. The most popular battery technology so far has been Lithium-ion (Li-ion), but research in this has declined the last 5 years, due to its low energy density. According to the battery technology roadmap from Applied Physics (Ma et al., 2021) there are increasing research on Lithium-sulfur type batteries (Li-S) due to its high energy density and low cost material. Their research report describes different battery technologies, their advantages and challenges, and where they are heading. Battery types such as Lithium-ion, Lithium-oxygen, Lithium-sulfur, solid state Lithium, Sodium-ion, Zinc-air, Aluminium-ion, Aluminium-air, Potassium-ion, Dual-ion, flow/aqueous/flexible-batteries, and bio-degradable batteries have been studied, and also put in perspective with superconductors and capacitors which is much faster to charge and discharge.

Another groups of researchers (Cao et al., 2020) have studied the theoretical electrical density in 1683 types of batteries, and found 51 of them to be interesting to study further. The selection was done based on criteria for energy density, cost and risk of hazard. Researchers are looking for energy storage for the extreme demand due to electric vehicles, green power, power tools, appliances and to find safer, cheaper, and more environmental friendly ways to make batteries when exploiting the raw materials needed. Therefore theoretical energy density was calculated. Lithium-ion batteries we currently use the most, typically have density of 250Wh/kg^{-1} and 550Wh/L^{-1} (energy density based on weight and volume), but this is unable to meet the high demand in electric vehicles and portable devices. The results of screening these batteries and calculating their theoretical energy density shows that Lithium-oxygen ranks highest with 5217Wh/kg^{-1}, Aluminum-air ranks second with 4311Wh/Kg^{-1}, and Magnesuium-air ranks third with 3924Wh/Kg^{-1}. It needs to be taken into account toxicity, corrosion, flammability, stability, environment and cost, so the practical energy density will be lower. Based on experience with existing batteries, the researchers conclude that it could be possible with a practical energy density at 1000Wh/Kg^{-1} and 800Wh/V^{-1} from the materials studied, which is 4 times denser per weight, and almost 2 times per volume, than what we currently have over the next 10 year period.

Batteries have the advantage of storing energy over a longer tine, and discharges slower than energy storing passives such as capacitors and conductors. Batteries are slow to charge, requires space and costs money, while energy harvesting doesn't have those issue.

According to an article in Embedded.com (Davies, 2021), energy harvesting can provide potentially inexhaustible electrical energy captured from the ambient environment, ideal for IoT sensors. Evolution of optimised radio protocols, ultra-low power microcontroller, low power sensors, and the increasing efficiency of energy harvesting, ambient energy has become a viable source to help reduce or eliminate reliance on batteries and extend the operating lifetime of IoT endpoints in the field.

According to a group of researchers (Shi et al., 2020) the progress of wearable electronics, the advancement of the next-generation wearable continues. Realising a long-term functionality is difficult to achieve using batteries as the power sources, the rapid innovation of energy harvesting and energy storage technology provides an alternative promising solution where available energy such as contact, vibration, heat, and light in the ambient surroundings can be effectively converted into useful electricity through piezoelectric, triboelectric, thermoelectric, pyroelectric, photovoltaic effect, and stored in integrated storage units for the continuous operation of wearable systems. But, even with the use of hybrid energy harvesting mechanisms, the actual average power from most current energy harvesters is still unsatisfactory to support the real-time operation. On the other side, with the prosperous development of AI, wearable electronics has facilitated the emergence of a brand-new research area, that is, intelligent and smart wearable systems, with broad applications in personalised healthcare monitoring and treatment, identity recognition, smart home/office/building, and intelligent interactions in VR and AR environment.

A comprehensive review (Akinaga, 2020) published in the Japanese Journal of Applied Physics describes energy harvesting technology as "enabling technology" that expands the use and opportunities of IoT utilisation, enriches lives and enhances social resilience. This technology harvests energy that dissipates around us, in the form of electromagnetic waves, heat, and vibration, and converts it into easy-to-use electric energy. The review concludes with energy harvesting will power ultraslow power wearable devices, as they get smarter and more efficient with the introduction of AI.

A group of researchers have made a detailed study of piezoelectric materials and energy harvesting (Mahapatra et al., 2021) and refer to such materials as “smart” materials because they can transduce mechanical pressure acting on them to electrical signals and vice versa. They are extensively utilised in harvesting mechanical energy from vibrations, human motion, mechanical loads, etc., and converting them into electrical energy for low power devices. Piezoelectric transduction offers high scalability, simple device designs, and high-power densities compared to electro-magnetic/static and triboelectric transducers. The detailed research concludes with a very bright future for energy harvesting in wearable devices for smart homes, smart cities, smart factories, health and environmental monitoring, and intelligent transportation. According to the research critical issue which needs more research is effective power management since the output power is dependent on multiple internal and external factors that causes high variations in power output. Another research (Chen et al., 2021) also explain self-powered systems based on energy harvesting from mechanical energy, thermal energy, solar energy, triboelectricity, piezoelectricity and electromagnetic power. This research also describes biofuel cells which uses enzymes or microbes as catalysts to convert chemical energy into electrical energy.

A key factor in creating a power source for wearable sensors is how the energy is harvested and how well it fits the application, how many sources it is harvested from, how the power is managed, how it is stored, and how it gets used to power the wearable sensor. The advantages of achieving battery-less wearable IoT sensors are many. A comprehensive review (Estrada-López et al., 2018) gives an overview of different ultra-low power management units (PMU) when harvesting energy from multiple sources. By characterising the power consumption of the sensor hardware in quiescent and active (peak and total energy consumption), duty cycling of the application can be planned, and from this a power system with one or more harvesters can be set up. The research describes simple methods for multi source energy harvesting, either by complementary sources, power O-ring, or voltage level detection. Next it describes architectures for multi source energy combining, either by energy combining through linear regulators, multiple-input boost converters, shared-inductor DC-DC converters, or fully integrated switched-capacitor converters for concurrent energy harvesting. How to design the power system, to get a stable output power to the sensor, can be done within of these techniques, but can also be achieved by charging capacitors or superconductors. It all depends on the duty cycle of the application. And much can be adapted in the software also, to reduce peak power for instance, and spend it over a longer active period. Additional techniques can be added for two step wake up, and maybe the application requirements can be adjusted.

Another interesting research project (X. Wang et al., 2022) shows the combination of energy harvesting and sensing. In many cases there are movements or temperatures, or that is sensed on anyway, which can also be used to extract energy from. This project illustrates a fish-wearable behaviour monitoring also can harvest energy, from the fish tail when it is swimming. The fish-wearable contains a processing unit, energy harvester, motion sensor, and a wireless transmitter.

Another interesting research (Gomez et al., 2022) by a group of Swiss researchers is a sensing systems powered by energy harvesting introduces *Julienning*: an automated method for optimising the total energy cost of battery-less applications. Our optimisation can partition data- and energy-intensive applications into multiple execution cycles with bounded energy consumption. By leveraging inter-kernel data dependencies, these energy-bounded execution cycles minimise the number of system activations and nonvolatile data transfers, and thus the total energy overhead. Partitioning results demonstrate that compared to ad hoc solutions, this method can reduce the required energy storage by over 94% while only incurring a 0.12% energy overhead. According to researcher (Gomez, 2022, p. 6:30) the advantage on cost and size for a typical wearable sensor, can be up to 90% in size and 50% in cost, so altering the application to facilitate for this can be a huge gain. Additionally, you will gain an environmental friendly, safe and maintenance free wearable sensor.

4.2.6. Wireless sensor energy conservation

A recent research (Sanchez-Iborra, 2021) studied the two most critical parts for wearable sensors in terms of reducing energy consumption; communication and processing. The research studied the Low Power Wide Area network (LPWAN) standard, and the recent addition of tiny machine learning (TinyML). These in combination, compared to transmitting raw sensor data to the cloud for inferencing there instead, improve the total energy consumption for the wearable sensor drastically, especially in combination with ultra-low power microcontrollers. Depending on application the wearable sensor is part of, this means either a smaller sensor, since the battery can be reduced, or longer time between charging. Or if the application allows for it, it could mean removing the battery, only using energy harvesting instead. This will fix a couple of the other issues too, such as privacy, latency, and will make the wearable sensors agnostic to network conditions. This study also claims that this will make it possible to personalise the wearable devices. Sanchez-Iborra's study propose moving machine learning to the wearable sensor, as well as shifting towards an object-centric IoT architecture.

As the edge devices gets ultra-low power processors and gets more capable of processing their own data, distributing the machine learning models makes much more sense. A group of researchers also propose to distribute deep learning training, in order to protect privacy better, and to reduce the load on cloud servers (Tanghatari et al., 2022).

Figure 23. Wearable sensors from needs, through requirements to technical solution

According to the CSEM (A.S. Porret et al., 2020, pp. 101-110) ultra-low power systems such as wearable sensors, is about an optimised system from the needs, which creates the requirements, which again can provide the technical solutions (fig.23). Needs for wearable sensors are low-cost, non-obstructive, worry-free and useful. This result in requirements like optimal BOM with only what is needed, small size, long life, low data traffic, smart and self-configuring. Technology and solutions that needs to be put together is ultra-low power microcontroller, energy storage, harvesting, ultra-low power wireless and machine learning. Then the wearable sensor, needs to be optimised with radio, IoT architecture and cooperation with the cloud.

4.2.7. Wearable sensors on cognitive objects

A recent market research (O'keke, 2022) states: *«In the wake of the looming global economic crisis, more businesses are pushing to lower bandwidth usage, resolve latency problems and solve privacy issues associated with big data to optimise their business. That's why edge computing adoption is hitting the IT industry like a tsunami»*. They report that the global edge computing market is expected to grow to over $150 billion by 2030, with a CAGR of about almost 39% (Compounded Annual Growth Rate). The market report include components, applications and industry vertical. The number of IoT devices is expected to triple from approx 10 billion units in 2020, to almost 30 billion units in the same timeframe. Some of this is expected to go into consumer devices, healthcare, and agriculture.

A solution proposed by a group of Spanish researchers (Rodríguez-Rodríguez et al., 2020) is a safety alarm against Intimate Partner Violence (IPV). The wearable IoT sensor is based on passive continuous monitoring of body biometrics, which would be able to autonomously detect an aggressive situation and then activate an alarm without any user intervention. They list a number of wearable sensors capable of capturing these biometrics and detect abnormalities and events, but they also notify the importance of data security, trust by the wearer, handling of false alarms. Their research builds on short range low power communication, which is likely to be inadequate in terms of network coverage and limitation for where to use the alarms. This proposal was made in 2020, and since then low power communication with LPWAN such as NB-IoT, LTM, LoRa and SigFox has gotten widely deployed.

Edge Impulse, (Edge, 2022) a company founded in 2019, is one of the leading platforms for embedding highly optimised machine learning on constrained devices and sensor products. According to their own website, their machine learning models have by June 2022 been included in more than 103K projects already. Edge Impulse provide tools, algorithms and tuners for companies to quickly and easy enable machine learning in their products and projects.

One product using the Edge Impulse platform is BAND V2 (SlateSafety, 2022), a body monitor used on first responders and firefighters to prevent heat exhaustion. The machine learning algorithm tracks heart rate and core body temperature, and the products extrapolates other biometrics such as calorie burn, steps and exertion, and by monitoring trend it will alert team leaders, so the firefighter or similar can be replaced for a rest. This type of predicting workforce exertion, protects against accidents.

Another predictive device is the Bio-RFID(TM) (KnowLabs, 2022), a non-invasive diagnostic technology platform which uses radio waves to identify and measure what is going on inside the body, before inferencing it in the device. The Bio-RFID(TM) will scan the body without needles, and can read different molecules such as glucose, oxygen, alcohols and drugs, and can be used for 100+ applications.

Biometrics tracking is being used for many applications. Whoop 4.0 (Bullmore, 2022) is a small wristband, which looks like many other fitness trackers, but it represents a new generation since it can do inferencing and analyses biometrics continuously for 4-5 days before it needs to recharge. It tracks your fitness, sleep in several stages, respiratory rate, resting heart rate and heart rate.

A smart pet sensor, using machine learning algorithms from Edge Impulse, a 3D printed housing, and the Seeed XIAO BLE nRF52840 Sense AI development board, can be found in the open source project from Mithun Das (Das, 2022). This pet tracker uses a six-axis inertial measurement unit (IMU) for sensing motion, and was initially set up to detect resting, walking, running, and climbing up stars, when attached to the dogs collar. This show how available machine learning in small sensors is getting. Creating machine learning models is no longer just for the large corporations like Google, Facebook and Amazon. It is getting everywhere.

The worlds first biotelemetry tag that combines edge computing with wireless sensing of in vivo physiology such as electrocardiogram (ECG) and electromyogram (EMG), behaviour in the sense of activity level and tail beat frequency (TBF), and ambient environment such as temperature, pressure and magnetic field. The sensor called «Lab-on-a-Fish» (Yang et al., 2022), can last for 8 months du to its power-saving algorithms, weights 0,8g when submerged in water, with the dimensions of 5,5mm*6,5mm*37mm, small enough to be injected to the fish. It can send measurements over 400 meter, or store them if unable to send. The project tested on the three species rainbow trout, white surgeon and walleye.

Another fish-wearable (X. Wang et al., 2022) sensors designed to be attached to the fish tail by using an elastic band, for two reasons. The first reason is to harvest energy from the fish tail in order to power the device, and by doing so removing the size and weight of a battery, and avoiding the issue of battery lifetime. The second reason is to sense the swing angle, swing frequency, swing power of the tail, and from this detect the fish behaviour and mood.

A third sea creature tracker the FaunaTag, also called «Fitbit for whales» (Palminteri, 2022), is a multi sensor device which measures movements, acoustics, depth of travel, along with physiological factors such as heart rate, cardiac energetics and blood oxygen level. The FaunaTag uses suction cups to attach to the dolphins to ensure that the device is as minimally intrusive as possible.

The SnapperGPS (Beuchert et al., 2022), is an open-source project for wildlife tracking, which captures GPS position. The sensor can run for more than a year on a 40mAh battery, with an average accuracy of 12m. The project has already been used in two projects; for tracking sea turtles, and on sea birds. The SnapperGPS was attached to loggerhead sea turtles on the island of Maio, Cape Verde, and tracked the movements over two weeks. The snapperGPS was also attached to Manx shearwaters. Since these birds only weigh between 400g and 450g, so the weight of the sensor had to minimised down to 8,3 g. The plot of the route showed a roundtrip from Wales to Northern Ireland.

Researchers at MIT have fabricated a chip-free, wireless electronic «skin» (Chu, 2022). The device senses and wirelessly transmits signals related to pulse, glucose levels, blood pressure, heart rate, sweat, activity levels and ultraviolet exposure, without bulky chips or batteries. This is the latest innovations and a new kind of chip-free wireless sensors, a flexible, semiconducting film that conforms to the skin like electronic Scotch tape. The heart of the sensor is an ultra thin, high-quality film of gallium nitride, a material that is known for its piezoelectrical properties, meaning that it can both produce electronic signal in response to mechanical strain and mechanical vibrate in response to an electronic impulse. The researchers found that they could harness gallium nitrate's two way piezoelectric properties, and use the material simultaneously for both sensing and transmitting wirelessly, according to the article in MIT news.

There are several fitness and health trackers on the market today, from Apple, Fitbit, Garmin, Withings and Samsung, but all of them are still not satisfying the criteria as a real wearable sensor. According to TechCrunch, the Oura Ring (Wiggers, 2022) is a very good candidate, since it runs on battery up to a week before it needs a quick charge, and it looks like a piece of jewellery (Gucci, 2022). The rings sensors are located on the inside surface, and are totally hidden when worn. It has an internal battery, and is able to talk to a smartphone via Bluetooth. Since it can stay on for such a long time, it makes good tracker for sleep, and it recently got an upgrade for tracking SpO2 and breathing regularity, which provides many metrics such as sleep efficiency, REM, length, deep-sleep, dozing, body temperature, heart rate variability, respiratory rate, resting heart rate, calorie burn, inactive time and steps.

Another health tracker ring, the Happy Ring (Song, 2022), is targeting the mental health, since it detects and tracks the «mood» as a brain monitor. It uses an EDA sensor to determine the mental state, and it works by detecting when the sympathetic nervous system, which is what regulated the fight or flight response, starts raring up. According to Dustin Freckleton, the Happy Health CEO, EDA sensors measure the electrical changes that occur on the hand in response to the small amounts of sweat that starts to be produced on the palm of your hand. The ring continuously adjusts the AI model to an individual person's data, as opposed to comparing that person's data to a predetermined user set. The ring will detect the mood on an ongoing basis so you understand when you are calm, alert or tense.

Another project (Aich et al., 2019) which analyses activity and emotional patterns of dogs, is using a combination of two wearable sensors located in two spots, one on the neck for capturing the dogs body movements, and one on the tail to detect the tail motion and swing. The two wearable sensors works together, and they both have accelerometers and gyroscope. The project used machine learning techniques for automating the detection and evaluation process. The sensors captured movement data, and a video camera recorder the movements, in order to label the data. The project detected seven types of activities such as walking, sitting, stay, eating, sideway move, jumping, and nose-work, as well as three types of emotions states, such as positive, negative or neutral. The project used devices that leveraged incremental machine learning model, and resulted in an accuracy of 96% on activity, and 92% on emotions. The project suggested to combine with biometric signals in order to improve the accuracy.

5. Discussion

In this chapter, I will discuss my findings from the interviews and literature study. The first two research questions focused on how far the relevant technologies for wearable IoT sensors had gotten, and what might happen when adding machine learning to them. The chapters 5.1 and 5.2 is discussing this. Based on advancements in technology, I will consider a new IoT service concept for cognitive objects, where machine learning in wearable IoT sensors can bring new values and smarter IoT services, and enable innovation in business models, according to the third research question. The chapters 5.3 and 5.4 is discussing this. Such a new concept is also likely to affect ethics, which is covered by chapter 5.5. A summary of my newly proposed paradigm is discussed in chapter 5.6.

5.1. Technology

The research front is rapidly moving forward. Wearable IoT sensors are becoming higher performing while consuming less energy, and related technologies continue to evolve. IoT architectures are adapting to service needs and capabilities. The big question is if wearable IoT sensors are capable of becoming true wearable as defined by Steve Mann, and if these sensors can get optimised for cognitive objects such as humans, animals, birds and fish, in order to create IoT services caring for them. The environment is harsh, the resources are constrained, the cognitive objects the wearable IoT sensors will be placed on, are all unique. High performance technology is required, but can it be done?

At first, I will look at the challenges these sensors needs to face, before discussing how this can be solved, both in terms of the wearable IoT sensor's relation to the cognitive object, and the relation to the network it belongs to. The discussion will evaluate an IoT paradigm shift, as a result of more performance at lower energy consumption in the sensors, and machine learning to inference on the raw sensor data when it gets captured.

5.1.1. The challenge

Sensing on *cognitive objects* is very difficult, since the sensors cannot assume exact similar characteristics from the objects it gets attached to, in fact it will be unique and individual for each cognitive object. This means the sensor has to handle the variety, and be *object-centric*, in order to capture data that can be trusted with accepted level of quality. To make it more challenging, the sensor cannot run out of battery, be obstructed by lack of network, or be too difficult to use, it needs to be *true wearable*. These requirements can be hard for a constrained device in challenging environments.

5.1.1.1.Constrained devices

Both respondents reflected over the conflicting terms for a wearable IoT sensor, as a constrained device with very few resources, while having to operate in demanding environment. To reduce energy spending on radio transmissions, the constrained devices must use machine learning to inference on the captured data directly in the sensor. But machine learning was not originally made for constrained environments, it was made for large data centres using MPU's, NPU's and GPU's. Still the respondents are convinced that running machine learning in the MCU's, is using much less energy than power-expensive radio transmissions do. Respondent A's company works on making the wireless MCU compute at ultra-low power, with the target of battery-less operation at some point, while respondent B's company works on optimising the machine learning models to fit these energy efficient controllers, and to compress the models so they use as little memory and energy as possible. As stated by the respondents, wearable devices on battery is limited by access to infrastructures, both for charging and for swapping batteries, or network for communicating with the service. IoT in the early days was M2M with for instance wired vending machines and POS terminals which would communicate with each other and servers in the cloud to operate a service and do transactions without the intervention of humans. IoT services evolved and got more sophisticated. Sensors went from wired to wireless, and along came the constraints. In order to reduce these constraints, the term Fog computing got introduced, as a local resource of the cloud. This would assist the wireless sensors as a communication gateway so the sensors could communicate using low power radios, and offload raw data to the Fog for machine learning and reasoning. This reduced latency, improved privacy and handled the sensors communication.

Wireless IoT sensors have been sold and marketed as wearable sensors, basically since they are wireless, and are physically wearable, such as GPS watches, fitness trackers, iWatch, dog trackers, and more. But at the same time they are constrained devices, and therefore can't meet the definition of wearable computing. Either they perform ok but are too large and heavy, or they are small enough but limited in functionality and battery time. There are some difficult trade offs. On one side they need to blend in as a natural part of the wearer, without requiring any attention from them, while on the other side they need to compute the sensed data and detect behaviours of the *Cognitive Object*, and then communicate the necessary events and patterns to the service, but without draining the limited battery, or getting interrupted by lack of network. That is a difficult combination.

According to the respondents, there are also a users acceptance pyramid, which works in steps of one day between charge, one week, or one year. So when these wearable IoT sensors are attached to cognitive objects, there are usually a caregiver in order to administer charging of batteries, either the user himself, the prison guard, the nurse, the veterinarian at the fish farm, or family members. Both respondents mentioned various roles which somehow participated in different things such as installing a wearable sensor, changing battery, a person which can participate in the training of the local machine learning models, or many types of services which cares for the cognitive object in elderly care, nursing, coaching, wildlife preserve, fish farming, dog owner and much more. This made me realise that the caregiver is a tightly connect role in the IoT service using wearable IoT sensors on cognitive objects. Looking at all the literature I have studied, that pattern also persist there. Therefore the roles of the Caregiver will be covered in a later chapter.

5.1.1.2. Cognitive Objects are unique

Sensors attached to non-cognitive objects are very different from sensors attached to *Cognitive Objects;* the conditions the sensors must operate under, are very different, in several perspectives. The first perspective is the cognitive object that the sensor is attached to. With non-cognitive objects, there are most likely similarities, like what material it is made of, or functional parameters or metrics, which can be used to compare sensed data between sensors, or to train the machine learning models based on classified data of same class, gathered from many devices. This is difficult with *Cognitive Objects*, since they are all unique. Even identical twins are different. The second perspective is the treatment and handling the sensor is likely to get exposed to. *Cognitive Objects* are likely to fight a rival, crash into obstacles, swim in the ocean, dive under water, or fall to the ground. So sensors must be ingress protected, resistant to water and dust, and to be able to withstand fall from a certain hight. These wearable IoT sensors might be attached to humans, from adults to small children, so the need to be physically small, with comfortable shape and size, or they get connected to salmon at a fish farm, or a bird in the sky; so physical shape, size and weight matters. If the wearable sensors physical appearance is not accepted by the wearer, it will fall off, be taken of, or as stated by respondent A:

> *«In case the wearable device is to big, clumsy or difficult to use, it will end up in the grandmothers drawer.»*

5.1.1.3. Challenging environments

A third perspective is the environment the sensor and the cognitive object is in. A non-cognitive object is more likely to be attached to equipment, walls, containers, pipes, suitcases, bikes, cars and more. Most of these things will be in areas where infrastructures are present, such as communication and power. While *Cognitive Objects* such as humans, birds, animals and fish much more often will be in conditions where there are no infrastructures, in the mountain, in the skies, in the woods or under water, for shorter and longer times. According to respondent A:

> *«And for every place with weakened or no coverage, the battery will drain faster, since the radios likely will try harder to amplify the signals, process it harder, and boost the transmitter.»*

In terms of wearable IoT sensors, it is extra challenging since they need to be physically small, which also makes the antennas smaller. Poor antennas makes situations more challenging and deteriorate the radio conditions, and thereby force the sensor to boost the transmitter and spend more energy.

Since wearable IoT sensors will be attached to *Cognitive Objects* which moves around, it is very likely they will loose contact with the service from time to time. It is not possible to restrict a cognitive object by requiring him to stay in good coverage of communication. Animals move freely around, and often the purpose of the sensor is to find its position, and notify where they are. Or if we place wearable sensors on humans such as kids, prisoners, elderly people, athletes, we cannot expect them to be in the vicinity of radio masts all the time. Wearable sensors must work offline, and work without communication. This makes it even harder for the constrained devices.

5.1.1.4.Cloud centric IoT Paradoxes

In the cloud centric IoT topologies, the large amount of raw sensor data is transmitted over radio connections, to get access to computing resources for inferencing and classification. But this also creates a paradox of *«spend power to save power»*. The wireless IoT sensors was constrained, and had limited computing power and energy available, they were forced to spend that energy on the radio transmission for offloading the raw data, all the time, instead of just sending events and abnormalities. Often, additional energy also had to be sacrificed on retransmissions, network latency, or bad network coverage, with regard to the cloud centric topologies. And this even worsened when the wearable IoT sensors got placed on cognitive objects, since they moved around in much larger habitats, and wider areas than sensors on non-cognitive objects did.

According to respondent A, it is no longer a question about computing in the cloud for wearable devices, because of the energy intensive radio transmissions, even though we have gotten LPWAN and low energy Bluetooth.

> *«Until now, the main reason for transmitting the raw data has been access to computing power, but that is in the change.»*

Another issue with sending large amount of raw sensor data away from the sensor is the paradox of *«personalisation-privacy»*. IoT services on cognitive objects will require sensing and capturing a wide variety of data from them. In cases where the wireless IoT sensors are attached to humans, concerns about loss of privacy are likely to increase, which results in loss of trust in the service for the user, a big problem for deploying IoT services on humans. We have started collecting data from humans using welfare technology, fitness services, we monitor our kids whereabouts with GPS watches, not to mention all the apps we use on the smartphone which collects huge amount of data. So far, IoT has collected lots of raw data, forwarded it to the cloud where it gets analysed and stored, in order to reveal known or unknown events, trends or abnormalities.

But there are great issues with trust when collecting such personal data, and there are concerns about the quality of data. So if the wearer of the wearable IoT sensor does not trust the service, it will break the definition of wearable computing, so personalisation of the local machine learning model is required. But this leads to a privacy issue on a new level, on the personalised model. Mann said the wearable computer should protect the wearer from the outside.

In the case of wearable IoT sensors and privacy, it is a paradox that stopping the stream of private sensor data, leads to a new privacy issue. Machine learning comes into the wearable sensor to make sense of the data when it gets captured, so no data has to be sent away from the sensor. The privacy issue is that the machine learning model gets trained to recognise the cognitive object based on the personalisation. That is a paradox. For the user of the service or the wearer of the sensor, it does not matter if privacy gets violated on the raw data level or the personalised model, they will feel surveilled.

This likely triggers the paradox of «*surveilling the surveillers*» and the users desire for sousveillance. As stated by respondent A:

> *«There is also something about privacy, since device computing does not have to send any raw data, it will be safer for customers; the data never leaves the sensor, only the result of the data, and that does not reveal anything about the objects privacy. This is visible in smart homes, where the focus is to not send that data out of the house, since that might reveal privacy issues in the family for instance. What happens in the house, shall stay in the house, is a saying. At the same time it meets the true wearable requirements».*

5.1.2. The solution

Sensors on cognitive objects have to adapt to the object it is placed on, and be *object-centric.* A machine learning model which has been trained using data from other individuals, might not recognise sensor data from another cognitive object if it hasn't seen similar data before. And the sensor must be *true wearable*, if not it will not be worn. These requirements can be hard for a constrained device in challenging environments, but latest technology and shifting away from the old paradigm of sending all the raw data to the cloud, opens new and smarter services for cognitive objects.

5.1.2.1.Wearable IoT sensors becomes true wearable

As shown in the literature study, there are already products commercially available in the market which lasts for 5-8 days without charging such as the Oura ring. It senses many biometric signals and gives the user very good insight to activity, sleep patterns and restfulness, and even suggest when to calm down for the evening in order to maximise sleep quality. The Happy ring is on the same path, except it works on the mental and emotional health. Both of these blend in with the person wearing it, and does not take away the users attention and stays in the background as a secondary computer. This actually means that Oura ring and Happy ring meets the definition of wearable computing . And to blend in even more, the Oura ring has been made into jewellery available from the fashion brand Gucci.

According to respondent B:

> *«The value of machine learning in the sensor can be a new level. For instance a fitness tracker, where you might have an accelerometer, skin temperature and combinations of LEDs looking at blood flow, so basically looking at heart rate and heart rate variability. Those combinations of sensors are used to derive lots of stuff. In extreme low-power case running some machine learning algorithms as well, off a battery, that fits in the ring. This is a real product today, the Oura ring, which can be active for 6-8 days without charging.*

According to respondent A:

> *«We are probably getting to a point for some products and applications, where the technology is energy efficient enough, and evolution on energy harvesting is getting good enough, at the right cost and size, and interest and demand is establishing in the market, in such a way that a market for non-battery products might establish.*

5.1.2.1.1.The Tipping Point

It is all coming together, we are at a tipping point (fig.24); from the processing side with ultra-low processors, from the algorithms side with TinyML and very optimized machine learning models, and from the energy side energy harvesting or high density and compact batteries. Of course, it all depends on the application. This is good news, since 90% of a wearable sensors size and 50% of its cost can be removed by removing the batteries. These numbers are of course depending of what it compares to, but it shows how significant part of a wearable product the battery represents. That’s a good thing, since battery-less also means environmental friendly, safe and maintenance free.

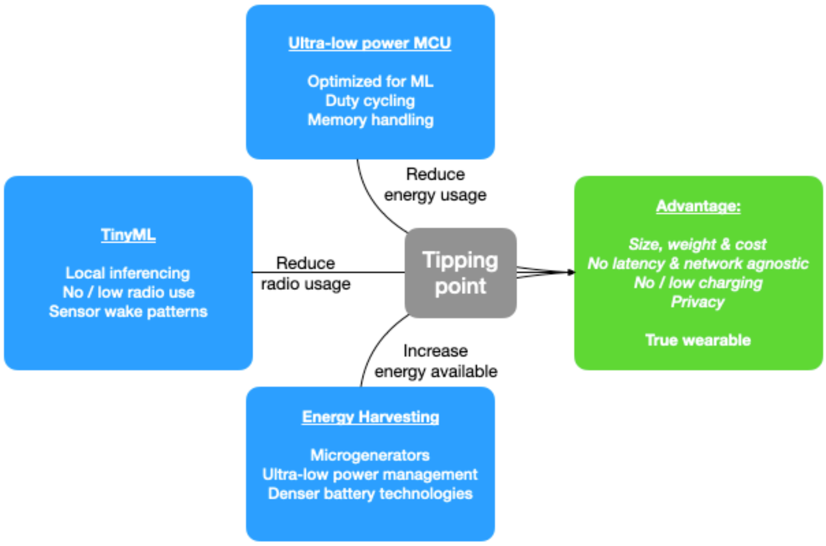


Figure 24: Tipping point for True wearable

The two respondents shared much about the inner workings of ultra-low power processing, memory handling, techniques such as duty cycling and batching, fast wakeup, low power radio standards and techniques, and how machine learning uses the resources, optimising for memory and power, and elaborated about their customers use in products which are entering the market as wearable sensors.

The literature study confirms their stories, also shows other research with a different approach, but heading the same direction. Respondent A's microcontrollers are also integrating the wireless short range and long range portion, while some are bringing out purpose-built processors for accelerating deep neural networks, or neuromorphic processors which can inference at very low power, adding to the research of AI at the edge. Much of this research is still in labs around the world, but some is showing as prototypes and products. An example is Akida which is in the concept car Mercedes EQXX. The car is of course no wearable sensor, but it shows the processors technology in use, when it listens for wake words almost without using energy. This neuromorphic processor also show how it can do on-chip learning by using the trained model as a guide to add new classes to its final layer in the neural network only by experiencing a sample one time at the edge. Another good example is the world leading chip manufacturer ARM, which recently launched their new generation «Total Solution for IoT» which is targeted for ultra-low power machine learning at the edge. There are several other solutions too, heading the same way, such as purpose built ASIC chips and FPGA cores. On the long term, the NeuRRAM processor, which prototypes these days, reduces power consumption needed for AI inference at the edge drastically. Compared to other AI chips, the NeuRRAM chip will not suffer from bottlenecks due to data movement internally in the microcontroller, basically since it computes directly in memory. This chip is expected to go to production in a couple of years, and another sign of the trend for wearable sensor processors.

«Sensor 2.0» is an expression being used regards smart sensors, which inference the data directly in the sensors, without off-loading it to the network. That makes perfect sense since 95% of all the sensor data captured could actually be handled directly at the edge by TinyML. Additional to reducing energy usage, the raw sensor data would not be affected by network latency, loss of network coverage, or poor conditions. And since the data did not have to be sent from the sensor, it would not represent any privacy issue either. The list of advantages is long.

The possibilities and advantages of running machine learning directly on the data is also confirmed by the respondents. Sensor data that never leaves the device is no privacy issue according to them. Still there are the important subjects of ethics, since even though the data is safe, the trained model can reveal if people are home, or discriminate. Therefore the respondents are emphasising the «Tech for good» and the «Ethical responsible AI license». This is still very important, and depending on what it is intended for, there are topics regards guard-rails and regulation. Respondent B also made an assumption if the window to be inferenced was short enough:

> *«Machine learning can possibly inference data on-the-fly, without sending to the network»*

Research shows many types of sensors, as tags, in clothing, or as stickers or e-skin. They sense on different bio signals from physical signals, to electrics, or chemicals in the sweat. They also show energy harvesting in different types, proving battery-less sensors that even communicate wireless.

Wearable IoT sensors are at a tipping point these days (fig.24), they are getting smaller and smarter, while at the same time lasts for much longer between charging, some even without battery, and they work without network connecting. The wearable IoT sensors are becoming true wearable.

5.1.2.2.IoT Architecture becomes object-centric

Over time, several architectures have been adopted, but one common denominator persists; the raw data had to move from the sensor and upwards in the architecture. This makes perfect sense for many types of services. But, when wearable IoT sensors becomes true wearable, and attached to humans, animals, or birds, we actually introduce a large shift in IoT. These objects are not homogenous, or possible to group in a good way. Even though they are within species, and possible to group by gender, age and more, they are unique individuals. They are physically different, behave differently, and, unless restrained, in unique and shifting environments. The raw data collected by wearable sensors are specific to the object, and will likely not be of any relevance for all the other objects. But their data is important when looking for events, abnormalities or trends within the object itself, in an *object-centric paradigm*.

The major difference between the cloud-centric and object-centric paradigms, is the purpose of the sensed data. If it is collected, and communicated, for the interest of the correlation between many sensors, and to figure out events, similarities, abnormalities and trends compared to the population, then it is cloud-centric. But if the raw data from the wearable sensor only needs to correlate to its own limits, boundaries, trends and statistics, then it is object-centric.

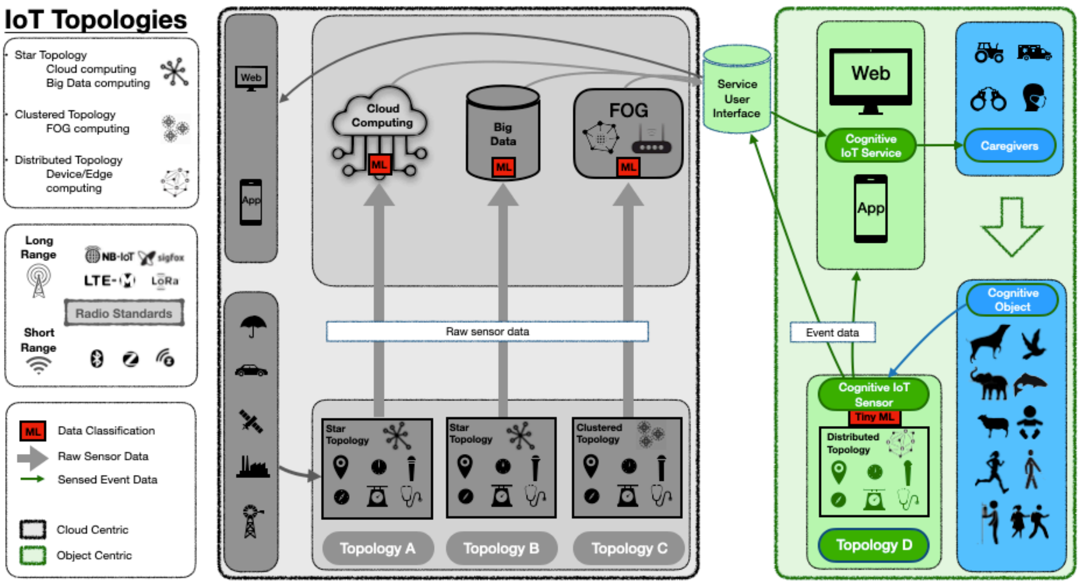


Figure 25: Cloud centric IoT service versus Object-centric Cognitive IoT Service

The different IoT architectures (fig.25), in grey, shows the cloud centric with the most commonly used topologies today in star topology and the cluster topology, and in colour the *object-centric* with the fully distributed topology which by 2020 was not much used yet. But much has happened with technology since. Since then, sensors have become true wearable, and new 4G narrowband standards NB-IoT and LTM has established, as new long range standards additional to LoRa and SigFox, and Bluetooth Low Energy has become more and more popular as short range standard additional to Zigbee and Z-wave. Respondent A stated that they only focus on these low power standards, long and short range. They also focus on different kinds of positioning, from GPS, to basestation triangulation, BLE positioning as well as supporting dead reckoning using IMU. They have also added cloud support in order to speed up positioning, as well as toggling between standards that uses least energy. Both respondents stated that inferencing at the sensor, and avoiding radio communication, was obvious to them. Another important point, as the IoT sensors becomes true wearable, it is actually very straight forward to switch from a cloud centric paradigm, to an object-centric paradigm. No central machine learning model needed, which would be the case in a star or cluster topology. True wearable IoT sensors and object-centric IoT service is newer and infrastructure agnostic. For example, to use Oura, it only required the ring, and an app on the mobile phone, and it works everywhere, all the time, and it syncs once the ring comes close the mobile phone again. As described in a recent study for AI semiconductors, there are a large shift from cloud computing to edge computing underway. That is also the conclusion of another research, where Sanchez-Iborra claims that the combination of LPWAN (low power wide area network) and TinyML is the enabler for the next generation wearable services.

IoT used to capture raw sensor data, transmit to the cloud, to analyse it and figure out how to act, before updating the service user. But that is changing now, with true wearable IoT sensors which does not have to send data to the cloud service to work, it is becoming object-centric.

5.1.2.3. Wearable sensing on cognitive objects

Most wearable sensors, are custom made for specific IoT services. Or as respondent A stated:

> *«The key to the wearable sensor is to optimise it for the smallest size and cost, while still achieving the key objectives for the sensor».*

A fitness tracker contains only the sensing hardware it needs, to capture the biometrics, movements and positions, similar to a safety alarm or another health sensor. By optimising for the actual application, reducing features and parameters for the algorithms, and tuning them to as low sample window as possible, and only spend computing power on what is relevant, the models can become small and efficient. Data from wearable sensors on cognitive objects, this is most likely from movement sensors or biometrics, which are quite simple, compared to high resolution high frame rate video streams.

Studies are giving good overview of various wearable devices that has come far in monitoring movements and biometric data from the human body, such as fall detection, activity recognition, eating monitoring, fitness tracking, stress detection, arrhythmia detection, seizure detection, rehabilitation tasks, hydration monitoring, emotion recognition, sleep monitoring and disease diagnosis. On the other side, it also identifies several challenges for wearable devices that needs to be further developed. As also stated in the study, wearable sensors will have several issues in a cloud centric paradigm, since large amounts of raw sensor data has to be transmitted over a wireless link, to get inferenced at a computational point in the network. That drains battery, and will from time to time cause issues with poor network conditions, latency, and functional stop if network is missing. And of course privacy issue since the raw data which gets sent to the network contains private information about a persons biometrics. Since sensors must spend their limited energy to communicate raw data to the network, there are a trade-offs to make. Either have a large battery to extend the battery time, or get recharged more often.

In a cloud centric paradigm, where sensors gets trained based on raw data from many nodes, the sensors will not get personalised. Accurate inferencing on cognitive objects such as humans, animals or birds, requires good quality raw data and machine learning models which «knows» the object. For instance, in order to detect abnormal stress level from one person, it is of no use with a model of the whole population. To detect newly developed limping on a person which already have a walking disability, it needs to be trained and personalised on that specific object. Studies points out, that there are disadvantages if running the machine learning inferencing in the wearable devices, and that the main disadvantage will relate to the limited device computing power, storage and battery life, and as a result of these limitations offloads to an edge device or a point in the network is the solution. These disadvantages will affect trust in the service and hesitation to wear the sensors. Some study seems to be very conclusive that machine learning had be done in the fog or cloud.

My research, which captures the story from two experts in leading technology companies, backed by a wide literature study, disagree with the conclusion that machine learning and inferencing must be done in the network. My research is quite conclusive that, at this moment, inferencing is much better to do in the sensors at the edge. Training of the models, still needs to be done in the cloud, where there are computing power and energy, That seems to be temporarily though, since research continues towards smarter, more efficient, and better training. It remains to be seen, if it involves hardware at the sensor, only the algorithms, or a semi-model.

There are some very interesting research on «Human-in-the-loop» using re-enforced learning together with «cognitive computing» in a framework so machines and humans can train together. Another framework is federated learning which is a collaborated method for training models at the edge, before combining them at a central location, and sharing them back to the edge. In this simple term, this framework will not provide personalised models, but it is a way to distribute training. Researchers are at the moment working on reducing the model size, reducing the communication of model, while still being personalised. There are also interesting research in neuromorphic computing which simulates the human brain learning which can learn only on one pass in a spike. According to responded B, the focus is shifting to personalisation:

> *«let's say you want to detect when your dogs is barking, but your dog might bark different from the general machine learning model. Then we can train better barking recognition. So think of it as the better algorithm that personalised to your dog. That's a next level of things, personalisation.»*

There also seem to be a shift from model centric AI, using large models in the cloud, to data centric AI, using local models on the edge. Data centric AI focuses on the quality of the captured data, so that it will not suffer from drift or biasing. My expression is *Object-centric,* and while data-centric seems to be the same, there are a distinction. The difference in my perspective, is that object-centric also includes the notion, that the cognitive object the sensor is attached to, is unique. Data centric AI or object-centric AI, are also in many terms the same, since it is about tiny local machine learning models, and how well they are trained. The important factors are how we supervise the training datasets, and how we validate the trained model. It concerns personalisation of the model, and handling of training drift and bias to get quality of the captured data. It is about training the model, and doing the inferencing, as close as possible to where it got captured. This will remove latency, increase accuracy, remove network dependency, reduce or remove privacy issues on raw data. But this is still in its early infancy.

According to respondent B, edge computing with local models, data centric or object-centric, helps democratising machine learning. Then it is not only dominated by large models controlled by the gigantic corporations such as Amazon, Google, and Microsoft anymore, and that is a good thing. Machine learning at the edge can even improve privacy, since data no longer has to be sent from the sensor. That bring with it a new responsibility though, since the machine learning models must be handled without misuse. There are almost endless possibilities, but also endless responsibility. Ethics, best practice and personalisation, is the next step according to respondent B.

The literature study showed that machine learning in wearable sensors already had been used for detecting falls, but also can be used to predict the risk of a fall in the near future, predict type 2 diabetes, warn about epileptic seizures, detect COVID-19 infection two days prior to first symptoms, and many more examples. Some of the mentioned products has already achieved medical grade certification in biology, but also in neurology, and are in commercial trade already, and others are in clinical trials. Other examples of use on humans is fitness trackers, workforce monitor, health tracker. But wearable sensors are also used with animals, fish and birds, such as for sheep, dogs, fish, or sea turtles. And there are «e-skin» sensors coming only as sticker, which can measure heart beat and send it over wireless. Or a tracker to notify parents if their toddler gets separated from their caregiver.

The literature study revealed many examples of capturing movements, electrical signals and biometrics, analysis of sweat and breath, and even substances in the blood such as hormones, toxics, nutritions, drugs and blood gases. And the sensors are starting to train and personalise to the cognitive objects unique biometric. Sensing on cognitive objects is becoming real.

5.2. Paradigm is shifting

The paradigm of object-centric IoT service is rare today, and true wearable IoT sensors is a brand new concept. But it is becoming clearer and clearer, it just hasn't found its final shapes yet. It is true that we already carry sensors around, while they collect raw data for a service, so in that sense, we already have wearable sensors. But these are far from optimal, since the disadvantages are remarkable. One major problem for todays wearable sensors is their disability to process raw data at low power consumption. As a consequence, wearable sensors, so far has had no other option than to send raw data inwards in the architecture. The communication of raw data is a big waste, first of all since it will spend a lot of energy just to transmit over radio, and if the radio connection is poor, it will drain the battery even quicker. Next, it will need support from a computational point in the network; either centrally in the cloud, resulting in latency, or on an edge device or a Fog controller, resulting in restrictions on availability, since the wearable sensor has to be within reach.

For an object-centric sensor, it does not make sense to send raw data. True wearable IoT sensors are still in their infancy, but technologies are evolving, and motivation for object-centric service architectures is growing, and the sensors are starting to enter the market. There are many unanswered questions, regarding model training, model training framework, personalisation, ethics and good practices, security, regulation, and when coming to healthcare, medical certification will be needed.

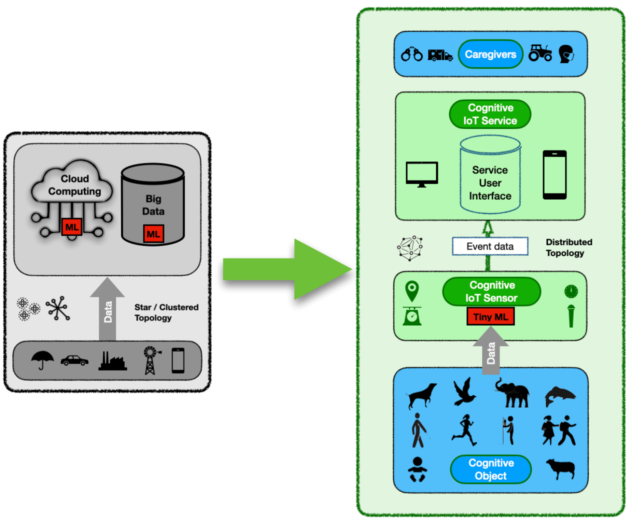


Figure 26: Paradigm shift from cloud centric IoT to object-centric IoT

The new paradigm of object-centric IoT service (fig.26) using true wearable IoT sensors brings many advantages, such as less (or no) charging of the sensors, no latency and agnostic to network conditions, smarter sensors and services, abnormality detection, smaller sensors, cheaper sensors, environmental friendly sensors, and improved privacy. The new paradigm fixes the paradoxes of «spend energy to save energy», «personalisation-privacy» and «surveilling the surveillers», it democratises machine learning, and gives developers and companies the ability innovate new products and services which will give caregivers more and better information when they provide care to kids, elderly, student, players, fish or wild animals.

A paradigm shift is in development, from old traditional cloud centric IoT with large centralised machine learning models, to the new and much simpler object-centric IoT paradigm with local distributed machine learning models at the edge devices. According to TechRepublic (O'keke, 2022), one of the quickest growing markets currently, is IoT and edge computing, with an expected growth from approx 10 billion units in 2020 to nearly 30 billion units by 2030.

5.3. Conceptualising

The research respondents were introduced to the simplified models of *cognitive object*, *object-centric IoT service* and *true wearable IoT sensor*, with the intention of focusing their narrative storytelling into specific fields of interest, such as machine learning on constrained devices. They where asked to elaborate, and help me dive deeper into the research questions, while keeping within the research limitations. Their stories were analysed, and compared to other literature and recognised theories, and formed my foundation for conceptualising, and restorying to my narrative portrait and my proposed concept of *Cognitive Care IoT* (fig.27). The simplified models got improved and developed into the conceptual models of *Cognitive Objects*, *Cognitive IoT Service* and *Cognitive IoT Sensors*.

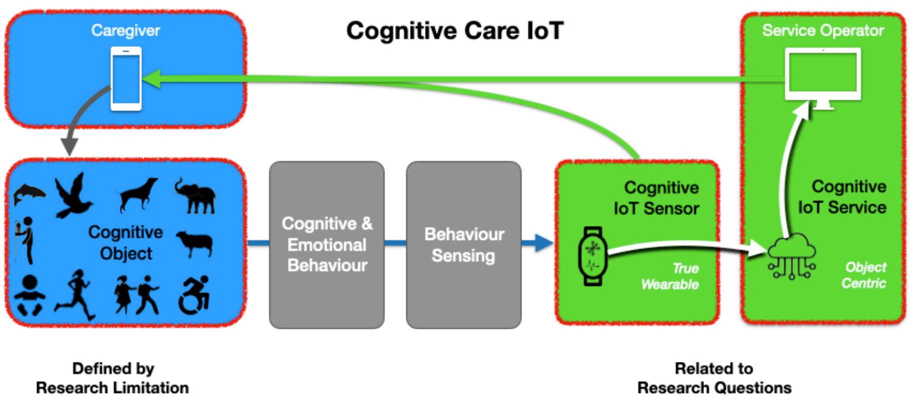


Figure 27: The relations between the conceptual models

5.3.1. Caregivers

During this research, it became apparent to me that there where several caregiver roles mentioned, both by the responders, and in various literature. The roles were either as the user, the dog owner, the nurse, the veterinarian, the wildlife preserver, the technician or the coach. They were mentioned in relation to changing batteries on the sensors, charging them, caring for the dogs, feeding the fish, working on diagnosis, installing the wearable sensors, or trying to understand what has happened to the cognitive object. All of these roles had things in common, as they where either related to the sensor or the person or animal wearing it. In other words, in close contact as the *Caregiver*.

Humans, animals, birds or fish will be cared for by caregivers at certain points through life. These caregivers are responsible for them at that time, acting as parents, nurses, babysitters, elderly caregivers, prison guards, dog owner, wildlife preserver, coaches or farmers. All cognitive objects have been infants, which have required parenting, sick which have required nursing, or been cared for by society either in kindergarten, school, in health care or maybe in police custody. This is also the case with animals, birds and fish, even though they receive a different kind of care. Farmers and wildlife preservers share the same need for a connection between their cognitive objects and the caregivers. Even with insects, a good example is farmed bees, which are very important for the environment and the ecosystem, due to their function with pollination of flowers. These insects are cared for by the beekeepers, which would need to know where they are, when to move them, health in the tribe, swarming, and so on. Bees are also within the concept of cognitive objects. But sensing on bees is another question, which currently might be difficult, since bees are very small, and live the way they do. Dogs or goats are much easier, since these cognitive objects have much less constraints. How to sense on them will be heavily influenced by the size of the cognitive object, its habitat and environment, and what is required by the service and the caregiver. An elephant can of course carry a much bigger sensor, than a bee. Likewise, there will be different requirements for sensing on a dog, versus a nomadic bird, specially when it comes to energy and the need for network. Which cognitive object to add IoT sensors to, must be decided by the technical feasibility and the business model. Some cognitive objects will definitely be easier than others. Sheep, dogs, kids, dementia patients or goats have already been connected to IoT services, but they are all limited as described in the research topic. The *Caregiver's* role has three perspectives.

5.3.1.1.Caregiver as a provider of care

The first is obvious in terms of caring for the cognitive object, in a form of responsibility or a contract, written or spoken, to make sure kids, dogs, fish, elderly people or patients are ok, based on their situation, resources and opportunities. To care for someone in the best possible way, it is important to have access to all the relevant information. When the sensor discovers that information gets abnormal, then it is important to bring that to the caregivers attention. For instance changes in heart rhythm, temperature, sleep pattern, fish which are swimming abnormal, or dogs that suddenly sleeps more than normal. The caregiver might also play an important role as the «guard-rail» in crucial services, since machine learning is probabilistic in nature, and not 100% accurate. In business model terms, this would fall under the category of adding gain points in the value proposition, by providing more information who is of value to the caregiver, and in turn the cognitive object.

5.3.1.2.Caregiver as a service installer

The second perspective involves handling the wearable sensor, charging it and making sure it works as intended. This means making sure of correct placement, checking it for damage, and making sure is within the necessary infrastructure. In terms of business model, this reduces jobs, and maybe even removing jobs, in the value proposition for the caregiver.

5.3.1.3.Caregiver as a sensor trainer

The third perspective is maybe much less obvious. In the discussion in chapter 5.1.2.3 regards sensing on cognitive objects, it was mentioned by the respondents, as well as described in literature, the challenge of training the true wearable IoT sensors, and the need for personalisation. Since the true wearable sensors are constrained, training and personalisation of them, needs to be done within those constrains. Respondent B said this about the dog owners role, or the caregiver:

> *Or in the case on anomaly detection to detect that something is different from what we already know, and just ask the owner: "hey, we just detected that your dog did something new, at this time, could you tell us what that was?" Then the sensor will, together with the user, start to learn new behaviour, which we want to tag, and then we can put that back into our dataset.*

The caregiver's role in the concept is more important than I first could foresee. How the caregiver gets involved, is up to how the IoT service is, and how its application gets implemented. In terms of business model, this would be removing pain points, in the value proposition for the Cognitive IoT service provider. The caregiver will also be part of value creation, both in terms of taking part in personalising the wearable IoT sensors, but also in terms of providing better care for the cognitive object. The caregiver will become very important in business model innovation.

5.3.2. Cognitive Objects

Plutchik's theory of emotion describes a mental process with a cognitive and an emotional stage which leads to behaviour and other research have shown how emotions produces body responses which can captured by sensors (fig.28). My concept of a *cognitive object* includes any living creature, which is capable of thinking, feeling and acting on instincts, such as humans, animals, birds, fish, reptiles or even insects. On the opposite side, and not part of this concept, is things such as machines, pipes, mechanics, factories, cars, mobile apps and so on. All of those are much easier to group together, compared to cognitive objects, since they are equal and share attributes within the group, while cognitive objects are all different and unique.

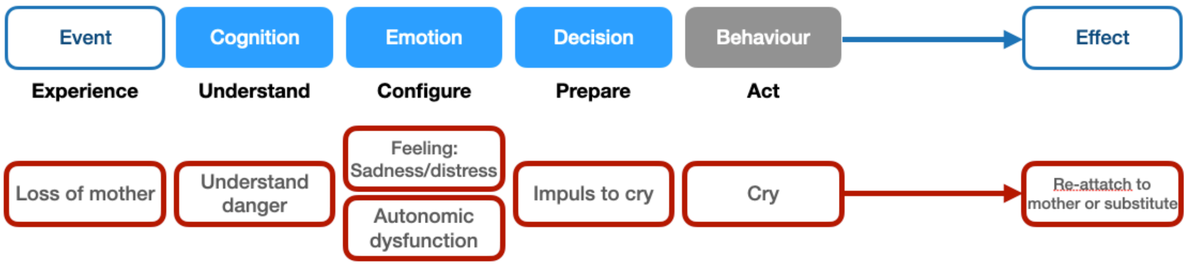


Figure 28: Simplified cognitive and emotional process leading to behaviour based on Plutchik

The variability of cognitive objects is big. They can be very different in size, from very large, such as elephants or whales, to very small, like insects or birds. They are very different in their habitats, from pets living in our homes, to fish living in the deep ocean, or birds in the mountains. They are active in very different ways, since some fly, others walk, and some swim. They experience different things and situations every day. My research will not go into all of these differences, since that is related to theories of evolutions, psychology, physiology and much more.

5.3.3. Cognitive IoT Sensors

Wearable sensors attached to living creatures, is not simple. They will be purpose built, to fit to a specific living creature, in its habitat or range of operation, and for the specific applications it's intended for. Cognitive IoT Sensors will meet the definition of wearable computing by Steve Mann, and most likely be embedded into clothing, shoes, jewellery, stickers or small items, depending on the Cognitive Object wearing it, the body signals to capture, and the service requirements. They will be small, light weight and possible to hide on the body, and they will be robust and ingress protected, and if achievable, they will be battery-less. Cognitive IoT sensor will be able to communicate with the

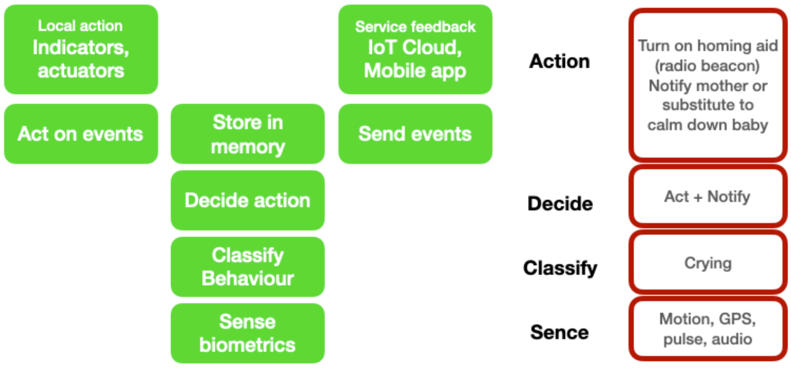


Figure 29: Cognitive Emotional behaviour sensing

service to share events, abnormalities and discovered patterns with caregivers, to share learning, carry our further personalisation, or updates of the service.

A simplified model of a Cognitive IoT sensor (fig.29), illustrates the sensing layer at the bottom, and up to the interaction layer, either by sharing the events and abnormalities, or by acting directly. It is still early for such sensors, and depending on application, there are ethics to work out, guard-rails and topics in relation to the usage and application that needs to be worked out. As an example, there are quite a difference in Cognitive IoT sensors for measuring biometrics in a fitness application, versus a similar sensor on a patient in an ambulance, even though it might measure the same biometrics.

5.3.4. Cognitive IoT Service

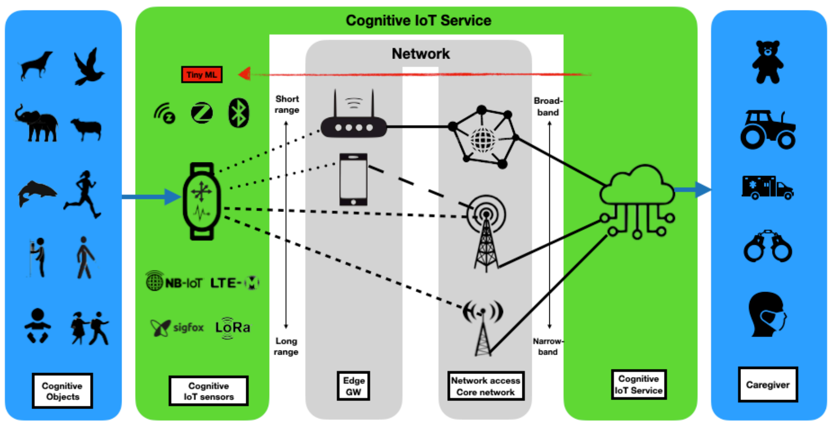


Figure 30: Cognitive IoT Service

The conceptual model of Cognitive IoT Service (fig.30) uses a distributed topology, which is different from the most common topologies today. The main difference is that it flips the paradigm upside down. It moves machine learning inferencing to the edge device, and reduces the large amount of raw data which would otherwise have had to be sent over radio transmissions. The sensors attached to Cognitive Objects will only transmit over long range radio to a central point in the Cognitive IoT Service, or directly over short range radio to a trusted app in the caregivers mobile device, which then share the event with the Cognitive IoT Service this way.

Cognitive IoT Sensors will have personalised models, trained and retrained, to adapt to the specific object. This research does not consider how the machine learning models are trained, only describing the general principles of the Cognitive IoT Service for Cognitive Objects. Inferencing will happen in the Cognitive IoT Sensors from the beginning. Training of the machine learning models is most likely to be done in the network in the beginning (ex-situ), but is likely to gradually transition towards the edge device (in-situ) (fig.31). It is still in the early days of doing on device machine learning and deep learning for wearable sensors, but there are already examples for on-device (in-situ) learning and retraining, especially targeted for wireless sensor nodes and low energy edge devices. The important aspect here, is that these models gets trained on sensor data from the actual object it is sensing on, which will personalise the sensor, instead of being trained on large datasets from other cognitive objects, which might be irrelevant.

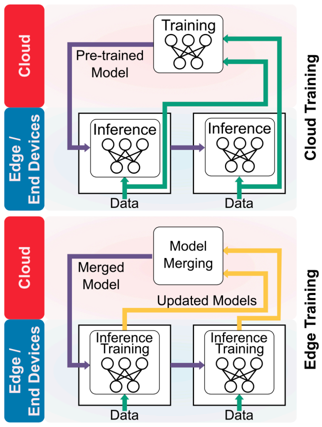


Figure 31: Edge training versus Cloud training

In cases where models needs to update each other, they get merged in the cloud. All of this is part of personalising the sensors, and improving their quality to become better and better in detecting what they are intended to. This will start basic, Cognitive IoT Sensors will move machine learning onboard the sensors, and then start building trust in the Cognitive IoT Service.

5.3.5. Cognitive Care IoT concept

True wearable (Mann, 1998a) cognitive IoT sensors, attached to Cognitive Objects, such as humans, animals, fish or birds, operating in a Cognitive IoT Service, can provide valuable information to caregivers, so they can deliver value in the concept of Cognitive Care IoT. The caregivers are multirole, as they also administer the sensors, and can participate in training them as value creators. The caregivers are very important links between the IoT service and cognitive objects they care for.

5.4. Business Model Innovation

The third research question, and the secondary part of my mixed method research, is regarding how machine learning added to the wearable IoT sensors can enable business model innovation. My research concludes with a paradigm shift from cloud centric to objects centric, and I have proposed a concept based on true wearable IoT sensors, attached to cognitive objects, with the support from caregivers. This chapter will look at the business opportunities, discuss it in light of the business theories I build the research on.

Edge ML and true wearable IoT sensors are still very new. Some products have started to enter the market as previously described, and the amount of research in this field seems to be very large. The market-leading semiconductor companies are launching their new ultra-low power offerings, such as ARM, and the platform providers of edge machine learning are focusing towards the true wearable sensors. My research shows that technology is at a tipping point, a point where technology is getting good enough, with smaller and cheaper solutions, to stop the extreme transmission of raw sensor data, and instead deal with it in the sensors where the data originates. This flips the paradigm upside-down.

5.4.1. Artificial Intelligence in the business model.

Artificial intelligence in business and operating models can give companies strong competitive advantages, since AI can enable new value propositions, new ways of delivering the values, new ways of creating it and it might change cost and income models. The first major point to make is that algorithms does not need a coffee break and works 24/7 without getting tired, they are unbeatable at some types of tasks, specially those who are repetitive, and they are always precise. A sensor for example, will continuously track biometrics, and will immediately see if something is abnormal, and it can do this on hundreds, or thousands, of persons, animals or fish at the same time. This is completely different from what nurses, fish farmers, shepherd and farmers can do. Such sensors haven't been available so far, but as this research shows, we are getting there, since the paradigm shifts to true wearable IoT sensors and object-centric IoT services. Ultra-low power hardware, and optimized machine learning algorithms, allows for moving AI to the edge device, in a fully distributed way.

But AI on an edge device, computing on sensor data about a persons biometrics and behaviour, cannot be compared to AI working on relations between persons, in the service core. Therefore the characteristics and strengths of AI also changes. It becomes different.

In the Cognitive Care IoT concept, there are no central machine learning model, instead local machine learning models gets distributed to all the cognitive IoT sensors. This will affect network effects, learning effects, long tail effects and other effects, some positively, and others not. First of all, machine learning gets closer to the capture point of the sensor data, and closer to the cognitive object. To illustrate an example, this can give advantage in terms of training the models, since the cognitive object or its caregiver can be involved. This in some way breaks the principles of wearable computing (Mann, 1998a) by interrupting the wearer, but at the same time it helps personalise and creates trust which is also important (Liu & Tao, 2022). Moving machine learning closer to the cognitive object, allows for gaining better knowledge about it too. This can become valuable when figuring out how to use the long tail effect. On the other hand, moving machine learning to the edge, also moves it away from the network connections and network effects, which is important for sharing value, and learning from others. Cognitive objects are unique, but also share a lot of parameters with others in the same species, such as body temperature, which can be used to learn about abnormalities, and discover for instance epidemic or pandemic diseases. The network effect, learning effect and long tail effect will be described closer. In some aspects, machine learning to the edge, brings positive value, while in other aspects, it brings a challenge. Training the local models seems to be where the research front is at the moment. One framework trying to tackle sharing of learning is federated learning (Lim et al., 2020).

Any company works with a business model, which defines the company's way to create and capture value, together with the company's operating model which describes how the company delivers that value to its customers. AI can be a part of the value proposition which provides the product the customer pay for. It can be part of how a company deliver the value to the customer, and AI can help find new customers, interact with them, or to do personalised marketing to them. Or AI can be part of how a company creates value for the customer, either as a key resource or a value creating activity. As explained by (Iansiti & Lakhani, 2020), it is key to business and operating models to be capable of scaling, scoping and learning, and a way to do that is by using AI in order to overcome the constraints in current products and services, and to turn issues into opportunities. True wearable IoT sensors in an object-centric paradigm turns things around, since large amount of sensor data does not have to be transmitted any more, instead machine learning models gets fully distributed to the edge device and the sensors where the data gets captured. I will discuss what this means to the network effect, learning effect, and if it enables any long tail effects. Then I will seek to understand what machine learning might affect in the value proposition, and how it is delivered, created and captured from the customers.

5.4.1.1.The Network Effect

The network effect is the phenomenon by which the value for a user from a service depends on the number of users having the same service, either direct or indirect. Direct network effects arise when a given user's utility increases with the number of other users of the same sensor or technology, meaning that adoption of a product by different users is complementary. My proposed concept of Cognitive Care IoT does not operate with an active network, since the intention is to reduce networking in order to save power. Still there is a network in the concept. The question is how to use this network in order to create value for the service provider. On one side, this must be within the capabilities for the cognitive IoT service and the cognitive IoT sensor. On the other side, it also depends on the cognitive object and the caregiver regarding their needs.

There is a balance in this, especially in the early days of machine learning on the edge; on one side to reduce communication, to get small and cheaper batteries (maybe remove them), but on the other side there is a need for communication between the caregiver and the cognitive IoT service, to inform about events, abnormalities or patterns. But there are also needs to train and personalise the machine learning models, to make the sensor more accurate on more patterns.

In the beginning, training and personalisation is likely to happen in the cloud, since it requires a lot of power. But there are already frameworks which have a baseline model in the cloud, and uses all the distributed sensor nodes to update the cloud model. Due to the network effect, the more users, the faster it can learn. In this perspective, the network effect will depend on how the training framework is designed, the capabilities of the cognitive IoT service and sensors, as well as the needs from the cognitive object and the caregiver.

Indirect network effects arise when there are at least two different groups that are interdependent, and the utility of at least one group grows as the other group(s) grow. For example, the cognitive IoT sensors intended for one group of cognitive objects, may become more valuable to another group. Maybe sensors can be trained on dogs in a pet care service, where there are plenty of access to training data, but later transferred to wolves in a wildlife preservation service, where there are no access to training data (Bence Ferdinandy, 2020). Or the development of a fitness tracker can be both in hardware, algorithms, training methods and frameworks, or regulation, can develop into an elderly care sensor. Or as in the example with trying to develop a stress and emotion tracking technology, suddenly had a solution for detecting epileptic seizure to alert a caregiver to help immediately, which ended up FDA approved as a commercial neurological product as healthcare products (Empatica, 2022).

As a general rule, businesses that rely on weak network effects, at a time when there are technology with strong network effects entering the market, will have much less sustainability against competitors, while companies which make use of strong network effects and increased market concentration, can claim a more substantial competitive advantage.

5.4.1.2.The Learning Effect

Generally, the more data used to train and optimise an algorithm, the more accurate the algorithm's output and the more complex the problem that the algorithm can be applied to solve. With Google's search business, for example, the more searches conducted by users, the more (and more quickly) Google's algorithms can figure out common search patterns, and the better the service will become. According to (Iansiti & Lakhani, 2020, p. 127), the accuracy of most algorithms rises with the square root of the number of data points, at least for a while, and then levels off as the algorithm is fully trained. The square root law is an approximation, and in the case of algorithms that operate in isolation, accuracy does not improve that quickly, because most data points gathered are not uncorrelated. In the case of AI in the edge, it becomes a significant point on how the algorithms are trained. As described the edge devices are constrained, and the paradigm of object-centric IoT service are constructed to use the network as little as possible, to save energy. And since all cognitive objects are unique, and personalisation is a need for the users to trust the service (Liu & Tao, 2022), it becomes a challenge how to train the local models. This challenge is also an opportunity for business.

These days, there are different directions in research on how to increase accuracy, while reducing the models, and figuring out how to train the algorithms with access to little or no labeled training data. One way is to let all edge devices participate in a distributed training (Lim et al., 2020), anther way is to mimic the human brain with neuromorphic processors and train the model while it runs (Covi et al., 2021), or it can be done in a cooperation between human and machine (Zheng et al., 2017). Respondent B also mentioned cooperation between a dog owner and the service, by asking the caregiver to verify and share learning, on what the machine learning algorithms discovered.

This is where the research front seems to be at the moment, working on frameworks for efficient learning and training the network, within the constraints of wearable IoT sensors, and object-centric IoT service, particularly for cognitive objects. This is also where there are large opportunities for business. And like with other markets which gets AI and algorithms in the business models, there are possibilities for a winner-takes-it-all market. The reasons for this are the combination of network effect, learning effect and the understanding of the constraints and requirements for the wearable IoT sensor service. Even though AI, when put in system, can create very strong competitive advantage, and since the various sensors is constrained, especially to achieve battery-less, then they need to be highly optimized in terms of size, cost, features, practical use, and security. This opens up for business model innovation on the value proposition, value delivery, value creation and value capture. And just to bring the risk side into the equation, when trying to achieve the network and learning effects, there are risks for the trained models to become biased, or to drift with for instance trends, phenomenas or environmental factors. Therefore, most model training is likely to happen in the cloud in the beginning. But that is also a business opportunity, since personalised models must come at some points. The question is how it is put in system, how it uses the network to train and learn. In the long term, the bigger the sensor network, the greater the scale, the more learning that is available, and the greater the value.

5.4.1.3. The Long Tail Effect

As is defined by (Anderson, 2006) as the long tail is a statistical pattern of distribution that occurs when a larger share of occurrences occur farther away from the centre or head of distribution. This means that a long tail distribution includes many add-on values that are far away from the original value. In this context the original value is the information from the *cognitive IoT sensor* to the *caregiver* so that he or the *cognitive IoT service* can provide necessary care to the *cognitive object*. This can be information about biometrics to set a diagnosis or provide medical assistance, it can be information about eating in a fish farm to adjust the feeding to a better state, or it can be information about general condition for a dog so it can get treated for cancer. This is the original value.

The long tail effect is being used in statistics and business, but in many different perspectives. The two most obvious for the Cognitive Care IoT concept, is in Value Creation and Value Capture. In a user-driven innovation model, services can rely on users of their products and services to do a significant part of the work. Users want products that are customised to their needs, and in my context the caregiver is the user, and personalisation is needed, both for accuracy but also for trust (Liu & Tao, 2022). They might be willing to participate in the training of the sensors, which creates value for the service. Another way of creating more value in the service of caring for a cognitive object, is to enable more partners to share their value in the service, and to give them accurate access to caregivers according to the cognitive objects needs. In a case where for instance a dog gets infected by ear mites, the cognitive IoT sensor might discover symptoms such as scratching and head shaking, then the cognitive IoT service can ask the dog owner (caregiver) to check the ear for dark wax and maybe inspect the dog from scratch marks and rash around the ear (Weir & Ward, 2022). If the dog owner confirms, this becomes valuable information in learning, as value creation in terms of participating in user-driven innovation, but this is also where the marketing long-tail comes in, since the cognitive IoT service can automatically suggest sending a shampoo from the online pet store, or making a reservation with the veterinary to check the dog. This is more value for the caregiver, and new value creation for the cognitive IoT service, since it might not have been possible to keep stock of all kinds of products to meet all the conditions, and it could be difficult for the service to have a vet standing by. Given the diminishing cost of communication and information sharing, long-tailed user driven innovation will gain importance for businesses. This will indirectly also affect value capture, since it becomes possible to innovate in the business model on how to capture or share the new value. This is possible to transfer to other types of services, in fitness, fish farming, wildlife preservation, health care or elsewhere, with products, services or insurance.

5.4.1.4.Digitalisation and Scaling Effect

Most of the services caring for cognitive objects involves personnel in many stages, to do analysis, diagnosis, medicating, feeding, nursing or only having social contact. And in all of this, in all kinds of caring, the demand for efficiency is also very high. We live in a world with an increasing population, which also lives longer, we expect and elderly wave which we need to care for (Rowe et al., 2016), we need to grow food to this population without over-harvesting on the planets food chain. We need to make sure the personnel works efficient, using their expertise in conducting the care, and to establish a good connection between the cognitive object and the caregiver. This is where digitalisation comes in, with the help of AI. To take over more of the repetitive, information collection, which can be done by sensors, detect patterns and events within the data from the sensors, and digital systems to enable the caregivers to have time to be social, or help them understand what is needed in the care service. There are big opportunities to automate and digitise clinical testing, diagnosis, monitoring, and services which previously has been local with personal interaction, where the caregiver needs to know about everything, it could be split in professions instead. In terms of business model innovation, the addition of machine learning to wearable IoT sensors, opens up possibilities of digitalisation of tasks and service which earlier hasn't been possible.

5.4.2. Business Model innovation using Osterwalder

One of the most common ways of looking at business models is through Osterwalder's Business Model Canvas. It can be broken down to four main categories, in value proposition, value delivery, value creation and value capture. I will discuss how machine learning in wearable IoT sensors can open up new possibilities to innovate in each of these categories, before looking at how business models have shifted before, and if a new shift is coming. My proposed Cognitive Care IoT concept includes the Caregiver as a central part in the Cognitive IoT Service. Before going into the categories of Osterwalder, it is important to discuss the caregivers role, since it is apparent that it is a multi role.

5.4.2.1. Caregiver as value creator

The machine learning algorithm that works in the sensor to provide information to the caregiver, does that 24/7 without getting tired, and it is extremely precise. The high precision is a huge advantage, but can also be a challenge. Since algorithms don't have any common sense compared to what caregivers have, they can only repeat exactly what it has seen and done before. The caregivers roles are several as indicated with red squares (fig.32).

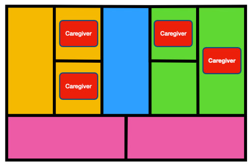


Figure 32: Caregiver as value creator

On the left hand of the Osterwalder model, we can see Value Creation (yellow background), with the caregiver plotted in red squares participating in two of them, either as key activity in the actual service, such as providing medication, changing the feeding, nursing the elderly, coaching the athletes, or to be a key resource for the service, if for instance participating in training of the sensors by for instance interacting with the algorithms to validate classification, and help the algorithm with common sense.

On the right hand of the Osterwalder model, we can see Value Delivery (green background), also showing the caregiver plotted in red squares in two places. On caregiver role is in the customer segment, if the caregiver receives the value proposition, such as with a fitness tracker or many other consumer type of wearable IoT sensors. The second role is in customer relationships, since the caregiver which provides improved care, also creates trust and satisfaction with the cognitive objects that is receiving the value proposition. An example is the mother that writes back to the inventor of a ML sensor service, to say thank you for providing the technology that saved her daughters life (Picard, 2019). The mother, in the role as a caregiver provided a *key activity* when rescuing her daughters life, but she also built a strong *customer relationship* back to the inventor or the service provider. The inventors first reaction was to get worried about all the «what ifs…», the battery could fail, the network could go down, or the sensor could be worn wrong. That would have been fatal. But it raises very important aspects, of safety, trust, ethics, use, quality or security. The caregiver could also have a role as a «guard-rail» to the service, since machine learning is probabilistic, and not 100% accurate. The caregiver has a responsibility to the cognitive object anyway, so being a «guard-rail» could make sense. Important to remember; «trust makes blind» so the service must take care of that.

Caregivers have multiple roles, depending on what the service is for, which constrains and requirements, and for which cognitive objects.

5.4.2.2. Value Proposition

The value proposition (fig.33) is new value increments which is provided to the defined customer, in terms of removing *pain point* for the customer, *fixing jobs*, or adding new *gain points*. The proposed Cognitive Care IoT concept flips the paradigm upside-down, since now sensor data needs to be sent to the cloud anymore.

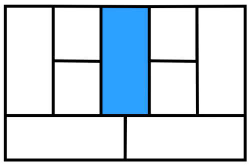


Figure 33: Value Proposition

IoT was initially created as M2M, communication between machines connected to network and power, then wireless IoT sensors with its constraints came along, and created a lot of *pain points* since sensor data had to be sent to the cloud for computing power. Since the wearable sensors are becoming true wearable and service is becoming object-centric, privacy is no longer an issue (this does not mean that there are no ethical issues anymore), with very long battery time, or in some cases without battery. This means removing *jobs* since the need for frequent battery charging, gets much less, or gone. Maybe the biggest value add, is all the new *gain points* as a result of adding machine learning to the sensors. The distributed machine learning models will immediately start to find abnormalities and patterns in the data, and able to classify events and symptoms compared with the data it got during training. As innovation continues, this will become personalised and the sensors will start to classify based on the cognitive object, and not the general model. Once the local machine learning models starts to get personalised, they will provide information about the cognitive object, since they can «interpret the body language», and not just collect information about the sensors, like before, which does not say anything about the cognitive object.

5.4.2.3. Value Delivery

By moving machine learning to the wearable sensor, all the sensor data can be inferenced locally, which means the service value can be delivered anywhere, instead of only on specific places (fig.34). Together with very low energy usage, and much less need for charging, these wearable IoT sensors can be

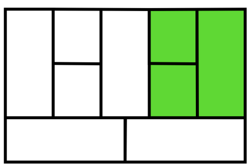


Figure 34: Value Delivery

placed on almost any cognitive object, and the cognitive IoT service can deliver the value propositions anywhere without being interrupted by lack of infrastructure. This is of course defined by how the cognitive IoT service is set up to use its network to include both delivering the value, and training of the local machine learning models in the cognitive IoT sensors.

They can deliver the value propositions without sending sensor raw data it will help provide trust with the user, a very important factor in the customer relationship.

Since the sensors in many aspects become self contained, they will also become very easy to install. They will get smaller and lighter, so it will be easier to attach them to the cognitive objects. The forms and shapes of such sensors makes it even easier, as stickers for the skin, clothes, socks, rings, bras and many more. Distribution and onboarding will not require other than a web browser and mailbox, as simple as that. Network and learning effects, long tail effect and digitalisation can play a big role in value delivery, as described earlier.

If comparing cognitive care IoT services with other care services, there are strong competitive advantages, and the caregiver can, by using the information received from the service, take caregiving to the full potential. This can create a huge benefit in the customer relationship and create strong relationships in the value delivery. If the total energy used by the cognitive IoT sensors, is less than it harvests from the surrounding, it becomes battery-free, and creates a huge competitive benefit as environmental friendly.

5.4.2.4.Value Creation

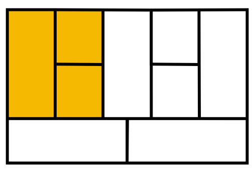


Figure 35: Value Creation

A successful business will continue to create new value (fig.35), to either satisfy customers, or improve own operations. Either by improving the value proposition, or the value delivery, or making the operational model more effective. Value can be created by making sure the cognitive IoT sensors become more accurate, personalising them, and adding new patterns or events for them to recognise. Some of this depends on the framework for learning, but one way to create more value is to involve the caregiver to participate in sharing expertise and help learning.

The caregiver's role is as previously described to use the information from the sensors to conduct the actual care, as a key activity. This is the largest value creation in the cognitive IoT service. For instance a sensor in socks can diagnose a patient based on how he strolls and may suggest a change in walking, or a new footwear. Or it can be to get information from the cat collar about a high energy impact, and then locate the cat and get him to the vet and save it. The cognitive IoT sensors can provide high value information, which gets inferenced and analysed, enabling the caregiver to heal, help, save, improve or prevent situations. Another way of creating value for the caregiver is to be a key resource, and take part in training the sensors, so they become more accurate, to detect more events and patterns, and to make reason from abnormal situations. This is important for personalisation, but also if using the network and learning effect, to share learning with others.

A third way of enabling more value for the customers in the cognitive IoT service is to enable partners or additional value into the value proposition. Since cognitive IoT sensors will be able to learn from the cognitive objects about events, patterns and abnormalities, it is possible by using the long-tail effect to enable more value for the customer, but also more business for the company and the partners. It is previously mentioned about the example with ear mites, and the introduction of shampoo or a visit to the vet. Or if the cognitive IoT sensor is a smart bra that can detect early signs of breast cancer then the cognitive IoT service can recommend a visit to the hospital to get a health check and diagnosis. Or if the cognitive IoT sensor is an emotion tracker that can detects stress which can offer a visit to a spa and wellness service. Or if cognitive IoT sensors detects early signs of Covid or pre-diabetes, an isolation or a diabetes information program can be started. The additional value created by the knowledge about the cognitive objects behaviour can be connected with a valuable offering, service, product or treatment.

But in the end, there are always the question regarding the trustworthiness of the sensors. There is a fine line, since machine learning works with a certain accuracy. This was also highlighted by respondent B. But the cognitive IoT sensors can be used as valuable information as symptom descriptions to show to the doctor or the veterinarian, so they can make a proper diagnosis. Accuracy and trust needs to be established gradually, hand in hand.

In terms of fitness and obesity, one value creation can be gamification of activity. The cognitive IoT sensor can issue new badges or digital credits, as the cognitive object earn a new reward or level. This can be added to fitness trackers, kids trackers, health trackers, dog trackers (since usually the dog owner also needs to walk). Either it can collect steps and burned calories, or it can open more of the map, as you visit new areas just the way Livingstone explored Africa. It is important to map the social networks and understand the potentials and figure out if there can be customers and value creators to connect.

5.4.2.5. Value Capture

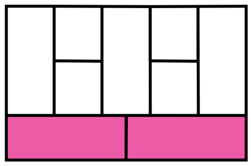


Figure 36: Value Capture

In recent years, because of the ease with which digital networks can connect various types of users and businesses, options for value capture (fig.36) have grown dramatically. Optimising the value captured by a business can be a significant undertaking, drawing on economic analysis, strategic thinking, and technological capabilities. Digital value capture technologies allow for careful usage metering, sophisticated pricing algorithms that react to product inventory conditions, and even outcome-based pricing models. The key here is to realise that network effects open new types of value capture options. Take, for example, a system that has direct network effects; some companies may find it useful to charge customers for the value the companies are generating by giving customers access to the network. In simple terms, the business value is about what comes in, versus what goes out. Over time, a business can decide to spend more, to build momentum to gain more. Businesses with the opportunity to bring AI and machine learning into their business models, also have the opportunity to create a competitive advantage by using the network effect, learning effect and long tail effect, together with digitalisation of the operation model. But since these effects might behave different since machine learning has been moved to the edge of the network, all the internal business value and their streams should be mapped. When mapping values, it is more than just cash. Value sources, positive and negative, should be located, and their type of contribution should be marked. A value can be a cost or an income, it could be good reference customers, or on the other side bad reputation. Sometimes it is value as cash, or it is value as relations, as resources, or access to something. Since the Cognitive Care IoT concept is about relations between cognitive objects, the cognitive IoT service and their caregiver, important values can also be traditional values, secular-rational, survival or self-expressional values (WVS, 2020), as well as ethics such as trust, loyalty, environmental focus, child safety. To exemplify, if sensors are without batteries, this will have a high environmental value. This value cannot be measured in cash, but can if connected to the right customer segment become cash in the future.

This brings me to the next point of bridging social networks together, maybe they can learn from each other, or service each other. Users in a fitness tracker service might be of additional value to health care. Another way is bridging together a customer segment with a partner that can offer additional value through the cognitive IoT service. For instance the cognitive IoT sensor in the form of a sock discover signs of odd strolling when walking, can connect physicians to offer a treatment or a preventive solution. Or a cognitive object can be linked to other cognitive objects which share the same symptoms. Network effects, learning effects, long tail effects and digitalisation enables a business to gain competitive advantage when bridging various value sources and creating new value streams. When mapping the value streams, the most obvious is the direct income sources. Value increments typically based on the value propositions, such as removing pain points, fixing jobs and adding new value increasing gain points. The question is how much are the customer is willing to pay for this. Before making the pricing strategy, it is also necessary to locate the indirect incomes, which can be additional sales from partners as a result of the long tail effect, or as indirect payments from government, donations or stakeholders. This depends on the type of business model the business use. The digitalisation allows for optimisation in operations, and in some service it is possible to compare with existing services, for instance in elderly care, to understand how much cost is reduced because of the Cognitive Care IoT concept.

There is also a question if the value captured is from 1st (consumer), 2nd (industrial) or 3rd (society) level. These factors will play a role in determining how to price the service. If it has a direct *consumer value*, such as fitness tracker, dog tracker, the service is used to amuse, or care for one self. If it has an *industrial value*, such as fish farming, football league coaching, or sheep farming, the service will be paid indirect from another business model, which uses the service to optimise their operation or to improve their product. If it has a *society value* such as of welfare, environmental, political or wildlife preservation, the service will be paid indirect by society.

5.4.2.6.Business Model shifts

Never before has the world of business changed faster than today. Disruptive technologies enter the market faster and faster. It is not long ago, that the internet was invented, with the opening of the World Wide Web by Tim Bernards Lee (Clark, 2022). When parents today talk about technology or business that was common only 10-20 years ago, their kids does not have any idea about what they are talking about. Not many kids know what a *tape cassette* is, or a *floppy disk*. They have never heard the *dial tone*, and certainly have no clue what *snow on the TV* is. Twenty-five years ago, only a very small group of people in the world were connected to the web. Early 2022, more than 5 billion people, or 63% of the earths population, were connected (Kemp, 2022). Today, it is possible to make contact with 67% of the people on the earth in less than 30 seconds. Twenty years ago, the major innovation was the Internet. Ten years ago it was the smartphone, and today, it is about the algorithms. The dynamics in the world is changing fast, and accelerating. Businesses and business models must adapt, or they risk dying. There have been many business model shift through time, where a business innovate in the way it operates. Just think about how music has changed from LP, to cassette, CD, mp3, and now streaming. The same thing has happened with books stores, travel, taxi, shopping, business meetings, and much more. The point is increasing value, for the customer, at lower cost. There has been some shifts in business models which are more significant than others (Pijl et al., 2021). One, is when the business model changed from products to «The Service shift», where revenue changed from one-off to recurring. Others are «The Stakeholders shift», «The Digital shift», «The Platform shift», «The Exponential shift» and «The Circular shift».

This research suggest that a paradigm shift is on its way, from cloud centric with large AI models, to object-centric with local machine learning models, which opens up for a shift in business models too. Previously, business models have shifted from physical to digital, from products to services, and from incremental to exponential. All of these shifts gave new opportunities in ways we paid for the values we received, the way we consumed the values and the way we found and got exposed to the values. This time there are combinations in these, and we bring in a new role which is the caregiver. Some might say the caregiver role is part of creating a service, but on the other side this role is also partly the customer, which gets pain points, gain points and jobs solved. Since some of the value gets created by the algorithms in the sensors, there are definitely a business model shift happening. The local machine learning can detect events, patterns and abnormalities that can generate business value for the company and service value for the customer. This can be called «The Smart-Care Service shift»

5.4.3. Other Business models and Strategies

There are also other strategies to follow when developing business. My research is basing the discussion regards business model innovation on (Osterwalder, 2004), which is a very recognised model. But there are ways of describing it, in particular together with strategy, that might suit *new companies* and startups, a strategy which can be good for creating *new market*, or a strategy for bringing *new technology* to market. These can be relevant in a paradigm shift and business model shift.

A simple way of describing a business model is by using the Lean Canvas (Maurya, 2022), which can be easier for startups, since it focuses directly on the key elements first, and works on solving the most uncertain parts first by understanding the customer needs and problems. This business model strategy simplifies by directing focus to the solution, and the keeps the product-value fit close. This might mean rapid prototyping, and a quicker and lower cost entry for startups. This is specifically relevant since the paradigm shift previously described also simplifies the service infrastructure, by making the sensors agnostic the network. Since the Lean Canvas is very focused on the problem and solution, it might be more challenging to map out the network effects, learning effects, and long tail effects. On the other side it might be easier to establish new markets and market conditions.

Another way of doing that can be by reconstructing the market boundaries with a Blue Ocean Strategy (Kim & Mauborgne, 2015). This means to increase value where it matters most for the customer, reduce what matters the least, and redefine the service in a Blue Ocean Strategy Canvas. In terms of the Cognitive Care IoT concept, the Caregiver is added as a new role and value in the service, and the service brings valuable information to provide care to the cognitive object. The costs in operating this service can also be low, which can create a competitive first mover advantage. The Blue Ocean Strategy is very much about staying ahead of competition, by offering low price, maximising the value for the customer, and minimising the costs of operation for the company.

Another important strategy to be aware of fits quite nice together with Osterwalder is the technology marketing strategy of «Crossing the Chasm» (Moore, 2002), since the Cognitive Care IoT concept is about bringing new technology into the market, maturing it while establishing a market foothold and enabling partners to offer a complete offering. This means selling to innovators, and early adopters, while building reference customers as trust, at the same time as establishing the total offering for the customer.

The possibilities for using the new technology are endless, as stated by respondent B. From the market side, the need is also extreme, as described in the introduction chapter, within welfare, elderly care, wildlife preservation, fish farming, pet care, fitness, or dealing with overweight, diabetes, covid and other diseases and issues. There are still plenty of research needed to solve ethics, service implementation, or service integrations. In other words, the conditions are getting optimal for business model innovation.

5.5. Ethics and sustainability

IoT and machine learning continues to establish useful ground, by becoming a key part of wearable IoT sensors, with the research front seemingly working on how we can personalise these tiny algorithms so they adapt to each one of us, in order to understand us better, currently with the intention to serve us better. That raises some critical questions about the way we design and use this artificial intelligence.

Let’s take one step back. Collecting data raised a privacy issue, since the raw data had to get labeled and tagged for use in training. This teaches the AI algorithms to find the same data again, to a certain accuracy. The next problem is if, or when, that also gets linked together with personality. This should not happen for ethical reasons, but it does, such as when people gets tagged in images in newspapers, in Facebook posts, Instagram posts, LinkedIn profiles, Snap facial warps. Then the large centralised model have what it needs to actually revers this process, by taking an image and returning the name of the person. According to Vox (Fong, 2019), if you upload a photo to Googles reverse image search, you will get results where that same image, or similar composition and colour, has appeared. The leading search engine in Russia called Yandex has reverse image search too, but it does not only search for similar images, but it looks for the same face. Simply by feeding in an image, you can get back the name, and other images the same person has appeared. The difference is that Yandex has its facial recognition turned on. In this case, surveillance gets automated. To stretch this idea, if this happens, then it can, and possibly will, be misused to get political power, military power and police power. Maybe Steve Mann’s sousveillance (Mann, 2002) using personal body cameras will not be of any help then. The same thing is the case with voice recognition, since Siri, Alexa and OK Google to a certain degree can recognise your voice when trained. Luckily these algorithms are used as wake words, and therefore a part of a local AI model. The same thing with face recognition to unlock the phone, or fingerprint scan. But if we imagine wearable sensors collecting biometric raw data in a cloud centric way, towards a large model, where the AI algorithms will get trained to recognise the biometric footprint, and if that also gets tagged and linked to a person, then we have the same privacy risk. One thing is what companies and governments promise, but things change quickly with new political power, war and pandemics. As this research concludes, a paradigm shift to object-centric service with local machine learning in the wearable IoT sensors, will help overcome issues with data latency, network dependency, short battery lifetime and frequent recharging, sensors size and cost. It will also democratise AI, since distributed machine learning models eventually will be optimised to work on only one cognitive object, and not on the whole population of sensors. This means large firms like Facebook, Google or Amazon will not be able to build their large cloud machine learning models anymore. Since raw sensor data does not have to be sent to the cloud anymore, it will remove the issue of privacy, at least on the data level. Companies add local machine learning to their products, and as respondent B states:

> *«We enable them to work with data, and develop new features in those products, using machine learning. So it's about democratising machine learning, and what we do, we provide all the tooling in the Cloud, for all these engineers».*

Contemporary technologies of networked things and artificial intelligence, as well as data capitalism they have made possible, differs from the logic of traditional services. New values from technologies that continue to «learn» while in use, and adapting over time (Giaccardi & Redström, 2020). The issue is how it uses the network to share learning, and what part of the model is shared. This means the issue of privacy is no longer on biometrics and raw sensor data, but rather on the next level on what the machine learning model has classified and detected. Services that figures out the network and learning effects is likely to gain competitive advantage. Sensors are constrained, but the process of training can be shared. Another important question is how much of the personalised model gets shared. The network will also be used for communicating what the personalised machine learning models detect. The more personalised they are, the more accurate they get. And that is a good thing, since the service then will be able to offer best treatment, or recommendations, to us. With today's advances in machine learning in cognitive sensors, and the better they get, a consequence can be that we allow the algorithms to make consequential decisions for us, including those related to access to credit or medical treatments etc. Algorithmic decision-making processes might lead to more objective decisions than those made by humans who may be influenced by prejudice, conflicts of interest, or fatigue. However, algorithmic decision-making has been criticised for its potential to lead to privacy invasion, information asymmetry, opacity, and discrimination. (Lepri et al., 2021). A new value can be that a cognitive IoT sensor detects something and due to the long tail effect, it triggers the cognitive IoT service to automatically send an offer. Imagine the health tracker detects Covid-19 , and sends an offering for a special medallion that supposedly will cure the person (Berglund, 2022). The bottom line is, once we start to get comfortable with the cognitive IoT services, and we establish trust, it can be easy with unethical intentions to exploit it. Once misuse occurs, the users will find out, and stop trust the service anymore . In other words, if not dealt with, there is a road to unethical misuse.

A research paper (Giaccardi & Redström, 2020) suggest that we must learn to design with, and include, internet of things, machine learning, and artificial intelligence, in order to enable functionality and performance for the interest of people and the environment, which will require broadening our views and balancing human and nonhuman perspectives. Instead of waiting for a better understanding of the impact of algorithmic logics on current regulations and for review of legal frameworks and professional ethics, designers might already move forward by thinking towards human values, social norms, nuanced interests, and aspiration of specific context in which they come to operate and «respond». We need new design practices, move beyond blind spots of human-centred design, and address the expanding universe of algorithms, casting them as partners in a more-than-human design practice. With the vast amount of human behavioural data, combined with advances in machine learning, we are enabled to tackle complex problems through algorithmic decision making process. But in order to do so, we need to focus on existing risks related to the use of algorithmic decision-making process, and make sure we have privacy, power and information summitry, algorithmic transparency and accountability.

According to participant B, in certain cognitive IoT services, guard-railing and regulation is a mandatory, such as in healthcare. And companies working with machine learning should endure on core values and «tech for good». The caregiver can be used as the «guard-rail», since this role is already trusted to care for the cognitive object.

It is important that there are good enough routines when training the models, and with validating them to ensure the correct quality and accuracy. But it is also important to remember that the algorithms are probabilistic in nature, and therefore there needs to be a guard-rail around them that suits the application. As stated by respondent B:

> *«And autonomy, we need to be careful with that, with good guidelines, and guardrails, when you are not in control, yeah because, remember that machine learning in particular, is probabilistic in nature, so you may have probabilities of things happening that you have never seen before. We need to make sure there are some rule-based guardrails around the probabilistic algorithms.»*

The bottom line, it is not AI that is unethical, it is the choices we humans make on how we implement them, train them and use them. In fact this is no different from raising a child, we all understand we should train them to become good members of society, it is the same with machine learning. And machine learning is like other technology. Hydrogen is key to life, and an energy source, but if used unethically, it can also be very dangerous. In my opinion, the concept of Cognitive Care IoT can be a powerful tool, but we need to establish ethical attitude and practices.

5.6. Cognitive Care IoT - My Narrative Portrait

This research used narrative inquiry as a method for collecting qualitative data from two participants, which represents leading technology companies for wearable IoT sensors; one microcontroller vendor, and one machine learning platform vendor. Their narrative stories was recorded and analysed. Based on their told stories as lived experience, I conducted a wide literature search of 239 pieces of literature, such as journal, press releases, news, industry reports, product reviews, research articles and conference presentations, which was analysed and discussed together with the narrative stories. This was then compared and discussed in light of recognised theories, before conceptualising and discussing business model innovation and ethics. This formed the foundation for my restorying to my narrative portrait. My research concluded with a couple of common denominators. The research has been limited to cognitive objects, which in terms of a vast number of unique possibilities isn't really a limitation. Cognitive objects represent everything from blue-whales living in the big oceans, to all kinds of humans, to small insects. In this sense, not much of a limitation. But in technical terms, this limitation excludes most of the IoT we know of today, such as machines, cars, computers, phones, and other equipment. Since true wearable sensors has to meet the strict definition (Mann, 1998a), and «blend in» on the cognitive objects, they have to be small and light, while at the same time not have to be taken off too often to be charged, and have to be capable of communicating. Wearable sensors are constrained devices, in challenging environments. Since the technology for wearable sensors is in its infancy, not many wearable IoT sensors meets this combination yet, but it's coming. With this in mind, my scope is reduced. With all the research going on in hardware, algorithms, training, energy harvesting, sensors, and radio communications, many more cognitive objects will get serviced by true wearable IoT sensors as we go forward. Additionally, there are also lots of research going on to understand how sensors can inference on various kinds of cognitive objects, in various conditions such as falling, limping, infections, fitness, sleeping and much more. Scientists are figuring out how different features such as body signals and movements can be interpreted into more valuable information to use for treatment, diagnosis, prevention, recovery or caring for a cognitive object. This has just begun. The complete proposed Cognitive Care IoT concept (fig.37) shows the outer layer as the actual care between the Cognitive Objects and the Caregivers. Sensors will be custom made for a particular care service, either as consumers verticals such as fitness or self care, in industrial verticals with harvesting or farming, or in community verticals such as welfare, wildlife or environment. In case of care service for consumers, the Cognitive Object and the Caregiver can be the same person, but that is irrelevant for the technical side of the concept.

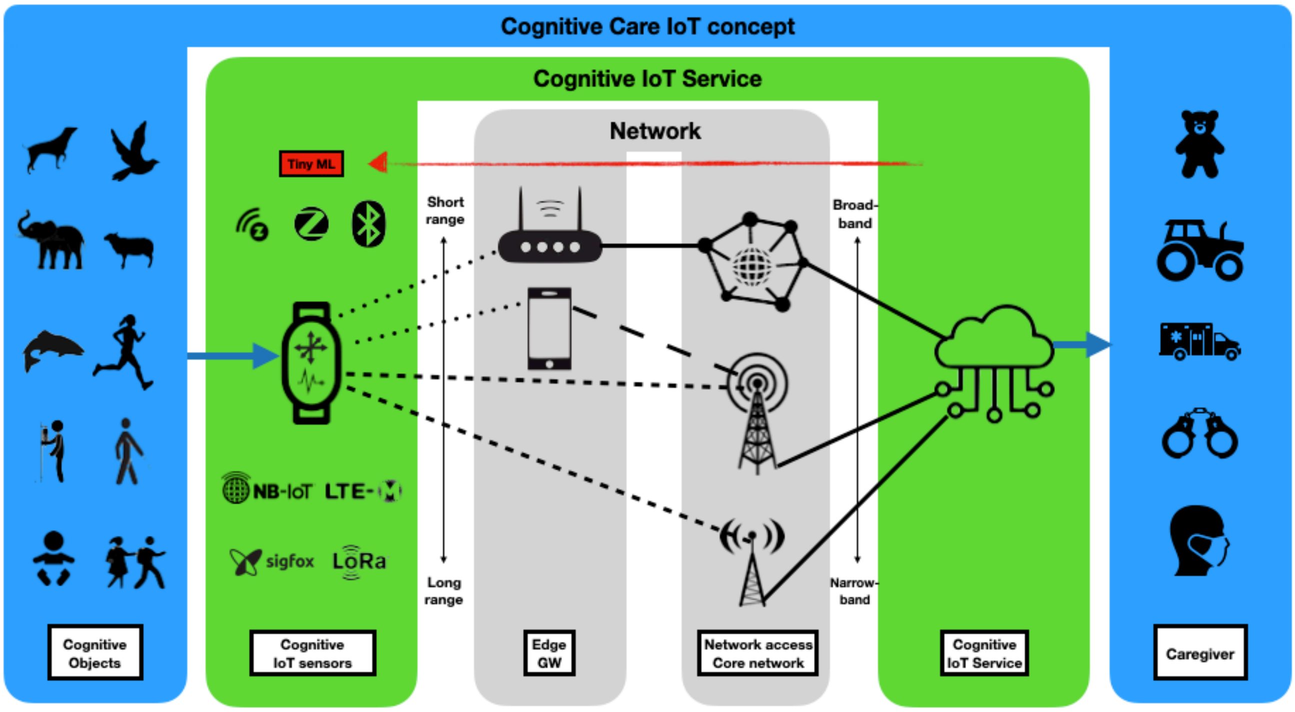


Figure 37: The Cognitive Care IoT concept

Technology is now at a tipping point, where high performing microcontrollers execute machine learning at low power, which results in stopping the massive transmission of raw data away from the sensor, since reasoning can be made directly by the machine learning algorithms, which will reduce the use of energy drastically. Some sensors are already at the point where they can remove the battery completely, and make them much smaller and cheaper, as well as making them environmental friendly. But not all sensors can become completely battery-less, due to the service requirements, but they can get much smaller, while also lasting for much longer than before; weeks, months or years instead of hours or days. This is set by what the Cognitive Object and Caregivers need, versus what the Cognitive IoT Sensor and Service can deliver.

Cognitive IoT Sensors already come in many shapes, specifically built and adapted to the Cognitive Objects they are intended for, in the form of socks, e-skin, bras, tags, or jewellery rings. They are made to blend in, and they will provide new benefits such as 24/7 operation, data from real life use, and not just only from artificial test. Once the sensors have gotten personalised, they will be able to detect events and abnormalities as they happen, which is very helpful for detecting epidemic diseases, cancer, injuries, or damages, so healing can get started as soon as possible. But they can also predict fall, heart conditions, diabetes and similar, based on pre conditions, so preventive measurements can get started. Cognitive IoT Sensors will be trained and personalised in the field, in some cases based on very little training data. Personalisation will get assistance from the Caregiver, since the Caregiver in most cases already have knowledge about the situation the Cognitive Object is in, which can be used to tag the abnormality the Cognitive IoT Sensor detects, to update the model, or help compensate if the machine learning model drifts. Since the Caregiver already is in some sort of responsibility with the Cognitive Object, and will have own motivation in improving the Cognitive IoT Sensor's precision, since that will enable the Caregiver to provide even better service to the Cognitive Object.

The Cognitive IoT Service talks over radio using the most power effective standard available at the time. Depending on what the service need, and how the service is set up, The Cognitive IoT Sensor will communicate events, predictions, abnormalities, or patterns, either direct to the service via long range low power radio, or short range to a smartphone or gateway, which will update the service. In case the network is missing, the Cognitive IoT Sensor will store the information until network becomes available again, which will make the Cognitive IoT Service agnostic to network condition.

The Cognitive Care IoT concept meets the definition of wearable computing (Mann, 1998a), even though it has just begun and there are still much to innovate. This means smart sensors and service can start reading all the body signals, and get the aid from tiny algorithms to understand what the bodies are «expressing». Some of these signals are biometrics and biomechanics, which can be interpreted to understand physical conditions. More so, according to the theory of emotions (Plutchik, 2001), emotions, or feelings, are likely to produce behaviours, either as motions or as changes to the body signals. Lots of research is currently put into understanding these behaviours in order to do cognitive sensing and establish care services for humans, animals, fish and birds.

For obvious reasons it is not possible to equip all kinds of Cognitive Objects with Cognitive IoT Sensors, since we are in the very beginning. The Cognitive Objects are very different, in size, habitat, movements, and since the sensors are very constrained, everything will be purpose built. In the light of business models, plenty of service verticals will be created, such as Cognitive Care IoT for farming fish, another for tracking dementia patients, or for tracking the dogs whereabouts and health.

The proposed Cognitive Care IoT concept is in line with the paradigm shift from compute in the cloud to compute at the edge, and the start of a new era, with true wearable IoT sensors, which are object-centric and focused on the cognitive object it is attached to. My objectives when starting this research was to contribute with more knowledge in this area, in order to handle future service needs in public health diseases, fitness, welfare, food production, environment and wildlife. The Cognitive Care IoT concept will enable the Caregivers to serve the Cognitive Objects much better.

The complete model (fig.38) when merging together Plutchik's model of cognitive and emotional process leading to behaviour (in blue), with the proposed model of cognitive and emotional behaviour sensing (in green), as described in chapter 5.3.2 and 5.3.3.

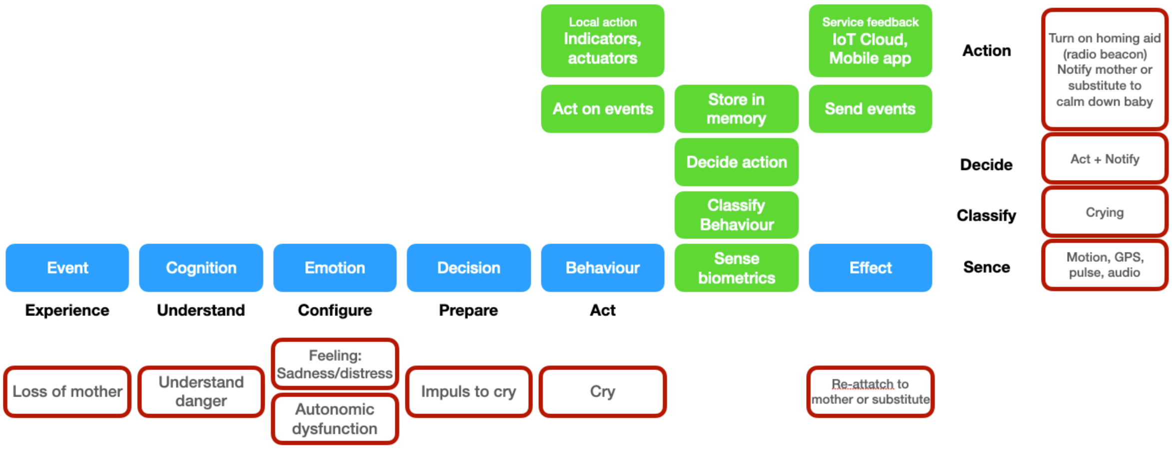


Figure 38: Sensing biometrics, to detect behaviour, and provide information to Caregiver

6. Conclusion

This chapter concludes what I have learned by working on this master thesis. Elaborative stories from two technology experts, study of other relevant research, product announcements, technology reviews, technical reports, webinars and industry conferences, are indicating the same trend and consensus.

This research concludes; ***the paradigm is shifting for wearable IoT***. The evolution of ultra-low power microcontrollers, sensors, battery and energy harvesting, will provide wearable IoT sensors with high performance at very low power. Additional techniques such as duty cycling (scatter power peaks) or batching (maximise sleep cycles) will reduce energy usage even more when the wearable IoT sensors gets configured for service and attached to humans, animals, birds or fish.

Research reports and products announcements shows huge advancements in relevant technologies for wearable IoT sensors lately, both from hardware and from algorithms. Some experts call it «Sensors 2.0», while experts I interviewed called it a «tipping point» for wearable IoT sensors. <u>This answers my first research question.</u>

Originally, machine learning as a concept, was not intended for small and constrained sensors, but recent evolution of hardware, together with heavy optimisation of machine learning to fit on the small wearable IoT sensors, stops the need for communicating sensor data over radio, which results in significant upgrades. The energy needed, will be significantly less, reducing battery size, cost and weight, while extending the battery time. With no transmission of raw sensor data, there is no privacy issue either, and the sensor will become agnostic to network conditions. The sensors are becoming ***true wearable IoT sensors***, and the service is becoming ***object-centric***. Research reports shows that the research front is focusing on how to train the local machine learning models in the field, how to personalise them to the object they get attached to, and how to share learning with other sensors. For cognitive objects, the researchers works on figuring out which features and body signals to connect machine learning models to, to detect behaviour and emotions from humans, animals, birds and fish.

According to experts I interviewed, it wasn't a question if true wearable IoT sensors would happen, but rather when it would be done. Products of this kind have already started to become available in the market, such as the Oura ring health tracker (Miller, 2022), also as jewellery (Gucci, 2022), and the Happy ring emotion tracker (Song, 2022). There are also commercial available medical grade products that is reported to have saved lives (Empatica, 2022; Picard, 2019). <u>This answers my second research question.</u>

The true wearable IoT sensors needs to be tailor made, to fit exactly on the cognitive object they intend to monitor, the service requirements, and it needs to be fine-tuned using the exact parameters the caregiver needs. There is no room for extra weight, size or cost. Cognitive objects can be generalised and grouped to humans, animals, birds or fish, since this defines something about its habitat, the sensors physical parameters, and necessary service availability. That's almost where the resemblances stops. At the same time, this is also where the business opportunity starts, since there will be many verticals to cover. Sensors will be made for a specific wearer, for instance a human. It will contain only the exact sensing it needs, it will be as small as possible, preferably without a battery, at least a small one. Then the sensors must be trained to match exactly the cognitive object, including personalisation. New innovation must figure out exactly how to use body signals and movements captured by the true wearable sensors, and present that to the various caregivers, which needs these new values provided in a useful way, as abnormalities, symptoms, trends or states. The caregivers can have multiple roles, both providing the actual care, or to help the service provider train and personalise the sensors. My research concludes that there are huge possibilities to innovate in the business and operation models. AI and algorithms have for the first time entered care services, with true wearable IoT sensors. The paradigm shift from cloud computing to edge computing, also opens up a ***possible shift in business models from «Service» to «Smart Care Service»***. This answers my third research question.

Moving machine learning from cloud to the edge, allows for technology companies to innovate with smarter and better services. According to one of the experts I interviewed, it actually democratises machine learning, with small local models, instead of large massive models controlled by the big techs like Amazon, Google, and Facebook. And since we don't move raw data anymore, privacy on that level is no longer an issue. But the question of ethics and security is not removed by that, it is just on a different level. When the local machine learning models gets personalised, they will need to be handled safely. Since the wearable IoT sensors will be able to discover and interpret behaviour, and eventually emotions, the security and ethics must be applied so no-one tries to exploit this unethically. With algorithms in the sensors, and a network between, strong techniques such as network effect, learning effect and the long tail effect can be used with potentially large business opportunities. This is a two edged sword, since we need good business opportunities to drive investments and innovations, but unfortunately the strong capabilities in algorithms and digital operations there are also a potential for greed and unethical exploitation. With this research, I want to shed light on the business opportunity, but also on the «Tech for Good» movement, which is a key to get users to trust such services and for service to unfold.

The progress that has been made in technologies for wearable IoT sensors has been huge, and we are now in the early days of true wearable IoT sensors, and the very first smart services are establishing. Both self-service for consumer services, farming for industrial services, and welfare and wildlife for society service. It is important to avoid misuse which leads to accidents, greedy business operations, discrimination, fraud and theft, since that will create distrust by users, which will hinder the use of this technology. I believe we need true wearable IoT services to solve our big challenges going forward.

To the question regards regulation, I am certainly not sure. Regulation might slow down the innovation, and it might hit wrong. But I am sure, that ethics must be discussed deeply, in order to find the right approach to it. And it will not be the same approach in a consumer fitness service, as in life dependent services in welfare. I hope my research conveys that there are many large business opportunities within the many verticals, but I also hope it sparks the necessary debates regards ethics and regulation, since trust is a key for such smart services to establish. This concludes my research topic.

6.1. Further research

The future is at the edge, that is where 95% of the data is captured (Anadiotis, 2021). This is also where the understanding of that data can happen.

The sensor hardware and algorithms are now powerful enough at a low enough energy level, to flip the paradigm from cloud to edge. But research needs to continue, in ultra-low power controllers, neuromorphic processors, NeuRRAM processors, and FPGAs, which needs to optimise for sleeping at ultra-low power, waking up momentarily, and executing neural networks efficiently at lowest amount of overhead, and without to much moving data around internal in the controller. Sensor technologies also needs to continue the research to figure out how to capture from biometrics, and how to connect to cognitive objects, not only humans, but also animals, fish, birds and insects, including bees.

Algorithms, and TinyML, needs to continue to develop types of machine learning such as supervised, unsupervised and reinforced, but also deep learning and spiking neural networks. These various types of algorithms each have their strong sides, but also weak spots, and needs more research and innovation, to extend usability, optimise accuracy and reduce energy usage. The machine learning research front at the moment seems to be on how to train the tinyML algorithms within their constrained environments, to achieve on-device learning. It is about how to distribute the process of learning, so all devices can update the main model, but at the same time have ability to get personalised. It also concerns learning from small data sets, but on the same time avoid model drift and biasing. In some sense this needs to be seen in connection with the computing architectures, as well as the sensors. The sensors, processor and algorithms needs to cooperate with regard to the logic of going between deep sleep, sleep, hibernate and active, and the use of wake words and such.

The role of the Caregiver needs to be further researched. Since this is already a trusted person, he can be a valuable resource both for training, personalisation, caregiving and handling issues with the sensors and service. The Caregiver can also handle many more Cognitive Objects at the same time if the Cognitive IoT Service allows for it.

The hardware, microcontrollers, algorithms and sensors, are at the tipping point, and have managed to stop the massive raw sensor data communication to the cloud. Some sensors have managed to get battery-less already, but with limited functionality. Still this is a very important benchmark, since it means environmental friendly, and not having issues with charging, it will always work. More sensors needs to become battery-less, in order to reduce size and cost, and to add more functionality and smartness. Therefore research in energy harvesting and energy management must continue, but also more energy dense and low cost battery needs to be invented, since not all sensors can become battery-less. The same goes for combined sensors and micro generators.

In order to create algorithms which can start to interpret signals from the brain or the body, research is needed to figure out exactly what features of the cognitive object the trained algorithms to inference on to spot an event, abnormality or pattern. This means researchers needs to study human behaviour, human psychology, animal behaviour, animal body signals. Since this paradigm is in its infancy, I believe there are a lot of research still to be done, especially in the field of interfacing a sensor on Cognitive Objects in order to make sense of the signals they pick up. This is where the research front seems to be today. With the paradigm shift, and with the opportunities with artificial intelligence in the business models, comes the possible business model shift from «Service» to «Smart Care Service». This opens up for more innovation and research in the business models. There seems to be huge opportunities since there are many market verticals to cover.

Lastly, there must be more research in ethics, in how these true wearable smart IoT sensors gets used in consumer verticals such as fitness and self care, industrial verticals such as fish farming and animal care, or in the community verticals such as welfare and wildlife preservation. Business, ethics and responsibility is different in these verticals.

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Appendix A: Statement of privacy

NTNU – Trondheim
Norwegian University of
Science and Technology

TO WHOM IT MATTERS

Request for participation: university research / master thesis:

« New business models enabled by AI in high performance and low power wearable sensors»

Purpose

The research subtitle is:
«How can evolution of technologies allow battery operated sensors to become true wearables, and can the addition of AI make them autonomous and self contained?»

This research will discuss the current state of various technologies in order to consider bringing AI to wearable sensors, discuss what impact that can have on business models for services using such wearable sensors in their services, and explore opportunities which might arise from that, in general, by interviewing companies delivering technology and service today. The research will be exploratory against the researches hypothesis.

Since your company is active innovator of technology and/or service in using wearable IoT sensors, the researcher would like to invite you to participate by interviewing you, in order to compare with the researchers conceptual hypothesis.

Conducting the study

You will be presented to the research topic, as well as the general hypothesis of the researcher, before the interview. You will be responsible for keeping your business secrets undisclosed. In case of questions you cannot answer, you will be encouraged to state that you cannot disclose your view on that particular question. During the interview you will get questions in relations to the description of the purpose.

The research will keep you, as a respondent, anonymous, and the research has already been registered and approved at NSD (www.nsd.no). The research will be conducted according to NTNU's ethical guidelines (https://innsida.ntnu.no/wiki/-/wiki/English/Collection+of+personal+data+for+research+projects)

Privacy

The researcher will only be using the information you provide, for research in relation to the purposes stated in this document. You, as a respondent, will be kept anonymous according to the privacy regulations. The researcher does not want to collect any information about persons, nor any intellectual property rights or business secrets. The interview will be recorded, only for transcriptions and notes for the researcher. In case you have any complaints, you need to direct that to the data protection officer or The Data Inspectorate.
It is volunteer to participate in the interview. If you wish to withdraw from the research, you can at any time do so, without stating any reason.

Best regards

Einar Aaland

Appendix B: Interview guide, respondent A

Warm up

1.1 A: Oppvarming, bli kjent med respondenten

1.1.1 Hvem er dere

1.1.2 Hvem er du og hva er din posisjon

1.1.3 Hva er deres kjernevirksomhet

1.1.4 Hva er deres posisjon i markedet

1.1.5 Hva er dere mest anerkjent for

1.1.6 Inn i hvilke markedsområder er dere på vei (visjon)

1.2 B: Introduksjon til min forskning

1.2.1 Problemstilling for forskningen

1.2.1.1 Hvordan kan evolusjon av teknologier gjøre det mulig for batteridrevne sensorer å bli ekte bærbare (true wearable), og hvordan kan Maskin Læring bidra til å skape nye forretningsmodeller?

1.2.1.2 Forklare konseptene om True Wearable IoT Sensor, og Object-centric IoT Service

1.2.2 Forskningsspørsmål

1.2.2.1 Hva er mulig med dagens fremste teknologier myntet for bærbare IoT sensorer?

1.2.2.2 Hvordan kan Maskin Læring i IoT sensor forbedre driften av sensoren og IoT tjenesten

1.2.2.3 Kan Maskin Læring åpne opp nye forretningsmodeller, og nye muligheter i forbindelse med Value Proposition, måten man leverer tjenestene på, måten man skaper tjenester og inntjeningsmodeller

1.2.3 Forskningsmetode

1.2.3.1 SDI: Stegvis Deduktiv Induktiv metode. Forklar prinsippene. Starter med intervju, som kodes og grupperes, før et konsept utvikles og deretter testes det om det er generaliserbare til teori.

1.2.4 Avgrensning

1.2.4.1 Master assignment limitation - Cognitive Objects Model: Humans, animals, birds, fish

1.2.5 Datalagring

1.2.5.1 Søknad i NSD - Norsk senter for forskningsdata, er godkjent

1.2.6 Konfidensialitet

1.2.6.1 Du må selv vurdere hva du vil dele med forskningen. Du vil få sitatsjekk etter transkripsjon. Intervju slettes etter transkripsjon.

1.3 C: Kort introduksjon om meg

1.3.1 Mine personalia

1.3.1.1 Alder, sivilstand, bosted, jolbbsted, interesser, hobbyer

1.3.2 Min erfaring i telecom / internet markedet

1.3.2.1 Utviklet VoIP og IP telefoni, 70% norsk marked, 30% global shipment i 2007, startet det raskeste teknologiskiftet (0-100% opptak) tdd

1.3.3 Min yrkeserfaring

1.3.3.1 Grunder av 4 selskap, CEO, CTO, CPO, Produksjon leder, produkt leder, konsulent

1.3.4 Mitt studium

1.3.4.1 Master in Organisation and Management, specialising in strategy and business development.

Setting scope, discussing models

2 Hardware

La oss starte med det dere er mest kjent som, et ledende selskap for low power radio chipsets.

2.1 CPU / NPU

2.1.1 ARMV8 -> ARMV9

2.2 Peripherals

2.2.1 sensors

2.2.2 Battery energy harvest

2.2.3 eSIM

2.2.4 radios

2.2.5 HMI

2.2.6 memory

3 Firmware / OS Zaphire

3.1 Drivers BLE Zigbee

3.1.1 Mobile App BLE / Zigbee AP

3.2 GPS Modem LTM / NB-IoT

3.2.1 Mobile Network

3.3 Algorithms

3.3.1 Machine Learning Respondent B

3.3.2 Crypto

4 SDK

4.1 Dev Kits

4.2 Tools

4.3 compilers

4.4 Power measurement

5 Cloud

5.1 IoT Architecture

Device Computing Edge Computing FOG Computing Cloud Computing Big Data

5.2 Assist

FOTA Positioning

Dept interview

6.1 Technology Evolution

6.1.1 Battery & Energy Harvest

6.1.2 CPU / NPU / GPU

6.1.2.1 ArmV9

6.1.3 Accelerators and algorithm support

6.1.4 Process technology and Moores Law

6.2 SiP (System in Package)

6.2.1 Ultra Low Power Integrate Circuits

6.2.2 Bottom-up design

6.2.3 Optimize HW, FW, toolchain, SDK

6.2.4 Duty cycling, quick wakeup, sleep & deep sleep

6.3 Business Development

6.3.1 Target applications

6.3.2 Future IoT trends

6.3.2.1 Object-centric - konsept

6.3.2.2 True wearable - concept

6.3.2.3 Autonomous IoT devices

6.3.3 New business Models

6.3.3.1 New Value Propositions?

6.3.3.1.1 Solving pain points?

6.3.3.1.2 New Gain points?

6.3.3.2 New Value Delivery?

6.3.3.3 New Value Creations?

6.3.3.4 New Value Capture?

6.3.3.4.1 Capitalize higher in the value chain, from resource access to resource result

6.3.4 Any new challenges?

6.3.4.1 Ethics

6.3.4.2 Limitations

Round-up

7.1 Hvordan tror du fremtiden vil bli med bærbare sensorer?

7.1.1 Vil vil monitorere nærmest alt?

7.1.2 Hvordan vil kunstig intelligens utvikle seg til å kunne forstå alt vi gjør?

7.1.3 Hva tenker du om å sende dat til skyen i fremtiden versus oat vi behandler dataene der hvor dataene er og skapes?

7.1.4 Er det noen fordeler ved det?

7.1.5 Er det noen ulemper ved det?

7.1.6 Er det noen etiske utfordringer som vil dukke opp ettersom sensorer blir smartere og kan ta avgjørelser på egen hånd?

7.1.7 Hva tror du blir det neste store temaet innen bærbare sensorer koblet til kognitive objekter?

7.1.7.1 Teknologisk

7.1.7.2 Etisk

7.1.7.3 Markedsspotensial?

7.1.7.4 Arkitektur?

7.2 Frykter du kunstig intelligens i sensorer?

7.2.1 På hvilken måte kan det være positivt?

7.2.2 På hvilken måte kan det være bekymring?

Appendix C: Interview guide, respondent B

Warm-up

Short introduction about the researcher

Personal facts

- Age, work, interests

My roles

- Founder of 4 tech companies. Roles CEO, CTO, CPO, Production manager, Product Manager, consultant

Experience - telecom and internet market

- Developed and lead the VoIP and IP telephony paradigm shift, 70% Norwegian penetration, 30% global shipment i 2007/2008, one of the fastest technology shift ever to go from 0 to 100% uptake.

Introduction to the research

My research

- Master in organisation and management, specialising in strategy and business development

Problem description - true wearable sensors for cognitive objects

"Has evolution of technologies enabled battery operated sensors to become true wearables, and how will the addition of Machine Learning improve value propositions, and enable new business models? "

- The goal is to understand capabilities and relevant technologies, and explore possibilities if applying machine learning directly to the sensor data and avoid sending raw data to any computational point in the network. Will this improve the operations of the wearable sensor, and will it add value to the IoT service it belongs to?
- By **"true wearable"** I mean an IoT sensor shall not be obstructed or interfered in its function by any disadvantage in size, weight, charging frequency, or network coverage causing annoyance, disturbance in natural behaviour, or limiting the sensed objects in its function. Sensors today that claims wearable, are at best portable, since they either have to recharge often, are too big, or have network limitations and cannot operate freely. Example iWatch
- By **"object-centric"** I mean IoT sensors which focuses on the specifics of the sensed object, and not just compare to the general population. Discovering what is natural and abnormal of unique and cognitive objects such as humans, animals, birds and fish, must "learn" normality and abnormality

from the object, where the standards of the general population is only a starting reference point. Object-centric is opposite from could centric.

Research questions

- What is the current state of relevant technologies for battery operated wearable IoT sensors?
    - Interview companies: chip (Respondent A), algorithm (Respondent B).
    - Exploring the research front from hardware, through firmware, to service architectures
- How can the introduction of machine learning improve the wearable IoT sensors?
    - By moving machine learning onboard the sensor, to where the raw data gets captured, how will that change the way data gets used, communicated, stored and processed? How can that affect battery life of the sensors, energy source, size and weight, security, privacy, trust and coverage.
- Will machine learning improve value proposition and open up new business models for wearable IoT sensor services?
    - I am curious if the addition of machine learning to sensors change IoT architectures, improve functionalities, add use-cases, and enable new value adds for the IoT service providers?
        - Value Proposition
            - Solving pain points (examples)
            - Adding gain points (examples)
            - Removing jobs (examples)
        - Value Deliveries
            - New ways of delivering the Value Propositions to the customer
        - Value Creations
            - Training / adapting the sensor to the object
            - Enabling new partners
        - Value Capture
            - Increase income
            - Reduce costs

    New technology (in my case machine learning on wearable IoT sensors for cognitive objects), allows for improvements in the business models where the new technology is applied. This can be new value added functionality (gain points) the customer is villing to pay for, that the new technology solves challenges (pain points), or that the technology removes jobs from the customers day journey. The new technology allows for new ways to deliver the service, or to connect more and new partners. The sum of all these improvements will either increase the income (drastically?), or reduce the costs (drastically?)

The new technology might improve in two areas, true wearable, and object-centric. I am curious to learn how can affect the business model, and to learn some examples of this.

Research design - SDI: Stepwise Deduktiv Induktiv method.

The Stepwise Deductive Inductive method works step-by-step, from raw data to concepts and then theories. The SDI model builds on curiosity from the researcher, with generalisable understanding as a goal. Very often the researcher has a good knowledge in the field of research, as a foundation for the curiosity.

The SDI research model starts with interview(s) for generating raw data, which gets coded and grouped. Then concepts gets developed, before they are generalised to theories.

Limitation - Wearable IoT Sensors for **Cognitive Objects**

My master assignment is limited to wearable IoT sensors for cognitive objects, such as humans, animals, birds and fish. The purpose of this is to focus the research towards areas where machine learning might improve data gathering, reduce power usage, or deal with privacy issues. The limitation will put focus to object-centric IoT, where the object is cognitive (has its own mind, instinct and feelings).

I am using a **model for a wearable IoT sensor**, which includes a processor hardware, using some kind of energy source, internal or external sensors, radios and access to network, internal ofr external memory, and some sort of HMI.

Additional to hardware, the model has OS, drivers, algorithms, infrastructure stacks (GPS, bluetooth, narrowband mobile etc), cloud functions and assistance (assisted GPS, OTA, compute offloading etc).

GDPR / data storage

Approved application with NSD - Norsk senter for forskningsdata

Confidentiality

You need to make sure you don't reveal company confidential information. Interview will be deleted after transcribed

Getting to know Respondent B

Who is Respondent B?

What is Respondent B core income based on?

How would you describe your position in the market?

What are you most known for? And what are you most special for (differentiation)?

What is your company vision (where are you heading)?

Who are you, and what is your position?

Can you explain, in brief, Respondent B, and what you provide?

- Platform? Algorithms? Tools? Code? … and what does it do?

What is EON - Edge Optimised Neurone?

- Will EON help developers choose algorithms, configure them, optimise use, and simulate, is that so? Why is this important?

How much memory (RAM or ROM) do you require? Try to explain

- What do you require for running ML for various types? Try to give me an introduction?
  - Sensor data
  - Audio data
  - Image data
  - Video data
- How is Respondent B memory usage compared to others, and who are they? And why is it so?

What do Respondent B add to the sensor technologies?

- What is your target industries (industrial, infrastructure, conservation, wearables)?
- Inference directly on the sensor, is that the key? Convert raw sensordata, to recognising events, states and abnormalities. Reduce/remove need for power/cost intense communications. Elaborate?

Setting scope, discussing the models

Technology front for ultra-low power sensors

Can you try to describe extreme cases of operating on low power?

- How does a typical ultra-low power solution look like?
- What does these solutions do? Some examples?
- How are they powered? Battery? Energy harvesting?
- What CPU solutions do they use?

Let's talk about what the biggest challenges for wearable sensors is?

- Battery time and charging?
- Size and weight?
- Cost?
- Environmental hazard?
- Coverage and offline mode
- HMI and user-friendliness

What is your ideas about the future of new ultra-low power CPUs

- Accelerators for Neural networks (NPU)
- ARM9 architecture
- Others, custom, application processors?

Will we have more optimised NPUs for ultra-low power ML in the sensor?

- When can we drop the battery?
- How can the sensors achieve true wearable?
- Will the sensors become autonomous? Offline with memory?

Some expressions and definitions

What do you think about the expression True Wearable sensor

- Definition: A sensor can be called true wearable, when the sensor, with its limitations, doesn't affect the normal operation of the user (as if the sensor wasn't there).
- What are your thoughts about this?
- Isn't this a point where ML can remove pain points (VP)?

What do you think about the expression Object-centric IoT Service?

- How do you interpret this expression? Does it make any sense? In what way?

- Where will ML happen (in IoT services) going forward? In the cloud? On the edge? In the sensor? A hybrid model?
- Why will ML move more to the sensor? Is that a trend or just in specific cases? Elaborate?
- What will the advantages of object-centric IoT services be?
- Will new challenges we will have to deal with arise from object-centric IoT sensors and services?
- How about ethics? Privacy?

In-dept Machine Learning capabilities

ML in wearable IoT sensors for cognitive objects

My research is narrowed down to True Wearable Object-centric IoT sensors, placed on cognitive objects (humans, animals, fish or birds)

What does ML add to True Wearable and Object-centric sensors?

- How can Respondent B help drive towards true wearable? And Object-centric? What is your addition? Please elaborate on each and why.
    - Battery operating time?
    - Reduce latency?
    - Offline?
    - Autonomy?
    - Reduce size and cost?
    - Reduction of communication?
    - Smarter use of sensors and battery intense functions (such as GPS)?

How is ML different on a sensor for non-cognitive objects versus cognitive?

- How would you describe the difference?
- Why are cognitive objects different?
- What will be the challenges with ML for sensors for cognitive objects?
- Will sensors on cognitive objects have ***unique*** trained ML algorithms? How can that be achieved?

How is ML used?

- ML on sensor to wakeup
- ML in NPU to detect abnormality.
- ML in NPU to find/group unknown (unclassified) events. Can this be used to detect what to classify on? And then re-train the ML model?
- ML in NPU to detect known patterns (classified) events

Communication. - Sensors with ML on Edge/Fog/Cloud, versus on the sensor?

- What will communication to the cloud be for? When will communication happen?
- Why will communication be reduced/changed? (Reduce cost, battery, offline)
- How will raw data be treated (dumb sensor versus smart ML sensor) in terms of communication?
- How much can data communication be reduced?
- How about updating the sensor firmware with updated / re-trained ML models.
- Will the ML training models be based on training data sets from the a) general population or b) the unique objects?

Is object-centric smart IoT sensors a new trend?

- Is the IoT architectures changing in the way we collect, use and treat sensor data?
- Is there a change from treat data, to treat events? Is that the trend?
- Is the sensors shifting from general sensors (across the service) to a unique sensor only matching one unique object.

ML in the sensor, will that improve power usage?

- Different types of ML, to be used for switching between power modes, and to compute only on the necessary raw data (ignore the rest).
- Inference directly on raw data, avoid communication and power intense use of NPU
- Maximise time in sleep and deep sleep.
- Inferencing on raw data, eliminates / reduce communication drastically

ML in the sensors, will that cause any ethical or privacy issues?

- Will we fix privacy and ethical issues by using ML in the IoT sensor? (Hint: GDPR, data privacy, I.e in surveillance we can limit to only suspicious)
- Will we raise any new ethical issues? (Misuse, legal, privacy) Please elaborate

ML in the sensors, how about trust? Please elaborate on these…

- How about trust for the sensors and the services when ML are used?
- Will trust be more sensitive when the sensors are connected to cognitive objects?
- Animals, fish and birds are one thing. How about when humans wear the sensor?
- Will it matter what the sensor does? From detecting events/abnormalities, the offline mode (with memory) to autonomous?
- Will it matter what application it is? From sensor only, to sensor which can act automatically?
- Will trus be different in tracking animals, versus a part of healthcare? Will scepticism be same or different?

Will ML in Sensors impact business models

(True Wearable Object-centric - TWOC)

Will smart TWOC sensors improve Value Proposition in business models?

- In terms of Value Proposition, can we improve sensors for animal tracking, elderly care, wildlife monitoring, farming, pre/post operative medical, in such a way that their services improves?(Please elaborate):
    - add **value points?**
    - solve **pain points?**
    - remove **jobs**? (I.e collecting data in wildlife monitoring, collect, analyse data, weeks/ months)

Will smart TWOC sensors affect Value Delivery to the end users?

- Can the delivery model be changed, from buy/own, to rent/lease, to lend/use?
- Will it be easier for the service provider to find new customers bases (matching to new type of customers, new needs, new payer groups (which has less money), new users (less responsible)
- Will it be possible to find and create love relation to the customers (binding the customers), or deep-need relations?
- Can the Value Propositions (events, detections) be delivered with block-chain contracts? Safer? Flexible?
- Reduced data communication
- Less privacy issue

Will smart TWOC sensors open new ways of Value Creations for the IoT SP?

- Can new partners be added to the IoT SP offerings (I.e insurance company, communities, medics, vets), to deliver their value add services, at better prices?

Will smart TWOC sensors create new Value Captures for the IoT SP?

- **New income** and money flows because of the addition of ML?
    - From new payment sources?
    - In new forms (credits, bitcoin, micro payments)?
    - As new types (pay per event, free/advertised)
    - Value Propositions
        - Detection behaviour
        - Detecting emotions
        - Detecting health

    - Add-on services
- **Reduced cost** of:
  - Value Propositions
    - Sensors adapting to object?
    - Reducing jobs for collecting data from the field?
    - Consolidated services with other partners?
  - Value Delivery
    - Less use of communication data?
    - Less need to protect raw data, less GDPR issues?
    - Customer installation since sensor can adapt to object?
  - Value Creation
    - Can offer more value (from partners) at no/low additional costs?

Round-up

- How will the future of wearable IoT sensors be?
- How was this conversation?
- Anything else I should consider

NTNU

Kunnskap for en bedre verden