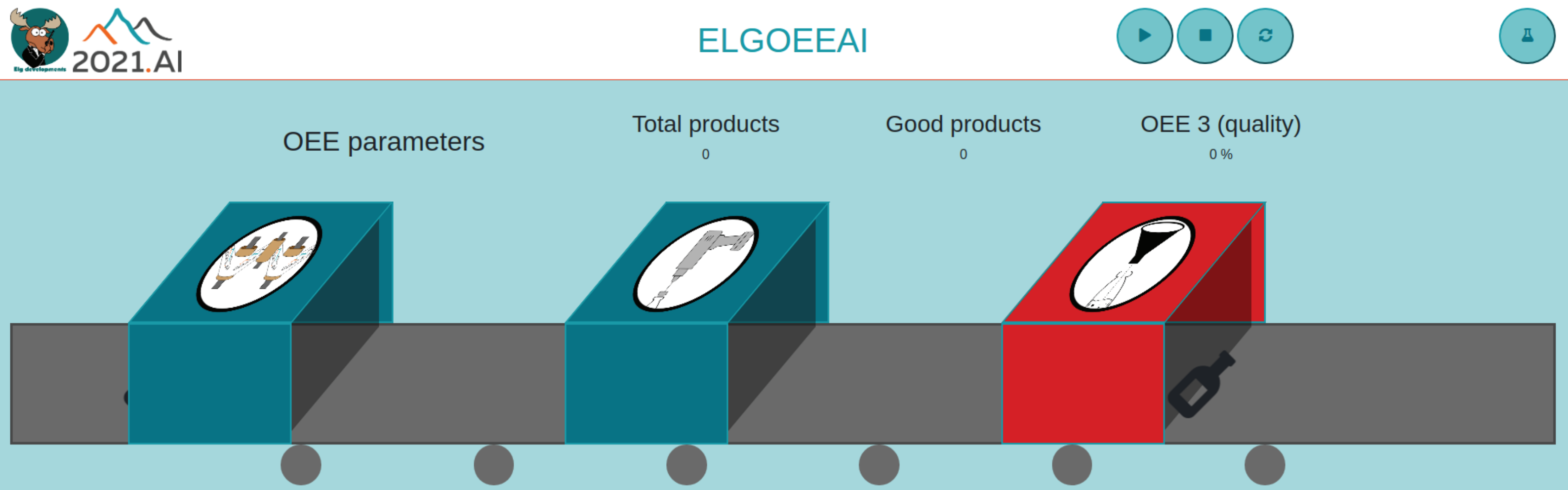
# ElgoeeAI




## A demonstration system of the potential of AI in manufacturing



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Through the thesis several different coding languages are utilised for development of the different system components. System coding is based in Python and the Django framework, whereas statistical analysis is conducted in R. All materials produced belong to the author and 2021.Ai.

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STUDENT REPORT

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**Abstract:**

The thesis is concerned with developing a demonstration tool showing the potential of implementing AI solutions in manufacturing and engaging the viewers in AI. It is done by exploring the manufacturing industry and interviewing different individuals working within the manufacturing industry to create an understanding of the industry and its systems and from this a hypothetical manufacturing example is conceptualised Following an image recognition model have been trained as a DNN, which is used to classify different states of a conceptual production. Then different mediation techniques are investigated spanning over text, graphs and icons in various nature. Here it was found that a mixture of the icons and text was the best mediation technique. From this a HiFi system is developed, aimed at presenting the classifications from the machine learning model to the viewer in an engaging manner. This system is shortly tested in casual settings, which despite some bugs sparked great interest and debate concerning implementation of AI.

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**Abstract:**

Projektet omhandler udviklingen af et presentations værktøj til at illustrere potentialet for implementering af AI i fabrikationsmiljøer. Dette er gjort ved først at undersøge fabrikationsindustrien og interviewee mennesker herfra. Ud fra dette er et hypotetisk fabrikations eksempel konceptualiseret. Herfra udvikles og trænes et deep neuralt netværk, som således kan klassificere de forskellige produkt stadier som er konseptualiseret igennem eksemplet. Hernæst er forskellige formidlingsmetoder undersøgt, hvor der har været fokus på ikoner, text of grafer til at formidle modelens klassifikationer. Her blev det fundet at en blanding af text og ikoner var foretrukket af forsøgspersoner. Til sidst er et HiFi system udviklet som implementere ovenstående elementer og på bedst hvis illustrere klassifikationer af produkt stadier. Dette bliver kort testet igennem en uformel demonstration, som trods et par fejl, startede stor interesse debat vedrørende implementering af AI.

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# Chapter 1

# Introduction

As technology enhances, so does the industries benefiting from them. This has in the last decade lead to the introduction of Artificial intelligence(AI), which today is being implemented and used in many industries. The rapid growth of AI can be attributed to three major drivers, huge amounts of data, enhanced processing power, and the open source community [Tosti, 2019].

A common goal for all industries is to make profit, which can be simplified into profit over cost. Meaning that the expenses for a product to be produced or delivered, whether in production or customer service, should not overstep the profit. This therefore leads to a great demand for optimisation, as even small optimisations can lead to a great reduction in production cost, which can be especially noticeable within mass production.

For decades manufacturers have invested in automation and sensors to optimise and monitor production with the purpose of optimisation Tosti [2019]. This creates great amount of data giving insight into the production. which traditionally various statistical methods are applied to understand causes and summarise data into key performance indicators(KPI). However they have only captured around 20% ot 30% of the potential value of data and analytics to date McKinsey and Company [2016].

This therefore indicates a great potential for further insight and better exploitation of the data collected. 2021.ai believe that they are equipped for the task and therefore want to assist manufacturing business with handling the data using AI. Due to this it is desired to develop a demonstration system that can be used in meetings with manufacturers to illustrate the potential benefits of AI implementations for handling data.

# Chapter 2

# Manufacturing

Manufacturing is concerned with creating products, such as everyday products. The products can be classified as either discrete, like bolts, nuts and screws, or continuous such as wire spools and metals which are then cut into the desired shapes. [Kalpakjian and Schmid, 2014] These are examples of simple products, however manufacturing also covers complex products, such as medicine, cars, and much more. In other words manufacturing can be said to include all production of tangible products Sassani [2017]. The processes to form the individual products are therefore very different in nature and in the quantity that is needed. For instance, production of water bottles are needed in much greater quantities and a much less complex process compared to fighter-jets.

Conventionally manufacturing systems can be classified according to their flexibility and rate of production, leading to three classes, job shop, batch- and mass production. Job shop production is the one with the lowest production quantity and rate as they operate with variable product production often by customised requirements every time. Therefore this manufacturing plant will have to be flexible with highly skilled operators to adapt to the new task given. Examples of job shop production plants are aircraft, experimental equipment or prototyping factories. Mass production oppositely are specialised for producing a singular product, often producing at high quantity and rate due to the highly automated equipment specialised for the individual processes. Batch production is then the type in the middle, characterised by creating medium sized batches of a given product one time or in an interval such as seasonal. Due to the possibility of planning the batches gives the opportunity to prepare the environment to the given production. This therefore leads to it being able to produce at a higher rate as production is more predetermined than in the job-shop production. [Sassani, 2017]

As many technological advancements have been made within the last few decades, especially within, automation, software, hardware and communications, so have advancements been implemented into the manufacturing industry. This has led to several implementations such as using computers and robots for increasing productivity, replacing humans, or solving complex problems. With the implementation of computers and automation, monitoring became evidently more important. Encapsulating the processes, operations and states of the production on a whole and for the individual machines. Another aspect of investing and advancing in technological systems and equipment is the optimisation of the manufacturing process, such as increase in quality, production rate etc. [Kalpakjian and Schmid, 2014] Especially when considering mass production errors, or short downtime can have a huge economical impact Daisyme [2018] Immerman [2018]. Such considerations can be made by calculations such as total preventive maintenance first suggested by Ford in 1950, and overall equipment effectiveness (OEE). [Stamatis, 2011] The production or manufacturing process can be depicted as the figure 2.1 (highly simplified).

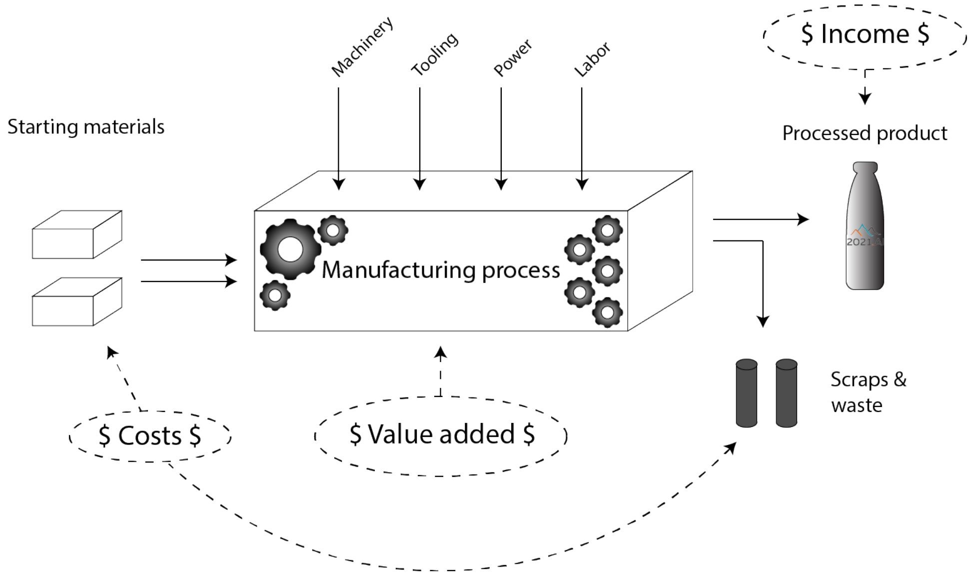



**Figure 2.1:** Figure depicting where value is added in manufacturing processes, further showing the technologies that can be optimised for increasing added value. The figure is created based on two figures from Madsen [2017].

The figure depicts how manufacturing is the process creating value, hence also being the area of interest of optimisation.

## 2.1 Technology in manufacturing

With the increasing automation and implementation of computer integrated systems(CIM) to operate and control production, new user interfaces and personnel skill requirements are required. Since many of the operations are now controlled by computers and states are monitored through advanced sensing technology, personnel to code and plan the settings of the different machines are required. [Kalpakjian and Schmid, 2014] In other words less personnel is required, however more skilled and expert knowledge is required.

### 2.1.1 Sensory technology

Nowadays sensors are embedded in many manufacturing processes and systems, and essential for computer control and data acquisition of individual machines and systems. Sensors can be classified as either analog or digital, where analog sensors send signals proportional to the measured quantity at the given time, whereas digital sensors outputs discrete and typically binary values Ksix-blog [2017]. The sensors can take many different forms and can be said to resemble the human sensory system. Sensors can measure parameters such as vibration, temperature, magnetic, even complex images using a camera as sensor. [Kalpakjian and Schmid, 2014] The measurement of relevance differs on the individual processes and circumstances, thereby the sensors applied vary. [Issar and Navon, 2016] As an example visual sensing is especially useful for measuring large numbers of small features or hostile manufacturing environments. Visual sensing is usually processed by software commonly known as computer vision, which in turn can be said to be a smart sensor. Smart sensors can perform logic functions, conduct two-way communication, make decisions and take appropriate action. The knowledge required is built or coded into the smart sensor, so that it for instance can stop a robot arm from accidentally harming a human within its reach. [Kalpakjian and Schmid, 2014]

### 2.1.2 Monitoring and control

Having all these sensors measuring various aspects of the production and machines, monitoring is required in order to react to the measurements. It is required for detection of anomalies, preventing malfunctions or communicating which adjustments need to be done. Process monitoring can be seen as the manipulation of sensor measurements to determine the state of the process. This can take the form of everything from simple calculations and statistical analysis, to complex signal processing methods and artificial intelligence(AI). [Wang and Gao, 2006] Especially in the recent years AI algorithms, such as support vector machines(SVM), neural networks(NN) and Fuzzy logic have been applied for monitoring machine processes. These are seen implemented for monitoring tool wear, chatter detection and surface integrityLi and Chen [2014].

Aforementioned algorithms falls into the category of machine learning, which is defined as algorithms that can solve problems without be explicitly coded for it. Many of the ML algorithms are designed to analyse large amounts of data and many dimensions, making it a prominent candidate for processing of data collected from the sensors. Machine learning techniques have matured significantly in the latest decades due to the increase of processing power of computers, hence also lead to a great interest of implementation. As such several industries have had success with implementing machine learning algorithms for monitoring and control. [Thorsten Wuest and Thoben, 2016]

This can take several forms, as there is the supervisory monitoring of the overall production all the way down to the individual machines user interface, dictating a set of interactions for control. The different levels of control can be characterised in three levels, machine, process and supervisory control, depicted in figure 2.2.

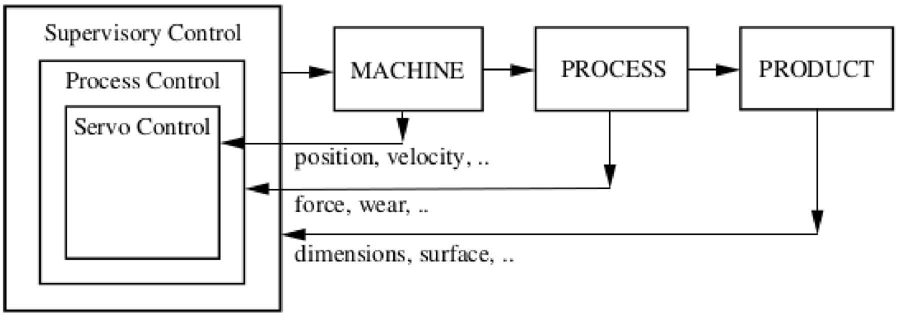



**Figure 2.2:** Figure depicting the different control levels in manufacturing. Image is used from Wang and Gao [2006].

The first and lowest level are the control of the machine, depicted as servo control on figure Wang and Gao [2006], concern control of the machine, such as positioning, velocity etc. The second level of control is the process level, in which process variables are in focus to maintain high production rates. Process variables are such as tool wear and cycles runned etc. The last level is the supervisory level which embraces directly product related variables, such as shapes, dimensions and surface roughness. Also when humans are the intended target, sampling frequencies vary, depending on how often the given parameter is to be inspected, for instance with maintenance of a machine it might need it every 30 days, thereby a sampling frequency of every hour makes little sense and creates an abundance of redundant data and should be considered for development of controllers. [Wang and Gao, 2006]

The control of the individual machines in CIM systems takes foundation in computer numerical control (CNC) systems, in which the machine takes a coded instruction in the form of numerical data, as input. The first CNC system was implemented in the early 1950s, and have since matured significantly and led to further advancements in control. [Kalpakjian and Schmid, 2014] This means that in the classical CNC systems, numeric codes had to be inserted for control, and this quickly became complex and inefficient for humans to operate due to the limitations of working memory Baddeley [1991] and visual search performance Wolfe [2007].

Luckily the user interfaces on machines have developed alongside research in the field of human-machine interaction (HMI), meaning that modern machinery are commonly equipped with touch interfaces for inputs automation [2018] Hooper [2017].

Similar for control at the processing and supervisory level, such touch-interfaces are now widely implemented due to the possibility of intercommunication of the individual systems. The networking of the systems thereby leads to the possibility of transferring commands, and in many cases not having to go to the individual machine for control. This is especially beneficial in large plants and facilities, where great distances otherwise have to be covered Kalpakjian and Schmid [2014]. Further the touch-interfaces give new interaction opportunities, more intuitive than the older numerical codes. This is especially beneficial for the supervisory and process control, as these often require more flexibility and decision making in the required action, than such as positioning of the machine. This could for instance be what action to perform according to the calculated operation equipment effectiveness(OEE) Stamatis [2011].

## 2.2 Optimisation methods and metrics

As earlier stated the production is where value is added to the product, and hence where profits are generated. Even small improvement is worthwhile investing in, as over time it adds up to a large total over time. This could for instance be reducing waste, power consumption or manual labor, or improving parameters such as production rates, production methods or quality of the product and subcomponents manufactured. [Stamatis, 2011]

Trying to embrace these different aspects of improving production, the term and concept "total productive maintenance" was introduced in the early 1900s by Henry Ford. The concept basically aims at a proactive approach to prevent inefficiencies before occurrence, by keeping an appropriate maintenance flow. The goals are thereby to maximise machinery effectiveness, implementing productive maintenance, actively involve all employees related to the machinery and promotion through motivational management. TPM has been borrowed and adapted into new concepts for optimisations on various levels of production. These are concepts such as lean manufacturing, 5s, visual factories and OEE. [Stamatis, 2011]

These methods therefore embrace a much broader area than the manufacturing process alone, such as design and planning of the processes, and are therefore commonly implemented at the management level of production. [Stamatis, 2011] Lean manufacturing is a concept that aims at reducing waste, such as through manufacturing on demand instead of manufacturing in excess. 5s is a concept developed by Toyota, and concerns optimising the workspace organization for efficiency. Visual factories refers to using images and visual communication to display machine layout or operators, and is based on the principle "a picture is worth a thousand words". Lastly the OEE is a measuring metric for the effectiveness of equipment operations.[Stamatis, 2011] The OEE is thereby a measuring metric that can be implemented at lower control levels than the others which are more focused for supervisory and management levels of control. The OEE is calculated from multiplying the three parameters;

$$Availability \times Performance \times Quality = OEE$$

Where the Availability metric represent the percentage operation time scheduled of the total time available to actually operate, and hence is calculated by the formula;

$$\frac{Available - time}{Scheduled - time} = Availability$$

Performance concerns the operation speed compared to the designed speed(such as machine specifications) and is calculated following;

$$\frac{Actual - rate}{standard - rate} = Performance$$

Lastly quality is the measure concerning production quality and is calculated by dividing good units with the number of started units;

$$\frac{Good - Units}{Units - started} = Quality$$

The first equation is denoted in percentages, whereas the units of the different calculations can vary. [Stamatis, 2011] The important factor is to use the same units individually in the equations 2, 3, and 4 and then multiply by 100 to get percentages before calculating the final OEE in equation 1.

This therefore provides a fairly simple calculation of the effectiveness of the machinery in a given factory, and is widely used in the manufacturing industry. An OEE value of 85% and more is considered to be very efficient and hence benchmark values. [Stamatis, 2011]

Performance measures such as the previously mentioned can be implemented in various decision support systems(DSS) to convey the various metrics continuously, represented in various key performance indicators (KPIs). In order for a DSS to be effective, it must contain critical and relevant KPIs, meaning that these should not present irrelevant information for the given decision. Further the content presented in the DSS should be accurate and used, meaning that care should be made when deciding the individual parameters, and they should be reviewed routinely. As an example of accuracy, maintenance is often done on a timely basis, like every week, yet not considering different usage cycles, hence varying equipment wear. [Issar and Navon, 2016] The methods mentioned in this section also benefits from the advances in technology, such as machine learning. It is seen employed in maintenance of machines with the purpose of predicting when maintenance is required, hence avoiding unnecessary maintenance or run the machine to failure Gian Antonio Susto [2014]. Optimising the maintenance thereby affect the OEE Availability parameter. The Quality parameter have also seen optimisations, such as using pattern recognition models to classify the state of the product M. S. Aksoy and Cedimogly [2003].

## 2.3 The fourth industrial revolution

From the earlier sections it can be derived that the technological advancements in the manufacturing industry are improving continuously, with some technologies contributing more or less to changes in the industry.

Those technologies that contribute to major changes are referred as enabling technologies for an industrial revolution, which in writing time the world are currently in the process of the fourth industrial revolution see table 2.1. The fourth industrial revolution, denoted Industry 4.0, is interconnected with cyber-physical systems(CPS) and Internet of Things(IoT) which gives rise to major impact on the manufacturing industry, similarly to the development of the steam engine. [Zivana Jakovljevic and Pajic, 2017]. CPS are an in short an interconnection of a physical manufacturing system with a virtual one, in which the output of one affect the other and vice versa. In other words a virtual representation of the physical factory site and processes is created in which changes can be simulated and hence determine where adjustments are to be made to optimise the physical production. Such systems rely on complex analysis methods such as machine learning and IoT [Zivana Jakovljevic and Pajic, 2017].

However even with these advancements there is still a significant proportion of products manufactured in conventional form and have yet to employ the newest technologies. Sassani [2017]

Adopting new technologies and process optimisations presents new challenges that are to be overcome. Some key challenges are identified as adoption of advanced technologies, utilise advanced knowledge and innovation of products, services and processes. [Thorsten Wuest and Thoben, 2016] This therefore indicates that one major reason for new technologies, such as machine learning, not being adapted is due to lack of domain-knowledge McKinsey and Company [2016]. As adopting and innovating products require knowledge, and if that is missing it presents a great challenge.

For machine learning these challenges lies in the acquisition of relevant data, handling large data sets and which machine learning model to utilise. Making the right choice only becomes more complicated as more algorithms become available, and then when finally having this achieved the results then have to be interpreted and the model evaluated on metrics such as over-fitting bias and variance. Thorsten Wuest and Thoben [2016] Utilising machine learning therefore requires domain knowledge on the topic, such as which data to use, model that is best suited and how to develop and interpret the model. To implement it therefore requires an employee with that expertise or partnering up with a third party with the required expertise.

**Table 2.1:** Table summarising the four great industrial revolutions Zivana Jakovljevic and Pajic [2017]

| Industrial revolution | Enabling technologies | Characteristic equipment | Market needs |
|---|---|---|---|
| Industry 1.0 | Water and steam power | Machine Tools | Customised products |
| | Mechanisation | Steam engine | |
| Industry 2.0 | Electricity | Transfer lines | Low cost products |
| | Division of labor | | |
| | Interchangeable parts | | |
| Industry 3.0 | Microcomputers | PLC-based control | Products variety |
| | | CNC machine tools | |
| | | Robots | |
| | Information technologies | | |
| Industry 4.0 | Cyber-physical systems | Reconfigurable manufacturing systems | Low cost customised/ individualised products |
| | Internet of things and services | | |

# Chapter 3

# Delimitation of thesis

As the previous chapter explores, the technological advancements in sensors, computer systems and automation are being developed and applied in a fast rate. This leads to new challenges that the personnel have to overcome, requiring training in handling the new technologies. With the increasing data measures available in manufacturing, machine learning are showing to be a prominent optimisation tool for several optimisation processes. However here the great difficulty to overcome is lacking expertise in the area, within the manufacturing personnel McKinsey and Company [2016]. Even with the assistance of a third party for developing the machine learning models, interpreting the results and monitoring the model are still a challenge.

2021.AI are a company with the expertise to develop and implement AI in various industries and organisations [2021.AI, 8 20a]. They believe that they can help manufacturers with this process, and furthermore their Grace platform offers the flexibility required for efficient implementation in various systems. [2021.AI, 8 20b]

To tackle the interpretation issue, a demo system, elgoeeAI, is proposed in cooperation with 2021.ai. The aim of elgoeeAI is to illustrate a machine learning implementation in a simple manner, so that domain knowledge is not required to interpret the results. This model will show an example of predicting future states, illustrating the advantage of future state knowledge. Hence to achieve this both a classifying model is required to classify different states and a forecasting model, which from the classified states can predict future states. For this to be possible a production process have to be constructed on which the machine learning models can collect data from. Then the model have to be trained on historic data, so that it can adapt to future production measurements. Lastly, who and how the elgoeeAI system mediates information should be investigated, as the information parameters and expertise base will differ, hence different presentation methods might be optimal for different control levels, depicted in figure 2.2.

The focus of this thesis will be on the presentation and mediation of the machine learning model, with the purpose of being a demonstration interface for clients. Hence a theoretical simplified manufacturing example is developed so that there are no issues with confidential processes and ensure free usage for 2021.ai. As the focus is on the presentation and mediation, only the classifying machine learning model is developed, as the forecasting model can be "faked", hence the classifying model is enough to investigate presentation and mediation methods.

Within the hypothetical example it will be tried to investigate how a machine learning model should mediate predictions of future outcomes to prevent downtime or deficiencies. Hence following research thesis are formulated:

*Can predictions from a machine learning model be conveyed to manufacturing personnel in an intuitive manner so that they can prevent production deficiencies?*

The following will therefore be a thesis concerning the development of the elgoeeAI system, encapsulating, development of the hypothetical production example, development of the machine learning model, investigation of mediation techniques, and finally encoding of all the components together.

# Chapter 4

# The hypothetical manufacturing plant

Due to not being able to access real manufacturing data, and following use in the demo-model, the manufacturing data have to be simulated through a hypothetical manufacturing example. In order to assimilate real life manufacturing the hypothetical example must concern production of a product existing in several states. These states should be possible to replicate for monitoring. Furthermore, 2021.AI requests that the example remain simple in nature, so that only basic manufacturing knowledge is required and no specific domain knowledge herein. The reasoning behind this is that operators will rarely be part of the decision making process of acquiring new systems and solutions for improving production. Additionally they would like to utilise image recognition as monitoring methodology due to their belief of it being more compatible for a demo-model illustrating a concept and potential in contrast to other machine learning models.

Due to these requirements and requests, it is decided to take standpoint in a manufacturing process of a water-bottle, illustrated in figure 4.1.

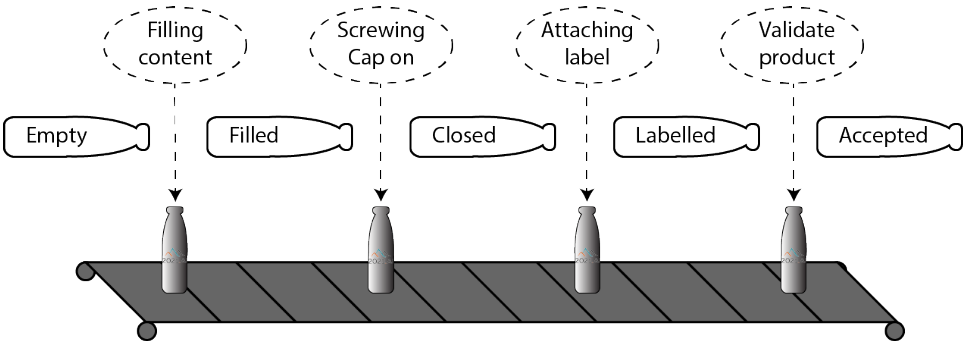



**Figure 4.1:** Simplified hypothetical process for manufacturing a water bottle, where solid bottles shows passive states and stippled lines are processes.

## 4.1 The manufacturing process

A water-bottle is used due to having them in excess at the 2021.AI Copenhagen office, thereby not having to invest in products. It follows the requirements such as existing in several states, in which the five illustrated in figure 4.1 are easily replicable by simple manipulations of a water-bottle. To archive these 5 different product states, various machinery operating and processing the product must be applied, however to make the example remain simple, these are simply specified by the process that they do, e.g. “Filling machine” and the adjustment operations possible. This is in order not to go too much into detail with machines as they quite quickly become complex and specialised for a given operation and facility, especially in mass production and transfer line systems, which the water-bottle manufacturing example resembles. The filling machine is conceptualised as a tank with content funnelled into the water bottles and blocking the funnel after 500 ml has passed through. The cap screwing machine is conceptualised as a drill, with the cap as the “screw”. The labelling machine is conceptualised to work by spinning the bottle, enwrapping the label around the bottle.

Each product state can either be a classified as a good product, meaning no errors in the product, or it can be faulty, meaning that it has gotten some defect for a given reason. For the examples “processing states” these can be derived to the areas content, cap and label. So a cap can either be screwed properly on or not defined by a threshold, as illustrated in figure 4.2. (Threshold is typically more stringent in real life situations.)

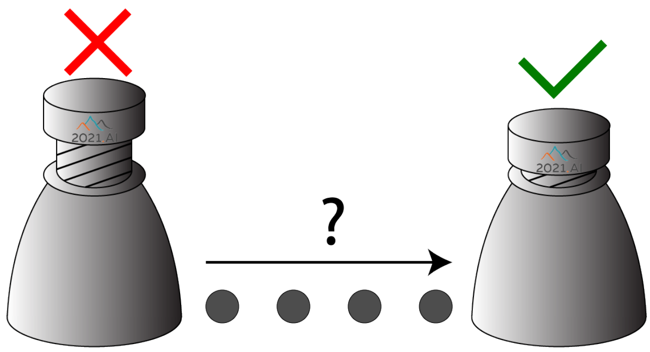



**Figure 4.2:** Erroneous and accepted bottles according to how much the bottle cap is screwed on.

Similarly label position and content can be validated as good or faulty. For monitoring a camera is conceptualised at the “validate product” stage, in which pictures of each passing product can be taken. The data created on monitoring will therefore be images, hence an image recognition model can be utilised for predictions.

### 4.1.1 Defining the error parameters

As each error type in real life manufacturing is due to some parameters, similar parameters causing the error types in this hypothetical production must be defined.

For the filling machine dirt-particles in the content are monitored, the number of dirt-particles is therefore in relation to dirt-particles in the content. This is hypothesized to originate from either the content that is filled, the bottle in which content is filled, or from dirt-particles on the funnel. Thereby three different machine parameters, affect the amount of dirt-particles in the content. The difference is conceived to be the rate of contamination where funnel affects slowest, and liquid fastest. On the cap-screwing machine two different settings is theorised to affect the product state, power and the angle of the drill. The label machine errors can be affected by initial y-position of the label, and angle of the label when spinning it on the bottle. The initial y-position determines the correct position and the angle affects the evenness of the label. Adjusting the different parameters will therefore lead to changes in the product state output. For the filling machine it is thought that the components will have to be changed, for instance a new funnel if at fault, hence also requiring downtime. The other adjustment of the parameters on the other two machines are thought to be adjustable during production, hence not requiring downtime. This differentiation is to add the level of decision making of when it is best to do the given maintenance depending on requiring downtime or not.

These different parameters thereby make up the possible solutions for fixing faulty production and now need to be conveyed to the user in an insightful and understandable manner.

## 4.2 Developing the image recognition model

With the production defined it is possible to create a image recognition model that can classify the different bottle states possible, when simulating production. To do this a deep neural network (DNN) is utilised to detect image patterns and hence predict the different classes. DNN's are often compared to the human brain, in the sense that it operates by processing received information through a series of neurons connected with axons. A simple representation of a three layer DNN can be seen in figure 4.3.

Here the circles are the neurons which will contain a value between 0 and 1, known as the activation value. The "axons" are the connecting lines, which is denoted as weights, and are initialised randomly and then iterated through training. The neural network training process can be summarised in four repeating steps, calculation of activation values, defining cost function, determine local minimum and back propagation.

The activation values of the hidden and output layer are calculated by summarising the earlier layers activation values multiplied with the connecting weights. Hence

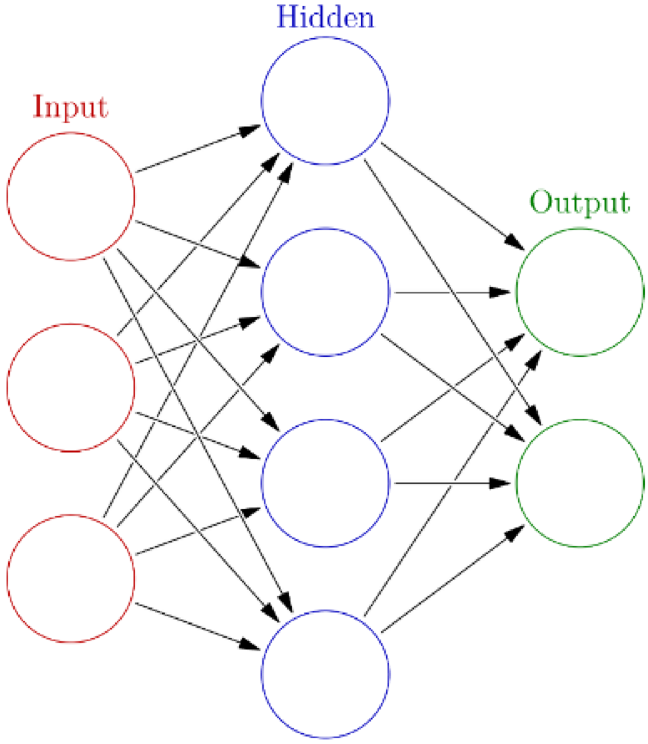



**Figure 4.3:** Illustration depicting a simple 3 layer neural network with three input parameters, four hidden neurons and two output neurons.

the formulae for each neuron calculation goes:

$$a_0^{hidden} = \sigma(W_0 a_0^i + W_1 a_1^i + W_2 a_2^i + b_0) \tag{4.1}$$

As this quickly becomes quite complex as neurons and layers are added it can be advantageous to write it in a matrix as below

$$a^{hidden} = \sigma\left(\begin{bmatrix} w_{0.0} & w_{0.1} & \dots & w_{0.n} \\ w_{1.0} & w_{1.1} & \dots & w_{1.n} \\ \dots & \dots & \dots & \dots \\ w_{k.0} & w_{k.1} & \dots & w_{k.n} \end{bmatrix} \times \begin{bmatrix} a_0^i \\ a_1^i \\ a_n^i \end{bmatrix} + \begin{bmatrix} b_0 \\ b_1 \\ b_n \end{bmatrix}\right) \tag{4.2}$$

From this the cost function is defined which is a measure for how well the network performs. This is calculated by adding up the squares of the difference between system outcome activation and expected outcome activation.

$$c = \sum_{k=0} (o_{val}^{outk} - e_{val}^{outk})^2 \tag{4.3}$$

If the value of the cost function is high the network performs badly and low when the network performs well. The third step is then to compute the gradient descent, and find the local minimum of the cost function (c), which is a way of optimising the network values, like whether weights should be increased or decreased to increase the networks performance.

Hence the progress working backwards manipulating the values in the network for optimised output, this process is known as back propagation. These four steps are then repeated for a given each 'training cycles' which is denoted epochs. When having trained a satisfactorial network in a given amount of epochs, the model then have to be evaluated. This is done by applying the network on new images that it have not yet "seen". If the network performs bad on new data but good on the training data, overfitting have occurred. Overfitting is a term used to describe a machine learning model, which is trained for a specific dataset, and usually quite good, however when feeding it new data, it performs poorly. In the image recognition context this could for instance be that the new image is taken from a different angle, then an overfitted model will perform poorly due to the change of parameters. To prevent this the training dataset have to be more diverse in order to be able to perform on a broader range. Hence it can be said that overfitting is a term concerning how narrowly or broadly a model can be applied. Making the dataset more diverse can be done in multiple ways both by expanding the dataset, but also programmatically by manipulating the images in the dataset, such as turning the images, etc.

As can be seen, already with the simple network illustrated the process of training the network is complex and cumbersome to do by hand, but luckily the computer can do most of the processes automatically, especially if using various libraries, packages or similar. NN is considered a part of supervised machine learning meaning that the it will learn from already known outcomes. This therefore means that an "answer" sheet have to be given to the model for the training process.

In order for this a dataset first have to be created so that the model can be trained and tested before implementation in the elgoeeAI system.

### 4.2.1 Creation of the dataset

As earlier stated the products can either be defined as faulty or good, which requires at least two different defined states. However as the purpose is to prevent the faulty state, there must be at minimum three defined states, two accepted states and one faulty state. The reason for this is that tendencies towards error would not otherwise be able to be predicted before the faulty state occurs. This has to be defined for each of the adjustments variables in the four machines. In other words knowing multiple states crossing the threshold, see figure 4.2, leads to the opportunity of predicting future states.

#### Defining the states

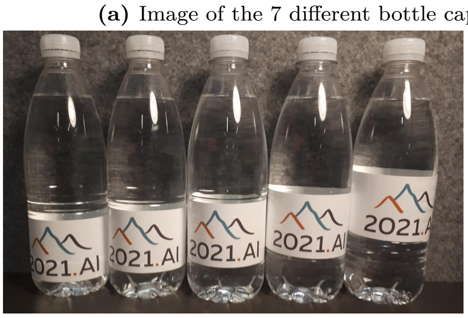
The output product states of each of the machines are defined according to different features. For the filling machine three different adjustments parameters are defined to affect the content quality, the funnel, bottle or liquid. However the adjustment parameters all affect the product on the same dimension, dirt-particles in the filled water bottle. Hence difference is defined in the amount of dirt-particles that the individual machine parameter contributes to the content. To represent dirt-particles peppercorns are utilised, as the phone camera available is not capable of detecting actual particles. To summarise 15 different output states are defined with their corresponding particle amount, see figure 4.1. The colours indicate the filling machine parameter it is associated with. Changing every third is done to illustrate the differing rate, but still reaching a high level of contamination.

**Table 4.1:** Table depicting the classified states and the number of dirt-particles in each state . The colour indicates which filling machine parameter the value is associated with. The colors are associated with the funnel(yellow), bottle(orange) and liquid(red) parameters.

| State | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Particles | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 15 | 20 | 25 | 30 | 50 |

For the other two machines the defined adjustment parameters affect the product on different dimensions, hence different like power and angle in the cap-screwing machine. For the cap-machine four different cap height levels are defined connected to the screw-power parameter, and then two different angle parameters, see figure 4.4a. The labelling machine are adjusted on the parameters height and angle of the label, hence output states for each are defined. Here four different output states are defined for each, see figure 4.4b and 4.4c.

**(a)** Image of the 7 different bottle cap heights after screwing. (reference bottle right)




**(b)** Image of the 5 different height levels of even labels. (reference bottle right)


**(c)** Image of the 5 different height levels of uneven labels. (reference bottle right)

**Figure 4.4:** The figures are illustrating the 10 levels for the label parameter. (reference bottle right)

This adds up to a total of 29 different output states from the machines plus the optimal state (reference bottle), hence 30 product states. However as these states can be mixed and combined it adds up to a total of 840 product state combinations.

$$6 \times 8 \times 15 \times 1 = 840$$

### Methodology

The dataset is created in an controlled environment, in which visual parameters can be controlled. Here a photo-shoot is carried out on a bottle in each of the defined states. To amplify the data for each of the defined bottle states and minimise the risk of overfitting, images of each state are shot three different angles and lighting conditions, see figure 4.5. In this way there will be nine different conditions for each of the product states, hence the total amount of different images to take equals

$$840 \times 9 = 7560$$

. The images are taken using a Samsung Galaxy A5 (2017). To amplify the data for each condition, stressly clicking the button for taking the image aiming for about 4-7 image per condition. These amplifications are made on the basis of ensuring multiple images for each condition and state to create enough image data for both training and testing of the image recognition model. Due to the large amount of images that have to be shot, some combinations are left out to make the task more manageable. The combinations left out are some of the combining error classifications, like faulty cap and label state. Hence the combinations of multiple bottle errors have a decreased measuring precision than when only one error state is present. The selection of which error combinations to include is based on a logarithmic function. This is logarithmic function is applied on the particle error states until reaching 15, hence leading to the sequence 1, 3, 7 and 15, thereby decreasing from 15 different to 4 variables. The bottlecap parameter is decreased to 4 variables and label 5, thereby changing the formulae for total number of different images to,

$$63 + 90 + 135 + (4 \times 5 \times 4 \times 9) = 288 + 720 = 1008$$

### Procedure

A structured approach is utilised to manage overview of the large dataset and process in shooting them. The session is therefore divided into sessions each focusing on images related to a given machine, to make the data amounts more manageable for processing. Each session thereby focus on shooting all the different images for the given machine or the machine combination images. The three lighting conditions are controlled using the roof light and the two table lamps seen on 4.5. Similarly the three angle positions can be seen. In order to not get lost in the repetitive photoshoot task, order guidelines are used. Firstly the lighting condition with no table lights are

**Figure 4.5:** Image of the setting in which the photo-shoot occurred, where the post-its show the different angles(including can on post-it).

shooted in all three angles in constant order. Then the same process is done for one table light on and both table lights on. When then going to the next product state, the order of the lighting condition is reversed, hence going from both table lights on to neither. Apart from assisting in process control it also saves time.

For each condition 4-7 images are taken, to ensuring capturing at least one clear image per condition.

After all states for each machine have been shot, the images are transferred to an external drive and deleted on camera due to space limitations.

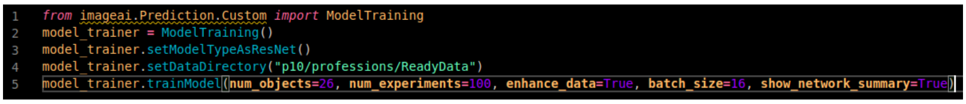
### Results

The photo-session results in a total of 4926(1734) images over the different state combinations. Furthermore the individual states contain between 28-40 images. The total session lasted approximately 8 hours.

Due to recommendations from colleagues at 2021.ai cap class 2 merged with level 1 and so is the twisting angles of the cap, leading to four classes for the cap machine. Similarly is done with uneven labels, reducing the classes to two different classes, one for each side. The recommendations are made due to doubts of the model being capable of differentiating all the classes with the few images in each image-set for each class. Therefore from this point on there are 26 different state classes.

### 4.2.2 Training the machine learning model

With the image dataset an image recognition model, to predict the different states that the bottle can be classified to be in, can be trained. The image recognition model is developed in Python as this is what is best compatible with the 2021.ai personnel and systems. For development, Visual Studio Code is utilised, which is a light integrated development environment (IDE). To further simplify the coding process the library ImageAI is utilised to build the neural network. The ImageAI library has functionalities to simplify the process of training the model and evaluating it. Training the model itself in fact only requires 5 lines of code see figure 4.6. This



```
from imageai.Prediction.Custom import ModelTraining
model_trainer = ModelTraining()
model_trainer.setModelTypeAsResNet()
model_trainer.setDataDirectory("p10/professions/ReadyData")
model_trainer.trainModel(num_objects=26, num_experiments=100, enhance_data=True, batch_size=16, show_network_summary=True)
```

**Figure 4.6:** Screenshot showing the required lines of code for training the model

therefore makes it very simple to start training an image recognition neural network.

For the model types, four different types are provided, 'SqueezeNet', 'RestNet50', 'InceptionV3' and 'DenseNet121. These differ in their network architecture and processing requirements Kurama [2020]. ResNet50 is selected as it is broadly applicable and processing power is not a delimiting factor.

Following a path to the dataset must be declared. However for it to work it is important that the dataset is sorted in a certain "folder-structure". (quite common) The folder-structure goes as illustrated in figure 4.7.

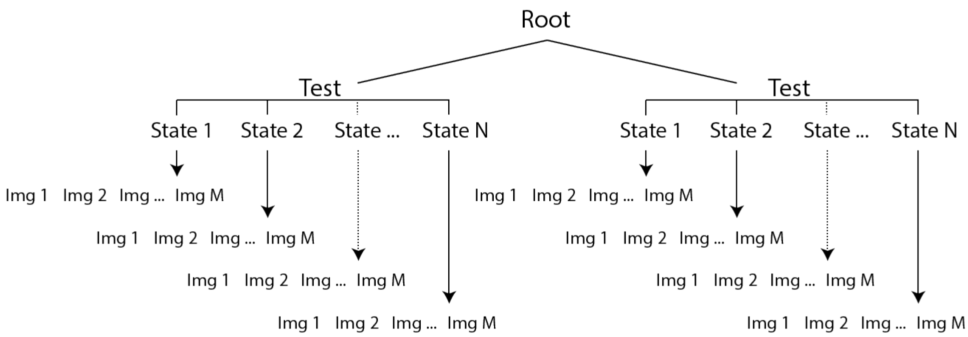



**Figure 4.7:** Illustration of the directory structure required for the machine learning model to know the classifications for states. Here N is the number of classes and M the number of images for each class.

Thereby all images depicting a given state need to be collected in the same folder, apart from the division into train and test samples. Here the splitting is made so that the test sample contains 10 images for each state, and the remaining are used for the training.

Lastly the different parameters for the training have to be defined. Here it is required to define the number of output classes, which should be consistent with the number of defined states, thereby 26. Further it is required to determine the number of epochs, which is the number of times that the model will train through the entire dataset. The remaining settings are optional, however here three additional parameters are adjusted. The first is setting the option of enhancing data to true, as this enlarges the dataset and decreases risk of overfitting, similar to using extra angles and lightings, just digitally. Secondly a batch size is determined, which is the sets of images that are looked at at a time. This is set to 16 instead of the default 32, due to memory constraints. Last the network summary is set to true, in order to see the structure of the trained neural network. This network structure can be found in appendix A. Running the experiment for 100 epochs, results in a model with a 0.48 validation accuracy overall. This means that it predicts the correct state 48% of the times on the test set.

### 4.2.3 Evaluating the model

The evolution of the model accuracy and losses are logged during the training trials. This evolution is illustrated on figure 4.8.

From the graphs it can be seen that it has a steady increase of accuracy and decrease of loss for the training set, but not for the validation sets. The validation lines has large amplitude spikes making great jumps in accuracy and loss, but after approximately 60 and 40 epochs respectively the spike amplitudes decrease notably. A reason for the large spikes could be due to the few images in the dataset and large amount of classes. Overfitting is not seen as an issue due to the training loss and validation loss functions following each other after 40 epochs, whereas the validation loss would be expected to increase if overfitting. However the very low loss that the functions show are a bit unexpected due to the low accuracy of the validation set, hence a higher loss expected. Due to the flattening of the graphs it indicates that further training will not make the model better, and new parameters are required for improvement.

The model with the highest validation accuracy had an overall accuracy of 0.48. This might not sound like a lot however it should be noted that it is not just two options to pick between, but 26. Hence there are a probability of 0.004 for each class. However even that this makes it a bit more impressive, a model with an accuracy of 0.48 is still not good and it should be improved. This would, as earlier stated, require new parameters such as more data, training, etc. therefore very time consuming. As the focus of this report is not the machine learning model, the developed model on 0.48 overall accuracy is deemed satisfactory for proof of concept at this stage. Due to this the accuracy values are not really used further only the classification names, hence assuming a good prediction of the given class.

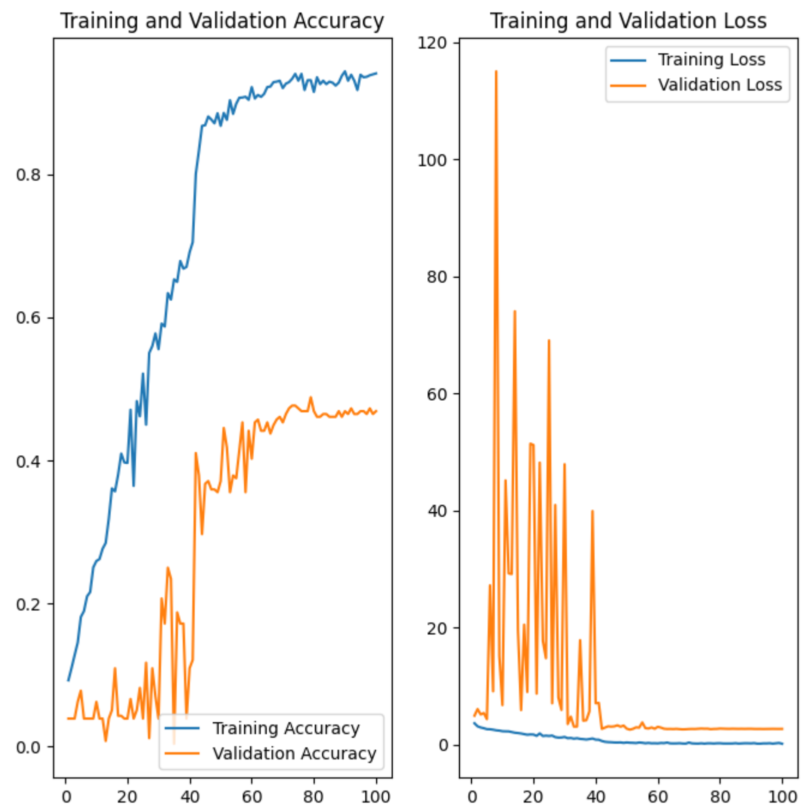



**Figure 4.8:** The graphs depicts the accuracy and loss respectively for both training and validation set.

### 4.2.4 Using the model in action

Using the best trained model with 48% accuracy, it is time to "deploy" the model, using it to predict new ingested images. Again for this ImageAI provides a standardised script for this and the trained model. This requires a path to the model, a path to the json class file, the number of output states and lastly a path to the image to predict, as input. The json class file is generated during training. Running the script the model will run and output a list of predictions ordered in how certain the model is in its prediction. The number of predictions are determined by the user and the default is the three most likely predictions. An example output is illustrated below where an image of the state class "aref bottle" is ingested:

- aref_bottle : 89.33

- p_lvl1 : 7.74
- cap_lvl1 : 2.23

Thereby it can be seen that it is not completely sure, but almost 90 percent sure that it is of class “aref bottle” which is optimal product state. The number of output classes presented can be changed and manipulated after needs. However it should be noted that the images used here are used from the test set, as new data have not been generated. It has therefore not been validated on new data.

The scripts for the training process and using the model can be found in appendix A.

# Chapter 5

# Mediating data to people

Having the back-end functionality of state predictions ready, it is time to start conveying this information to the intended people who are to interact with the system, hypothetically. This chapter will therefore focus on exploring who the users are, how they interact with the systems and how information can be presented in a user friendly manner.

## 5.1 Interview

To explore the shop-floor environment and how the employees herein interact with systems currently a semi structured interview is conducted.

### 5.1.1 Methodology

As the purpose of the interview is to get a better insight in the users and their environment a semi-structured interview is chosen to let interviewees speak freely. Construction and design of the interview are based in the five following research questions(RQs);

- How is the environment in which production occurs?
- How are machine-states and production monitored?
- How are the need for user input on a machine conveyed?
- How does the operator interact with the machine? (input)
- How often is interaction with the machines needed?

Interview questions are then formulated in order to answer each of the RQs, leading to a total of 29 questions.

Due to unfortunate environmental circumstances it is not possible to conduct the interview in person as normally, but instead have to be conducted online. This therefore creates a somewhat other format and interaction between the interviewer and the interviewee.

Conducting online interviews opens up for new possibilities such as asynchronous styled interviews, such as e-mailing, blogs, file exchanges, and synchronous communication as instant chatting, video calls etc. On the other hand, going online also presents new issues and factors to be prepared for. Firstly a key component of an online interview is a stable internet connection, especially in synchronous interviews Salmons [2015] However as the interviews have already been constructed and designed, a video call styled interview is selected. It is selected as it provides the closest resemblance of a normal face-to-face interview and studies show that semi-styled interviews fit well. Conducting the interview online does however affect the quality and perception. Further extra precautions have to be made regarding a stable internet connection and not talking at the same time. This is important as the video-call-systems use "two-way" communication, meaning that when one speaks, the others are muted, and can lead to misunderstanding and loss of information. Similarly to when using a "walkie-talkie". Therefore in order to decrease potential misunderstandings connection issues and assist the interviewee, the questions are shared with the interviewee. These are formulated on a PowerPoint, with a question on each slide so that the interviewee can follow the questions asked and process. Further the Powerpoint might also assist in creating a common environment, which physically is uncontrolled, as they can be sitting at home, work or some place else. However this freedom of environment also provides some form of ease, as neither interviewer or interviewee have to move geographical location [Braun et al., 2017]. The interview is recorded as a video recording, so non-verbal communication can also be included in analysis, along with the audio.

The PowerPoint presentation can be found in appendix B. As the interviewees acquired for the interview are danish, the interviews are also constructed and conducted in danish. The questions and their translation can be found along the PowerPoint in appendix B.

### 5.1.2 Process

The interview is scheduled with each interviewee according to their preferences over a period of two weeks. Here a time has been agreed upon, after which the interviewer sends a Google-Hangout meeting request to the interviewees mail. Through this a calendar event is created at which the video-meeting can be started. On starting the meeting, basic formalities and small talk underwent. From this the PowerPoint is shared live with the interviewee, which starts out by introducing the interview agenda, structure and how data is collected and handled. After receiving consent the presentation is continued and the interview begin. Following the conduction of the interviews a semi-transcription of each interview is conducted, hence leading to a partial analysis of relevant context during transcription. This is selected over a complete transcription, as it is mainly to get an overview and insight into the environment and processes, and thereby strict analysis is not required. Further the interviews are conducted in danish, leading to also having to translate them. Together these reasons result in partial transcriptions of the interviews.

### 5.1.3 Participants

The interviewees consist of various personnel working with manufacturing and the production machines herein. From this they have been chosen due to availability, through opportunity sampling. In total four interviewees participated, from these two are personal contacts, while the remaining are professional relationships. One of the four interviewees is also the client of this development, hence is used for pilot-testing.

### 5.1.4 Pilot-testing

The interview is pilot tested with a colleague from 2021.ai, who works with manufacturing. Through this 2 additional questions are added, along with rephrasing 3 questions. Further a lot of general knowledge is acquired due to the colleagues long experience within manufacturing and their processes. Due to these valuable insights and only few adjustments of the interview it is included for further analysis among the other interviews.

### 5.1.5 Conduction of interview

One interview is conducted with two interviewees at the same time due to the interviewers relationship to the interviewees this was the only natural option. The pilot and interviewee 3 are interviewed separately and conducted over two sessions. This was due to bad scheduling, where the pilot was conducted on the same day with about 1 hour apart, where the third are conducted with more than a week in between. Due to this there became doubt whether the “interaction with machines” section was conducted previously or not. To be sure it was therefore covered on the second session, which was lucky as it had not been part of the previous. Regarding the environment of the interviewees, the first three were located in their home, and the last was at their job location. The interviewees being interviewed simultaneously experienced disturbances from their dog a couple of times, but apart from that no special disturbances were noted throughout the interviews.

### 5.1.6 Results

The three interviews lasted 1 hour and 29 minutes, 2 hours and 10 minutes and 1 hour and 34 minutes, respectively. A total of 5 hours and 14 minutes have hence been transcribed and analysed for relevant information. The transcriptions can be found in Appendix B. From the recordings and transcriptions a subjective analysis is carried out, aimed at answering the 5 research questions. Furthermore notable information exceeding the 5 questions but in relation to the scope of the thesis are included. This will be presented in the following section.

### 5.1.7 Analysis of the interviews

The four interviewees each had different roles at their respective company, two have roles of project managing, and the other two have roles of repairing and servicing of machines. They all work in the pharmaceutical industry, which implies much more strict requirements and control of the shop floor environment. Thereby many operations are level controlled, meaning a certain clearance level is required to do the given operations. Operations that are critical to the product are rarely possible to adjust by others than a few people, whereas operations not relevant to the quality of the products are more adjustable by operators. On the shop-floor different roles are part of the production in different manners. Operators work with the machines and production processes on a normal basis and do not require any specific educational background. Technicians and other forms of technical support are usually denoted “service”, work with calibration and repairs of machines and equipment used for the production. These commonly have a background in a craftsmanship or technical specialisation, such as electricians or coders. Lastly there is the QA department which is responsible for quality inspection of the machines, processes and product, ensuring that it lives up to the requirements. These are the three main departments making up the shop-floor and production process and interacting with the machines, then there are also departments which are concerned with the planning of production, such as acquiring materials and parts for the product, scheduling downtime, optimisations, repairs, etc., which is also concerned with production, however in a more indirect and supervisory manner. The machines and processes on the shop-floor are both monitored through machine interfaces and by humans directly, meaning that they observe, listen etc. to the machines or processes, and report if any deviant behaviour is noticed. Thereby much of the everyday monitoring consists of human observations and the computer integrated systems collects data of various parameters and logs of interaction. Data reports created are commonly only looked at when faults occur or at monthly and yearly evaluations. For more daily monitoring digital displays showing OEE parameters and colour codes presenting how well production goes, are utilised. Computer systems mentioned as used at the sites are Zapp, Point, Tableau, DetlaV and SCADA. DeltaV is an operating system whereas Tableau, Zapp, SCADA and Point are used for various data collection and presentation of data, and Pit Stop is a user interface for controlling various elements. These systems in cooperation with the human observations can thereby be said to make up the monitoring at the shop-floor. Interaction with machines thereby occurs on a mixture of requests by the systems and human initiative. According to the interviewees the latter is the reason for the majority of interactions and is based on experience. However they also all mention that interaction with machines are based on step by step instructions denoted “subs” for each individual operation that can be performed. Most of the machines used contain digital displays for interaction, and tablets, phones and computers can be used for adjustments and calibrations if the sufficient clearance levels are met. According to the interviewees the machines do not require maintenance very often and not that dynamically as it is usually planned on the yearly evaluations. These yearly evaluations define much of the processes and maintenance that are conducted throughout the year, whereas the remaining maintenance is responses to defects. Much of the machinery is thereby running very autonomously, mostly requiring humans in the form of handling material ingestion and product output. How often machinery has malfunctions and thereby minor downtimes, are difficult to say, as this can be very diverse. However more comprehensive downtimes are estimated to be between 1 and 2 a year for both planned and unplanned downtimes of the entire factory production. They all believe that predictions about future states will increase production and decrease downtime, which they also do to some degree with the various statistical reports created and acted upon. As to what the interviewees find important in mediation, it majorly concerns machine operations and process related elements. This is such as the required specifications for how the individual machine operates, scrap rates and causes of malfunctions or machine stops. Further they all agreed that they like to be informed over mail or sms, and depending on the criticality of the information, the invasiveness should differ accordingly.

### 5.1.8 Conclusion

To summarise the production processes in the medical manufacturing environment, it is highly controlled and documented. Processes and monitoring of products are conducted by humans and machines in cooperation. Interactions of machines are commonly defined at yearly factory downtime, where most processes and procedures are defined.

# Chapter 6

# Lo-Fi prototypes

Interviewees all meant that informative and intuitive displays are important and that they would like a precise error description and as visually represented as possible while still presenting unambiguous information. This is therefore investigated further by exploring various ways the errors and causes can be presented, a few of these are then tested iteratively through Lo-Fi designs, after which a final version of displaying the information is achieved.

## 6.1 Presenting parameters and errors

There can be said to be two elements that need to be mediated from the elgoeeAI system to the user, the state predictions and what action is wanted from the user to maintain optimal state. According to the participants unambiguous and concrete information is the key factor, and in current solutions primarily text based. They therefore feel confident in text based mediation of information.

However the skill of reading is a complex artificial skills that humans have evolved in the last few thousand years and became common within the last five centuries. This is a skill taught similar to violin, games, etc. and each individual will have a different skill level. [Johnson, 2014] Explaining both predictions and intended action can quite quickly add up to a large amount of text which should be avoided in interactive systems. It might therefore be that other mediation techniques are more optimal for mediation of the information.

In the world of math and statistics, graphs are commonly utilised to visualise sums of information in a more intuitive manner than table values. Another mathematical method is social maths, which is used for presenting numerical data as a compelling story concerning a social issue. It is concerned with creating a message that resonates with the target audience by referencing or comparing the issue numbers to familiar and relatable events and numbers. It is aimed at making mathematical data more approachable by laypeople. It can be said to have several similarities to Nudging, as the aim is typically to change people's behaviour regarding a social issue, such as social distancing illustrated in the figure below 6.1. Such use of icons are also commonly seen in graphical user interfaces (GUI's) to replace a text description and mediate a given action, just look to your browser!

These mediation techniques could therefore all be manners in which the information is mediated, however as the interviewees mentioned unambiguous and concrete information is important. It should therefore be investigated how and to which extend visual effects can supplement or replace text descriptions, while maintaining unambiguous and concrete information mediation.

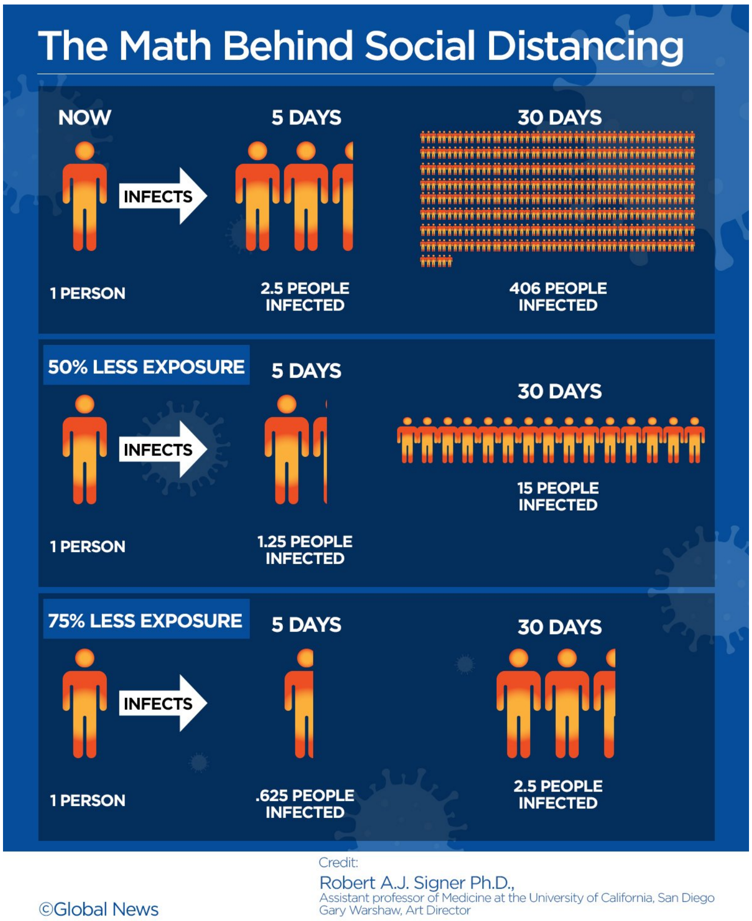



**Figure 6.1:** Infographic presenting the effects of social distancing using visual illustrations. (Found at https://globalnews.ca/news/6709071/coronavirus-social-distancing-math/)

## 6.2 Designing the LoFi prototype

To investigate the understanding of different mediation methods, three different designs are developed. The first version consists of short text descriptions concerning the given error and action required to prevent further errors. As an example it can be:

- *"Power error 1 detected at cap screwing machine. This is expected to increase to power error 3 in 10 minutes and further into power error 4 in additional 10 minutes if no action performed. To prevent errors it is suggested to increase drill power"*

And then a following description of what action to do in order to prevent error, such as:

- *"To prevent power error level 3 and power error level 4, an increased power of screwing machine is suggested."*

Such description pairs are created for each type of machine errors, resulting in 7 pairs. The second version utilises graphs to depict the same information as the text. Therefore they consist of pairs of graphs where one depicts the error description, and the other depicts the suggested solution, as an example see figure 6.2.

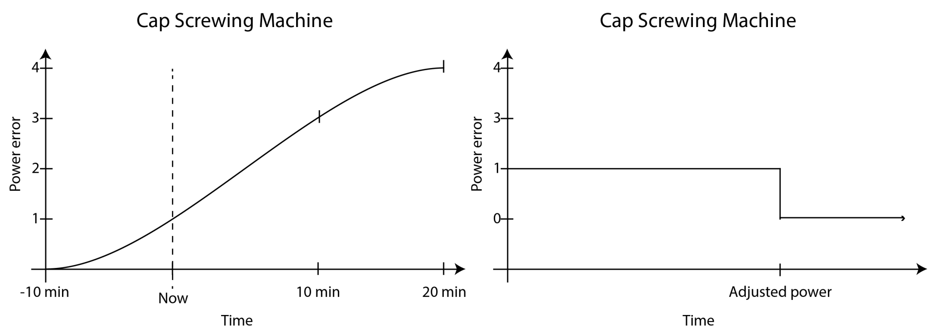



**Figure 6.2:** Figure illustrating two graphs depicting the same information as the text example.

As can be seen the first graph depicts the time parameter on the X axis, error severity on the y axis and then the product evolution as a function of the two. The second graph illustrates the error state as a constant function over time, changing only when a power adjustment is made, thereby depicting the solution suggested.

The third version uses icons for mediation of the information. Thereby different icons depicting the parameters of the description and solution suggestion are created. However as icons can have multiple meanings and differ depending on the context, a preferred icon should be selected. As an example see figure 6.3 for different representations of Power.

Hence a short preliminary Lo-Fi test is conducted investigating which icons best illustrate the different parameters in the context.

### 6.2.1 Preliminary icon test

Different icons are made for each of the parameters that need to be mediated. The parameters illustrated by icons are the product states, present and future, error

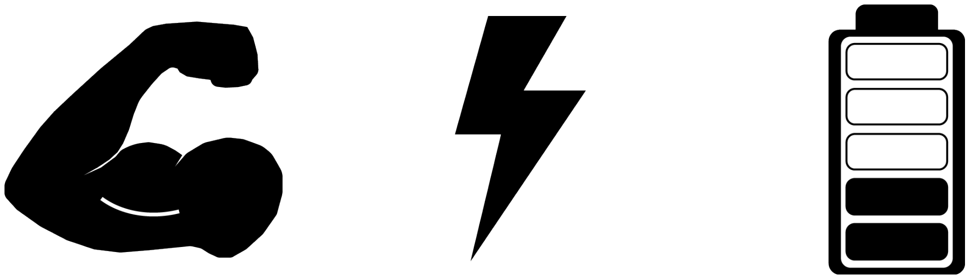


**Figure 6.3:** Figure illustrating three different icons all symbolising power.

level, time and the parameter to adjust for preventing the error evolution. For each parameter at least two icon representations are created and maximum four. These are then evaluated by participants through a questionnaire in which they vote which icon they like best for representing the given parameter. If they are not satisfied with either of the symbols an option of selecting "other" is given, with the possibility of suggesting a preferred icon to the ones presented. The questionnaire is created in Google Forms and can be found in appendix C.

### Results of preliminary icon test

Following the answers are summarised in English, the visual graphs and Danish phrasings of the summary and the raw data can be found in appendix C.

**Respondents** 21 people answered the questionnaire, where 14 respondents identified as male, and 7 as female. Furthermore the majority of respondents classified their roles as either being operators(9) or technicians (8), while the remaining 4 classified themselves as more specialised roles. The age of the respondents ranged from 25 years to 62 years with the same ages occurring twice at maximum.

**Indication of error and time** For indication of error development, 20 respondents preferred option C, which uses green, yellow and red to symbolise the increase of error significance. The last respondent also prefers this version but where the colours fill the entire figure height. This therefore means that all respondents preferred this presentation method. Indication of passing time is more ambiguous in respondent answers, 9 preferred option C, in which an arrow is utilised, 8 selected option A, where 3 dots are used, 2 chose option B, where a clock is used for symbolisation and lastly 2 selects the "other" option and suggest using a hourglass.

**Icons for the filling machine** For the bottle, 12 respondents selected option B, which is depicting the actual bottle, 5 selected option A, the chemistry flask. The last 4 respondents chose the "other" option, where one suggest a faucet running down in a bottle, another states that the bottle alone looks like a finished product, supported by another who thinks a more universal icon should be used. The last thinks that it depends on the content being filled in the bottle. For the icon symbolising the machine funnel best, 12 selected option A, the funnel icon and 8 selected option B, the faucet icon, and the last respondent states, "A if it is a conventional funnel, but would select something assimilating the real equipment more." To represent the liquid 16 respondents chose option C, the water droplet icon, 2 chose option B, the chemistry flask, 1 selected option D, the wave icon. The last 2 respondents chose the "other" option, one mentioning that using option B could be mistaken with the bottle being filled, and the other suggesting using a faucet running into the bottle as an icon instead. See figure 6.4 for the three most selected icons for each parameter.

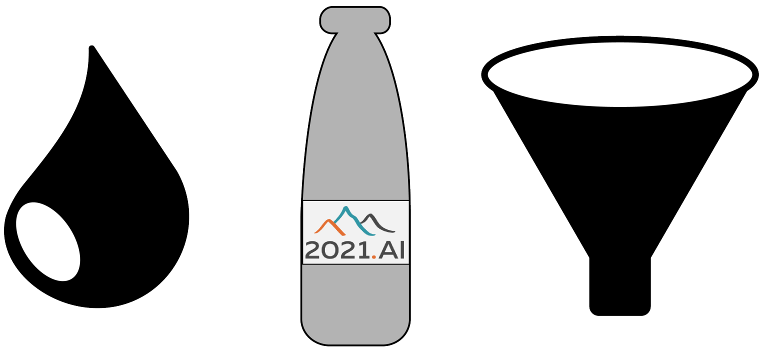



**Figure 6.4:** Figure illustrating the most voted icon for each of the three parameters.

**Icons for the cap screwing machine** To assimilate the power parameter of the cap screwing machine 11 respondents preferred option A, the "strong arm", 8 preferred option C, the battery icon and the last 2 selected option B, the lightning icon. For symbolising angle 8 respondents selected option A, the drill tilted drill icon, another 8 selected option B, 3 choose option C, the bubble level, and 1 picked option D, the protractor icon. Lastly one respondent chose the "other" option, suggesting a close up image as a pictogram instead of the presented icons. See figure 6.5 for the most selected options for both parameters, power and angle.

**Icons for the labelling machine** To represent the height parameter at the labelling machine, 11 selected option B, the ruler icon and 9 selected option A, the encapsulated pictogram. The last respondent chose the "other" option suggesting adding arrows in both directions as they assume adjustments in both directions are

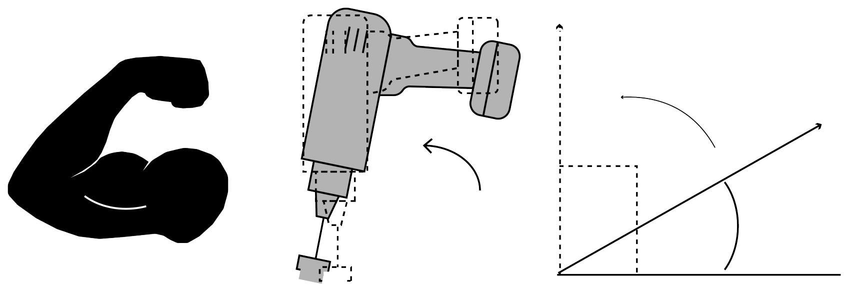


**Figure 6.5:** Figure illustrating the most voted icon for power and the two most voted icons for depiction of angle.

possible, and further prefers option B. To represent angle 12 choose option A, the angle pictogram, 6 choose option B, the geometric illustration, option C and D are both selected once, and lastly a respondent selects the “others” suggesting arrows in both directions and a preference for option A. See the figure 6.6 below for the icons with most votes in each parameter.

**Indication of user input** To mediate a need for user input 8 respondents selected option C, where a finger icon is used and an arrow pointing to the target, see figure 6.7. 5 choose option D, where the target is blinking and other possible inputs are static. 4 selected option B, an icon of a user, and 3 prefers the “attention” icon and both have an arrow pointing to the target action icon. Last respondent suggests a mixture of A and D, using the symbol from A over D while it is blinking.

**Movement and general comments** In regards to the question, whether respondents preferred dynamic or static icons on interfaces, 15 responded it depends on the situation, 4 preferred static icons, and the last two preferred dynamic. Lastly asking them for if they had further comments regarding using icons to mediate information 6 answers and 2 answers on the question for general final comments. Three simply answered “no”. Another one mentioned the importance of designing HMI’s according to the user and not the other way around, and further to be cautious towards usage of colours as color blindness is a taboo and more common than assumed. Further one adds not to make it too smart and more child friendly as it is easiest for peo-

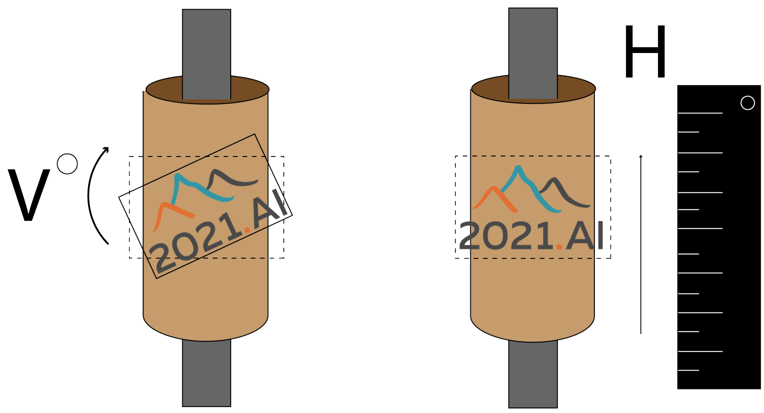



**Figure 6.6:** Figure illustrating the two most voted icon options for both parameters, height and angle.

ple to handle in the everyday, and another states the symbols and icons should be consistent over the machines. Lastly one states the importance of icons being logical and assimilate what they represent, and the other a phone number.

### Icons for the further design

The icons that have been selected the most are used for the further design and development of the system. For the angle parameter at the cap screwing machine two icons had equal votes, hence it is unclear which is best. One respondent mentions that consistency is important, therefore the pictogram is selected to go on with. This maintains consistency between the angle parameters of the cap screwing machine and labelling machine. It is further noted that one respondent warns about the usage of colours due to the possibility of color blindness in users being more common than to be expected.

## 6.3 Text, graphs or icons as mediator

Having the three different mediation designs, it is time to investigate the perception of these. Thereby it adds up to a total of 15 pairs of descriptions and solutions, derived from the 5 different errors each represented in the three mediation methods. This therefore also means that the errors are not tested exhaustive but exclusive, selected on the basis of covering all the errors once. Meaning that height is tested in

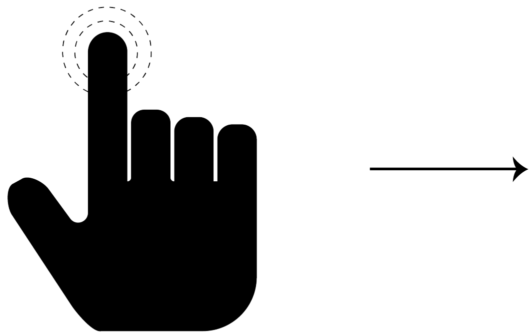


**Figure 6.7:** Figure illustrating the most preferred icon version to depict that the system need a given input.

one direction and not both, as this would give too many conditions and be repetitive. The developed Lo-Fi designs can be found in appendix D.

### 6.3.1 Procedure

First a short introduction to the experiment and an explanation of their given task is conducted, whereafter a consent form is signed and recording is started. The participants are tasked to imagine they are working at the hypothetical manufacturing line surveying the three different machines and their production, hence an introduction to the hypothesised production, machines and parameters to monitor are given. The participant will then be presented with one of the errors and solutions in either the format text, graphs or icons. They then have to speak out loud how and what they perceive in the presented design. After having explained their understanding, they are asked to rate the mediation method on three visual analog scale(VAS) parameters, quickness of understanding, clarity of message and likeability of the mediation method. This is then repeated 9 times, so that all the different mediation techniques for 3 different errors are covered by the individual participant.

### 6.3.2 Methodology

In the experiment a Latin Square randomisation is used for the presentation order of the different designs, both for the individual participant as for between the participants. Hence the experiment classifies as a mixed subject design. As measurements parameters, a recording is used to capture the participants thoughts and ideas expressed through the think out loud method. The think out loud method aims at getting the participant to put as many words on their perception and processing hereof. In order to get some quantitative data, it is decided to make measurements using visual analog scales(VAS), which gives data in the interval format Lewis and Erdinç [2017]. Here three VAS's are developed aimed at covering three different aspects of the experience, referred to as dimensions. The dimensions are quickness of understanding, ranging from slow to fast, message clarity, ranging from ambiguous to unambiguous and lastly likeability of mediation technique ranging from bad to good. Papers are used to cover the two presentation methods not in focus, in order to minimise participants from evaluating a mixture of the designs. Lastly the bottle parameter from the filling machine is used as familiarisation through the introduction for all participants.

### 6.3.3 Participants

Due to time pressure from both Novo Nordisk and project deadlines only 4 people participated. Out of these two were operators and two were technicians/smiths, all employees at Novo Nordisk.

### 6.3.4 Results

The results of the experiment are a collection of the VAS scores, which are measured with a ruler manually, and notes on the author's subjective analysis of the recordings. These results can be found in appendix D. The three VAS was designed to be 10 cm in length as is common practice, Lewis and Erdinç [2017], however when printed on physical paper they ended up being 9.35 cm in reality. Hence the highest score possible is 9.35.

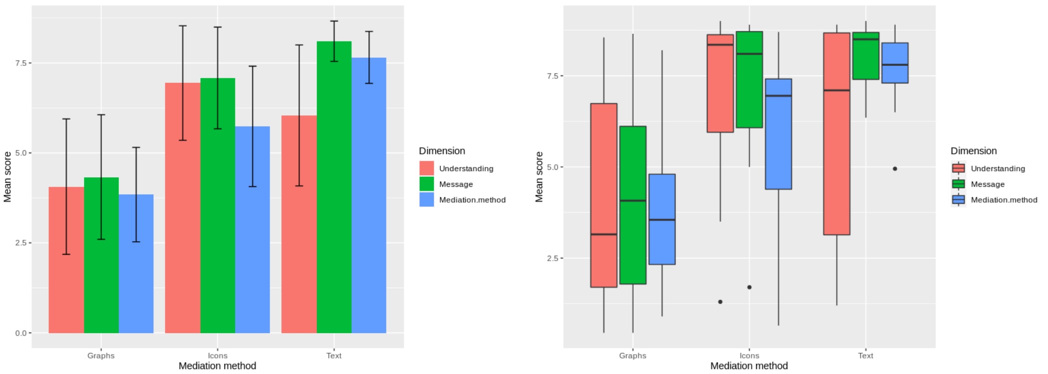
### 6.3.5 Data analysis

Data analysis of the VAS scores are conducted in R.Studio version 3.6.3 and a contextual analysis of the recordings are conducted by listening and noting down keywords. The script and recording data noted down can be found in appendix D.

#### VAS scores

The data is first imported and converted into long format and then explored from there. A bar plot is made, see figure 6.8a, which illustrates the mean scores over mediation technique and dimension of the VAS. It shows the mean scores are highest at the text parameter for the two dimensions Message and Mediation method, which represents how quickly they understand the information, and how clearly they understand it. However the Icon shows to have a higher mean score in the Understanding dimension, covering how quickly they perceive an understanding of the presented.

It should be noted that for the Message and Mediation method dimensions within the text parameter the standard deviation and spreading is a lot narrower than that of the Understanding dimension in the icon parameter. In fact it is narrower than all the others, meaning that there have been a small variation in the scores given for these parameters compared to the rest.




**(a)** Barplot of the three dimensions and mediation techniques **(b)** Boxplot of the of the three dimensions and mediation techniques

**Figure 6.8:** Bar and boxplot of the three dimensions(red=Understanding, green=Message, blue=Likeability) and mediation techniques

On figure 6.8b, a box plot is illustrated depicting the median score of the different dimensions and parameters. This shows that the Understanding dimension has the smallest variance in the Icon parameter and the largest in the text parameter. Message and Mediation method shows the smallest variance in the text parameter. These graphs overall show a trend towards the icon and text versions having the highest scores. This is supported by the below summary, table 6.1, of mean scores for the different dimensions and parameters.

**Table 6.1:** Text

| | Understanding | Message | Mediation techn. | **Ovall Mean** |
|---|---|---|---|---|
| Text | 6.04 | **8.10** | **7.65** | **7.27** |
| Icon | **6.94** | 7.08 | 5.74 | **6.59** |
| Graph | 4.06 | 4.33 | 3.84 | **4.08** |

However to support the suggested trend, a repeated measures ANOVA is conducted to see which factors are significant to the scores. A repeated measures ANOVA is selected due to the repetitive nature of the experiment, where 1 participant goes through multiple iterations. In order to prevent inflating familywise error, planned contrasts are made, see table 6.2.

The first hypothesis formed for Parameter is that graphs are different from the others. The hypothesis for dimensions is that the Mediation method differs from the two other factors concerning understanding and message clarity. Lastly there is checked for differences between machines, and here the contrast differs the filling machine with the others due to its differing classification. The second contrast for the three factors, is one differing the two that are the same in the earlier one.

**Table 6.2:** Text

| Contrasts sets | Group | Contrast1 | Contrast2 |
|---|---|---|---|
| Parameter | Graph | -2 | 0 |
| | Icon | 1 | 1 |
| | Text | 1 | -1 |
| Dimension | Understanding | 1 | 1 |
| | Message | 1 | -1 |
| | Mediation meth. | -2 | 0 |
| Machine | Cap machine | 1 | 1 |
| | Filling machine | -2 | 0 |
| | Label machine | 1 | -1 |

To create the repeated measures anova a generalised linear model approach is used, utilizing the function lme to create the linear modes presented in figure, 6.9.

```
# 4.1 lme (The multilevel approach) ####
baseline<-lme(Score ~ 1, random = ~1|Participant/Machine/Parameter/Dimension, data =
                long_vas, method = "ML") # ML = Maximum likelihood
# adding machine as a predictor
machineModel<-update(baseline, .~. + Machine)
# adding dimension as a predictor
dimensionModel<-update(machineModel, .~. + Dimension)
# adding parameter as predictor
parameterModel<-update(dimensionModel, .~. + Parameter)
# adding interaction effects
interactionModel_md <- update(parameterModel, .~. + Machine:Dimension)
interactionModel_mp <- update(interactionModel_md, .~. + Machine:Parameter)
interactionModel_dp <- update(interactionModel_mp, .~. + Dimension:Parameter)
```

**Figure 6.9:** Snippet showing the linear regression models that are created.

With these the anova model is created taking in each of these linear models as input parameters and gives the output seen in figure 6.10

The output shows that adding machine and dimensions as a predictor is not significant, whereas adding the parameterModel does show significance with a p-value of <.0001. Also for the interaction models only one, interactionModel_dp with a p-value of .0128. Hence

Diving further into the models, using the summary function of the interaction-Model_dp more details on the data variables can be explored as shown in figure 6.11.

The output first gives the two contrasts for the machine, which shows no significant effects on the score. Next are the two contrasts for dimensions added, which shows significant effect on score when comparing dimensions Understanding and mes-

| | Model | df | AIC | BIC | logLik | Test | L.Ratio | p-value |
|---|---|---|---|---|---|---|---|---|
| baseline | 1 | 6 | 488.8329 | 504.9257 | -238.4165 | | | |
| machineModel | 2 | 8 | 490.2679 | 511.7250 | -237.1339 | 1 vs 2 | 2.565030 | 0.2773 |
| dimensionModel | 3 | 10 | 488.3318 | 515.1531 | -234.1659 | 2 vs 3 | 5.936130 | 0.0514 |
| parameterModel | 4 | 12 | 471.9338 | 504.1194 | -223.9669 | 3 vs 4 | 20.397986 | <.0001 |
| interactionModel_md | 5 | 16 | 477.7696 | 520.6837 | -222.8848 | 4 vs 5 | 2.164173 | 0.7056 |
| interactionModel_mp | 6 | 20 | 483.9641 | 537.6067 | -221.9820 | 5 vs 6 | 1.805528 | 0.7715 |
| interactionModel_dp | 7 | 24 | 479.2631 | 543.6342 | -215.6315 | 6 vs 7 | 12.701011 | 0.0128 |

**Figure 6.10:** Snippet showing the output of running the anova analysis on above models.

Fixed effects: Score ~ Machine + Dimension + Parameter + Machine:Dimension + Machine:Parameter + Dimension:Parameter

| | Value | Std.Error | DF | t-value | p-value |
|---|---|---|---|---|---|
| (Intercept) | 5.977315 | 0.6265151 | 62 | 9.540576 | 0.0000 |
| MachinefillvsOthers | 0.386574 | 0.1944366 | 6 | 1.988175 | 0.0940 |
| MachinelabelvsCap | -0.226389 | 0.3367741 | 6 | -0.672228 | 0.5265 |
| DimensionLikevsOthers | 0.116435 | 0.1057383 | 62 | 1.101164 | 0.2751 |
| DimensionSpeedvsAmbig | -0.411806 | 0.1831441 | 62 | -2.248533 | 0.0281 |
| ParametergraphsvsOthers | 0.949769 | 0.1944366 | 18 | 4.884721 | 0.0001 |
| ParameterIconvsTxt | -0.339583 | 0.3367741 | 18 | -1.008342 | 0.3267 |
| MachinefillvsOthers:DimensionLikevsOthers | 0.065509 | 0.0747683 | 62 | 0.876164 | 0.3843 |
| MachinelabelvsCap:DimensionLikevsOthers | 0.107639 | 0.1295024 | 62 | 0.831173 | 0.4091 |
| MachinefillvsOthers:DimensionSpeedvsAmbig | 0.103472 | 0.1295024 | 62 | 0.798998 | 0.4273 |
| MachinelabelvsCap:DimensionSpeedvsAmbig | -0.056250 | 0.2243048 | 62 | -0.250775 | 0.8028 |
| MachinefillvsOthers:ParametergraphsvsOthers | 0.074884 | 0.1374874 | 18 | 0.544663 | 0.5927 |
| MachinelabelvsCap:ParametergraphsvsOthers | -0.055903 | 0.2381352 | 18 | -0.234752 | 0.8171 |
| MachinefillvsOthers:ParameterIconvsTxt | 0.163542 | 0.2381352 | 18 | 0.686760 | 0.5010 |
| MachinelabelvsCap:ParameterIconvsTxt | -0.346875 | 0.4124623 | 18 | -0.840986 | 0.4114 |
| DimensionLikevsOthers:ParametergraphsvsOthers | -0.000810 | 0.0747683 | 62 | -0.010836 | 0.9914 |
| DimensionSpeedvsAmbig:ParametergraphsvsOthers | -0.139236 | 0.1295024 | 62 | -1.075162 | 0.2865 |
| DimensionLikevsOthers:ParameterIconvsTxt | 0.309375 | 0.1295024 | 62 | 2.388951 | 0.0200 |
| DimensionSpeedvsAmbig:ParameterIconvsTxt | 0.480208 | 0.2243048 | 62 | 2.140874 | 0.0362 |

**Figure 6.11:** Snippet showing the output of running summary function on the anova model

sage clarity. Last of the additive models, the two contrasts for parameter are added, which shows significance for graphs vs icon and texts. For the interaction models only the last two show a significant effect. These are the interaction of icons vs text and dimension Like vs the others and Dimension speed vs ambiguity. Hence the icon vs text parameters have a significant interaction with all three score dimensions. These results therefore support the assumption that text and icons are preferred as mediators of the information.

In figure 6.12 is a plot depicting the interaction effect between the mediation techniques text and icon and the three VAS dimensions.

### Recordings

From the recordings and observations during the experiment, clear order and learning effects were noted, as the graph and icon examples were first really understood after they had experienced a text example. This is also mentioned by all four participants. However after trying a text version they quickly found the others more easy to interpret. This learning effect was also seen to affect similar versions, like when presented a graph the later graphs are perceived faster. They overall felt confident in understanding the text version even though two complained about the language being in English as this made the perception slower. This difficulty was especially

Fixed effects: Score ~ Machine + Dimension + Parameter + Machine:Dimension + Machine:Parameter + Dimension:Parameter

| | Value | Std.Error | DF | t-value | p-value |
|---|---|---|---|---|---|
| (Intercept) | 5.977315 | 0.6265151 | 62 | 9.540576 | 0.0000 |
| MachinefillvsOthers | 0.386574 | 0.1944366 | 6 | 1.988175 | 0.0940 |
| MachinelabelvsCap | -0.226389 | 0.3367741 | 6 | -0.672228 | 0.5265 |
| DimensionLikevsOthers | 0.116435 | 0.1057383 | 62 | 1.101164 | 0.2751 |
| DimensionSpeedvsAmbig | -0.411806 | 0.1831441 | 62 | -2.248533 | 0.0281 |
| ParametergraphsvsOthers | 0.949769 | 0.1944366 | 18 | 4.884721 | 0.0001 |
| ParameterIconvsTxt | -0.339583 | 0.3367741 | 18 | -1.008342 | 0.3267 |
| MachinefillvsOthers:DimensionLikevsOthers | 0.065509 | 0.0747683 | 62 | 0.876164 | 0.3843 |
| MachinelabelvsCap:DimensionLikevsOthers | 0.107639 | 0.1295024 | 62 | 0.831173 | 0.4091 |
| MachinefillvsOthers:DimensionSpeedvsAmbig | 0.103472 | 0.1295024 | 62 | 0.798998 | 0.4273 |
| MachinelabelvsCap:DimensionSpeedvsAmbig | -0.056250 | 0.2243048 | 62 | -0.250775 | 0.8028 |
| MachinefillvsOthers:ParametergraphsvsOthers | 0.074884 | 0.1374874 | 18 | 0.544663 | 0.5927 |
| MachinelabelvsCap:ParametergraphsvsOthers | -0.055903 | 0.2381352 | 18 | -0.234752 | 0.8171 |
| MachinefillvsOthers:ParameterIconvsTxt | 0.163542 | 0.2381352 | 18 | 0.686760 | 0.5010 |
| MachinelabelvsCap:ParameterIconvsTxt | -0.346875 | 0.4124623 | 18 | -0.840986 | 0.4114 |
| DimensionLikevsOthers:ParametergraphsvsOthers | -0.000810 | 0.0747683 | 62 | -0.010836 | 0.9914 |
| DimensionSpeedvsAmbig:ParametergraphsvsOthers | -0.139236 | 0.1295024 | 62 | -1.075162 | 0.2865 |
| DimensionLikevsOthers:ParameterIconvsTxt | 0.309375 | 0.1295024 | 62 | 2.388951 | 0.0200 |
| DimensionSpeedvsAmbig:ParameterIconvsTxt | 0.480208 | 0.2243048 | 62 | 2.140874 | 0.0362 |

**Figure 6.12:** Graph showing the interaction effect between the text and icon contrast vs the different dimensions.

noted by one participant being dyslexic and struggling with the processing. The understanding of the icons and graph versions was not as precise and some required a bit of help in order to understand them properly. All four participants suggest making a mixture of the text version and the icon version, as they argue that the icon version simply needs some contextual words regarding the presented icons in order to understand them. As for the graph versions three participants find them ambiguous and complex to understand due to the axis values. One of them further argues that graphs are more useful in continuous monitoring situations, but not for conveying singular actions.

### 6.3.6 Conlusion

The results from the repeated measures and the subjective opinions and analysis of the recordings shows consistency in that a mixture of the icon and text version should be developed. Hence a mixture of the two mediation techniques text and icons are incorporated and developed in the HiFi prototype. Graphs are not preferred and one mentions it fits better with continuous information or tendencies and is therefore not used in the further prototype.

# Chapter 7

# Creation of the complete system

Having the preferred mediation method it is time to collect it all in a digital system, hence a simulation of the manufacturing process, the machine learning model and mediation to the user.

As the platform is intended to be a presentation platform demonstrating the potential for AI in manufacturing it has to be easily accessible for both the presenting users and the users being presented to. Therefore it is desired from 2021.AI that the system is accessible online, hence has to be an online platform. Furthermore the machine learning model is coded in python, hence requiring compatibility with this language. From these requirements it is selected to develop the system in the Django framework, which is used for web development and is compatible with a variety of coding languages, with a foundation in python for backend handling. A depiction of the usage of different languages, what for and how they communicate can be seen in figure 7.1. Another advantage of django is the setup process of the development environment and files required herefor, is simplified to a few commands. After this the environment is ready for the programmer to develop the desired platform.

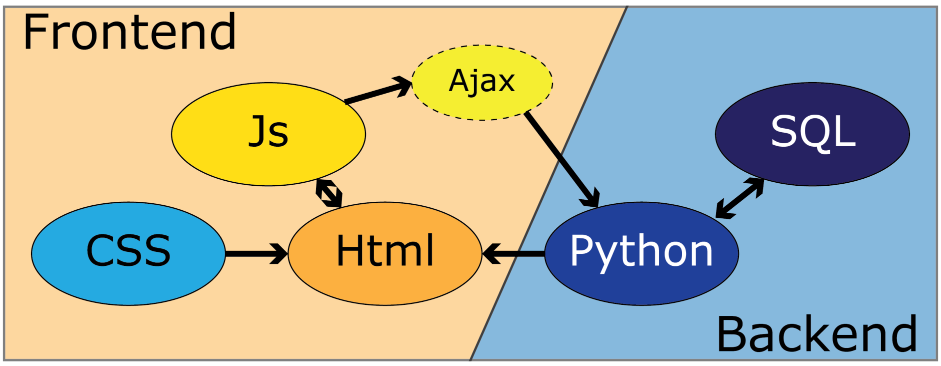


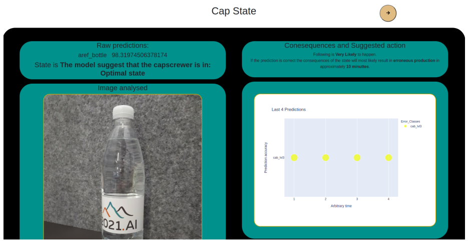

**Figure 7.1:** Flow chart of how the languages connect and are used.

The design of the system takes basis in Normans interaction principles and Gestalt perception principles. The Normans interaction principles in focus are sifnifiers, feedback, mapping constraints and the conceptual model. Where signifiers are elements that are used to communicate behaviour, thereby aiming at indicating appropriate behaviour, such as if something is clickable. They can therefore be said to communicate what the system is capable of, or in other words the systems affordance. Feedback is then the system responses to a given action, so in other words what the system does when interacting with the system, such as clicking a button. Norman [2013] Feedback is therefore provided on all actions so that the user knows that the system has received the given input. Mapping which essentially means the relationship between the elements of two sets of things, like a light switch mapped to the light in the ceiling Norman [2013]. Mapping is applied for creating relationships between elements, parameters and especially between the "tablet" and the simulated production. Constrains are used to delimit actions possible, hence leading the user to the desired behaviour by ensuring undesired behaviour is not possible Norman [2013]. This is often seen in install wizards, which require some decision before being able to proceed. Last of Normans principles in focus is the conceptual model, which is a term for a simplified explanation of how something works, in this case the system Norman [2013]. This is therefore influenced by the earlier principles and comes in different shapes and forms depending on the individual. This is therefore created from the developers conceptual model of the system, however through highlighting this model with the above mentioned techniques it is aimed at ensuring a similar conceptual model for the users. Since the user has to develop their conceptual model from the system image and thereby does not have the preexisting idea of the system as the developer. Further structuring of elements in the system are done according to the Gestalt laws, proximity, similarity, figure-ground and common fate. These are different guidelines for how objects and shapes are perceived in relation to each others Johnson [2014].

## 7.1 Structure evolution

During the development, the overall system has undergone three major structural layout changes from the initial. With structure is meant the html skeleton and base navigation pattern. The first stage, see figure 7.2, presented the user with three options at the home page. Each of the three options can then be entered for details about the machine it denotes. In the details html page layout examples showing either text, images or graphs, where their appearance depends on the latest predicted values in the database. The reason for dividing the content into four different machines is based on the theory of working memory Baddeley [1991] and Guided Search 4.0 Wolfe [2007]. Working memory has limited capacityBaddeley [1991] therefore a limited amount of elements displayed at a time will be easier to process. It is therefore tried to present only 4-5 elements per view to respect the capacity of working memory. The low amount of elements per view also speeds up the visual search as there are less factors to search between Wolfe [2007]. This idea of few elements per view will be tried to accomplish trough all designs.


**(a)** Layout of the home page in version 1

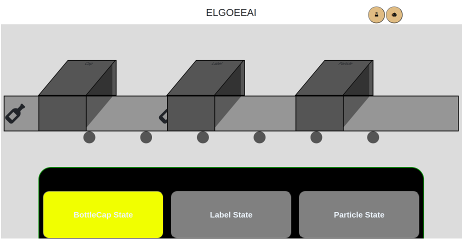



**(b)** Layout of prediction details for a machine in version 1

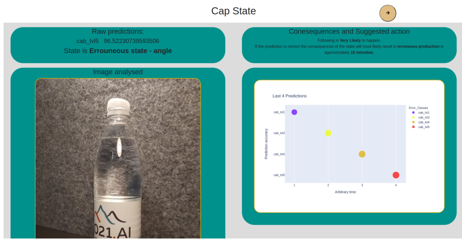
**Figure 7.2:** Bar and boxplot of the three dimensions and mediation techniques

The reason this contains a placeholder for all three different mediation techniques is that it was encoded before the test was conducted.

The second version is also predating the analysis of the Lofi tests, hence the same placeholders are present. The major structure change in the second version is the implementation of an animation of the production line, see figure 7.3, and the machine details buttons made smaller. The animation is added as a 'signifier' of the running production, and to create a mapping between the presented predictions and what the hypothetical production they relate to. This is in turn implemented to improve the system image, and thereby support the mediating the designers conceptual model onto the users. [Norman, 2013]




**(a)** Layout of the home page in version 2

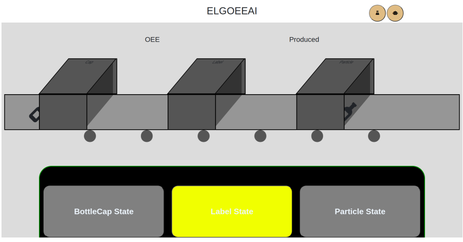



**(b)** Layout of prediction details for a machine in version 2

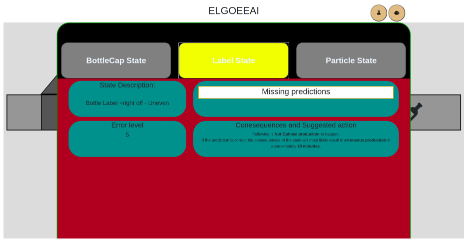
**Figure 7.3:** Bar and boxplot of the three dimensions and mediation techniques

The third version was restructured so that entering the details would not open a html in full screen view, but instead open the tablet and open the details html within this, see figure 7.4.

This was done to make it appear more realistic and assimilate standing at the production line with the Ml monitoring device, in this case conceptualised as a tablet. In this way the production will still be perceived as present according the law of figure ground. This is done to create a constant mapping to the manufacturing process. This in turn is again done to improve the system image and hopefully the users conceptual model Norman [2013].



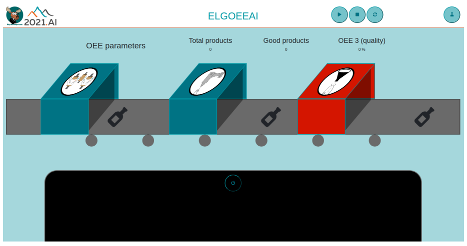

**(a)** Layout of the home page in version 3



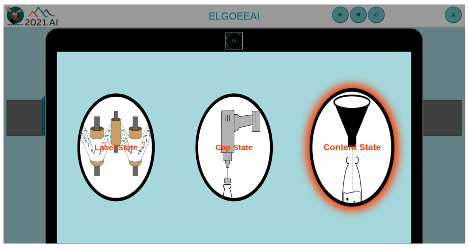

**(b)** Layout of prediction details for a machine in version 3

**Figure 7.4:** Bar and boxplot of the three dimensions and mediation techniques

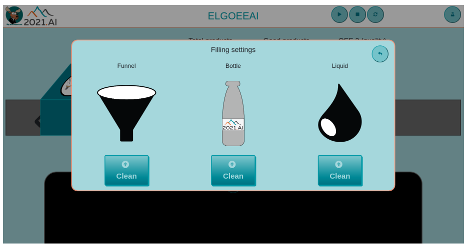
The fourth major restructuring, the final version of the system prototype, where an extra layer on the tablet, interaction with the machines on the production simulation and final colour themes, figures, final details, etc., is added. See figure 7.5 for screenshots of the system. Here the main focus have been on finalising the system design according to the mediation techniques and 2021.AI's colour themes, while still obeying the earlier mentioned theoretical guidelines. As an example with mapping, the machine icons have been utilised on both the machines in the simulation and buttons on the tablet, to create a relationship between, according to the law of similarity. The codes for the full system can be found in appendix A.



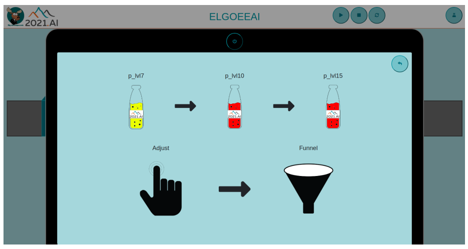

**(a)** Layout of the home page in version 4




**(b)** Layout when the tablet screen is open i "main menu"




**(c)** Layout of the machine parameters adjustable on a machine




**(d)** Layout of prediction details for a machine in version 4

**Figure 7.5:** Screenshots of the four main views in the system.

## 7.2 System flow and functionality

The different files developed and coded to make up the final system is illustrated in figure 7.6. Here files settings.py, wsgi.py and other django app files are excluded as minimal to no edits are made in these files. The dark icons with white text represent backend files, whereas the light icons with black text represent frontend files. The backend files are all of the python language, however two are made slightly darker 'models' and 'forms' as these are files defining the tables in the database. It is through the 'urls' file that all requests are handled and directed further down to views that call the other files as required. The demoRunner contains the simulation code for the production, and hence operates with the cycles of images and machine learning model through validator, which contains functionality for predictions. The two files above validator are the trained image recognition model in .h5 format and the class list as a json file, respectively. The last python file is the demoKPIs, which contains the functions for interpreting and transforming the predictions to more meaningful output variable values.

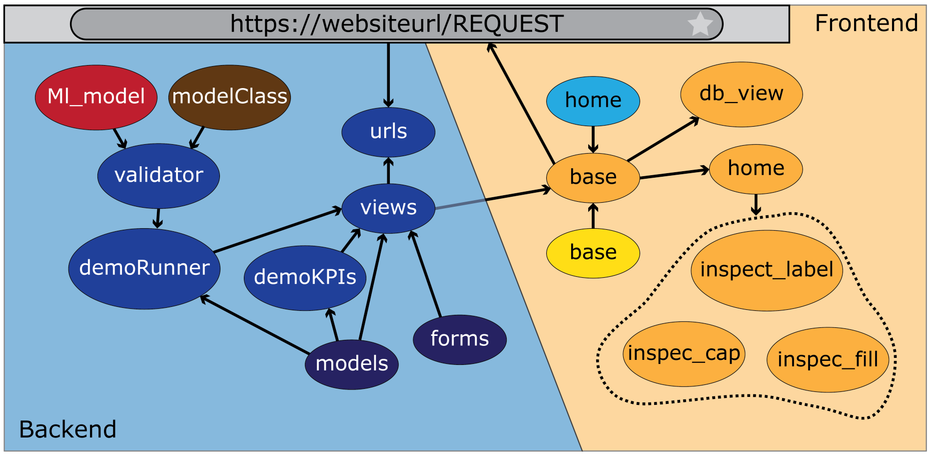



**Figure 7.6:** Flow chart of the different files making up the system code

On the frontend side the orange icons represent html files, lightblue denotes css files and yellow javascript(js) files. The base html which incorporates the home css and base js file, has the purpose of including all the elements that are constant over all the pages, so that repetitive code can be minimised. Loading and setup code can also be beneficial to put here, to prevent reloading static files such as home.css and base.js. The three files make up the systems backbone, frontend functionality and element designs. The html's 'home' and 'db_view' are then extensions of the base file, and hence incorporates everything from the base file. The 'home' html contains the core of the system's structure elements presented to the user, see figure 7.6 for the elements from home.html. The three html files encapsulated in a stippled line each contains the elements for the mediated predictions for a given machine.

These therefore contain all the different elements required to display the different parameters predicted. The dotted arrow from home to these, means that they do not extend home such as is done with base, it is simply a new html that is loaded within the boundaries of the tablet screen. This therefore means that the css and js files have to be reloaded whenever the html is opened. As the view is dependent on the last three predictions it adds up to 78 possible views, however for the individual machine it results in 9 different view combinations and 18 possible views for the cap and label machine.

### 7.2.1 The backend processes

As most of the presented frontend elements and features depend on the backend functionality, what happens behind the surface is firstly elaborated. Firstly when starting from a clean system, the database will be empty, and images for simulating a production is needed. To prepare this a html page to do the database setup in a GUI based manner is created to make the process simpler, see figure 7.7. In the right top corner a dark grey box is presented, which is a form for entering images, where there can be browsed for local images, then a label is chosen from a drop down and lastly a button for uploading the image in the database. The label selected should be one of the parameters defined to cause the error state.

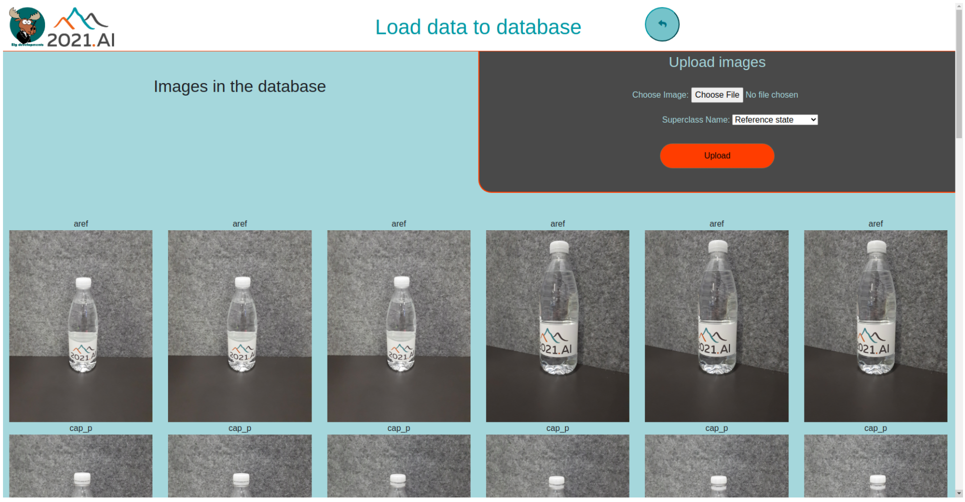



**Figure 7.7:** Screenshot of the database setup page, with images in the database.

When then starting the production processes in the demoRunner file, arrays for each of the parameter names are created and a random is chosen to go through as the “coming” production states. The machine learning model is then applied to each of the images in the array in a defined speed of 3 seconds. This value is only selected for during development, so that there do not have to be waited for values.

As the predictions are made by the machine learning model it saves the prediction to the database after each image prediction. Here the name and accuracy of the predicted prediction and image id is stored. This process is then repeated and in that way this functionality aims at simulating product states and predictions. The cycling of the images are encoded as backend functions without a view, and as parallel tasks, hence waiting for the function to finish is avoided. Some do however return a context in json format, which can be accessed from the frontend using ajax queries. Here the context will contain variables concerning the three latest predictions in the database, thereby making it possible to create the illusion of production state over time and predicting images in the future.

### 7.2.2 The simulated production

The simulation of the production line illustrates the current production state with the colours of the machines, with red being faulty. The production line is encoded in html and css having a great focus on flexibility of the machines depending on the window size. Thereby the window size can change margently with the machine illustration remaining in one piece. Here it was especially the top of the machine, the parallelogram with machine icon image on it, that gave complication when changing scale of the window ratio. The bottle icons on the assembly line are moving continuously in a loop(right to left) encoded in a short javascript.

Further variables for calculation of the OEE Quality parameter is presented, which follows the formulae:

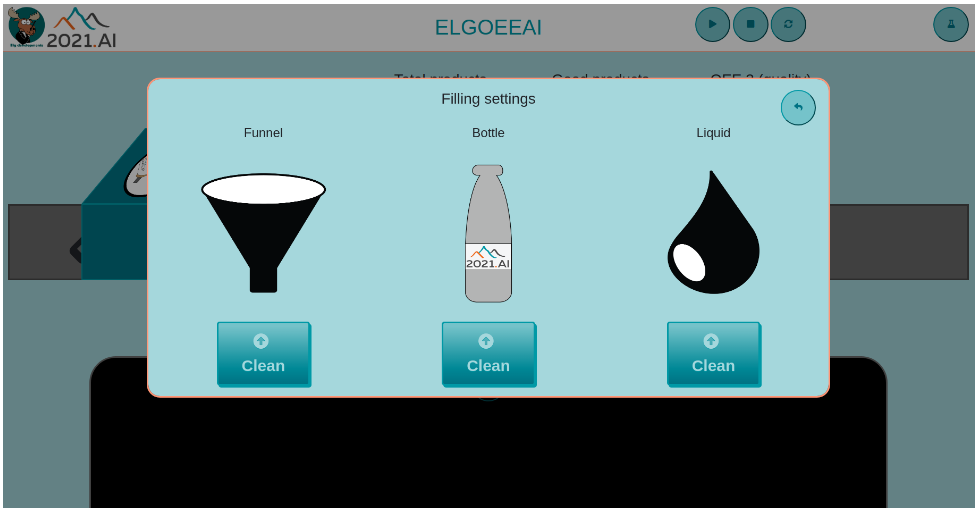
$$Quality\% = \frac{Goodproducts}{Totalproducts} * 100 \tag{7.1}$$

The variables are shown for transparency and giving better insight into the process occurring. The calculation is fake in the sense that no bottles are produced nor does it fit with the speed that the machine learning model is iterated. It is essentially a counting function repeating each two seconds and then depending on the current state it is either adding 10 to good products and total or only total products. It retrieves the current state from the database using ajax in a javascript function. The counting function is linked to the two buttons play and stop in the topbar, and as the buttons suggest either start or stop the function. The refresh button next to the two buttons reloads the url, and thereby also the function variables and presented values.

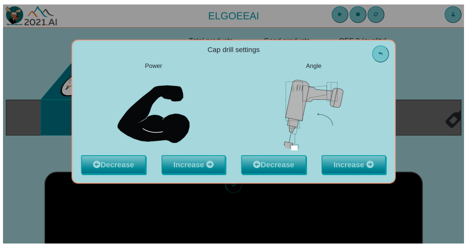
### 7.2.3 Machine interaction

Each of the machines in the production simulation are clickable, and when clicked a popup for the machine parameters and possible adjustments pop up, see figure 7.8. A shadow is added on the background of the popup to signify that the popup is in focus.

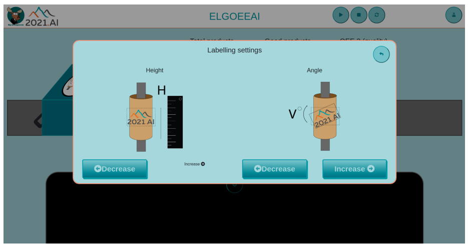
These are supposed to be linked to the current state and predicted states so that if clicking the corresponding parameter that is suggested by the machine learning prediction, the cycle iteration is restarted. Hence preventing the predicted state




**(a)** The filling machine layout




**(b)** The cap screwing machine layout




**(c)** The label machine layout

**Figure 7.8:** Layout of machine interaction popups for each of the machines.

from occurring or staying at the faulty state. Then if clicking a wrong parameter, in other words what was not suggested by the prediction, nothing should happen. This functionality has not been implemented yet, however as of now the button that is visually different (unstyled) restarts the cycle iteration. Hence it is currently always the correct button. This is a functionality that would have been implemented next in order to finish the interaction intended for the system. The colour change of the machine, which has a defect making products faulty are associated with the current state values. Therefore no future predictions are associated with the simulation visually in order to highlight the effect through the tablet. Further as this is a place where human errors can arise, in the sense of adjusting a wrong parameter according to the predictions, constraints should be implemented. This could be in the form of a popup stating that the adjustment is inconsistent with the predicted values. However as stated the functionality have not achieved finished state, hence constraints have not been implemented yet either.

### 7.2.4 The "tablet"

The tablet has firstly undergone a major redesign in appearance and functionalities to reach the final design. Firstly the tablet is made more realistic in that the screen is off by default, and turned on by a button usually the same colour as the tablet, hence only an outline is used. Clicking the button not only turns on the display, but also extends to fill the majority of the screen. These changes are animated with CSS, so that it occurs fluently over a 1 second time period. When the screen is on, see figure 7.9 the user is then presented with the three different machine options as in the earlier versions, however instead of presenting the content below in a “tab-column” style, it opens in a new window on top, the details html's. Depending on the state of the latest predictions, the targeted machine is highlighted on the tablet screen by enlarging itself and adding an orange ring around the icon in a pulsating pattern as seen in figure 7.9.

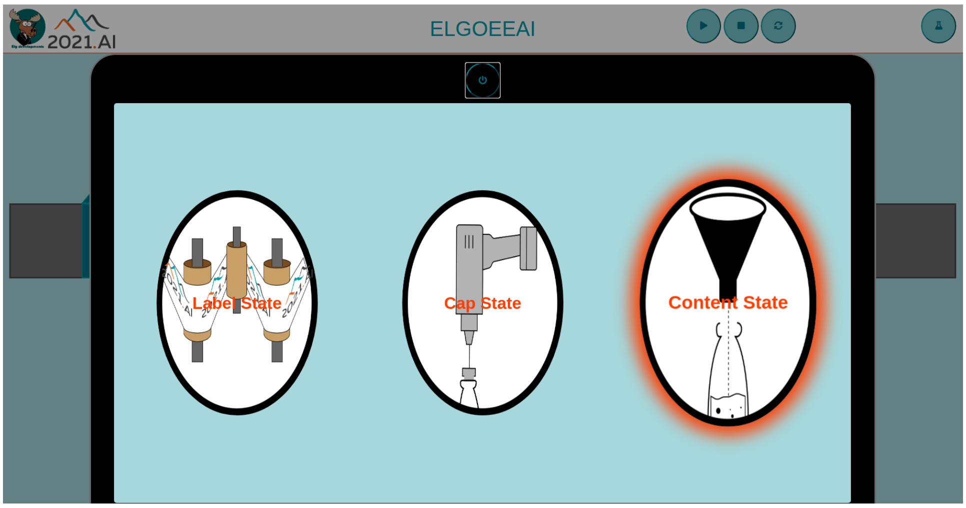
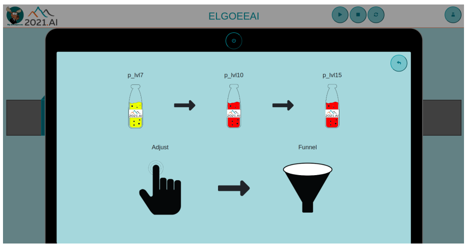


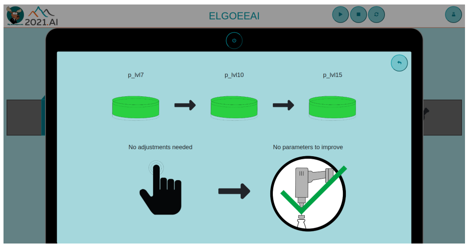

**Figure 7.9:** Screenshot of the tablet appearance when on and presenting a target machine.

Depending on which of the machines are entered the presented layout differs, as seen in figure 7.10, depicting either an erroneous evolution or optimal production trend. The erroneous layout is presented when the targeted machine is entered and corresponds to the predictions and classifications of the errors. The optimal layout is displayed when the other machines are entered, or the prediction state is simply good, hence all machine layouts will display this. Displaying optimal state even though another machine is erroneous is reasoned by indicating that this is the wrong destination, as changing parameters on the cap machine will not fix errors on the filling machine. Hence even though the product might be faulty on all machines, the individual parameters presented for each machine is not.

The state icons presented consist of the last three predictions, where the first is intended as current, and the two next are future predictions respectively. Further for the cap and label display the icons differ depending on the parameter that is to




**(a)** Screenshot of an example view with faulty states, action required




**(b)** Screenshot of an example view with optimal states, no action to take

**Figure 7.10:** Examples of when action is to be taken or no action is required.

change, as the icon representing angle errors and height or power are not the same, see figure 7.11.

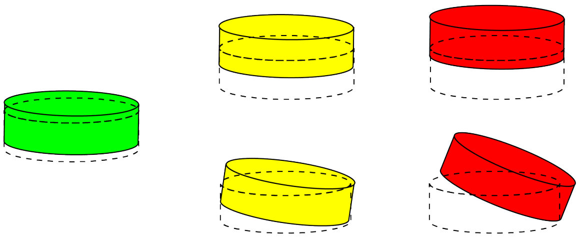


**Figure 7.11:** Image showing the different state icons for the cap screwing machine

Below the predicted solution, 7.10 is illustrated with the icon denoting a required action and an arrow pointing towards the machine parameter at fault. If no parameters at the machine is at fault an icon of the machine with a check mark is presented. Further as it was noted throughout the tests that icons in itself is not enough, the icons are supported with keywords, describing the reinforcing the meaning of the icon. At the moment it is simply the prediction names of the three latest predictions, however these are intended to be converted into more meaningful words and expressions. Like removing the underscore. The layout elements dependencies are encoded with Django if/else template expressions in the html files, which makes the html access the context parameters from the correlating view class, and hence create dynamic content. This however has the downside that updating the layout requires calling the view class again to refresh the context, hence the page has to be reloaded by clicking the close button or in other ways close and entering the content again. Apart from the return button which closes the details html again, if clicking outside the tablet also closes the content, but in addition the tablet will be “turned off” as well.

## 7.3 Demonstration of the system

As the system is developed with the intention of being a demonstration tool at meetings, to sell AI solutions for manufacturing, a short demonstration of the system is held at Novo Nordisk. This is done in a casual manner where colleagues and other interested and relevant parties are invited to see a presentation of the system. Here the purpose of the system and thesis statement of the project is explained and then the system is user interface is explored while telling about the elements. Here it is made sure to display the different menus and elements ensuring to demonstrate examples of different states, in other words how the system differs depending on the states. Out of 9 invited, 7 colleagues came to see the demonstration, ranging from operator team leaders and technicians/smiths, to project engineers, system developers and managers. This therefore gave a broad sample of the wide user group of manufacturing people.

The demonstration did unfortunately not run smoothly, due to browser cookies from testing, an outdated version of the javascript file was used, hence the OEE function did not iterate as intended. This was quickly fixed by switching to an incognito window instead. Another issue that arose was the changing of icons on change state, hence when cap error predictions where to be displayed, it showed the optimal state icon while having the correct name above. The display did change after closing and reentering some times, indicating it could be heavy content to load and some optimisation of the functionality should be performed. Apart from these two faults the demonstration went well, and multiple people also asked into details and machine learning. This quickly evolved into a larger debate concerning implementing ai at Novo, where technicians and managers where pointing out places they could see a potential. Overall they found it very interesting and the system got a positive response, with the note of expecting aforementioned errors fixed. However it was also colleagues so they might be more prone to not be as critical as real users. The demonstration did however spark great debate about the idea of implementing AI in order to prevent errors proactively as the project thesis intends.

# Chapter 8

# Discussion

The following chapter will discuss and reflect on the different choices and findings made during the development process of the elgoeeAI system. First the empirical research conducted during the project is covered and then the machine learning model and system are discussed. Lastly general reflections and thoughts on the project process and user groups are debated.

## 8.1 Empirical research conducted

During the development process empirical data are collected through an interview, a questionnaire, a user test of a LoFi design and a demo-presentation.

### 8.1.1 Interview

The interview was initially planned to be conducted in person and earlier in the project process, as part of the elaboration of the manufacturing industry. However due to the Corona pandemic this became impossible as it both prevented in-person interviews presenting a series of challenges. Firstly the interview had to be redesigned to be conducted online. Therefore a powerpoint presentation was implemented to create a better connection and assist the interviewee in the interview process.

Secondly, Corona complicated date planning for conduction with interviewees, where dates were changed several times and one interview was conducted over two different dates. This in turn led to a great delay of conducting the interview, due to having to redesign the interview and interviewees being more difficult to reach. In total this led to the interview being delayed by a month, compared to the initial planned time period. As part of the purpose of the interview was to explore the manufacturing industry, this delay was quite disruptive to the exploration of the topic. Some of the questions are therefore not as relevant as they would have been if conducted earlier in the process.

Thirdly as acquiring interviewees became more difficult, participants with personal relationships with the interviewer were utilised. Due to this relationship it was also conducted with both at the same time due to the nature of the relationship. Due to having two interviewees simultaneously, their individual responses sparked further comments from the other. Hence their answers have been affected by the other. This has mainly been considered a good effect, as it made the interviewees more prone to elaborate on their answers. However due to this interaction effect between the interviewees, the interview differs from the others, as this “ping-pong” interaction was not present. It can be seen as one interview being conducted with a focus group, where the others are individual interviews, creating some fundamental differences in style. The difference is not believed to have any negative effects however as they have not been analysed in a comparative manner, but rather a summarising way to encapsulate the topics covered. In other words the interviews act as supplementary.

A difference can however be seen in the duration differences between the interviews, with the focus group interview being the longest with 2 hours and 10 minutes. The other interviews lasted around 1 hour and 30 minutes, and are therefore also quite long in duration. It is therefore a very long time that the interviewees have had to be focused and answer open ended questions. Further adding that the interview is conducted online, decreasing the “immersiveness” of the interview could lead to interviewees losing focus in the later process. This might have led to some questions in the end of the interview being less engaged than the starting questions of the interview. This is especially unfortunate in the sense that the later questions are the most relevant to the project delimitation. In hindsight the first section regarding the shop floor environment should have been removed due to the low value after delay and to shorten the interview.

### 8.1.2 Questionnaire

The preliminary icon test was conducted as a online-questionnaire also due to the Corona virus and strict distancing rules at Novo Nordisk, making tests in person unfavored. Further it was advised to make it very simple and not require too much, in order to ensure participant participation. Due to this icons were developed prehand, giving the participants a selection of icons to choose between, and then an “other” option if not satisfied. This methodology has therefore by nature weighted the possible icons higher than what is to be imagined, as these options are easier. And as illustrated by some answers in the questionnaire, additional possible icons were suggested, showing that the icon samples presented have not been exhaustive, as noted. Due to time limitations, this was not investigated further, however if having time it would be suggested to further test the icons with the additional ones mentioned.

Further the icons developed to represent the different parameters, differ in range. Meaning that for some parameters two icon options were given while others had up to four icons to choose between. This was mostly due to the author not being able to come up with more ways of illustrating the parameters at the time and also having to move on. This therefore does give some inconsistency between how widely the icon representations have been tested. Furthermore the results acquired have not been statistically validated, meaning that the results might be a “coincidence”. Statistical tests could have been performed however whether icon preferences were significant or not, a choice still had to be made to go on. Therefore it was discarded ant the most frequent selected icons accepted.

### 8.1.3 Mediation techniques

As the Corona restrictions opened up a bit, it became possible to conduct tests in person at Novo Nordisk without putting the researcher or participants at risk. However operations still ran with a minimum staff, hence employee time was limited, leading to only having time to test on four individuals. This is therefore a very narrow sample size and therefore might not cover the entire population sample. Most likely not. Furthermore one participant also participated in the previous questionnaire thereby being innately primed around the icons. This might therefore have affected his VAS scores weight icons higher as they had already been part of selecting them.

Secondly due to the time pressure of participants, introductions and explanations were done briefly, which in hindsight was a huge mistake. Participants showed great difficulty with understanding their task, leading to very little out loud talk and explanations were many times vague. It therefore became clear to the researcher that the task was too abstract in nature and a deeper explanation of the information presented was needed in order to increase the participants' task. It was originally thought to also have a time measure in the recordings, and measure keywords mentioned when analysing the presented information, but this quickly showed to bear no fruit due to the lack of understanding. This might also have played part in the mayor order effect that was seen, as the text is somewhat self explanatory, however icons and graphs might need a bit more context to decipher. Therefore if the participants had a better understanding of the context that the information presented was in, the icons and graphs might have been perceived better, and hence a lesser order effect.

Due to the lack of understanding and heavy order effect, the experimental design should be optimised and conducted again optimally on a larger sample. In regards to optimisation, more time should be taken to explain the context and ensure participant understanding. So instead of just showing an example of the layouts, then make an actual familiarisation round to ensure understanding. In regards to the order effect it cannot be removed due to the repeating nature of the individual participants task, however it might be minimised due to better understanding. Further with a larger sample size the Latin square randomisation used for negating the order effects will have a larger effect, hence a more valid negation of the order effect.

Lastly due to the time constraints the experiment was conducted in an isolated area at the shop-floor. This has therefore not been a completely controlled environment for the experiment as if looking to the side, the entire production line could be seen with people running around. For one of the participants an employee also did work on a computer behind the researcher, therefore in front of the participant. This seating position was however maintained as it was decided that the whiteboard behind the participant was more attention grabbing. Due to these factors it might have been hard for participants to focus on the task at hand, as they might easily be distracted by movements from the production line. Or simply remind them of work they have to do when the experiment is over, as it was right next to them.

Another aspect which should have been researched more elaborately with more time is different graph examples, like the icons, to find the best suited before testing against the other methods. This is especially advised due to the comments of the participants which did not find the graphs intuitive, due to different elements. It could therefore be that if presented with better graph options it would also receive a different score. Similarly should be done with text descriptions.

### 8.1.4 Demonstration of system

The demonstration of the system was conducted in a casual manner, resulting in an interaction between the presenter and the people attending the demonstration. Further all the attending people were colleagues and knew that it was a demonstration of a system developed in regards to a candidate thesis. These factors can therefore be assumed to have influenced the viewers to respond more positively, in order not to offend the author, demand characteristics in other words. However with this in mind the spark of interest in AI and how it could be beneficial that occurred should not be discarded that easily.

It is argued that demand characteristics affect how they respond to the system, but when taking ownership of the concept by debating where it could create benefits for them, is not affected. It is therefore argued that the spark of interest that was created is genuine and unaffected by the relationship to the colleagues participating. This does not mean however that the system is done and confirmed, as there are still some errors and optimisations that should be carried out, such as improving the prediction model and faults demonstrated through the demonstration. However the demonstration does confirm interest in AI and that the system might be a potent tool when the last details are finished.

## 8.2 System elements

The system has been developed in two parts, first the machine learning model has been developed and evaluated, then following a compatible interface platform is developed. These will now be discussed and reflected upon respectively.

### 8.2.1 Image recognition model

If looking at the image recognition neural network developed, it does not exactly perform optimally. It was thought that the model performed well enough to illustrate the idea through the system, however this proved to be difficult. As there were several of the images that it had difficulties classifying wrong predictions were made, hence illustrating the wrong errors in the system. As illustrated earlier with the training graph, additional training does not seem to improve the model much and other factors must be applied. The best thing to do is to sample more data, or in other words conduct another photoshoot, thereby enlarging the pool of images of each class.

Further it was recommended to ensure different angles and lighting conditions in order to generalise the data and avoid overfitting. However in hindsight this is an irrelevant factor, as if it was to be implemented in a manufacturing setting, the camera would be fixed, and different angles and lightings would not occur. Lighting might occur minimally, however this can be done digitally. The implementation of different lighting conditions and angles are therefore not really relevant and have therefore made the classification more complex. It has however also added to the general pool of data, so it does still have some desirable effects.

If it is not possible to generate more data, delimiting to fewer classes could improve the model performance, especially the particles, as this has not been narrowed down as the others. Further the visual difference between the particle parameters are very small, making it sometimes difficult for even humans to differentiate. This is due to the peppercorns positioning randomly in the bottle when dropped in. Some floats and some drops to the bottom. This therefore makes some variation between images taken of the bottle states with differing particle level. Another thing that could be tried is to try training the network with different architectures, as RestNet50 was just one amongst four different architectures possible with the imageAI library function. As they differ in network architecture they might also give different results.

However if looking at the choice of image recognition, this might not have been the most convenient approach. It was selected primarily on the basis of being something visual and therefore appropriate for demonstration purposes, but at no time in the system are the images presented anyways. It could therefore just as easily have been a series of numerical values that for instance represented the different machines and their states. These could for instance be created with an Arduino through some sensors being periodically manipulated. In this way the time dimension and hence forecasting would also have been simpler to implement. This would also have eliminated the need for “faking” the forecasting effect, as an actual model could be developed. Creating this form of data would however require more knowledge about the machines in the manufacturing industry in order to make the simulation assimilate a real life case. This therefore requires a lot of domain knowledge, which the author did not possess at the time.

### 8.2.2 HiFi system

Apart from improving the AI in the system, there are also some other parameters that should be improved before using it as a demonstration tool. With the AI improved, the system is still process heavy. As experienced in the demonstration the system sometimes has difficulties loading the content, and more importantly updating the content to the newest predictions. This is assumed to be partly due to retrieval of state information from the database and partly due to the manner in which it is encoded.

The encoding of which elements to present are done in the html, using special django if else expressions. This therefore inevitably results in only updating as the html is updated. There should therefore either be implemented a refresh functionality of the details html pages, or re-coded in a javascript function. Another code factor could be the way the detail html's are loaded as this is not extending the home.html in the same fashion as base.html is extended on to home.html. The detail html's therefore do not inherit files and components from the earlier html, but has to load everything by itself. This therefore means that every time a details page is opened, it has to load css and javascript files every time. Implementing the extending methodology could therefore save some processing power.

The other factor is the retrieval from the database, which is thought to cause problems. These issues are thought to arise due to the several parallel tasks accessing the database simultaneously. This is not a problem as long as it is different tables that are accessed in the database. However this is not the case and might therefore be the cause for delayed retrieval and slow runtime. Further if running the system for a longer duration of time without refreshing the home view, (refresh web page), it eventually crashes. It is therefore believed that a lot of unnecessary cookies or similar are adding up when the system runs. These element improvements are however looking at it from the viewer's perspective, the ones demonstrated for, but if taken the actual user in perspective, more work should be done on the database setup page. Currently it is only possible to add new images to the database, therefore clearing the database requires system commands and is therefore not very user friendly. Therefore at minimum it should be made possible to delete and edit individual images in the database from the database setup instead of backend. Optimally more options for handling like creating a default database, etc. could be implemented for quicker use.

Another unexplored element is the timing of the desired action, as of current it has been thought of as immediate, in the sense that action should be taken when discovering a prediction of faulty state. However in reality it might be more time dependent for optimal production. Especially when it comes to adjustments requiring production stop, hence just before failure is optimal and not immediately. This is an unexplored parameter which could be beneficial in order to assimilate reality more effectively, but is not considered a criticality as potential can still be illustrated without. However it could somewhat easily be implemented by adding a production maintenance functionality on some of the parameters, hence displaying both adjustments made during production and adjustments made during production stop.

Lastly there are some visual details that could use some updates, like visually differentiating the system control buttons in the top with the return buttons in the system popups. With these improvements created a proper test should be conducted compared to the casual demonstration performed. Both to get a response when the system is more complete and working optimally, but also to get more valid responses and measures possible to analyse.

## 8.3 Process and user groups

If looking at the project as a whole, there are a few factors that should be clarified or made more concrete to simplify the development process a bit more. Firstly a more concise description of what is wanted developed from 2021.Ai should have been acquired, as there was some uncertainty about this from the authors side. This should therefore have been clarified to the company so that there was a better common understanding from the start of the direction desired of the project.

This however has been clarified along the project process, however in hindsight it should have been clear earlier in the process in order to avoid unnecessary research directions. Hence as the illustration of the swing in regards to product development, the author and the client company have had minor expectations. Partly due to the inclarity and the planning of the project, the time developing the image recognition model was not optimised as it could have been. Especially as development of the model was planned before actual research in the topic complexified the process of developing it in a meaningful manner. The reason for developing this first was the access to assistance in 2021.AI, however looking in hindsight, and how much assistance was needed, it would properly have been better to conduct the interview first and then develop the model as the quarantine hit.

Another aspect that should be noted is the wide user group that the system has considered. This ranges from people handling the machinery directly to developers and managing roles. As it is developed as a presentation tool to demonstrate the potential of AI, the people attending the meeting will most likely be managers or other leader roles. However as one of the leaders from Novo Nordisk emphasised to the author; “It is important to have alignment all the way from the operating people to the managing”. Heavy consideration is taken to the operators and technicians, as the example demonstrated by the elgoeeAI system is intended for them. In other words it will never be a manager that will adjust the machine parameters as the system displays. With more time more consideration and testing should also be conducted on the managing people, who in the end will be the deciding factors.

# Chapter 9

# Conclusion

If improving the issues highlighted in the discussion section concerning the system elements, hence finishing the interaction, improving the machine learning model and optimise code to require less processing power, the system is considered to be a success. With this is meant that it is a presentable system, as the system have already showed to be beneficial for sparking interest in AI. However to be certain of this it should be tested when finished in more controlled manners than the casual demonstration. This does not imply that there are not other parameters that cannot be improved, as more research in the mediation methods can be conducted and create value.

Furthermore to improve the system and illustration of AI a proper forecasting model should be implemented, hence not just simulating the error tendencies. Even though the forecasting can be simulated or "faked" it would create great value to implement, as it increases the potential of the system, in the sense of utilising more AI and thereby present further potential. As of now if actually only illustrates the effect of classifying but not the forecasting value, and therefore the illustration of forecasting is in reality an illusion.

With all this in mind it is concluded that the system shows potential for being a beneficial tool for illustrating the value of AI in an manufacturing context, however to be certain more research need to be conducted on the system after above improvements are implemented. It is therefore considered an overall success and proof of concept is believed to be achieved.

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# Appendix A

# Appendix System Codes

This appendix contains all the codes used for the development of the elgoeeAI system. This therefore includes code for training and testing the image recognition model and following the full application code for the web-based presentation of the system.

### A.0.1 Scripts for training and testing image recognition model and visualise training

Found in attached zip file in the following path;

- Zip-File / ML_codes / trainer.py
- Zip-File / ML_codes / validator.py
- Zip-File / ML_codes / visualiser.py

### A.0.2 Text file with entire network architecture

Found in attached zip file in the following path;

- Zip-File / ML_codes / nnStructure.txt

### A.0.3 elgoeeAI system code

Found in attached zip file in the following path;

- Zip-File / elgoeeAI_InterfaceV5

If wanting to run the system it is advised to run in an virtual environment and install the requirements.txt file from the elgoeeAI_InterfaceV5 folder.

# Appendix B

# Appendix Interview

This appendix contains all the presentation files, materials and results regarding the interview.

## B.1 Virtual interview: PowerPoint, questions and translation

This section contains the filepath for the powerpoint and a translation of the individual questions from the powerpoint.

### B.1.1 PowerPoint format

Found in attached zip file in the following path;

- Zip-File / Interview / Interview_NovoNordisk.pptx

### B.1.2 Translations

The translation is presented in the manner of the original Danish phrasing accompanied by the English translation in "quotation marks". As an example: *Hvad er et spørgsmål?* "What is a question?". Before each question is the given slide that the question is presented on.

- Slide 5: Hvilket produkt er det som i arbejder med at producere? "What product is it that you are working on to manufacture?
- Slide 6:Hvilke "stadier" og processer indgår i produktionen før det endelige produkt? "Which "states" and processes forms the production before reaching the final product?"
- Slide 6: Kan du beskrive nogle af disse stadier og processer? "Can you describe some of these states and processes?"

- Slide 7: Hvilke maskiner indgår i produktionen af produktet? "Which machines forms the production of the product?"
- Slide 7: Hvad gør maskinerne? "What does the machines do?"
- Slide 8: Hvem håndterer maskinerne? "Who handles the machines?"
- Slide 8: Hvilken faglig ekspertise har de? "Which professional expertise do they have?"
- Slide 9: Hvordan er flowet i produktionslinjen? (serielle/parallelle processer?) "How is the flow in the production/assembly line? (serial/parallel processes?)"
- Slide 10: Hvilke menneser indgår ellers i produktionsmiljøet/shopfloor? "Which other people also forms a part of the production environment/shopfloor?"
- Slide 11: Bliver der stillet fysiske krav til medarbejdere? (Eksempelvis, syn, hørelse, etc.) "Are there any physical requirements to employees? (As an example regarding vision, hearing, etc.)"
- Slide 13: Hvem står for monitorering af maskiner? "Who is responsible for monitoring machines?"
- Slide 13: Hvilken faglig ekspertise har de? "Which professional expertise do they have?"
- Slide 14: Hvilke parametre fra maskinerne monitoreres? "Which parameters from the machines are monitored?"
- Slide 15: Hvilke brugerflader sker monitorering på? "Which devices are used for monitoring?"
- Slide 16: Hvordan præsenteres parametrene monitoreret på brugerfladen? "How is the parameters monitored presented on the device?"
- Slide 17: Hvordan formidles det at en maskine arbejder optimalt? "How is it conveyed that a machine is working optimally?"
- Slide 18: Hvordan formidles det at en maskine **ikke** arbejder optimalt? "How is it conveyed that a machine is **not** working optimally?"
- Slide 19: Hvordan formidles et behov for justering af en maskine? "How is a need for adjustments of a machine mediated?"
- Slide 19: Hvor hyppigt er der behov for dette? "How frequent is there a need for this?"
- Slide 21: Hvilke brugerflader benyttes til at justere maskinernes tilstand? "Which user interfaces are used for adjusting machine states?"

- Slide 22: Hvilke handlemuligheder gives der igennem brugerfladen? "Which actions does the user have through the user interface?"
- Slide 23: Hvornår kræver en maskine justeringer? "When does a machine require adjustments?"
- Slide 23: Hvor ofte kræves det? "How often is this required?"
- Slide 24: Kan maskiner justeres fra ander steder end ved maskinens brugerflade? "Can machines be adjusted from other places than the machines dedicated user interface?
- Slide 25: Hvornår kræver justeringer at produktionen stoppes? "When does adjustments require the production to stop?"
- Slide 26: Hvornår kan justeringer laves *uden* at produktionen stoppes? "When can adjustments be made without stopping the production?"
- Slide 27: Sker interaktionen på egen opfordring eller information fra maskinerne? "Does the interaction happen on own initiative or information from the machines?"
- Slide 29: Hvor ofte sker produktionsstop?(Downtime) "How often does production stops happen?"
- Slide 29: Hvad ligger til årsag for disse? "What are the reasons for these?"
- Slide 30: Tror du at produktionsstop kunne mindskes hvis man kunne forudsige maskinernes tilstand? "Do you think that production stops could be decreased if you could predict the machines state?"
- Slide 31: Hvor tit skal maskinern justeres for at opretholde optimal tilstand? "How often does a machine require adjustments to maintain optimal state/condition?"
- Slide 32: Hvis man kunne forudsige maskinernes tilstand, tror du så at man kan producere optimalt i længere tid? "If possible to predict the machine state, do you then believe that optimal state could be archieve for longer durations?"
- Slide 33: Hvor lang tid forud ville maskinernes tilstand skulle forudsiges for at det har en brugbar effekt? "How long time in advance would these predictions have to be, in order for you to believe it to have a usefull effect?"
- Slide 34: Ser du andre fordele i at kende maskinernes tilstand forud? "Do you see other advangtagese in knowing the machine states ahead of time?"
- Slide 36: Hvilken information er vigtig for dig at vide om maskinen? "What information is important for you to know about the machine?"

- Slide 36: Hvordan vil du gerne have det præsenteret? "How would you like it to be presented?"
- Slide 37: Hvile elementer er vigtigt at en monitoreringsbrugerflade indeholder? "What elements are important for a monitoring device to contain?"
- Slide 38: Hvordan ville du gerne varsles om maskinernes tilstand? "How would you like to be warned about the machine states?"
- Slide 39: Har du nogle yderligere kommentarer? "Do you have any further comments?"

### B.1.3 Transcriptions

Found in attached zip file in the following path;

- Zip-File / Interview / TranscipPilot.pdf
- Zip-File / Interview / TranscripPerson1_2.pdf
- Zip-File / Interview / TranscripPerson3.pdf

# Appendix C

# Appendix Questionnaire

This appendix will contain all materials and files created for conducting the Preliminary Icon test. It therefore contains the questionnaire, raw data and the summary file created by google Forms.

## C.1 Questionnaire

As the questionnaire is created in google forms it is not possible to download in the manner it is presented to the user, hence a link to a copy of the questionnaire and path to a downloaded pdf version.

- Link: https://forms.gle/myXhzNgtECTS6wpd6
- Pdf: Zip-File / Questionnaire / Icon_choices - Google Forms.pdf

## C.2 Raw data

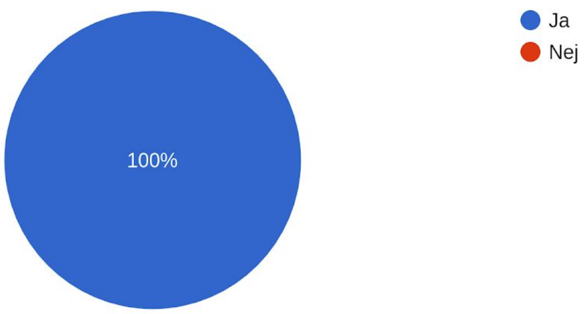
| Timestamp | Kan du give dit samtykke til overstående og indforstået med at data vil blive opsamlet ifm. besvarelser. | Hvilken rolle har du på din arbejdsplads? | Hvor gammel er du? | Hvad køn identificerer du dig som? | Hvilken af de tre figur illustrationer symbolisere bedst en stigning i fejlniveau? Eller har du et forslag til noget helt fjerde? | Hvilken af de tre figur illustrationer symbolisere bedst tid imellem stadier? Eller har du et forslag til noget helt fjerde? | Hvilke af de to "bottle" ikoner synes du bedst symbolisere flasken som påfyldes? Eller synes du det skal være et helt tredje? | Hvilken af de 3 "Funnel" ikoner synes du mest symbolisere fyldemaskinen som påfylder? Eller synes du noget helt tredje? | Hvilken af de 4 "liquid" ikoner synes du mest symbolisere væsken som påfyldes? Eller har du en ide til et bedre symbol? | Hvilke af de 3 "power" ikoner symbolisere bedst styrke ift. maskinens skrue kraft, eller er der et fjerde ikon som vil være mere sigende? | Hvilke af de 4 "vinkel" ikoner symbolisere bedst vinklen, ift. maskinens montering af skruelåg, eller er der et femte ikon som vil være mere sigende? | Hvilken af de 2 "Heights" ikoner symbolisere bedst højde indstillinger, eller er der et tredje som vil være mere sigende? | Hvilken af de 4 "Angle" ikoner symbolisere bedst vinkel indstillinger, eller er der et femte som vil være mere sigende? | Hvilken af de 4 måder at symbolisere behov for et givent brugerinput bedst? (Eller har du en bedre måde at symbolisere det?) | Foretrækker du dynamiske eller statiske ikoner, dvs. ikoner med eller uden bevægelse. | Har du nogle yderligere kommentarer ift. ikoner som informationskilde i fabrikation? | Har du nogle yderligere kommentarer generelt? |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5/26/2020 8:24:58 | Ja | Teknikker | 40 | Mand | C | B | A | B | C | A | C | B | C | C | Det afhænger af situationen | | |
| 5/26/2020 9:05:17 | Ja | Operatør | 56 | Kvinde | C | C | B | A | C | A | C | B | A | B | Det afhænger af situationen | | |
| 5/26/2020 9:06:11 | Ja | Teknikker support | 49 | Mand | C, men søjlen burde have farve i hele højden. | A | B, men ville nok vælge noget mere universelt. (og blev nok nudget af ikonet oppe i venstre hjørne.) | A, hvis det er en konventionel tragt, men ville vælge noget som lignede det aktuelle udstyr mere. | C | A | A | B | A | D | Foretrækker ikoner som er stilstående | Det er vigtigt at ikonerne er logiske og minder om havd de repræsentere. | |
| 5/26/2020 10:25:21 | Ja | Operatør | 52 | Mand | C | C | B | A | C | A | A | A | B | D | Foretrækker ikoner med bevægelse | | |
| 5/26/2020 13:09:49 | Ja | Forberedelse | 53 | Kvinde | C | C | B | A | C | C | A | A | A | D | Det afhænger af situationen | | |
| 5/26/2020 13:10:01 | Ja | Teknikker | 41 | Mand | C | A | B | B | C | A | A | A | A | C | Det afhænger af situationen | | |
| 5/26/2020 13:10:08 | Ja | Teknikker | 52 | Mand | C | C | A | A | C | A | B | B | A | A | Det afhænger af situationen | Symboler og ikoner går igen på alle maskiner | |
| 5/26/2020 14:31:51 | Ja | Operatør | 61 | Kvinde | C | B | B | B | B | C | B | B | B | C | Det afhænger af situationen | | |
| 5/26/2020 15:19:39 | Ja | Teknikker | 43 | Mand | C | Timeglas ikon m. minuttal under | B | A | C | C | Piktogram designet efter nærbillede af den aktuelle applikation | A | A | C | Det afhænger af situationen | Vær varsom med at anvende farver, da der er flere farveblinde end man tror (tabu). Vælg HMI størrelse efter nødvendigt indhold og ikke omvendt. Sørg for at skærmlayout, indhold, ikon størrelse mm. designes ud fra brugerens ønsker og ikke ud fra hvad programmøren "tror" brugeren har behov for. | XX.XX.XX.XX |
| 5/26/2020 15:26:02 | Ja | Operatør | 54 | Mand | C | A | B | A | B | C | B | B | A | D | Det afhænger af situationen | | |
| 5/26/2020 16:53:07 | Ja | Operatør | 57 | Mand | C | A | A | B | C | A | C | B | A | C | Det afhænger af situationen | | |
| 5/26/2020 18:33:34 | Ja | Operatør | 62 | Mand | C | A | B | B | C | B | D | A | B | C | Det afhænger af situationen | | |
| 5/26/2020 20:42:47 | Ja | Teknikker | 32 | Mand | C | A | Et symbol af en vandhane der løber ned i en flaske. | B | Et symbol af en vandhane der løber ned i en flaske. | A | B | B | B | A | Foretrækker ikoner som er stilstående | | |
| 5/26/2020 22:46:15 | Ja | Reviewer/Operatør | 45 | Kvinde | C | C | B | A | C | A | A | A | A | A | Foretrækker ikoner som er stilstående | | |
| 5/26/2020 23:20:06 | Ja | Operatør | 57 | Kvinde | C | A | A | B | C | C | A | A | D | B | Det afhænger af situationen | nix | nej |
| 5/27/2020 0:54:45 | Ja | Teknikker | 29 | Mand | C | evt et timeglas som tømmes (tiden render ud). Og igen, farver. Det er ikke kun børn der nemmest forstår dette. | billedet til venstre med tagten over flasken. Flasken alene ligner et færdigt produkt. | A | C | A | A | B men pilen skal pege begge veje (pil i begge ender <------>), da det kan justeres begge veje. | A men pilen skal pege begge veje (pil i begge ender <------>), da det kan justeres begge veje. | A og D, evt symbol fra A over D mens den blinker. | Det afhænger af situationen | Lad vær med at gøre det for smart, mere børnevenligt er nemmest for folk at have med at gøre i hverdagen. | |
| 5/27/2020 10:03:11 | Ja | Finplanlægger | 51 | Kvinde | C | C | A | A | C | C | B | A | A | C | Det afhænger af situationen | | |
| 5/27/2020 14:10:07 | Ja | Teknikker | 25 | Mand | C | C | B | A | D | B | B | A | B | B | Foretrækker ikoner som er stilstående | | |
| 5/27/2020 15:29:13 | Ja | Teknikker | 50 | Mand | C | A | B | A | C | C | A | B | A | C | Det afhænger af situationen | | |
| 5/28/2020 2:24:55 | Ja | Operatør | 50 | Mand | C | C | B | B | C | A | B | B | A | D | Foretrækker ikoner med bevægelse | | |
| 5/28/2020 13:25:08 | Ja | Operatør | 51 | Kvinde | C | C | Det kommer and på hvad der fyldes på flasken hvordan den skal se ud. | A | Hvis det er B så kan den komme til at line flasken som påfyldes | C | B | B | B | B | Det afhænger af situationen | nej | nej |

# Questionnaire summary

## Consent

Kan du give dit samtykke til overstående og indforstået med at data vil blive opsamlet ifm. besvarelser.

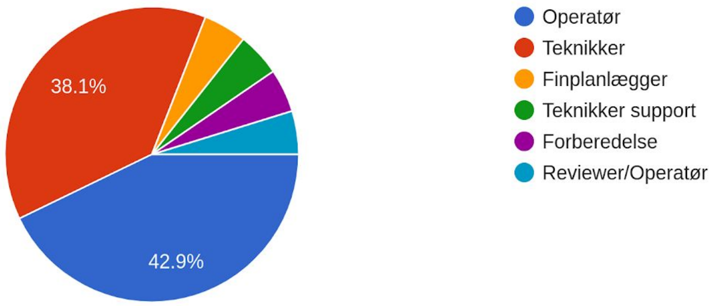
21 responses



# Demographics

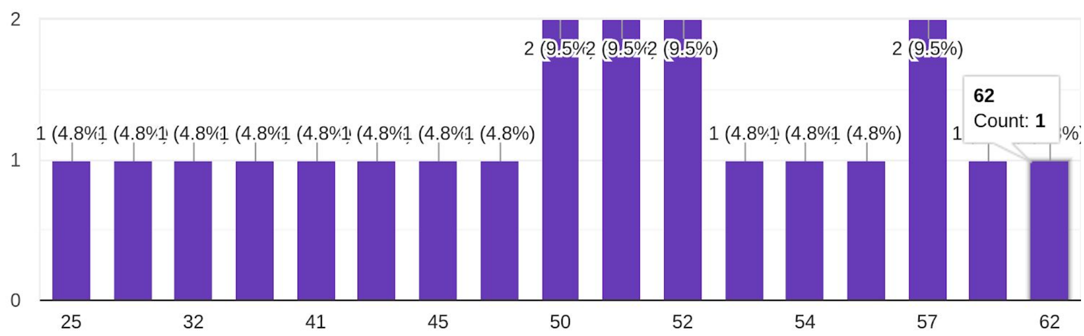
Hvilken rolle har du på din arbejdsplads?

21 responses



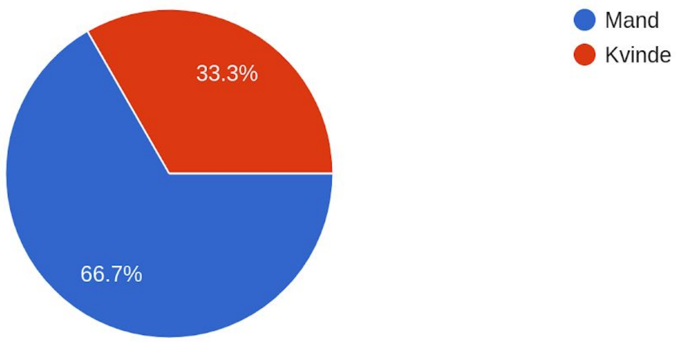

Hvor gammel er du?

21 responses



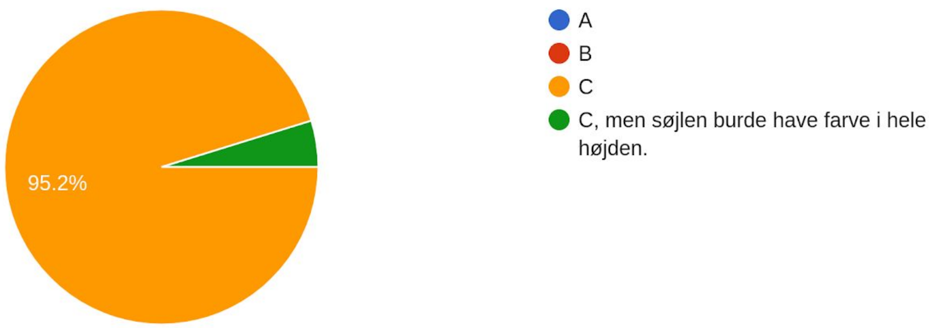

Hvad køn identificerer du dig som?

21 responses



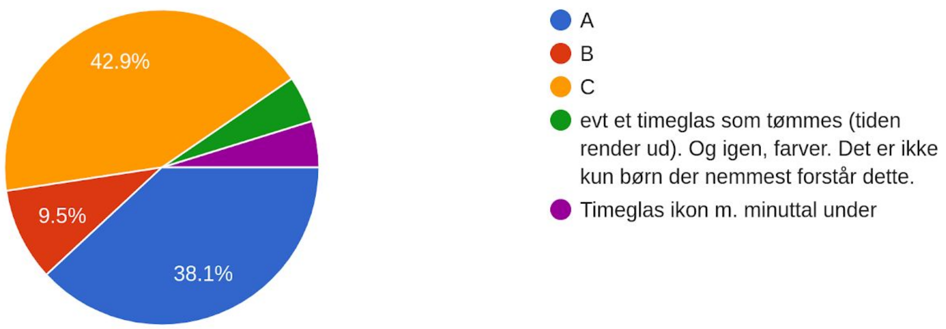
# Indication of error

Hvilken af de tre figur illustrationer symbolisere bedst en stigning i fejlniveau? Eller har du et forslag til noget helt fjerde?
21 responses




# Indication of time

Hvilken af de tre figur illustrationer symbolisere bedst tid imellem stadier? Eller har du et forslag til noget helt fjerde?
21 responses



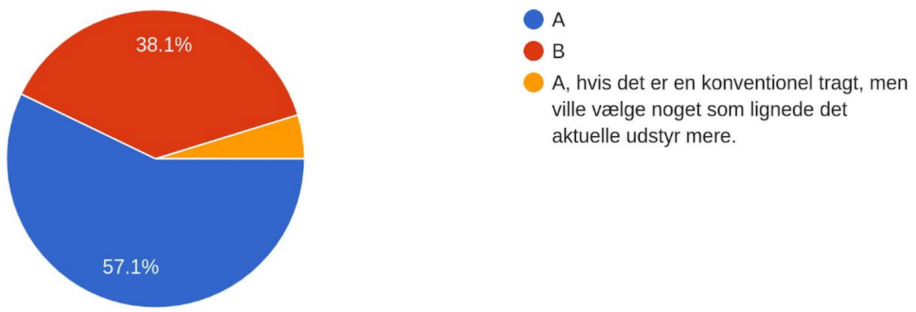
# Filling machine

Hvilke af de to "bottle" ikoner synes du bedst symbolisere flasken som påfyldes? Eller synes du det skal være et helt tredje?

21 responses

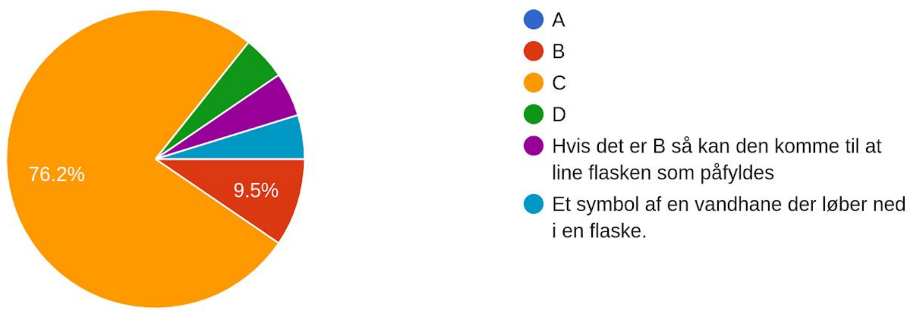

Hvilken af de 3 "Funnel" ikoner synes du mest symbolisere fyldemaskinen som påfylder? Eller synes du noget helt tredje?

21 responses




Hvilken af de 4 "liquid" ikoner synes du mest symbolisere væsken som påfyldes? Eller har du en ide til et bedre symbol?

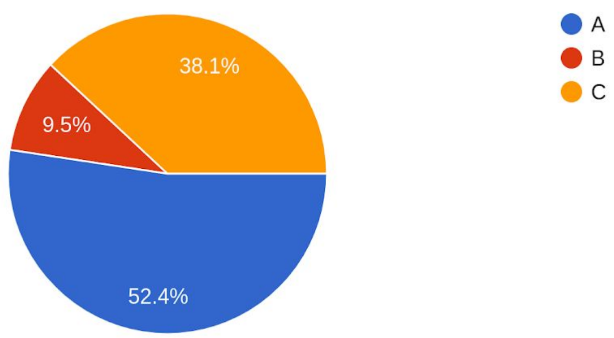
21 responses



# Cap screwing machine

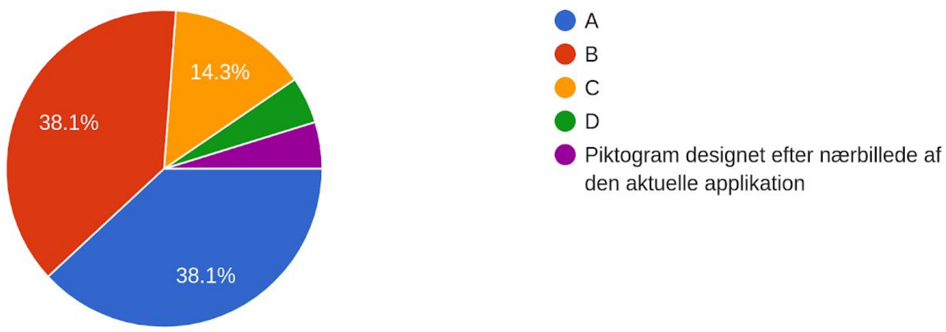
Hvilke af de 3 "power" ikoner symbolisere bedst styrke ift. maskinens skrue kraft, eller er der et fjerde ikon som vil være mere sigende?

21 responses




Hvilke af de 4 "vinkel" ikoner symbolisere bedst vinklen, ift. maskinens montering af skruelåg, eller er der et femte ikon som vil være mere sigende?

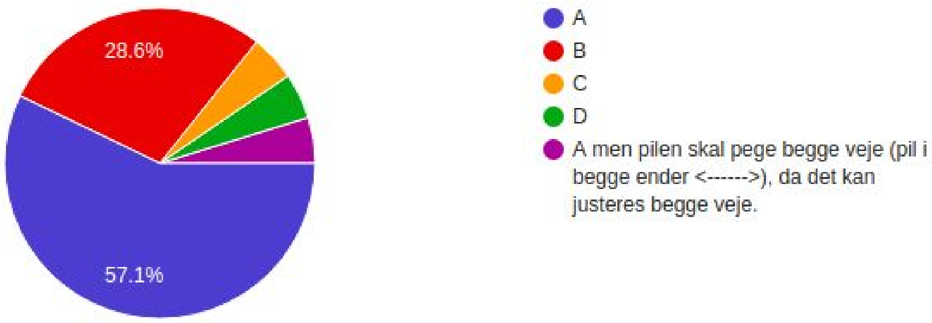
21 responses



# Labelling machine

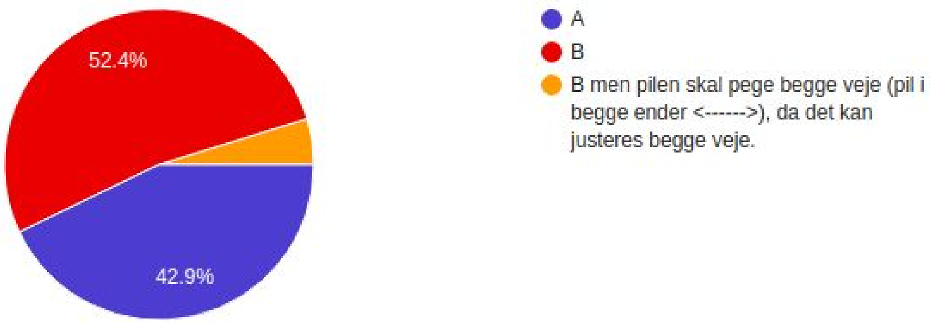
Hvilken af de 4 "Angle" ikoner symbolisere bedst vinkel indstillinger, eller er der et femte som vil være mere sigende?

21 responses



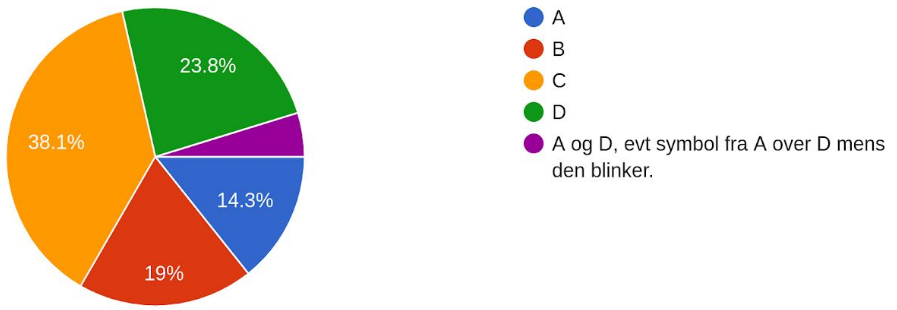

Hvilken af de 2 "Heights" ikoner symbolisere bedst højde indstillinger, eller er der et tredje som vil være mere sigende?

21 responses



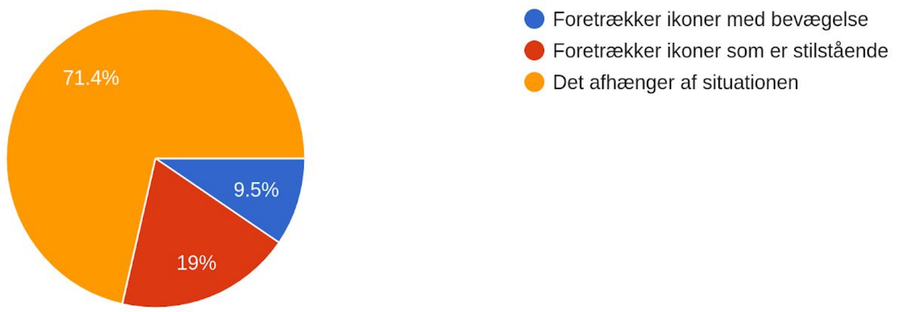
# Indication of user input

Hvilken af de 4 måder at symbolisere behov for et givent brugerinput bedst? (Eller har du en bedre måde at symbolisere det?)
21 responses




# Dynamic vs static

Foretrækker du dynamiske eller statiske ikoner, dvs. ikoner med eller uden bevægelse.
21 responses




# Further comments

- "Lad vær med at gøre det for smart, mere børnevenligt er nemmest for folk at have med at gøre i hverdagen."
- "Det er vigtigt at ikonerne er logiske og minder om havd de repræsentere."
- "Vær varsom med at anvende farver, da der er flere farveblinde end man tror (tabu). Vælg HMI størrelse efter nødvendigt indhold og ikke omvendt. Sørg for at skærmlayout, indhold, ikon størrelse mm. designes ud fra brugerens ønsker og ikke ud fra hvad programmøren "tror" brugeren har behov for."
- "Symboler og ikoner går igen på alle maskiner"

# Appendix D

# Mediation technique

This appendix contains file used and developed in regards to the second lofi test where different mediation techniques is tested. This therefore covers materials used for the test, raw data, and script code for statistical-analysis.

### D.0.1 LoFi designs tested

Found in attached zip file in the following path;

- Zip-File / MediationTechniques / **.png

As an example see D.1

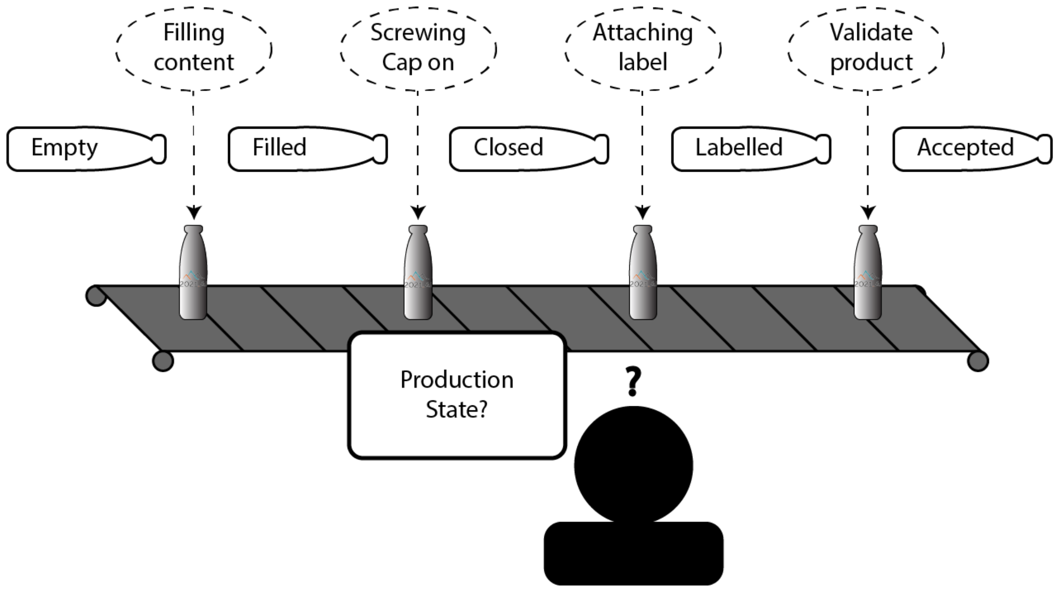
### D.0.2 R.script for statistical analysis

Found in attached zip file in the following path;

- Zip-File / MediationTechniques / Anova / lofi2.R

# Introduction to participants (LoFi2)

Du skal forestille dig at du arbejder på i en flaske produktion. Som illustreret på billedet herunder.




Som du kan se fokuseres der på tre maskiner fylde, skruelåg og mærkat maskiner. Disse er dit ansvar at overvåge ved hjælp af denne "tablet". Her vil blive præsenteret nogle af de fejl som kan opstå på maskinen, enten som tekst, grafer eller ikoner. Det er så din opgave at forklare hvad du mener bliver præsenteret omkring fejlen og dens udvikling, samt hvad der kan gøres for at hindre udvikling af fejlen.
Efter du har afgivet din forståelse af det præsenterede information vil du blive bedt om at vurdere præsentationsmåden på tre parametre hurtighed af forståelse, klarhed af budskab og sidst hvor godt du kan lide informationsmåden. Dette vil blive gentaget 9 gange i alt, hvorefter forsøget er færdigt. Forsøget vil blive optaget for videre analyse af din forståelse og oplevelse af de præsenterede designs.

# Samtykke erklæring

For at kunne få lov at udføre og indsamle data i forbindelse med testen er det nødvendigt at du har underskrevet en samtykkeerklæring. Det er derfor vigtigt at du er indforstået og kan give dit samtykke til følgende udsagn:

- Jeg forstår at testen vil blive optaget til videre analyse.
- Anonymitet vil blive beskyttet og alt persondata vil blive holdt fortrolige. (såsom optagelse)
- Jeg føler mig tilfredsstillende informeret vedrørende testen agenda.
- Jeg er klar over hvad jeg skal gøre som testperson.
- Jeg har altid ret til at stille spørgsmål.
- Jeg har altid ret til at stoppe testen uanset årsag.

Jeg er enig med ovenstående udsagn, og vil gerne deltage i testen.

Underskrift og dato: ________________________________________

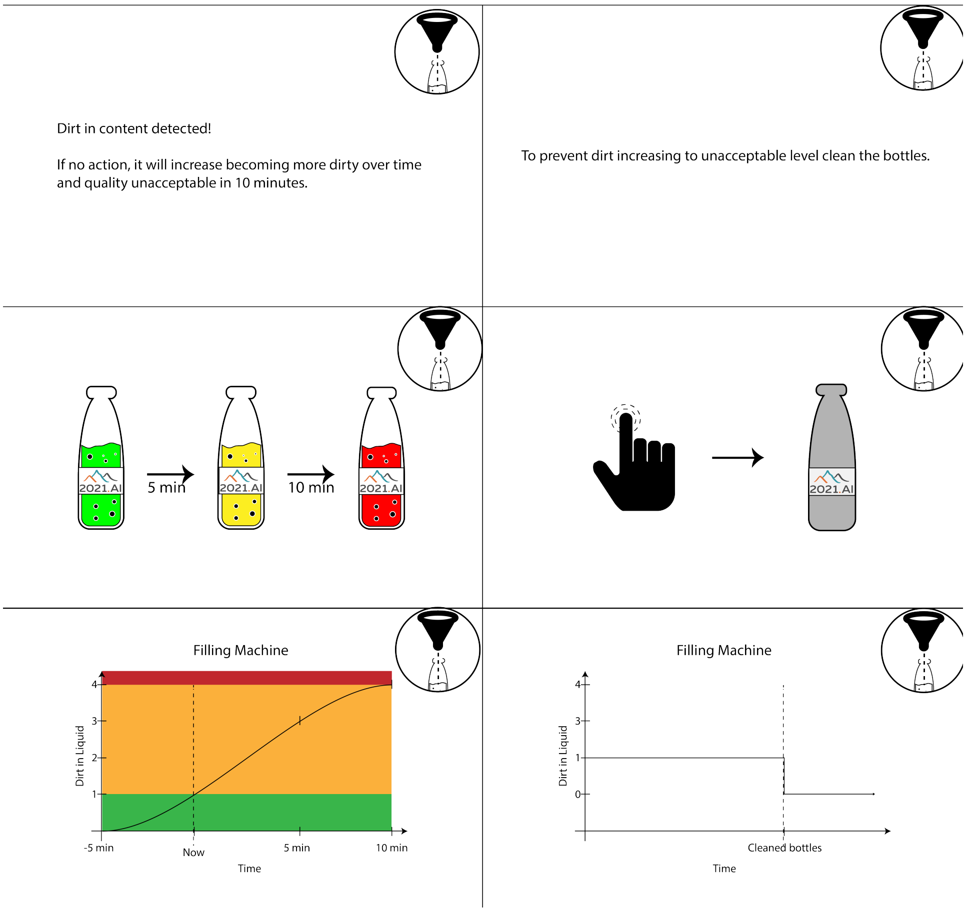



**Figure D.1:** Image of one of the 7 developed lofi design sets

### D.0.3 Raw VAS scores

| Forsøgsperson | Maskine | Parameter | Forståelse | Budskab | Informationsmetode |
|---|---|---|---|---|---|
| 1 (OP) | Filling machine | Text | 2.35 | 7.5 | 4.95 |
| | | Icons | 8.6 | 8.7 | 7.05 |
| | | Graphs | 8.5 | 8.65 | 8.2 |
| | Cap machine | Text | 8.6 | 8.65 | 8.1 |
| | | Icons | 8.6 | 8 | 7.15 |
| | | Graphs | 8.55 | 8.35 | 4.7 |
| | Label machine | Text | 8.4 | 8.3 | 8.1 |
| | | Icons | 8.7 | 8.75 | 8.7 |
| | | Graphs | 6.7 | 6.45 | 6.2 |
| 2 (OP) | Filling machine | Text | 6.25 | 6.35 | 7.4 |
| | | Icons | 1.3 | 1.7 | 1.75 |
| | | Graphs | 2.7 | 3.3 | 2.5 |
| | Cap machine | Text | 7.2 | 7.1 | 7 |
| | | Icons | 3.5 | 5.1 | 3.6 |
| | | Graphs | 2.5 | 3.2 | 3.7 |
| | Label machine | Text | 7 | 7 | 7.5 |
| | | Icons | 6.3 | 6.4 | 6.9 |
| | | Graphs | 3.6 | 5.55 | 3.4 |
| 3 (TEK) | Filling machine | Text | 8.9 | 8.9 | 8.9 |
| | | Icons | 4.9 | 5 | 4.9 |
| | | Graphs | 0.45 | 0.45 | 5.1 |
| | Cap machine | Text | 8.9 | 8.8 | 8.9 |
| | | Icons | 8.9 | 8.9 | 0.65 |
| | | Graphs | 5 | 4.85 | 4.6 |
| | Label machine | Text | 8.9 | 9 | 8.7 |
| | | Icons | 9 | 8.85 | 7 |
| | | Graphs | 6.85 | 6 | 3.2 |
| 4 (TEK)* | Filling machine | Text | 3.4 | 8.65 | 6.5 |
| | | Icons | 6.8 | 8.7 | 4.65 |
| | | Graphs | 0.7 | 1.8 | 0.9 |
| | Cap machine | Text | 1.4 | 8.6 | 8.3 |
| | | Icons | 8.2 | 8.2 | 8.2 |
| | | Graphs | 1.4 | 1.75 | 1.8 |
| | Label machine | Text | 1.2 | 8.4 | 7.5 |
| | | Icons | 8.5 | 6.7 | 8.3 |
| | | Graphs | 1.8 | 1.6 | 1.8 |

### D.0.4 Recording notations

- Participant 1
  - Would prefer the text descriptions in their native language (danish)
  - Suggest making a mixture/combination of the text and icon versions.
- Participant 2
  - Would prefer the text descriptions in their native language (danish)
  - Dyslexic so text is already complicated.
  - Suggest making a mixture/combination of the text and icon versions.
  - Finds the graph designs ambiguous and complex due to axis values and differences between graphs.
- Participant 3
  - Suggest making a mixture of the text and icon versions.
  - Finds the graphs confusing and notes an error on one of the axis values, and again find these ambiguous due to difference between them.
  - Suggest something named Io Factory for simulation of manufacturing processes.
- Participant 1
  - Suggest making a mixture of the text and icon versions.
  - Explains that graphs are for continuous trends that are to be monitored, but not for when direct action is to be made.
- Experimenter observations
  - Overall seemed more confident in understanding the text format opposed the others. Further most complained about the text version being in English compared to their native language Danish. 1 was dyslexic creating more difficulty in understanding the text version in English.
  - A strong order effect and learning/familiarisation curve can be seen in the understanding of the participants, as they show increased speed of understanding as they get through all the parameters. Understanding of graph and icon are first properly understood when having seen a text example as well. Severe difficulty understanding the text and graph examples were noted if they had not experienced a text example before.
  - All mentions the order effect themselves, that graphs or icons are only understood completely when having been presented a text example.
  - More context to the production were needed, as an example going through the introduction more elaborately and "with them" instead of briefly going over it.