Critical literature review, systematic investigation and implementation about innovative product development and emerging manufacturing technologies

Danial Nayyar, Faculty of Engineering & Science, University of Greenwich, UK. ID: 001138327; Email: dn1999o@gre.ac.uk
Sashenk Nalajala, Faculty of Engineering & Science **,**University of Greenwich, ID 001393523; Email: sn7367u@gre.ac.uk
Akshay kumar Pangunuri, Faculty of Engineering & Science ,University of Greenwich, ID 001396357 ; Email: ap9309f@gre.ac.uk

Ujval George Pasumarthy, University of Greenwich, ID 001364841; Email: up9833p@gre.ac.uk

ABSTRACT

This report features an introductory literature review of a variety of topics including digital twins as well as emerging design and product development technologies alongside Design for X mythologies, demonstrating their applications, and how they function. This report also features the demonstration of two case studies, one being the concept design and development and scoring of a concept design based on the telepresence robot featured in the brief. It also demonstrates the design and analysis of the winning concept through static simulations and topology optimization as well as the development of AM and CNC machine code through use of softwares like Prusa Slicer and SolidWorks respectively. Cloud-based CAD/CAM/CAE systems facilitate cross-border collaboration, while CAPP refines CNC machining (precision), additive manufacturing (material efficiency), and hybrid techniques (complex part fabrication). AI, IoT, and intelligent automation underpin Industry 4.0 (digitized processes) and 5.0 (human-centered green innovation), promoting agile, waste-minimized operations. These breakthroughs propel eco-aware, bespoke production, resonating with Industry 4.0/5.0's objectives for resilient, sustainable manufacturing systems.

Keywords: Innovative Design, Innovative Product Development, Computer Aided Manufacturing, Computer Aided Process Planning, Additive Manufacturing, Smart Manufacturing, Digital Twins, Industry 4.0, Industry 5.0, Telepresence Robots, Healthcare, Computer Aided Process Planning (CAPP), CNC Machining,

1. Introduction

This report presents an understanding of the literature reviews of various topics which are discussed below, one of them being the development of digital twins and their application in various industries. Advanced technologies are reshaping design and product development (DPD), fostering groundbreaking innovation and operational excellence. AI-enhanced design expedites prototyping, automates quality checks, and develops tailored solutions through user data analysis, halving development timelines. AI-driven personalization modifies products to align with individual preferences, improving user engagement. Design for X strategies, including sustainable practices, prioritize eco-conscious materials and methods to reduce environmental harm. Design for Additive Manufacturing (DfAM) leverages 3D printing's advantages—complex geometries, lightweight components, and part unification—to enhance performance while curbing waste. Together, these innovations deliver flexible, user-oriented results and address critical global concerns like sustainability and resource conservation.

Next-Gen Manufacturing Technologies
Cloud-based CAD/CAM/CAE platforms are transforming product development by enabling real-

time global collaboration, scalable solutions, and economical operations. Engineers access high-end tools without hardware barriers, accelerating design and simulation processes. Emerging technologies like AI-integrated additive manufacturing and hybrid systems use CAPP (Computer-Aided Process Planning) to streamline workflows. For CNC machining, CAPP automates toolpath design, enhances precision, and reduces errors through CAD/CAM integration. In additive manufacturing, CAPP refines material distribution and support frameworks, while hybrid approaches blend additive and subtractive techniques to produce complex parts. These advancements cut waste, speed up production, and support sustainable manufacturing, aligning with Industry 4.0's emphasis on agility and innovation.

Smart Manufacturing & Industry 4.0/5.0

The manufacturing sector is evolving through AI-augmented design, intelligent automation, and Industry 4.0/5.0 frameworks. AI optimizes design via generative algorithms, predictive analytics, and real-time adjustments, enabling swift product development. Smart manufacturing integrates IoT, robotics, and big data to create interconnected systems that enhance output, quality, and resource efficiency. Industry 4.0 focuses on automation and digital transformation, whereas Industry 5.0 emphasizes human-machine collaboration, merging advanced tech with creativity and sustainability. These shifts drive innovation, enable mass customization, reduce ecological impacts, and foster resilient, eco-friendly industrial systems.

2. Critical literature review and systematic investigation about emerging design and product development technologies

This section of the report aims to systemically present and discuss new emerging technologies for innovative DPD as well as manufacturing methods specifically with respect to new technologies such as Artificial Intelligence and the onset of industries 4.0 and 5.0

2. Emerging Design and Product Development (DPD) Technologies

2.1 AI-based Design

Significant progress has been made in fusing artificial intelligence (AI) with design techniques, according to recent studies. By automating intricate processes, enhancing performance, and cutting down on time-to-market, artificial intelligence has completely changed semiconductor design (Prashis Raghuweanshi, 2024). AI algorithms can produce a variety of design options for interior design, improving visualization and facilitating a more dynamic design process (Sonpol & Khalifa, 2024). Given its potential to foster combinational, exploratory, and transformative creativity across a range of design disciplines, a task-oriented framework for generative AI in design has been proposed (Furtado et al., 2024).

With techniques like machine learning, genetic algorithms, and fuzzy logic being applied to different design stages, AI-powered engineering systems have shown the capacity to work with ambiguous design parameters and solve complex challenges (Yüksel et al., 2023). These developments demonstrate AI's potential to improve design skills, lower development costs, and spur innovation in a variety of industries.

Recent studies examine how artificial intelligence (AI) can be included in engineering design processes, emphasizing how it could completely transform conventional methods. Automating monotonous activities, creating design possibilities, and offering insights based on user preferences and market trends are all possible with AI-powered tools (Bagnato, 2023). Deep learning techniques have demonstrated promise in effectively tackling challenging design issues. However, it is stressed how crucial it is for humans and AI to work together, with AI enhancing human creativity rather than taking its place (Zhu et al., 2024).

Concerns about transparency in AI-driven processes have led to a growing interest in the necessity of explainable AI (XAI) in engineering design (Mohseni et al., 2018). Considering various user groups and goals, researchers have created frameworks and criteria for developing and accessing XAI systems. There are still issues to be resolved, such as data protection, ethical concerns, and the requirement for interdisciplinary cooperation in AI integration.

2.2 Personalized Design

Creating adaptable design approaches to facilitate widespread personalization and modification of products has been the subject of recent study. A personalized product architectural design optimization strategy that considers production restrictions and consumer preferences was presented by Tan et al. (2020). In his evaluation of mass customization methods for product platforms, Simpson (2004) placed a strong emphasis on artificial intelligence and optimization strategies. Guevara (2021) presented a decision-analytic framework that links manufacturing complexity, consumer involvement, and product architecture. Examples of this framework were used for assistive technology and gearbox devices.

To enhance automation and performance in detail design, Jiang et al. (2022) introduced a data-driven generative design framework that incorporates user preferences and interaction data. By using modular structures, optimization algorithms, and data-driven techniques to effectively create customized product designs while preserving manufacturing viability, these strategies seek to improve product variety, lower costs, and boost customer happiness.

Virtual representations of products and customers can optimize designs prior to actual production thanks to digital twins, which are becoming cutting-edge technologies for individualized product creation (Lo et al., 2021). These methods combine production and product specification, enabling effective production planning and tolerance allocation (Wagner et al., 2019). Through the capture of user requirements and the visualization of simulation findings, extended reality applications enable consumer involvement in the design process (Mourtzis et al., 2022). Throughout the product lifetime, from design to maintenance, the idea of a "Digital Thread" links different Digital Twins, simplifying information flow and facilitating effective production automation for mass customization (Ramesh et al., 2020).

Although there is a lot of promise for product design and development using digital twins, there are still issues in developing a standardized framework for their comprehensive application. Future studies should concentrate on resolving these issues and investigating possible uses to improve product customization and innovation even further (Lo et al., 2021).

2.3 Design for X (DfX)

Design for X methodologies continue to evolve to address various product lifecycle considerations:

Design for Additive Manufacturing (DfAM)

To produce lightweight, high-performance structures, recent studies have investigated the combination of additive manufacturing (AM) with topology optimization. To overcome AM-specific limitations, topology optimization algorithms have been created, making it possible to design intricate geometries that are challenging to create using conventional techniques (Zhu et al., 2020; Prathyusha & Babu, 2022). These methods have successfully reduced weight without sacrificing structural integrity (Gebisa & Lemu, 2017). Research has concentrated on design approaches to deal with typical AM issues, such as dimensional accuracy and support structure optimization (Ranjan et al., 2017).

To increase manufacturing success rates for complicated geometries, researchers have put forth frameworks that incorporate design principles based on the link between AM process parameters and part geometry. Numerous industries, including aerospace and automotive, have found use for the combination of AM with topology optimization, which holds promise for the development of novel, lightweight components with enhanced performance.

Sustainable Design

The incorporation of sustainability and circularity ideas into product design approaches has been the focus of recent studies. The closed-loop sustainable product design approach put forth by Hapuwatte & Jawahir (2021) takes into account the effects on the economy, environment, and society over the course of a product's lifecycle. By combining sustainable design tools with change propagation, Basereh Taramsari et al. (2023) created a comprehensive framework that allowed for the simultaneous evaluation of design parameters' effects on sustainability dimensions. According to Hassan et al. (2016), integrated design tools and commercial software are essential for thorough sustainability assessments in product design.

The absence of information models and semantic interoperability were two of the main obstacles that Ramani et al. (2010) noted while applying eco-design techniques in the early stages of design. The significance of integrating lifecycle data, balancing various sustainability goals, and creating standardized methods for assessing design options are all emphasized by this research as ways to build more sustainable products.

3. Innovative Manufacturing Technologies

3.1 Cloud-based CAD/CAM & CAE

By utilizing cloud computing technology, collaborative product creation has been transformed by cloud-based design and manufacturing (CBDM) platforms. Geographically dispersed teams may collaborate in real time thanks to these platforms, which shortens design cycle times and enhances product quality (Wu & Schaefer, 2013). With their sophisticated computational capabilities and constantly evolving tactics, CBDM systems provide scalable substitutes for conventional desktop programs without requiring a large amount of local processing power. Product development and realization stages have become more efficient and data flow has been streamlined through the integration of CBDM with Product Lifecycle Management (PLM) (Khlifi et al., 2017).

By providing scalable and adaptable services via the internet, CBDM opens up new possibilities for contemporary businesses (Malladi & Tjprc, 2018). Collaborative design, distributed manufacturing, communal innovation, data mining, semantic web technologies, and virtualization are some of the main research topics in CBDM. CBDM promises to change the manufacturing and design industries as it develops further.

Cloud computing is increasingly being used in computer-aided engineering (CAE) and design, according to recent studies. For computationally demanding simulations and generative design procedures, cloud platforms provide greater flexibility, scalability, and cost-effectiveness (Dasgupta et al., 2024; Hochstein et al., 2011). To maximize workflow scheduling, resource utilization, and expenses, studies suggest hybrid cloud architectures that mix elastic cloud resources with on-premises HPC clusters (Dasgupta et al., 2024).

Significant cost and efficiency reductions have been demonstrated using an economy-based strategy that allocates resources through a bidding mechanism (Dasgupta et al., 2024). Although cloud-based CAE has several advantages, especially for smaller businesses, socio-technical obstacles might prevent its broad use (Hochstein et al., 2011). Cloud-based design and manufacturing (CBDM) is a new idea that aims to transform product development processes by combining cloud computing with data mining, distributed manufacturing, and collaborative design (Wu et al., 2012).

3.2 Computer Aided Process Planning (CAPP) for CNC Machining

Increasing automation and intelligence has been the main emphasis of recent developments in computer-aided process planning (CAPP) systems. To enhance machining processes, researchers have created AI-driven CAPP systems that make use of artificial intelligence techniques like fuzzy logic, artificial neural networks, and genetic algorithms (Ahmad et al., 2002). Based on feature identification and machining limitations, these systems seek to autonomously produce optimal tool paths and machining sequences (Yip-Hoi, 2017). According to Besharati-Foumani et al. (2019), knowledge-based CAPP systems have been developed to recommend the best process parameters by leveraging expert knowledge and previous manufacturing data.

Studies have demonstrated that these intelligent CAPP systems can significantly reduce planning time and improve machine efficiency. For instance, one framework for rotational components achieved reductions in machining time and cost through optimized process parameters and operation sequences (Siva Sankar et al., 2008). Despite these advancements, fully automated CAPP systems remain a challenge, with ongoing research focusing on machine learning and data analytics to further enhance their capabilities (Besharati-Foumani et al., 2019).

Research has indicated that these intelligent CAPP systems can enhance machining efficiency and drastically cut down on planning time. For example, one framework for rotating components used optimized process parameters and operation sequences to save machining time and cost (Siva Sankar et al., 2008). Even with these developments, fully automated CAPP systems are still difficult to implement, and research into machine learning and data analytics is still being conducted to improve their functionality (Besharati-Foumani et al., 2019).

3.3 CAPP for Additive Manufacturing (AM)

Addressing difficulties and improving results have been the main goals of recent research in additive manufacturing (AM) process planning. Sarma et al. (2021) suggested a hybrid slicing technique that eliminates support structures while cutting down on production time and material waste by combining horizontal planar and conformal slicing. To maximize cost and quality, Behandish et al. (2018) created an automated process planning method for hybrid manufacturing that combines additive and subtractive techniques. To increase efficiency, Tereshchenko & Osiponok (2024) examined important phases of AM planning, identifying algorithmic difficulties and suggesting a Unified Algorithmic Platform.

By introducing a topology optimization process that incorporates support structure limitations, Mirzendehdel & Suresh (2016) were able to reduce fabrication costs and create designs that require fewer support structures. To increase overall component quality and manufacturing efficiency, these studies show the continuous attempts to improve AM process design by addressing build orientation, support structures, slicing techniques, and multi-objective optimization.

By altering layer thickness according to local geometric parameters, adaptive slicing techniques in additive manufacturing seek to maximize the trade-off between build time and surface quality. More precise techniques for evaluating geometric differences and figuring out ideal layer thicknesses have been the subject of recent research. By calculating the geometric deviation volume to digital model volume ratio, Yang and Myant (2022) suggested a method that cuts build time in half without sacrificing accuracy.

Hu et al. (2018) introduced a technique that balances geometrical correctness and build efficiency using extracted candidate feature points. An approach to calculate surface error factors and maximize cost-effectiveness was created by Sikder et al. (2014). To overcome the practical constraints of variable thickness in current machines, Liu et al. (2020) investigated increasing layer accuracy with constant layer thickness. With potential applications in a variety of industries, these investigations have shown notable gains in surface quality maintenance and build time reduction.

3.4 Technology Trends and Emerging Manufacturing Paradigms

AI-based Design Impact

Recent studies demonstrate how AI technologies have a major impact on industrial processes, especially in the areas of process optimization and quality control. With up to 95% accuracy rates in defect detection, AI-driven systems have shown significant gains in this area (Kulynych et al., 2024; Parmar, 2022). According to several case studies, process optimization has improved by about 30% (Niveditha et al., 2024; Okuyelu & Adaji, 2024). With maintenance costs dropping by as much as 30%, AI integration has also resulted in significant cost savings (Kulynych et al., 2024).

Predictive analytics and real-time monitoring have improved overall production performance by facilitating dynamic process optimization and early fault identification (Okuyelu & Adaji, 2024). With accuracy of ±0.005 mm for gear tooth surface polishing, the use of AI in gear production for KrAZ trucks shown gains in precision (Kulynych et al., 2024). These developments highlight how AI has the ability to revolutionize manufacturing by improving productivity, product quality, and cost-effectiveness in a range of industrial applications.

Smart Manufacturing and Industry 4.0

Digital twins can be used in industrial settings using integrated frameworks that have been described in recent studies. This allows for real-time production process monitoring, prediction, and optimization. A conceptual framework for an integrated product-process digital twin in digital manufacturing was put up by Onaji et al. in 2022. Mo et al. (2023) created a framework for dynamic system reconfiguration that combines modular AI and digital twins, which improved process time by 10%. The "Expert Twin" framework, developed by Monek & Fischer (2024), boosted production line utility by up to 28% by including fuzzy logic for decision-making.

A data-driven approach was presented by Friederich et al. (2022) for the automatic creation of simulation models, which serve as the foundation for digital twins in smart factories. These methods show how digital twins can improve production flexibility, efficiency, and decision-making skills, tackling issues with shorter product life cycles and quickly shifting consumer needs in smart manufacturing settings.

4. Research Gaps and Future Directions

There are many potential and difficulties associated with integrating artificial intelligence (AI) into manufacturing. There are still significant gaps in the smooth integration of AI into coherent systems, even though it has the potential to transform manufacturing processes, optimize operations, and improve decision-making (Zarif Bin Akhtar, 2024) (D. Bourne et al., 2011). Issues with data quality, the interpretability of AI models, and knowledge transfer between fields are important obstacles. For AI systems to capture and use expert insights, effective knowledge representation is essential (Wu & Liang, 2024).

Models of human-AI collaboration are required to take advantage of complementary skills. Despite the development of automated planning tools, computational difficulties still necessitate a large amount of human input in many production fields. "A conceptual framework addressing key challenges and promoting a data-driven culture is necessary to bridge the gap between research and industry adoption" (Silva Peres et al., 2020).

3. Critical literature review and systematic investigation about Digital Twins

This section of the report aims to present an understanding of digital twins by introducing the concept and its working methodology, its applications across industries, the tools as well as some challenges for future developments.

The term “digital twin” (DT) was first introduced as a concept in the early 2000s by Michael Grieves and although the term has been around for some time, it is now being added to the “arsenal of cliches” due to the influx of digital infrastructure being embedded into industries, cities and communities. DTs are defined as digital replications of real-life physical processes, although it is an ideal thought that the digital twin is a perfect mirror, it is better to think of them as models that mimic the key features of the real system (Batty, 2018).

DTs are smart systems representing a physical, real-world system/ process. It consists of three separate elements, the real-world system/process, the digital system/process and the connection between the two. Its applications are endless, a digital twin can be made for a jet engine to a manufacturing robot and in healthcare as well (Le, 2025), they are designed to mimic the process the real world system will be designed to follow and then data is collected to see the performance output. Due to developments in machine learning and deep learning algorithms i.e. neural networks and physics informed neural networks (PINNs) the prediction accuracies can be much higher and representative of the physics of the process as well.

One of the key features of DTs is data that flows between the physical and virtual worlds. As such it is important to consider how data is utilized. A combination of past, present and predicted data is used for successful operation of the twin, the past data is the history of real-world machines and serves as the benchmark for operations, this includes operational parameters, FEA data, flow simulations etc. The present data is the data that comes from the real-world twin, i.e. velocity, pressure and temperature data from the attached sensors, this data is fed to the twin to allow it to update/maintain its parameters in the model. Finally, the predicted data, this is the data that is predicted by ML models and can also feature input from engineers that can allow the twin to update its operational parameters. (Le, 2025). In terms of operation, the digital twin begins as a standard simulation. However, due to the input of real-time data, simulation updates in real-time and as such are considered a twin of the real-world element, and due to this input, its prediction accuracy increases over time as well.

Digital Twins with Artificial Intelligence

Due to their versatility DTs, as mentioned before, can be utilised across various industries. (Zhihan Lv & Shuxuan Xie, 2022) wrote in their paper that discusses A.I. in DTs, that the impact of digital twins and A.I. as its integrated into industries/systems is very significant for example in aerospace it an be used for aircraft assembly, flight detection simulation and even unmanned flight. Lv and Xie reported that in a virtual simulation test of autonomous vehicles there was a saving of 80% in terms of time and cost. Additionally, they can be used in specific applications such as battery management. Wu et al conceptualised a battery digital twin to enable smarter control and increase battery lifespan. They utilized advances in modelling tools as well as battery degradation alongside machine learning methods to create twins. They stress the development of hybrid and surrogate models that leverage the multi-physics models alongside neural networks (NNs), to reach a faster model predictions (the older multi-physics models are computationally expensive) as well as utilising K-nearest neighbors (KNNs) and support vector machines (SVMs) M.L. models that can utilise the data better than conventional approaches, to increase the accuracy. However, the authors note that although battery DTs will have a massive impact on future battery development (across multiple industries) there exist some significant borders to cross first. As mentioned before, data plays a vital role in digital twins, and Lv and Xie echo that as well, they note that a significant challenge is the collection and transfer of data. They suggest a standardized method for collecting, testing and processing data across industries and academia. They also note that the development of multi-physics models (for this application) in terms of capturing nano-scale effects on the larger macroscopic metrics is vital alongside their development in hybrid models that utilise multi-physics models and the developments in data based M.L. models. (Billy Wu, et al., 2020). Algorithms such as Random Forests, Ada Boost etc can be used in manufacturing to improve production yield in petrochemical industries. Additionally, algorithms such as Deep Convolutional NN can be used to analyses cane of reinforcement. In terms of results, DCNN yields significantly better results relative to normal ML. (Stefan Mihai, et al., 2022)

Digital Twins and Healthcare

DTs for healthcare are a recent and upcoming development, although DTs have been used across other industries, governments and military, it's still under development in healthcare. However, its potential impacts are significant. DTs in healthcare can be used for a variety of applications ranging from management & delivery to disease treatment and prevention and overall improvement of life. Katsoulakis et al categorise the use of DTs in health and a significant one is biomarker and drug discovery. Traditional methods bare significant risk as well as being very expensive in terms of time and money. Katsoulakis et al reported that the estimated cost of bringing a new cost to market is approximately $2.6 billion (US) with a time to market of 10 years. DT modelling shortens the process and makes realistic biochemical predictions and has identified numerous drugs that can be used for HIV. Furthermore, companies like Takeda Pharmaceuticals have switched to a DT technology approach for their production to launch therapies across the world. Another area within healthcare is DTs for surgery. DTs can be used for surgical planning, a procedure that uses the DT model of anatomical structures allowing surgeons to simulate surgeries before carrying it out on the patient. Traditional methods bare significant risk for patients ranging from poor outcomes to death. (Evangelia Katsoulakis1, et al., 2024)

Digital Twins and Manufacturing

Digital Twins can be used to close the gap between the actual manufacturing and inspection of the part. The nature of part inspection currently involves waiting for the part to be CNC machined based on a CAD file and until the part is completed, tolerances won't be known. A digital thread was introduced in 2017 , which relates the tolerances of the part to the coordinate measurement of the machine & to the evaluation of quality results. The system can get dimensional data through the DT whilst the physical part is in the machine. The DT model is updated continuously with material removal calculations allowing the CNC machine to adjust the feed rate to maintain constant thickness. (Yuchen Jiang, et al., 2021)

Digital Twins – Technologies

There are many rising technologies that facilitate the rise of DTs such as NVIDIA's Omniverse. NVIDIA is known for their technological uprising in recent years due to the advanced GPU which are leveraged heavily in the data industry, using their GPUs the Omniverse functions as a collaborative platform that allows for real-time 3D design and simulation. Its scalable and open environment allows designers and engineers to work simultaneously. NVIDIA's Omniverse has many advantages in terms of DTs ranging from high-fidelity simulations which mirror the real-life twin to its flexibility, allowing businesses to create entire factories due to its open and easily integrable architecture. (RS, 2025)

DTs require significant computational power due to the processing of data as well as real-time response. Due to which cloud computing can be used. In the domain of manufacturing and automotive, cloud computing can be used to perform heavy processing tasks whilst the DT represents the most recent state of the real-world twin. For example, in healthcare, the cloud connects the medical service to the patient for real-time access to the analytical health data. (Stefan Mihai, et al., 2022)

Digital Twins – Its Challenges

DTs as of now have an unquantifiable Return on Investment (ROI) due to which the businesses are hesitant to adopt DTs. This is since DTs are very multi-disciplinary and have somewhat specific use cases which may not be suitable for businesses in the general sense. Furthermore, when investing in technological business generally look to see the profit a technology/product could bring in. However, DTs operate on a cost-saving philosophy (in general) which from an investment standpoint means that it will take long term and detailed investment plans which accentuates the advantages of DTs. DTs operate in the virtual, software realm and as such constant updates will be required to ensure suitable user experience, cyber-security for sensitive data and even updates to the real world twin. As such, this maintenance feature of DTs could be a big border that business is hesitant to cross. (Stefan Mihai, et al., 2022)

Digital Twins – Concluding Remarks

Digital Twins have come forth as a new and exciting technology with applications across various industries, as shown above, albeit their significant abilities such as improved product design and maintenance of products, they do have critical challenges that need to be attended to. One such issue is the collection and use of data, as many digital twins utilise M.L. algorithms, which rely on large amounts of data to be collected, processed and cleaned up before it can be used. This delays DTs applications and as such standardized methods for data collection and use need to be developed and then utilised across academia and industry. Furthermore, the lack of clarity on DTs from a business and monetary standpoint is another driving factor to its widespread use and adoption across the industry, which means further work must be undertaken for better understanding the economics of DTs.

Figure 1: Function Diagram

However, on a more positive note, the rise of Big Data and ability to handle large amounts of data through advanced NNs like DNN and CNNs is factor for its guaranteed success as a technology. Furthermore, much work is being done in terms of the technology behind DT such NVIDIA's Omniverse which allows advanced, scalable and collaborative working environments for developing DTs.

To conclude, the long term success of DTs as a technology is assured due to rapid advancements in technologies that DTs rely on, however the overall success does depend on DTs adoption in industry for which the economic aspect must be investigated further.

4. CASE STUDY 01 – Innovative Design and Product Development

To begin the development of the design concepts it is important to develop and work through a function diagram. Function diagrams are part of the design methodology that involve determining the overall function of the product as well as its sub-functions and determining the relationships between them. The function diagram features the inputs, the "black box" and the outputs. The inputs can include user input, power sources etc. The outputs include the functions that are outputted from the product, for example, for a telepresence robot that features conference calling necessary outputs include voice and video output from a screen. The "black box" represents the connection and methodology between the input and the output, it describes, diagrammatically how the product functions holistically. For example, for an RC boat, the black box would feature motors which allow for thrust and directional controls. However, it will not include the technical specifications i.e. motor power rating, RPM, motor torque, power requirements etc.

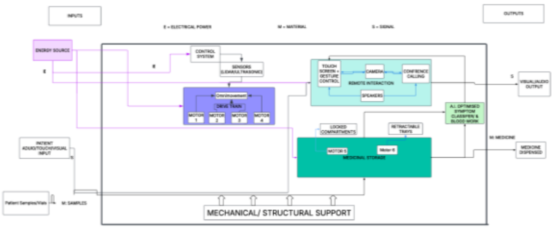


Table 0-1: Morphological Chart

The figure above presents the function diagram that will be used as the basis of developing concept designs using tools such as Prome AI and Vizcom as well as the development of the morphological chart
The function diagram was constructed on Lucid Chart (Lucid chart, 2011) and it features the inputs such as electrical power as well as user/patient input. The diagram in figure 1 has been color coded to allow ease in understanding the flow from input through the black box to output as well as distinguish the functions from one another. The purple represents the energy source, which for the robot is through an electrical power source that flows to the critical functions such as the drive train, disinfection system, the remote interaction system as well as the medicinal storage system. The black lines represent simple connections between the main functions such as the control system being connected to the drive train through the sensors and finally the blue lines represent the connections between the sub-functions within the major functions. For example, the remote interaction function features 4 interconnected sub-functions that must work together to complete the remote interaction function fully. The letters E,M,S have been defined above the "black box" as Electrical Power, Material, and Signal respectively, detailing the type of data/information that is being transferred from one end to the other. The overall function of this health care telepresence robot is to act as an aid to healthcare professionals through collecting blood test vials/samples or medication that can be taken to patient rooms for either the doctor/nurse themselves to take out of the storage compartments or allow the patient to take their medication out (the correct compartment would open whilst the rest remain locked). This telepresence robot can act as a a helping hand between patient and healthcare provider during quarantine situations such as COVID-19 where samples must be taken but contamination has to be avoided at all costs.

Functions	Possible Solutions	
Energy Source	Replaceable Battery packs	Rechargeable Battery
Movement	Omni wheels	2 wheel drive system
Control System	Remote control	Arduino
Medicinal Storage System	Pull-out drawers (lockable)	Motor driven retractable trays with lid on top
Sample Storage System	Retractable tray	Storage compartments in the base.
Remote Interaction System	Screen	No screen (for user interaction)
Sensors	LIDAR	Ultrasonic
Screen UX	Voice command +Swipe controls	Swipe controls

The next step in innovative design and product development is the morphological chart. It is a methodology to generate, analytically & systematically, ideas. It's also used to realize potential combinations of functional elements/components to then generate potential design solutions.
The table above lists the main functions as well as possible solutions which are selected from each row. A potential overall solution comprises all the individually selected components that aim to complement the function diagram and complete the products aims. From the morphological chart multiple design solutions can be produced using A.I. platforms like Prome A.I. and Vizcom.
From the morphological chart above, a few potential solutions can be formulated. The table above just presents possible solutions that can achieve the products' end goals.
The first potential design solution has features such as replaceable battery packs and having motor driven removable lids to act as the storage compartment whilst having a driving mechanism on two wheel.
Using Vizcom, a potential design concept can be created, shown in figure 2 below.

Figure 2: Design Concept 1 (Vizcom)

Another potential design concept (shown in figure 3 below) features rechargeable batteries and omni wheels to allow for efficient movement around the hospital environment. It also features a window style lock in front of the storage compartments that can be opened and closed by the appropriate staff. It features retractable trays for all compartments that allow them to be removed for easy cleaning and maintenance as well. Additionally, it features a touch screen that allows patients to interact with it alongside doctors and other healthcare professionals.

Figure 3: Design Concept 2 (Vizcom)

The final potential solution (shown in figure 4 below) features the same energy source however the movement system, the control system, sample storage system, remote interaction and screen UX are different. The third option includes a remote control system methodology as well as having a storage system is fixed trays, although it means that the trays will not be moved around and that the content inside will remain stable and will not jostle around this will cause problem if there was a spill of any potential blood samples or substances from a quarantine zone or even simple medication that needs to be cleaned when spilled. The fixed tray feature will prevent ease in cleaning and maintenance, additionally, the screen UX is very simple, a swipe mechanism.

Figure 4: Design Concept 3 (Vizcon)

(Note: The morphological charts for each potential solution are in appendix 02)

As there are now three potential design solutions the next step is to score each solution on a concept scoring methodology (Le, 2025), which is a careful analysis of a few concepts to choose the single best option. The table below was created. It features the criteria being judged, its weight as well as the individual rating and score for each solution.

		Potential Solution 1	Potential Solution 2	Potential Solution 3
Criteria	Weight	Rating 1-5 (Score)	Rating 1-5 (Score)	Rating 1-5 (Score)
Functionality	30%	2 (0.6)	2.5 (0.75)	2 (0.6)
Cost-Effective	20%	1 (0.2)	3 (0.6)	3 (0.6)
User Friendly	15%	1.5 (0.23)	3.5(0.53)	2.5 (0.38)
Feasibility	30%	3 (0.9)	3 (0.9)	3(0.9)
Innovative	5%	0 (0)	3 (0.15)	0 (0)
Total	**100%**	**1.93**	**2.93**	**2.48**

Figure 5: Concept Scoring Table

The table above in figure 5 shows that the solution 2 had the highest score. Below, each of the solutions will be evaluated to demonstrate the main reasons as to why that specific score was achieved for each solution.

Solution 1- Concept Score Breakdown

Solution 1 received the lowest score (1.93) out of the three solutions, this is due to the fact that the two wheel drive movement system coupled with the replaceable battery packs would provide stable and inefficient movement around the hospital environment. The telepresence robot should provide the hospital with adequate service and a jostle from a patient or instability due to uneven flooring could cause any medications stored in the compartments to be spilled. Additionally, the cup holder style storage system would allow anyone to be able to remove or insert anything into storage which would compromise the sterility of the samples as well as their safety as they could be easily removed.

Solution 2- Concept Score Breakdown

Solution 2 received the highest score (2.93) due to the stark differences relative to solution 1. Firstly, the energy source was changed to rechargeable battery packs, this provides a cost-effective methodology of operation within the hospital environment, multiple rechargeable batteries can be purchased per unit and once the battery levels are depleted the used one can be swapped and put on charge whilst the charged one can be inserted straight away with minimal downtime which is vital in time-critical environment like the hospital. Additionally, the storage system is different as well, the trays in all compartments are able to be removed, they are retractable and are inserted into each compartment after which the compartment can be locked and opened by the appropriate healthcare professionals. This not only secures the medications and patient samples but also ensures that nothing can be lost, and that sterility is maintained due to it being enclosed. Furthermore, the remote interaction system in solution 2 is significantly more advanced, allowing for use of A.I. (hence the higher innovation score) for voice recognition allowing patients who might suffer from arthritis, physical disabilities i.e. situations where patients are unable to use their arms and hands normally to use their voice.

Solution 3 – Concept Score Breakdown

Solution 3 received the second highest score (2.48) this was due to the similarities, in key features, to solution 2. However, the third solution still fell short and this is because of the screen UX, swipe only (i.e. touch screen only) ,system as well as the storage system. The fixed trays in the system although provide safety and ensure the samples and medications inside remain secure, the issue arises in needs of maintenance and cleaning. A hospital environment features many patient samples such as blood, urine and fecal matter that has to be transported from one hospital wing to another and as the telepresence robot will carry out these tasks, it should be able to be cleaned out easily and effectively in case of spillages to ensure there is no cross contamination when another batch of samples is used in the same compartment.

Although solution 2 and its concept design received the highest score due to the low score of 2.93, it can be further redesigned. As the main features for this study are the main frame and the storage compartments (the trays) those will be of focus when carrying out the 3D CAD modeling on SolidWorks. The figure below presents the updated version of the solution 2, with the screen and storage compartments with the retractable trays inside.

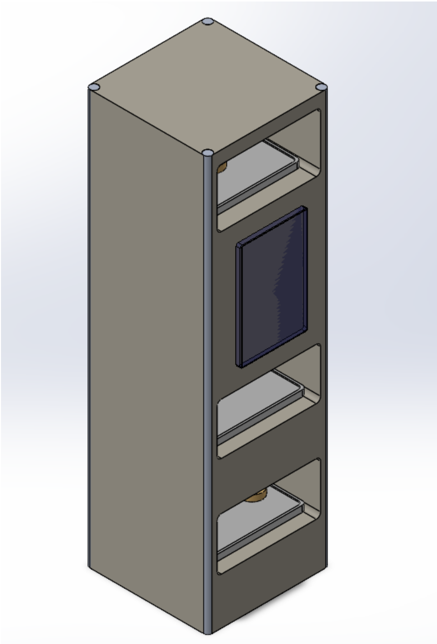


Figure 6: Updated version of Solution 2 (SolidWorks)

Figure 6 above shows a developed version of the solution 2 design; it follows the same structure of having storage compartments at intermittent heights and allows for multiple items to be stored at the same time. It also features the window lock system that swings open on a hinge and is able to move open and close allowing access to the inside of the compartment. Note for the purpose of this report only the main frame and the trays are being considered as per the guidance in the coursework brief.

4.2 Task C1.2 - Embodiment and Detail Design

The case study in this section features analysis of the design chosen in the previous section (figure 6). As mentioned before, the study will primarily focus on the main frame and the trays inside. As do all studies, the first step is to carry out a static simulation of the part/component in question. Figure 6 was modelled in SolidWorks and based on the idea that a telepresence robot will be essentially carrying the top frame it was important to keep it as light as possible. With that in mind the first simulation was carried out with the entirety of the frame being simulated with 5kg point loads on each tray. Each tray and the frame itself were made of plastic (ABS)

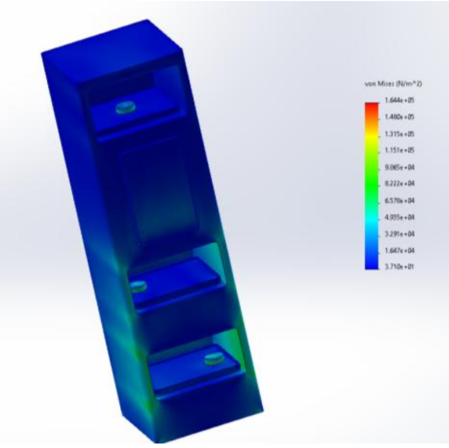


Figure 7: Von Mises Stress Distribution (ABS Frame)

Figure 7 above shows the stress distribution when a point load of 50N (approximately 5kg) is applied to the tray. There are three loading conditions shown in figure 7. The top compartment displays stress when point acts on the middle of the tray, whereas the middle and bottom compartment display the stress when the point load is off-center. This study was done by design in an effort to show stress distribution that could occur in real life situations where the load may not always be in the center and be off-center. For a better understanding of the stress distribution, SolidWorks' contour plots can be modified to have a lower highest value of stress.

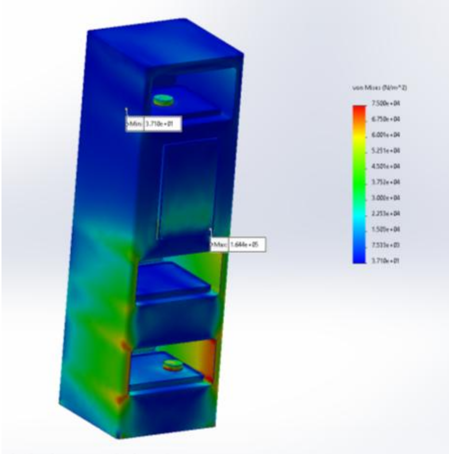


Figure 8: Modified Stress plot (ABS Frame)

The figure above shows the modified stress distribution, the modification was done to primarily counteract the fact that the plots are generated based on the highest stress value recorded by SolidWorks, if that value happens to be around a specific point it will alter the distribution based on the relative difference between the highest and lowest values of stress recorded. During the stress simulation, the highest value recorded by S.W. can be seen in figure 8 to be approximately 1.6 $\times 10^5$ N/m^2.

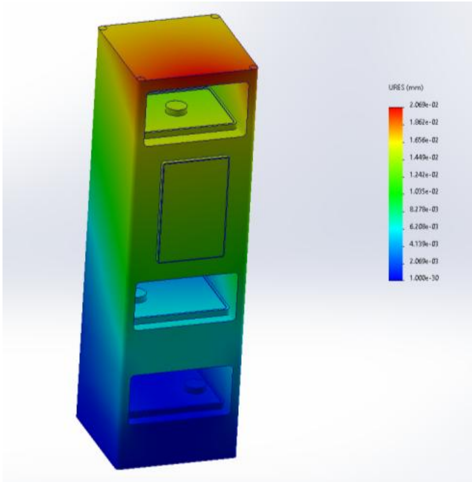


Figure 9: Displacement Distribution (ABS Frame)

The figure above demonstrates that the highest displacements are in the top regions of the structure. The displacements recorded as shown by figure 9 are as high as 2 $\times 10^{-2}$ mm. Although the value itself may not be seen as too high, overtime structure may weaken further due to fatigue.

To combat this, the material itself can be changed. Instead of having the whole frame being ABS plastic, it can be modified to have support pillars of aluminum alloy whilst keeping the main structure itself of ABS. this is to ensure that weight is not an issue relative to if the whole structure was aluminum.

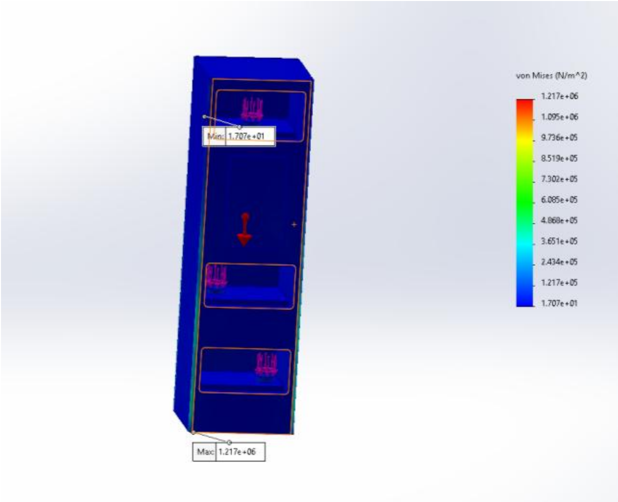


Figure 10: ABS + AL Support - Stress

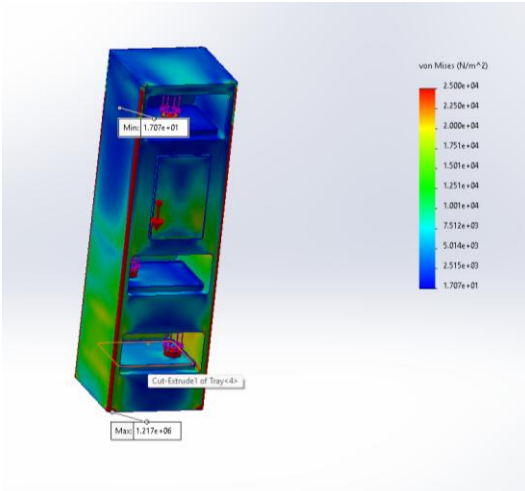


Figure 11: ABS + AL Support - Stress Modified

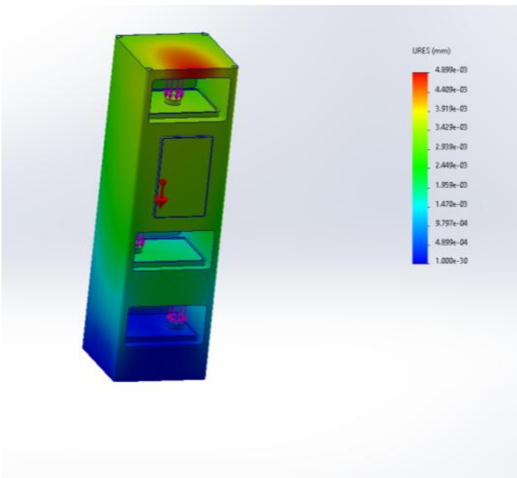


Figure 13: ABS + AL Support - Displacement

Taking a look at figures 10,11,12 it can be seen that although the highest stress recorded had increased to 1.2 $\times 10^6$ N/m^2 (figures 10 & 11) the actual stress distribution (shown in figure 11) had changed significantly from before. The aluminum support rods now bear the higher load/stress and due to aluminum's structural properties it can bear that load significantly well relative to a structure whose supports were also plastic ABS. Continuing with the analysis of the contour plots, figure 12 shows the displacement distribution, which shows the highest displacement to be approximately 4.9 $\times 10^{-3}$ mm, a further decrease by approximately a factor of 10. This shows that the use of Aluminum demonstrates promise.

Continuing with material based static simulations, another choice of material for the support rods was steel. The same analysis, i.e. boundary conditions and loads, were applied as above and the displacements contour plots revealed that steel based support is more effective than aluminum based support (as expected). However, the difference between the two max displacements was 2.1 $\times 10^{-3}$ mm, which is insignificant. The max stress from the steel based supports did increase however, that can be attributed to the self-weight of the steel being higher as opposed to aluminum. (All studies had the force of gravity applied to the vertical axis)

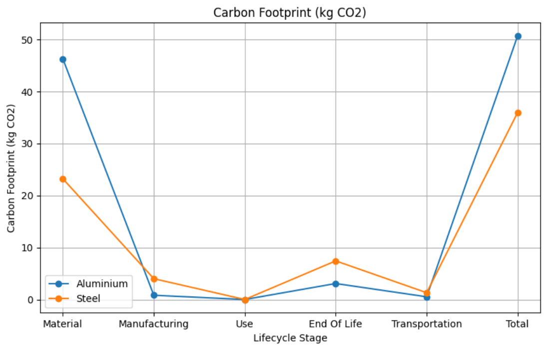


Figure 12: Carbon Footprint Steel vs Aluminum

Keeping in mind the design for sustainability ideology alongside the fact that the design is for a telepresence robot in a hospital environment, a sustainability study was carried out on SolidWorks. The initial material was selected to be Steel (ASTM A36) which had a material mass of approximately 10kg. (each steel support column had a mass of 2.5kg) Although the steel structures do not have a significant mass, for designing a telepresence robot, the design should be as lightweight as possible to allow efficient use of power supply. The next material was selected to be Aluminum which had a mass of approximately 0.84kg per support, putting total support weight to approximately 3.4kg, which is a staggering reduction in mass.

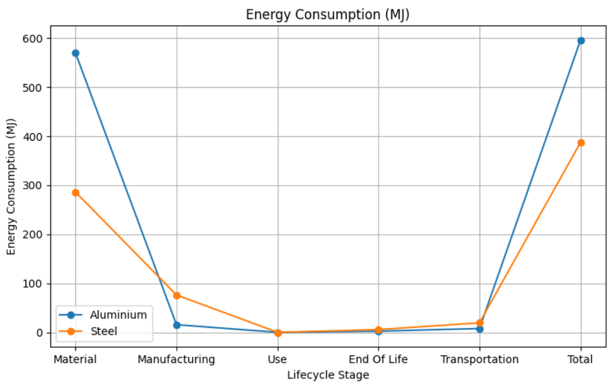


Figure 14: Energy Consumption- Steel vs Aluminum

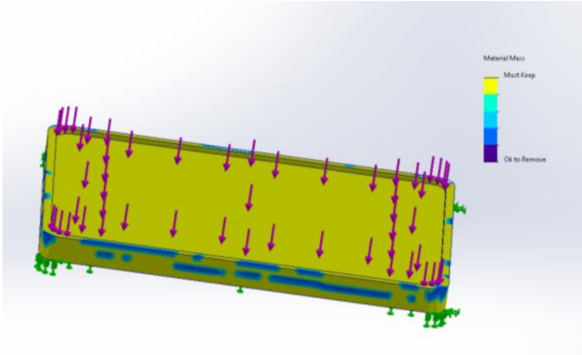


Figure 15: Topology optimization of tray

One of the most important aspects of desgin for sustainability is to design with the environment in mind alongisde the products specification and job requirements. Using the graph in figure 13 it can be seen that steel has less of a carbon footprint relative to aluminum overall and the only time its hihger is during the final end of life stage and its slightly hihger durin manufacturing and transportation. Keeping in mind that the telepresence robots main frame should be as lightweight as possible and using the data in figure 15, the final material that will be used for the support pillars in main frame will be aluminium.

Another factor that is important to keep in mind is the energy consumption for each material. Figure 14 above does look simiilar to the graph in figure 13 in terms of consmumption for initial stages in the material life cycle however that is where the similarity ends. From manufacturing to transportation the aluminium has a lower energy consumption making it a very suitable option to consider when selecting materials for the support pillars. Furthermore, the initial material carbon footprint will be offset due to its use in the product and the knock-on effects of using almminium are greater as well i.e. lighterweight leading to efficient use of power source for the telepresence robot. With that in mind the optimisation for the trays and frame can be carried out. For the trays, they were optimsed by simple material selection they needed to lightweight, so they could be easy to remove and clean for this reason ABS was chosen as its lightweight and can be cleaned. Additionally the design of the tray was also considered, using the topology optimisation both the main frame and the tray were optimsied.

The figure above demonstrates the end result of the optimization process. From figure 15 it can be seen that the original was already fairly optimized as the “must keep” section which is in yellow surrounds the majority of the component. The blue section demonstrates how little actually needs to be removed to lower the mass of the part even further. The initial part had a mass of approximately 0.6kg (per tray) and this was reduced to 0.4 (approximately a 30% reduction) whilst keeping the structural integrity under the applied load.

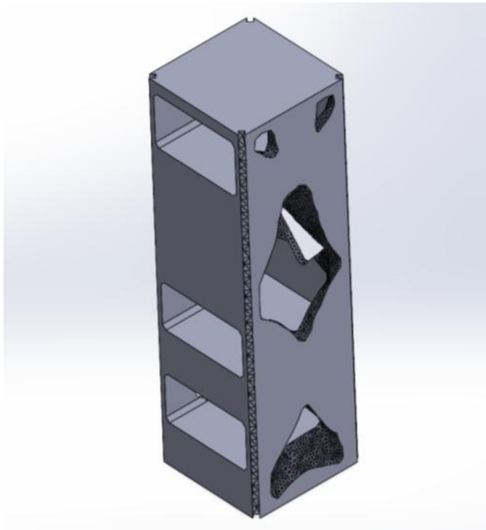


Figure 16 : Optimized Main Frame

Following the same approach as above, the main frame was also optimized. However, instead of the simple cuboid shape it is now more complex but with a significant weight reduction (approximately 30 %) from 62kg to nearly 40kg.

5. CASE STUDY 02 – Rapid manufacturing of a successfully designed product

5.1 Task C2.1 - Selection of emerging manufacturing technologies

CNC machining is a manufacturing procedure in which pre-programmed software dictates the movement of the tools. This code is generated by programmers meaning it can be edited therefore allowing tremendous potential control and customization. (astromachineworks.com, 2021) The main functions parts of a CNC machine are the input devices that generate the G-code, these devices essentially input the part program into the CNC machine. Another part is the machine control unit, the MCU essentially controls the CNC machine. It has numerous jobs ranging from reading the coded instructions to decoding them, and implementing them as it generates axis motion commands, and receives feedback signals for each and every drive axis keeping awareness of speed and position. The next part is the actual machine tool that controls the position and speed. Alongside drive systems and feedback systems the CNC machine also features a display unit to CNC machine data. The CNC machine uses G and M codes that have specific set of tasks for example G-codes such as G1 is a linear move, in general codes beginning with G are commands that cause a specific preset/pre-coded motion. On the other hand, M-codes are commands such as tool changing (M06), flood coolant on (M08) etc.

Additive Manufacturing & 3D Printing (AM-3DP), a subset of RPM, is the name of the processes that create the desired geometry by adding material layer by layer and as such AM is known as layer manufacturing as well. A major benefit of AM is that it allows parts to be produced layer by layer and as such complex geometries can be created with relative ease.

In terms of choosing between them, it is important to note that no one technology is suitable for each material and every process. For this case study, due to the fact that AM is great at printing layers and able to create small parts easily and efficiently, the tray will be made from that.
However, for the main frame it is important to consider the purpose and its use case. If the frame is designed to carry light loads at most 5kg per tray, then ABS is a great option due to it being lightweight therefore allowing the robot to be more efficient in terms of its battery usage. However, if the robot is designed to carry heavy loads, then a frame being made with aluminum would be better suited. For C2.2 both situations were considered hence the AM process for the tray was carried out for the main frame (using ABS) as well. Similarly, the main frame was also made with CNC machining, and its tool path planning and code were also generated.

5.2 Task C2.2 - Preparation of 3D CAD models and CAPP for CNC machining and Additive Manufacturing

For the purpose of this coursework, the CNC machining code was meant to be generated. Given that the final solution model was for aluminum based support pillar(s), a CNC code was generated through SolidWorks add in CAM feature.

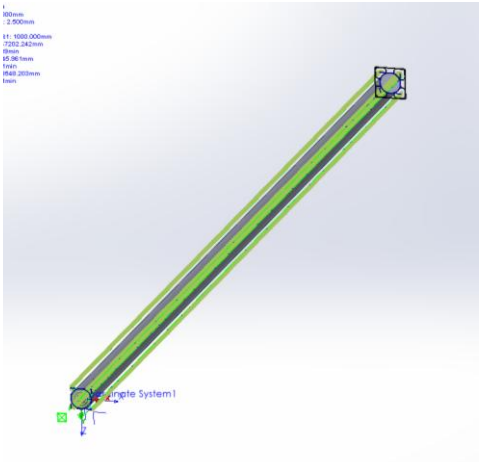


Figure 16: CNC Tool Path

Figure 17 shows the tool path the CNC machine takes to generate this part in aluminum through the CNC process. It is important to note that this part is used four times in total, the CNC code (figure 18) and data are only descriptive of one singular instance.

Figure 17: CNC code

The figure above is a screenshot of the actual code that can be used to machine the part as shown in figure 16. Due to the significantly long nature of the code, there is no extra code pasted in the appendix, it will be included in the shareable file as a text file. Referring back to the discussion of CNC code, the G and M commands can be seen in the file demonstrating the movement and tool change commands. Note a part of generating a the tool path and the code involved using a milling processer, as the SolidWorks software being used didn't have one, an external one was downloaded from (camworks.com). The appendix (6) also include a few screenshots during the procedure to generate the code and the tool paths.

The next part of this case study features the generation of G-code for the tray and main frame. Due to the size of the prusa slicer print bed, both the tray and the main frame were scaled down in an attempt to demonstrate the actual process of code generation. To begin, the tray was first imported into Prusa slicer as an stl file type. Due to the geometry of the tray, the tray itself didn't require supports, it had a flat area, no overhanging parts and thus, the part can be printed without any external support beings needed.

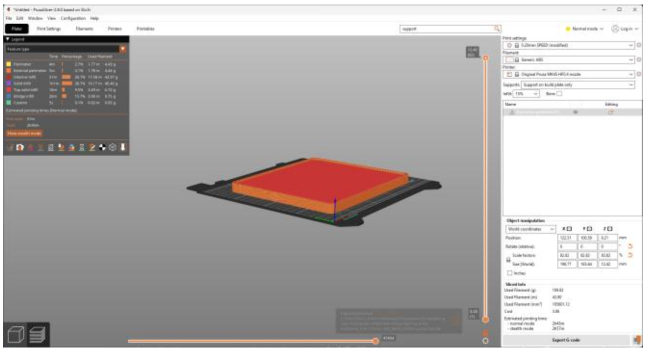


Figure 18: Tray

The figure above shows the tray on the print bed (scaled down slightly so that it could fit), the top left shows the print time and the time taken for each area. As the main frame is also being built by ABS to ensure it remains lightweight and that the telepresence robot is cost-effective i.e. less energy expenditure due to smaller mass, it can also be imported into Prusa slicer as an stl file.

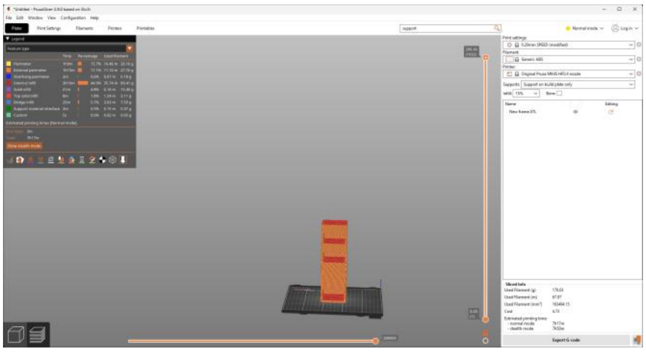


Figure 20: Main Frame

The main frame above has also been scaled down, it code is also added in the extension file submitted as a link in the appendix.

Although the main frame was chosen to be made of ABS and as such cannot be CNC machined due to the material; however to demonstrate understanding of the topic and procedure the same main frame was used to generate machine code as well, in this case the machine code was generated using aluminum 6061.

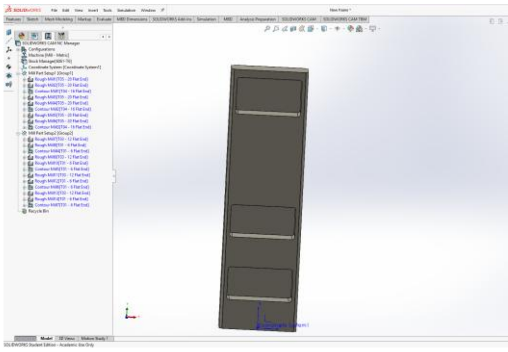
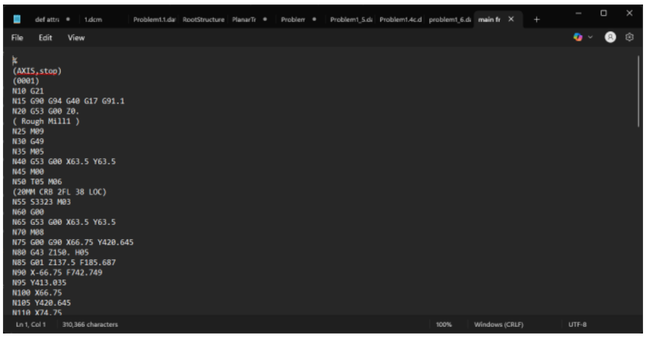


Figure 19: Main Frame CNC

As part of the code generation, SolidWorks uses feature extraction feature that has to be considered when machining, those features can be seen on the left side of the figure above. The recording for the simulation alongside the code is attached in the external link.



```
%
(AXIS,stop)
(0001)
N10 G21
N15 G90 G94 G40 G17 G91.1
N20 G53 G00 Z0.
( Rough Mill1 )
N25 M09
N30 G49
N35 M05
N40 G53 G00 X63.5 Y63.5
N45 M00
N50 T05 M06
(20MM CRB 2FL 38 LOC)
N55 S3323 M03
N60 G00
N65 G53 G00 X63.5 Y63.5
N70 M08
N75 G00 G90 X66.75 Y420.645
N80 G43 Z150. H05
N85 G01 Z137.5 F185.687
N90 X-66.75 F742.749
N95 Y413.035
N100 X66.75
N105 Y420.645
N110 X74.75
```

Figure 20: Main frame code

As presented above for the support structure, the figure above shows the code for the CNC machining of the main frame

6. Summary & Conclusions

This report aimed to provide a literature review on a variety of topics including digital twins and DfX, as well as the two case studies in which design concepts were generated using A.I. platofrms Vizcom and PromeAi, selected using concept scoring methods and then implemented analysis and optimsisation on the winning model and then finally generated g-code for main frames and trays.

References

Batty, M., 2018. Digital Twins. Sage Journals, pp. 817-820.

Billy Wu, W. Dhammika Widanage, Shichun Yang & Xinhua Liu, 2020. Battery digital twins: Perspectives on the fusion of models, data and artificial intelligence for smart battery management systems. Energy and AI, Volume 1.

Clare Rock, Bryce A. Small & Kerri A. Thom, 2018. Innovative Methods of Hospital Disinfection in Prevention of Healthcare-Associated Infections. Current Treatment Options in Infectious Diseases, Volume 10, pp. 65-77.

Evangelia Katsoulakis1, et al., 2024. Digital twins for health: a scoping review. Digital Medicine.

Füszl Astrid, et al., 2021. The use of a UV-C disinfection robot in the routine cleaning process: a feld study in an Academic hospital. Antimicrobial Resistance & Infection Control, Volume 10.

Le, D. C. H., 2025. GEEN-1059-M02-2024-25 Computer Aided Manufacturing (Univ of Greenwich at Medway). [Online] Available at: https://moodlecurrent.gre.ac.uk/course/view.php?id=105511

Lucid chart, 2011. [Online] Available at: https://www.lucidchart.com/pages

RS, G., 2025. NVIDIA Omniverse for Digital Twin Applications in Industry. [Online] Available at: https://www.rs-online.com/designspark/nvidia-omniverse-for-digital-twin-applications-in-industry

Stefan Mihai, et al., 2022. Digital Twins: A Survey on Enabling Technologies,Challenges, Trends and Future Prospects. IEEE COMMUNICATIONS SURVEYS & TUTORIALS, 24(4).

Yuchen Jiang, et al., 2021. Industrial applications ofdigital twins. Philosophical Transactions of the Royal Society A.

Zhihan Lv & Shuxuan Xie, 2022. Artificial intelligence in the digital twins: State of the art, challenges, and future research topics. Taylor & Francis.

Ahmad, N., Haque, A. and Dr. A. A. Hasin (2002). CURRENT TREND IN COMPUTER AIDED PROCESS PLANNING Authers : [online] Available at: https://api.semanticscholar.org/CorpusID:12286767.

Avinash Malladi et al., A.M. et al., (2018). A Study on Technologies in Cloud-Based Design and Manufacturing. International Journal of Mechanical and Production Engineering Research and Development, 8(6), pp.187–192. doi:https://doi.org/10.24247/ijmperddec201822.

Behandish, M., Nelaturi, S. and de Kleer, J. (2018). Automated process planning for hybrid manufacturing. Computer-Aided Design, 102, pp.115–127. doi:https://doi.org/10.1016/j.cad.2018.04.022.

Besharati-Foumani, H., Lohtander, M. and Varis, J. (2019). Intelligent process planning for smart manufacturing systems: a state-of-the-art review. Procedia Manufacturing, 38, pp.156–162. doi:https://doi.org/10.1016/j.promfg.2020.01.021.

Bourne, D., Corney, J. and Gupta, S.K. (2011). Recent Advances and Future Challenges in Automated Manufacturing Planning. Journal of Computing and Information Science in Engineering, [online] 11(2). doi:https://doi.org/10.1115/1.3593411.

Dasgupta, S., Gerndt, M. and Gholami, B. (2024). Elastic Workflows in Hybrid Cloud for CAE Simulations. 2024 IEEE International Conference on Cloud Engineering (IC2E), pp.251–252. doi:https://doi.org/10.1109/ic2e61754.2024.00037.

Friederich, J., Francis, D.P., Lazarova-Molnar, S. and Mohamed, N. (2022). A framework for data-driven digitial twins of smart manufacturing systems. Computers in Industry, 136, p.103586. doi:https://doi.org/10.1016/j.compind.2021.103586.

Furtado, L.S., Soares, J.B. and Furtado, V. (2024). A task-oriented framework for generative AI in design. Journal of Creativity, [online] 34(2), p.100086. doi:https://doi.org/10.1016/j.yjoc.2024.100086.

Gebisa, A.W. and Lemu, H.G. (2017). A case study on topology optimized design for additive manufacturing. IOP Conference Series: Materials Science and Engineering, [online] 276, p.012026. doi:https://doi.org/10.1088/1757-899x/276/1/012026.

Guevara, O.R. (2021). VALUE OF PERSONALIZATION: AN INTEGRATED PRODUCT DESIGN AND MANUFACTURING SYSTEMS APPROACH. doi:https://doi.org/10.25394/pgs.14737920.v1.

Hapuwatte, B.M. and Jawahir, I.S. (2021). Closed-loop sustainable product design for circular economy. Journal of Industrial Ecology, 25(6). doi:https://doi.org/10.1111/jiec.13154.

Hassan, M.F., Mat Saman, M.Z., Mahmood, S., Muhd Nor, N.H. and Abdol Rahman, M.N. (2016). SUSTAINABILITY ASSESSMENT METHODOLOGY IN PRODUCT DESIGN: A REVIEW AND DIRECTIONS FOR FUTURE RESEARCH. Jurnal Teknologi, 79(1). doi:https://doi.org/10.11113/jt.v79.8697.

Hochstein, L., Schott, B. and Graybill, R.B. (2011). Computational Engineering in the Cloud. Journal of Organizational and End User Computing, 23(4), pp.31–50. doi:https://doi.org/10.4018/joeuc.2011100103.

Hu, B., Jin, G. and Sun, L. (2018). A Novel Adaptive Slicing Method for Additive Manufacturing. pp.218–223. doi:https://doi.org/10.1109/cscwd.2018.8465247.

Hussein Khlifi, Choudhury, A., Sharma, S., Frédéric Segonds, Maranzana, N., Chasset, D. and Frerebeau, V. (2017). Towards Cloud in a PLM Context: A Proposal of Cloud Based Design and Manufacturing Methodology. IFIP advances in information and communication technology, pp.141–151. doi:https://doi.org/10.1007/978-3-319-72905-3_13.

Jawahir, I.S., Dillon, Rouch, K.E., Joshi, K.J., Venkatachalam, A. and Jaafar, I.H. (2006). TOTAL LIFE-CYCLE CONSIDERATIONS IN PRODUCT DESIGN FOR SUSTAINABILITY : A FRAMEWORK FOR COMPREHENSIVE EVALUATION. [online] Available at: https://api.semanticscholar.org/CorpusID:13808300.

Jiang, Z., Wen, H., Han, F., Tang, Y. and Xiong, Y. (2022). Data-driven generative design for mass customization: A case study. Advanced Engineering Informatics, [online] 54, p.101786. doi:https://doi.org/10.1016/j.aei.2022.101786.

KULYNYCH, V., ARHAT, R., Serhii SHLYK, Anastasiia SYMONOVA and Volodymyr DRAHOBETSKYI (2024). ANALYSIS OF MODERN METHODS FOR OPTIMIZING TECHNOLOGICAL PROCESSES IN MACHINE-BUILDING PRODUCTION USING ARTIFICIAL INTELLIGENCE. СУЧАСНІ ТЕХНОЛОГІЇ В МАШИНОБУДУВАННІ ТА ТРАНСПОРТІ, 1(22), pp.31–37. doi:https://doi.org/10.36910/automash.v1i22.1342.

Liu, S. (2017). A new adaptive slicing algorithm based on slice contour construction in layered manufacturing process. doi:https://doi.org/10.14711/thesis-991012555460203412.

Lo, C.K., Chen, C.H. and Zhong, R.Y. (2021). A review of digital twin in product design and development. Advanced Engineering Informatics, 48, p.101297. doi:https://doi.org/10.1016/j.aei.2021.101297.

Mirzendehdel, A.M. and Suresh, K. (2016). Support structure constrained topology optimization for additive manufacturing. Computer-Aided Design, 81, pp.1–13. doi:https://doi.org/10.1016/j.cad.2016.08.006.

Mo, F., Rehman, H.U., Monetti, F.M., Chaplin, J.C., Sanderson, D., Popov, A., Maffei, A. and Ratchev, S. (2023). A framework for manufacturing system reconfiguration and optimisation utilising digital twins and modular artificial intelligence. Robotics and Computer-Integrated Manufacturing, [online] 82, p.102524. doi:https://doi.org/10.1016/j.rcim.2022.102524.

Mohseni, S., Zarei, N. and Ragan, E.D. (2021). A Multidisciplinary Survey and Framework for Design and Evaluation of Explainable AI Systems. ACM Transactions on Interactive Intelligent Systems, 11(3-4), pp.1–45. doi:https://doi.org/10.1145/3387166.

Monek, G.D. and Fischer, S. (2024). Expert Twin: A Digital Twin with an Integrated Fuzzy-Based Decision-Making Module. Decision Making Applications in Management and Engineering, 8(1), pp.1–21. doi:https://doi.org/10.31181/dmame8120251181.

Mourtzis, D., Angelopoulos, J. and Panopoulos, N. (2022). Personalized PSS Design Optimization based on Digital Twin and Extended Reality. Procedia CIRP, 109, pp.389–394. doi:https://doi.org/10.1016/j.procir.2022.05.267.

Niveditha, Prof.K.P., Patel, Prof.A. and Sahu, Prof.R. (2024). AI-Powered Predictive Analytics for Semiconductor Manufacturing: Case Studies and Industry Applications. International Journal of Innovative Research in Science,Engineering and Technology, 13(06), pp.1–14. doi:https://doi.org/10.15680/ijirset.2024.1306280.

Okuyelu, O. and Adaji, O. (2024). AI-Driven Real-time Quality Monitoring and Process Optimization for Enhanced Manufacturing Performance. Journal of advances in mathematics and computer science, 39(4), pp.81–89. doi:https://doi.org/10.9734/jamcs/2024/v39i41883.

Onaji, I., Tiwari, D., Soulatiantork, P., Song, B. and Tiwari, A. (2022). Digital twin in manufacturing: conceptual framework and case studies. International Journal of Computer Integrated Manufacturing, 35(8), pp.1–28. doi:https://doi.org/10.1080/0951192x.2022.2027014.

Peres, R.S., Jia, X., Lee, J., Sun, K., Colombo, A.W. and Barata, J. (2020). Industrial Artificial Intelligence in Industry 4.0 - Systematic Review, Challenges and Outlook. IEEE Access, 8, pp.220121–220139. doi:https://doi.org/10.1109/ACCESS.2020.3042874.

Prashis Raghuweanshi (2024). REVOLUTIONIZING SEMICONDUCTOR DESIGN AND MANUFACTURING WITH AI. Journal of Knowledge Learning and Science Technology ISSN 2959-6386 (online), 3(3), pp.272–277. doi:https://doi.org/10.60087/jklst.vol3.n3.p.272-277.

Prathyusha, A.L.R. and Raghu Babu, G. (2022). A review on additive manufacturing and topology optimization process for weight reduction studies in various industrial applications. Materials Today: Proceedings. doi:https://doi.org/10.1016/j.matpr.2022.02.604.

R. Siva Sankar, Asokan, P., G. Prabhaharan and Phani, A.V. (2008). A CAPP framework with optimized process parameters for rotational components. 46(20), pp.5561–5587. doi:https://doi.org/10.1080/00207540701288108.

Ramani, K., Ramanujan, D., Bernstein, W.Z., Zhao, F., Sutherland, J., Handwerker, C., Choi, J.-K., Kim, H. and Thurston, D. (2010). Integrated Sustainable Life Cycle Design: A Review. Journal of Mechanical Design, [online] 132(9). doi:https://doi.org/10.1115/1.4002308.

Ramesh, A., Qin, Z. and Lu, Y. (2020). Digital Thread Enabled Manufacturing Automation Towards Mass Personalization. Volume 2: Manufacturing Processes; Manufacturing Systems; Nano/Micro/Meso Manufacturing; Quality and Reliability. doi:https://doi.org/10.1115/msec2020-8429.

Ranjan, R., Samant, R. and Anand, S. (2017). Integration of Design for Manufacturing Methods With Topology Optimization in Additive Manufacturing. Journal of Manufacturing Science and Engineering, 139(6). doi:https://doi.org/10.1115/1.4035216.

Sarma, R., Kapil, S. and Joshi, S.N. (2021). A Hybrid Slicing Method to Eliminate the Need of Support Structures in Direct Energy Deposition and Material Extrusion-Based Processes. Springer Proceedings in Materials, pp.299–312. doi:https://doi.org/10.1007/978-981-16-0182-8_23.

Sikder, S., Barari, A. and Kishawy, H.A. (2014). Effect of Adaptive Slicing on Surface Integrity in Additive Manufacturing. doi:https://doi.org/10.1115/detc2014-35559.

SIMPSON, T.W. (2004). Product platform design and customization: Status and promise. Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 18(1), pp.3–20. doi:https://doi.org/10.1017/s0890060404040028.

Sonpol, N.B.A. and Khalifa, Z.L.A.E.-H. (2024). Artificial Intelligence Tools for Generating Design Alternatives for Interior Spaces-Literature Review. 2024 International Conference on Decision Aid Sciences and Applications (DASA), [online] pp.1–5. doi:https://doi.org/10.1109/dasa63652.2024.10836356.

Tan, C., Chung, H., Barton, K., Jack Hu, S. and Freiheit, T. (2020). Incorporating customer personalization preferences in open product architecture design. Journal of Manufacturing Systems, 56, pp.72–83. doi:https://doi.org/10.1016/j.jmsy.2020.05.006.

Tarun Parmar (2022). Artificial Intelligence in High-tech Manufacturing: A Review of Applications in Quality Control and Process Optimization. International Journal of Innovative Research in Engineering & Multidisciplinary Physical Sciences, 10(6). doi:https://doi.org/10.37082/ijirmps.v10.i6.231961.

Vasyl Tereshchenko and Maksym Osiponok (2024). Process planning in additive manufacturing: a review of problems and methods of their solution. Bulletin of Taras Shevchenko National University of Kyiv Series Physics and Mathematics, (1), pp.128–136. doi:https://doi.org/10.17721/1812-5409.2024/1.24.

Vincenzo Paolo Bagnato (2023). Artificial Intelligence for Design The Artificial Intelligence of Objects. FORUM A+P Interdisciplinary Journal of Architecture and Built Environment, (27), pp.30–35. doi:https://doi.org/10.37199/f40002705.

Wagner, R., Schleich, B., Haefner, B., Kuhnle, A., Wartzack, S. and Lanza, G. (2019). Challenges and Potentials of Digital Twins and Industry 4.0 in Product Design and Production for High

Performance Products. Procedia CIRP, 84, pp.88–93. doi:https://doi.org/10.1016/j.procir.2019.04.219.

Wu, D., J. Lane Thames, Rosen, D.W. and Schaefer, D.J. (2012). Towards a Cloud-Based Design and Manufacturing Paradigm: Looking Backward, Looking Forward. doi:https://doi.org/10.1115/detc2012-70780.

Wu, D., Thames, J.L., Rosen, D.W. and Schaefer, D. (2013). Enhancing the Product Realization Process With Cloud-Based Design and Manufacturing Systems. Journal of Computing and Information Science in Engineering, 13(4). doi:https://doi.org/10.1115/1.4025257.

Wu, Z. and Liang, C. (2024). A Review and Prospects of Manufacturing Process Knowledge Acquisition, Representation, and Application. Machines, [online] 12(6), p.416. doi:https://doi.org/10.3390/machines12060416.

Yang, Q. and Connor Myant (2022). Adaptive Slicing Based on Accurately Assessing the Variations of the Model's Geometry for Staircase Effect and Dimensional Deviation Mitigation. doi:https://doi.org/10.1115/detc2022-90764.

Yip-Hoi, D. (2017). Computer-Aided Process Planning for Machining. CRC Press eBooks, pp.11–37. doi:https://doi.org/10.1201/9781420036749-2.

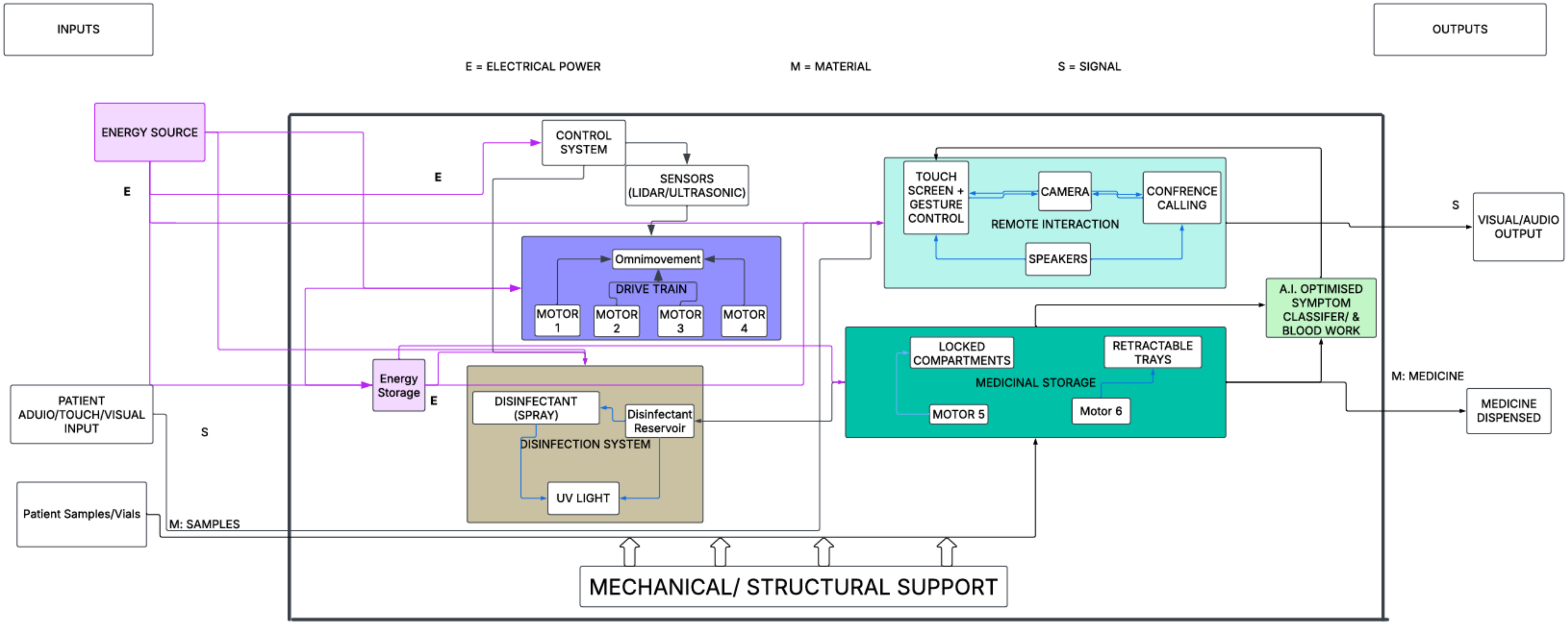
Yüksel, N., Börklü, H.R., Sezer, H.K. and Canyurt, O.E. (2023). Review of artificial intelligence applications in engineering design perspective. Engineering Applications of Artificial Intelligence, 118, p.105697. doi:https://doi.org/10.1016/j.engappai.2022.105697.

Zarif Bin Akhtar (2024). Artificial intelligence (AI) within manufacturing: An investigative exploration for opportunities, challenges, future directions. Metaverse, 5(2), pp.2731–2731. doi:https://doi.org/10.54517/m.v5i2.2731.

ZHU, J., ZHOU, H., WANG, C., ZHOU, L., YUAN, S. and ZHANG, W. (2021). A review of topology optimization for additive manufacturing: Status and challenges. Chinese Journal of Aeronautics, 34(1), pp.91–110. doi:https://doi.org/10.1016/j.cja.2020.09.020.

Zhu, Q., Wang, D., Ma, S., Wang, A.Y., Chen, Z., Khurana, U. and Ma, X. (2024). Towards Feature Engineering with Human and AI's Knowledge: Understanding Data Science Practitioners' Perceptions in Human&AI-Assisted Feature Engineering Design. Designing Interactive Systems Conference, pp.1789–1804. doi:https://doi.org/10.1145/3643834.3661517.

Appendix 1: Larger view of Function diagram



Appendix 2: Sustainability Function report from SolidWorks (imported into excel)

	Carbon Footprint (kg CO2)	Energy Consumption (MJ)	Air Acidification (kg SO2)	Water Eutrophication (kg PO4)
Material (Steel)	23.2295	286.072	0.0678085	0.0256835
Manufacturing	4.0008	76.2237	0.0267188	0.000973485
Use	0	0	0	0
End Of Life	7.42824	5.52779	0.00429182	0.0074758
Transportation	1.30701	19.329	0.00608219	0.00138028
Total	35.9655	387.152	0.104901	0.035513

	Carbon Footprint (kg CO2)	Energy Consumption (MJ)	Air Acidification (kg SO2)	Water Eutrophication (kg PO4)
Material (Aluminium)	46.294	570.043	0.316169	0.0109965
Manufacturing	0.815856	15.5438	0.00544858	0.000198516
Use	0	0	0	0
End Of Life	3.07473	2.28809	0.00177649	0.00309441
Transportation	0.520023	7.69048	0.00241994	0.000549175
Total	50.7046	595.565	0.325814	0.0148386

Appendix 3: Morphological Tables

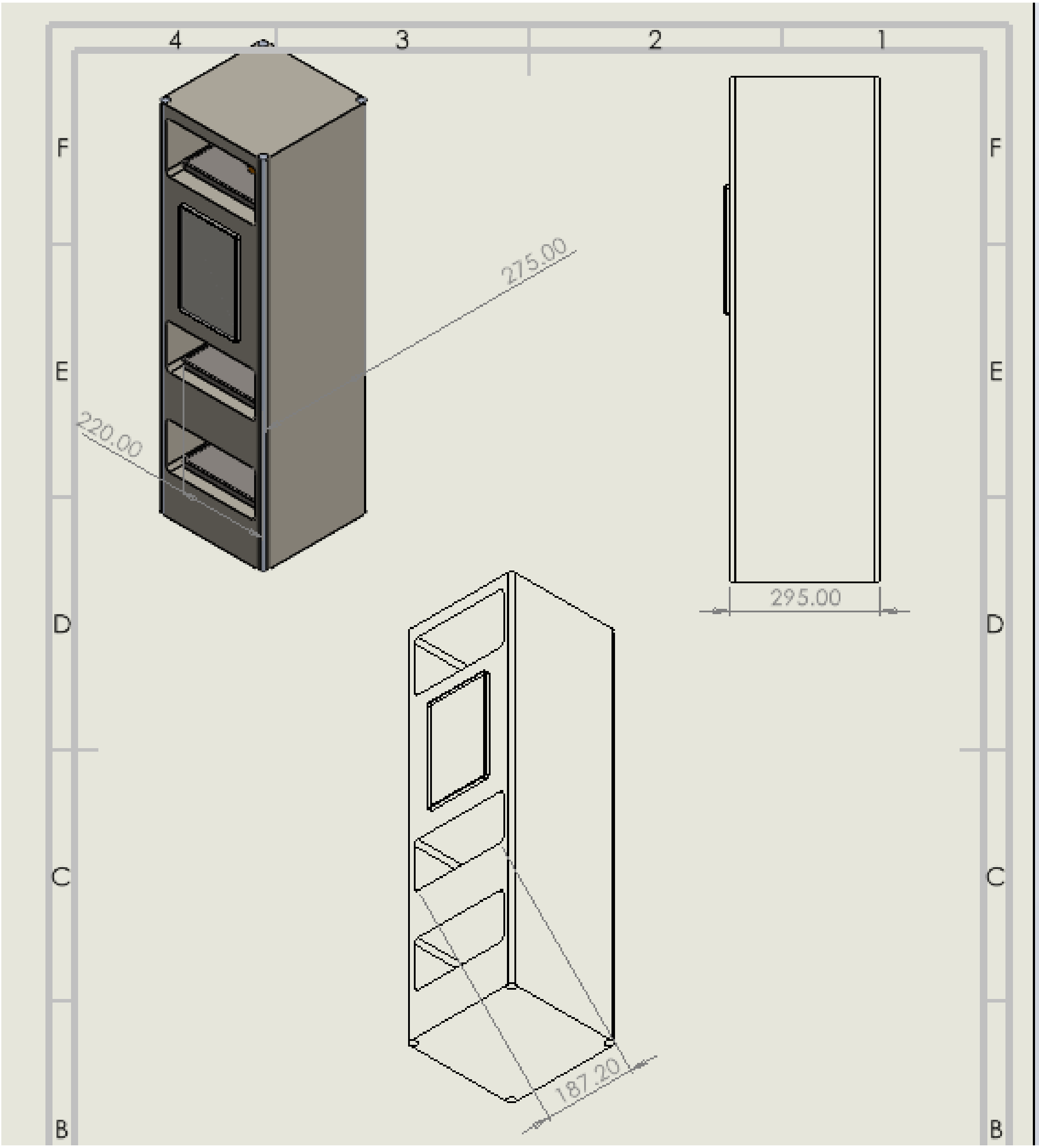
Functions	Possible Solution 1
Energy Source	Replaceable Battery pack
Movement	2 wheel drive system
Control System	Arduino
Medicinal Storage System	Motor Driven Moveable lids
Sample Storage System	Cup Holder style system
Remote Interaction System	Touch screen
Sensors	Infrared
Screen UX	Swipe Control

Functions	Possible Solution: 2
Energy Source	Rechargeable Battery
Movement	Omni Wheels
Control System	Arduino
Medicinal Storage System	Window Style lock in front of compartment
Sample Storage System	Retractable tray (for all)
Remote Interaction System	Touch screen + voice recognition (A.I.)
Sensors	LIDAR
Screen UX	Voice command +Swipe controls

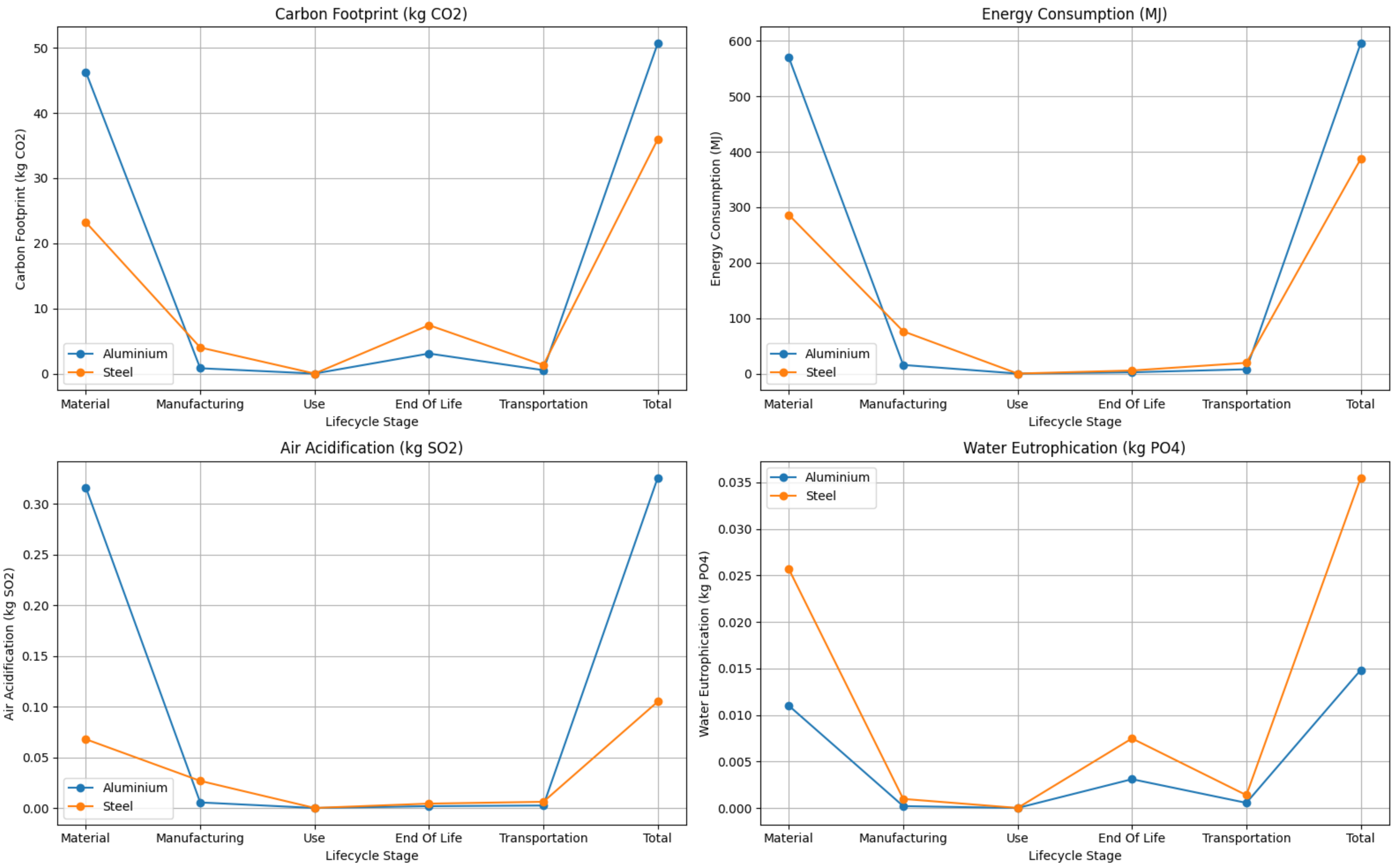
Functions	Possible Solution: 3
Energy Source	Rechargeable Battery
Movement	RWD
Control System	Remote Control
Medicinal Storage System	Window Style lock in front of compartment
Sample Storage System	Fixed Tray
Remote Interaction System	Touch screen
Sensors	LIDAR
Screen UX	Swipe

.

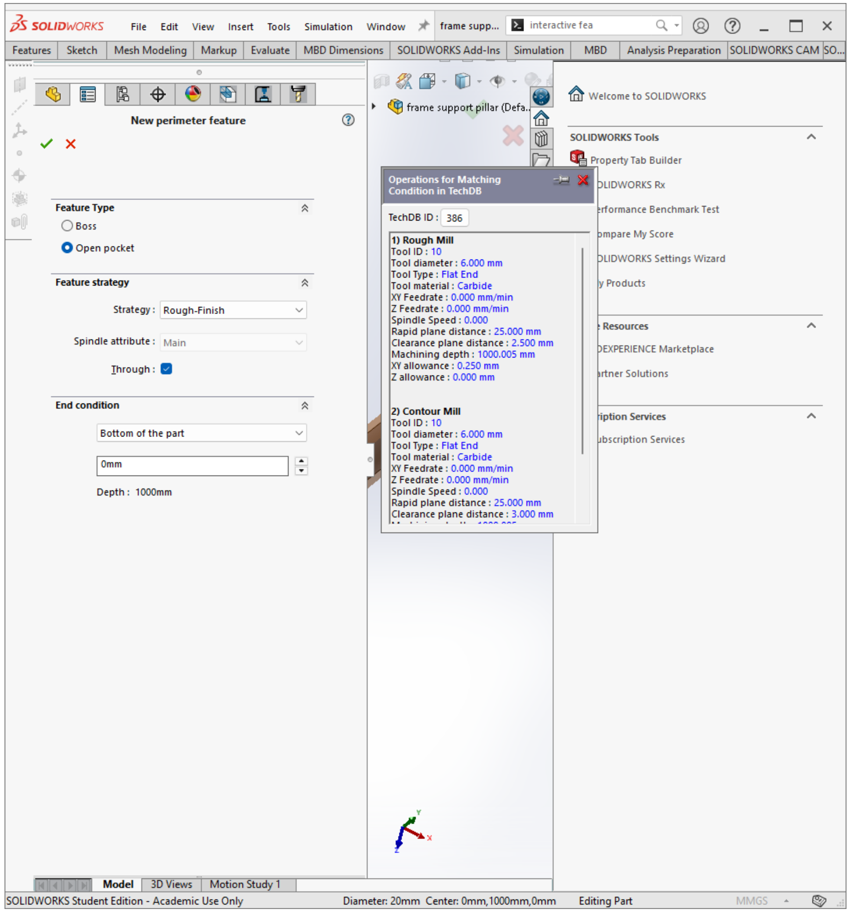
Appendix 4: Technical Drawings (SolidWorks)

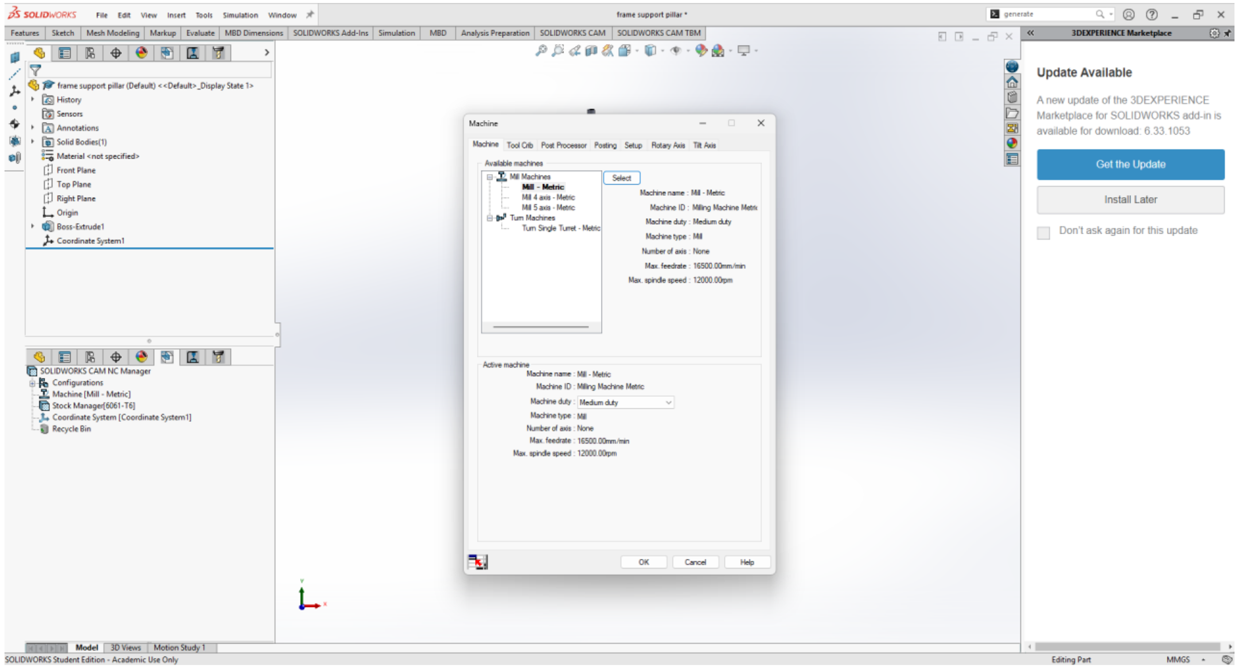


Appendix 5: Sustainability Data

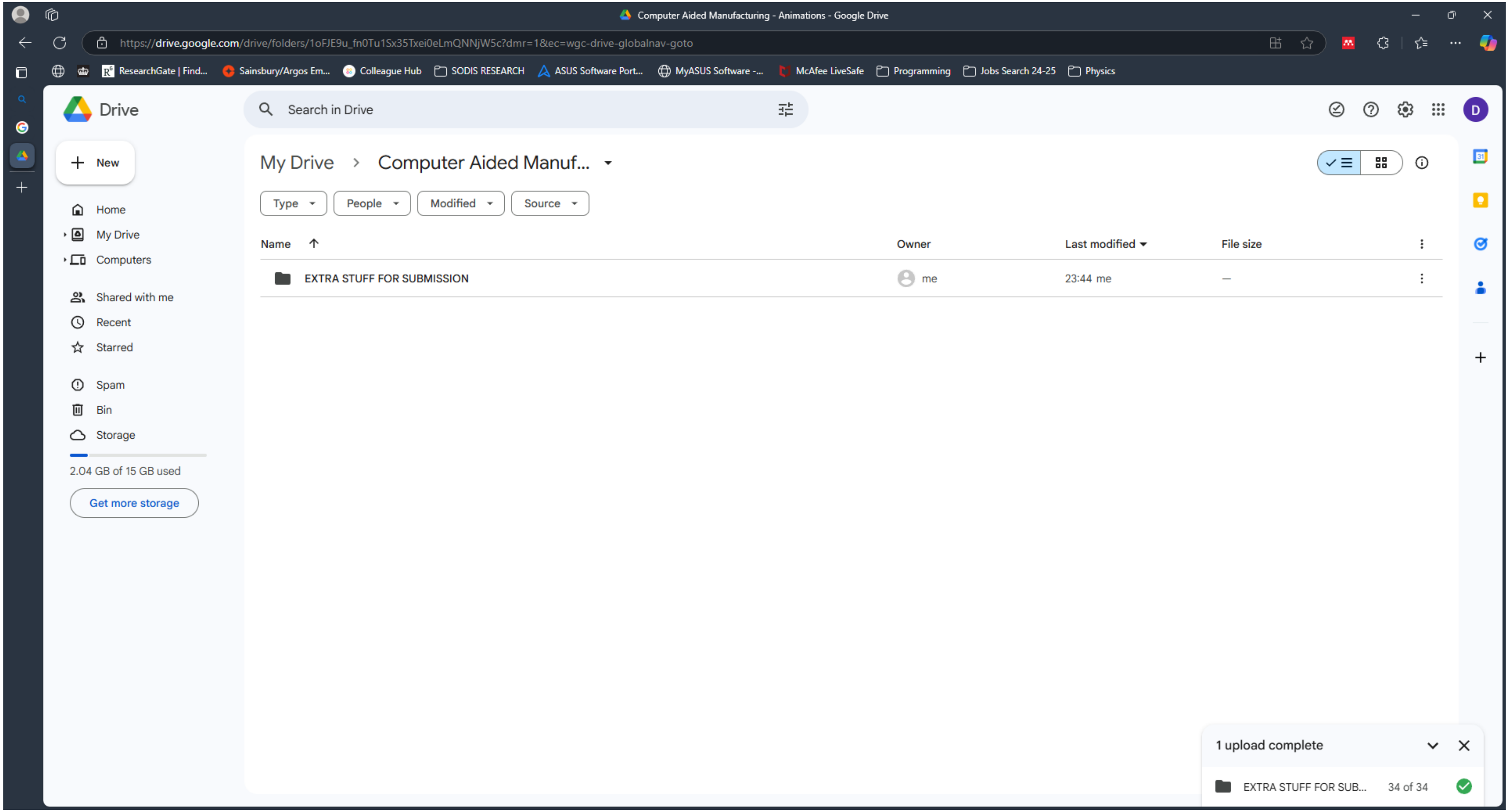


Appendix 6: CNC Machining



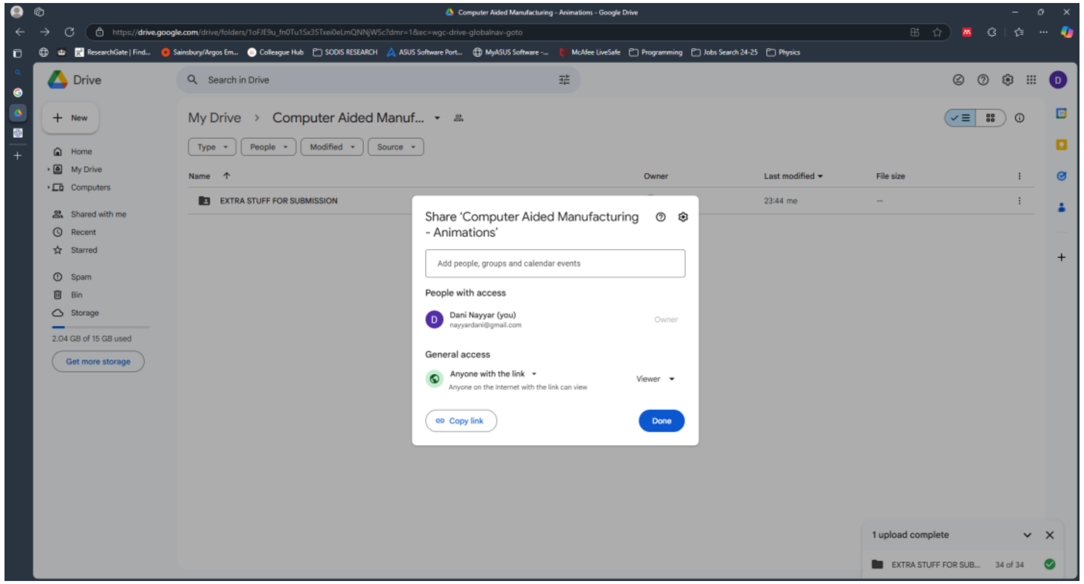


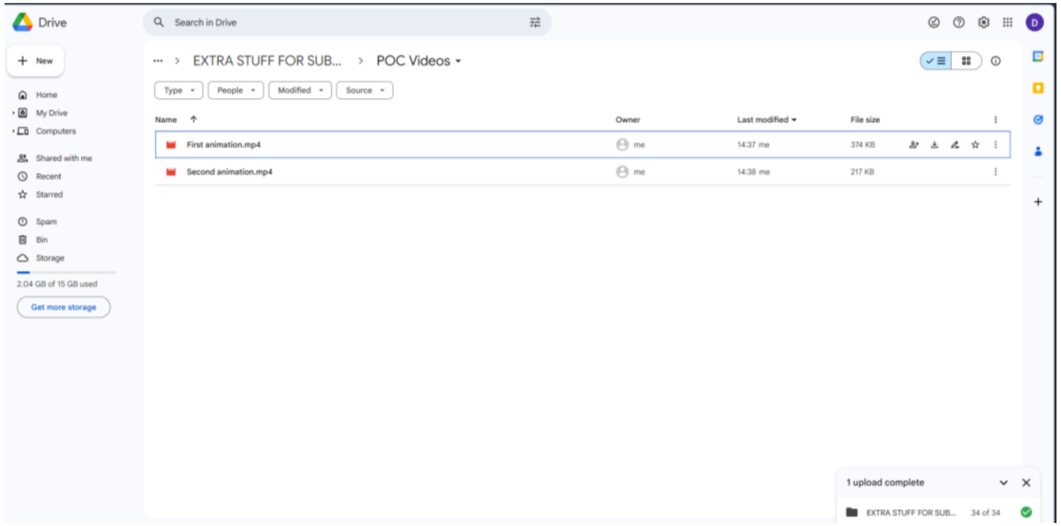
Appendix 7: External Link



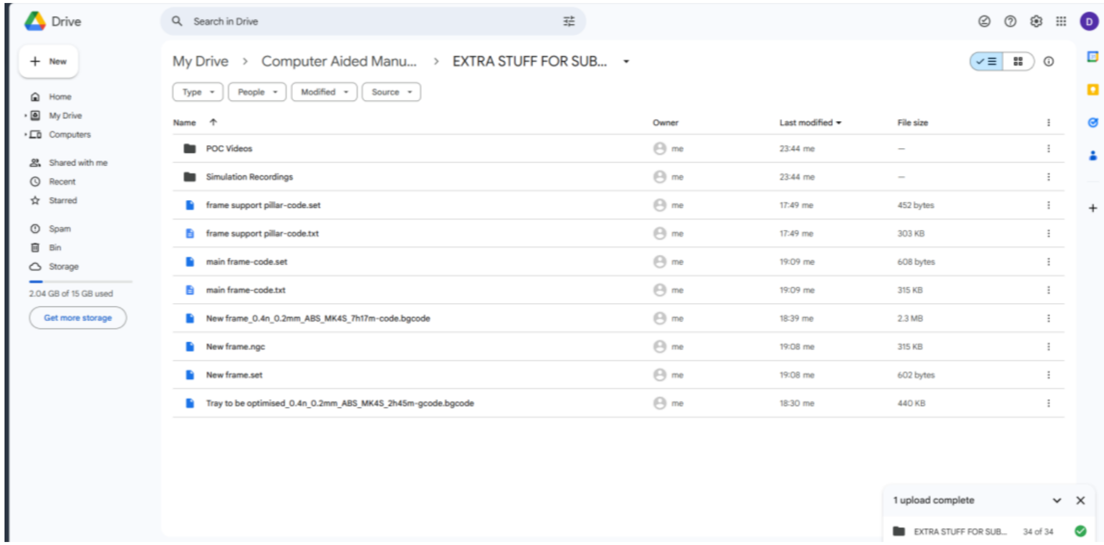
Appendix 7 continued

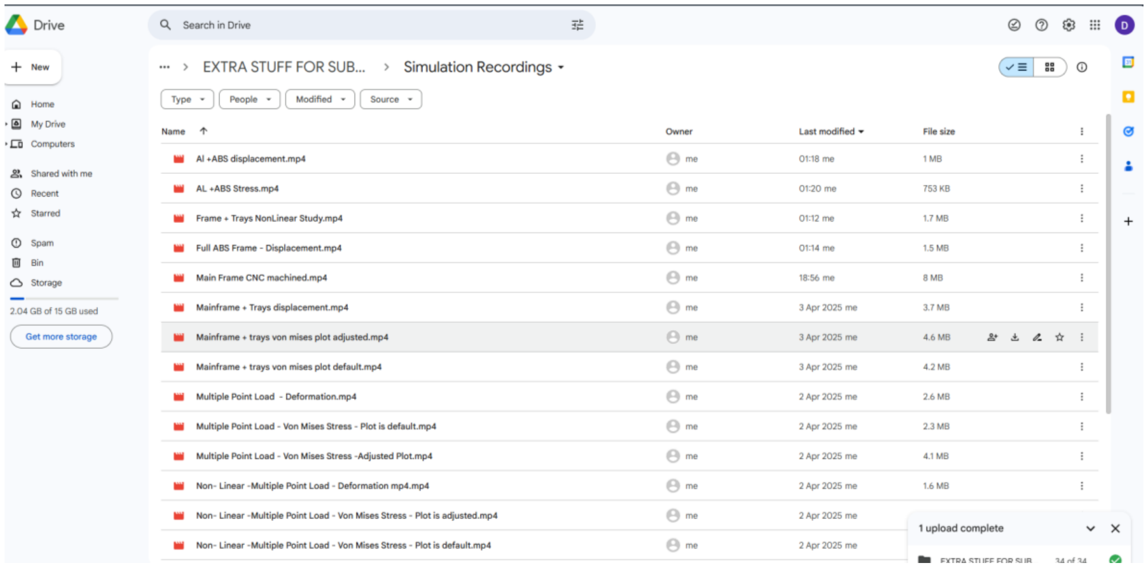
Link = https://drive.google.com/drive/folders/1oFJE9u_fn0Tu1Sx35Txei0eLmQNNjW5c?usp=sharing





Appendix 7 continued





Appendix 8:Decleration of AI

UNIVERSITY OF GREENWICH

Declaration of AI Use

Please append this page to the end of your assignment when you have used AI during the process of undertaking the assignment to acknowledge the ways in which you have used it.

I (DANIAL NAYYAR – 001138327) have used AI while undertaking my assignment in the following ways:

- To develop research questions on the topic –NO
- To create an outline of the topic –NO
- To explain concepts –NO
- To support my use of language –NO
- To summarise the following articles/resources:

1.
2.
3.
4.
5.
6.

- In other ways, as described below: as instructed by the brief to use AI platforms like Prome AI and Vizcom to generate POC concept videos as well as designs.