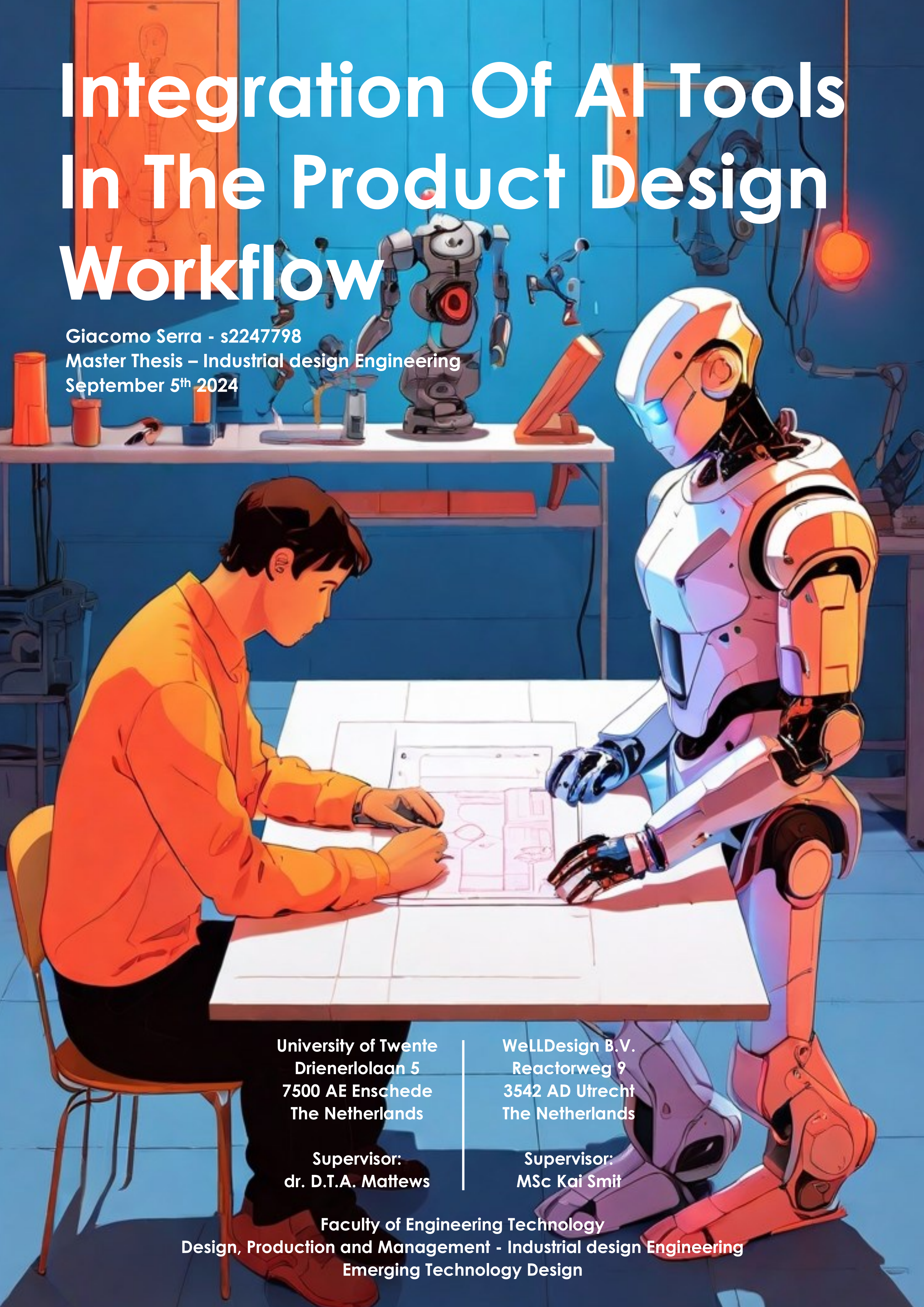

Integration Of AI Tools In The Product Design Workflow

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Abstract

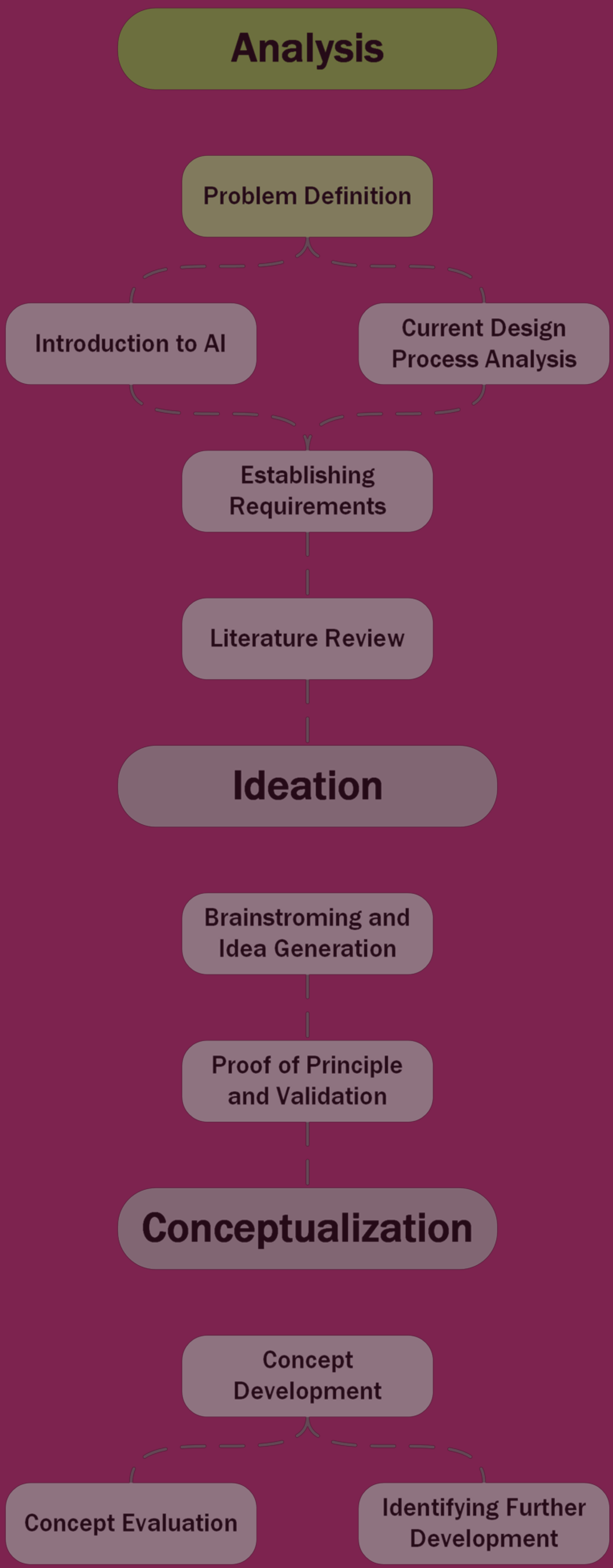
With the recent popularization of easy to access, commercially available Artificial Intelligence (AI) systems, both academia and industry have started exploring its potential uses and benefits. This holds true for the product design industry, where the use of AI is seen as a potential avenue for improvements in output quality and process efficiency. This thesis delved deep into the role of AI in the design domain, focusing particularly on how it can be leveraged by small and medium sized design agencies to optimize traditionally time consuming processes. The research was performed in partnership with WeLLDesign, a Dutch design agency, allowing for an inside-out approach to understanding the role of AI in design. Over the course of the partnership, the needs of the company were explored and, alongside literature research, were used to identify the needs of the industry. To guide the process of implementing AI, critical design tasks were identified and categorized according to five distinct task categories. From these, a series of category specific AI implementation methodologies were drafted and applied to a case study development project. Ultimately, eight concept methodologies were presented, outlining the critical interactions and transfers of data between designer and AI. This thesis discusses the implications of the proposed methodologies for both WeLLDesign and industry, pointing at promising increases in efficiency to tackle issues of cost reduction and offshoring. This research aims to set a precedent for the use of AI in an assistive rather than substitutive capacity.

AI Use Disclaimer

Given the nature of the topics discussed in this thesis, the use of AI throughout the duration of the associated research was inevitable. However, such uses were limited to the relevant research and implementation activities needed to evaluate the use of AI in design environments. The author affirms that, unless otherwise stated, all content is his own work, unassisted by AI, in line with academic requirements. Exceptions to this are the images used in the thesis's chapter spreads, which were generated using the LeonardoAI programme to visualize the core topics discussed in each chapter.

Nonetheless, in line with the findings of this thesis, it is the authors position that AI must be treated as an assistive tool. He thus urges academia to adapt its current stance to better accept the use of AI as a research tool, teaching students to leverage its strengths rather than antagonizing its use.

1. Introduction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"Do androids dream of electric sheep?" - Philip K. Dick (1968)

The Artificial Intelligence (AI) industry may still be too young to answer Philip K. Dick's famous question. However, in recent years, tremendous strides have been made in AI development, the likes of which would make the Turing test blush. The AI industry has entered what can be referred to as its third development summer (Muthukrishnan et al., 2020). Models are more accurate and powerful, access is widespread and affordable, and companies are rushing to implement AI at all levels of industry. This is to say; AI is changing the way industries work, and those who fail to adapt are likely to be left behind.

This poses a significant issue in the product design industry as, while AI adoption has flourished in industries such as banking, retail and manufacturing (Jyoti & Kuppuswamy, 2023), limited resources have gone into exploring and developing AI, and AI methodologies, specific to the product design domain (Brisco et al., 2023; Liu & Hu, 2023; Zhang et al., 2023). What research exists in this domain focuses primarily on highly specialized and customized applications of AI at industrial scales, seldom defining methodology frameworks capable of encompassing the full breath of the product development process. This focus on specialized enterprise grade implementations has led to a general neglect the needs of independent design agencies and freelancers who are unable to produce the time and economic capital to invest in such implementations. In recent years, this has started to change, with research emerging which explores the use of image generating AI in the design process, this body of research is however relatively miniscule and yet unable to bridge the aforementioned gap in research. Furthermore, unlike larger brands which may focus on optimizing individual development stages, independent design professionals and agencies employ more fluid workflows, with projects focusing on different stages of the design process, thus drawing little to no benefit from highly specialized applications of AI.

Accordingly, this research sets out to explore how small to medium sized design agencies can adapt by integrating AI in their product development workflow. In collaboration with WeLLDesign, an Utrecht based product design agency, a suitable AI implementation strategy will be established. The collaboration will act as a case-study to contextualize AI implementation in what is a generally overlooked segment of the industrial product industry. Herein, this research will focus primarily on the optimization of WeLLDesign's workflow using AI to minimize and streamline what can be viewed as negative time-sinks within their existing process. As such, the following research question is presented:

"To what extent can current and emerging AI tools be integrated within the product design workflow to minimize and streamline time-sink tasks?"

Scope

The realm of AI research, particularly given recent technological developments, is grandiose, with a momentous amount of literary research, much of which focuses on outlining the exact workings of AI technologies as defined by data and computer science disciplines. Given this veritable ocean of available information, in-depth explorations of the intricate architectures of AI tools, which fall outside the author's expertise, are beyond the purview of this thesis. The scope and depth of this research will instead focus on the direct application of AI tools by small design agencies and design professionals. That is, through the lens of WeLLDesign as a vehicle for small design agencies; wherein three goals can be defined:

- G1: To define and categorize the optimization needs and shortcomings of current design methodologies employed by design agencies, with focus on negative time-sinks.
- G2: To explore current, developing and future AI tools relevant the established optimization categories.
- G3: To establish a draft AI integration framework for small design agencies.

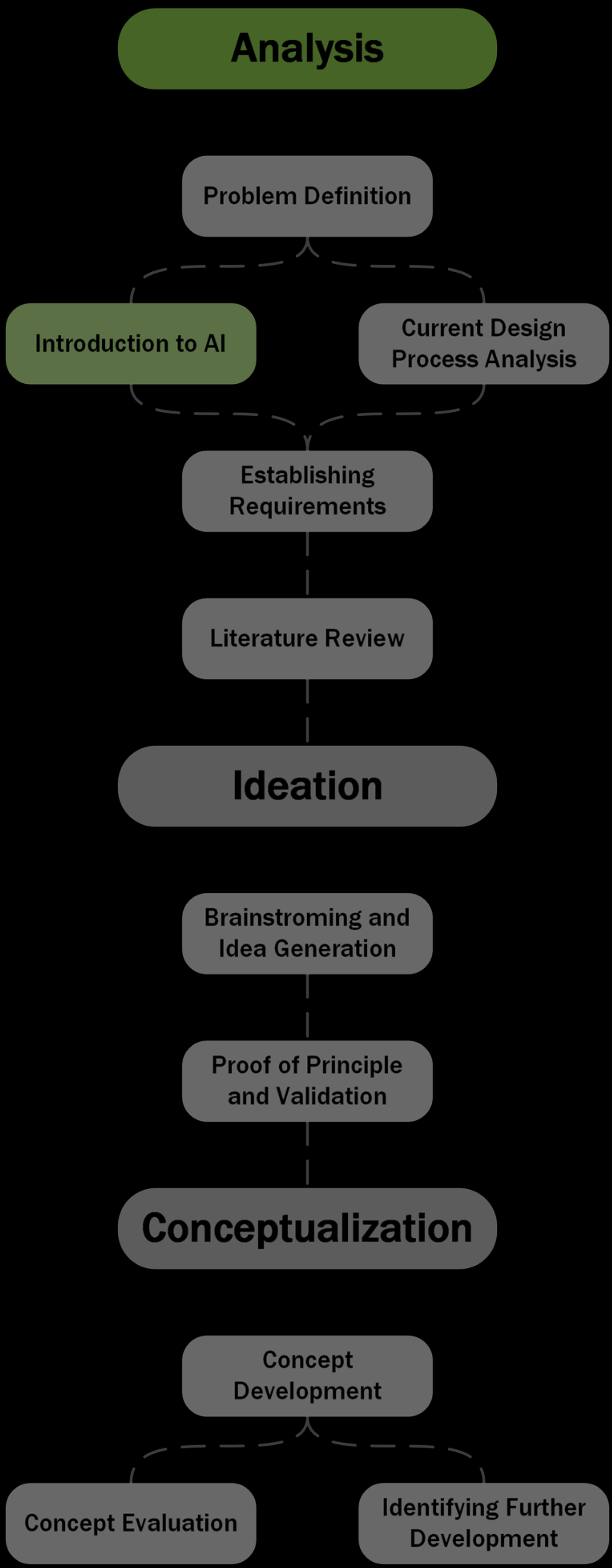
The company is interested particularly in the integration of AI tools, not to replace the role of designers in core design tasks, but rather to minimize and optimize their involvement in tasks which are often viewed as inefficient and unsatisfying time-sinks. This interest extends over the entirety of the design process, from market research and client acquisition to drafting bills of materials and production optimization.

Further, the author notes that research into design methodology often results in intangible and unintuitive models which are seldom applicable in industry. The core aim of this research is to outline methodologies which offer a tangible route to implementation for design agencies and freelance designers. As such, and in line with the expectations of WeLLDesign, the product of this research is represented in a conceptual methodology, developed to where WeLLDesign can start to implement AI in its workflow, with the intention of future in-field testing and refinement.

Structure

This report is structured to systematically address the scope of this research project as outlined in the previous sub-chapter. Chapter 2 briefly focuses on introducing the concept of AI, its typologies and its diffusion from novel research to industry standard. This is followed by a brief introduction, in chapter 3, to the partner company, WeLLDesign, which is used to contextualize the specific needs and expectations of AI in industry. Chapter 4 further explores these needs, developing them into tangible requirements to the development of AI integration frameworks (G1). Chapter 5 serves as a literature review, exploring current developments around applications of AI in both design industry and academia (G2). An AI integration framework is introduced in chapter 6, with an implementation case study and a framework revision being discussed in chapters 7 and 8 respectively (G3). Lastly, chapters 9 and 10 explore how the proposed methodologies, along with the current body of research into AI, can impact the industry, presenting strengths and shortcomings and highlighting avenues for future development.

2. Introduction to AI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History of AI

The concept of Artificial Intelligence (AI) is not novel to the data and computer science community, with the concept being alluded to by the likes of Allan Turing and McCulloch and Putts in the 1940s. The term itself, Artificial Intelligence, first appeared during a 1955 gathering between John McCarthy, Marving Minsky, Claude Shannon and Nathaniel Rochester (Toosi et al., 2021). During this meeting, the research of AI was defined as the process of "making a machine behave in ways that would be called intelligent if a human were so behaving" (McCarthy et al., 1955), McCarthy later rephrased this for the layman as "the science and engineering of making intelligent machines" (McCarthy, 2007). In the 70 years since that influential gathering, the field of AI and the underlying technology have greatly evolved and developed, leading to ever changing definitions and cycles of promise and failure (Muthukrishnan et al., 2020; Toosi et al., 2021). These cycles, where developments in AI research generate significant "hype" and expectations which the technology ultimately fails to meet, have so far occurred twice(Muthukrishnan et al., 2020; Toosi et al., 2021). Figure 1 represents this timeline visually.

The first winter hit the industry between 1974 and 1980. It was preceded by the gradual demonstration of the limitations of contemporary AI models throughout the late 1960s and early 1970s. It culminated in the termination of governmental funding towards AI research. This was not, however, wholly negative as, it sprung the research community into exploring alternative AI architectures and models. This was a driving factor in an industry shift towards the development of rule based neural networks. (Muthukrishnan et al., 2020)

Following a period of prosperity, research into AI fell into a second winter during the late 1980s and early 1990s. This second winter was intrinsically different from the first; whereas the first winter was brought on by a failure of contemporary architectures, the second was caused by bottlenecks in the underlying technology which powered the models. It was, in fact, a limitation in the available computing power which rendered novel neural network based AI models unsuitable for the times. In response to this limitation, researchers temporarily refocused on simpler and more practical algorithms until developments in chip manufacturing reignited interest in neural network AI in the latter half of the 1990s. (Muthukrishnan et al., 2020) Progress in AI development has since flourished, leading to the optimization of existing algorithms and the development of new architectures and AI sub categories.

AI Explained

Defining AI

The true definition of artificial intelligence is highly contested, with two prominent schools of thought (Toosi et al., 2021). The likes of John McCarthy and Marvin Minsky frame AI around the concept of allowing machines to perform activities which would otherwise require intelligence if performed by a human or, in Minsky's words: "[AI is] the science of making machines do things that would require intelligence if done by men" (Minsky, 1969; Toosi et al., 2021). Here, Minsky places the onus of AI onto the output rather than the process itself. By contrast, IBM, as well as McKinsey & Company, define AI around its ability to mimic the capabilities of the human mind and, as such, prioritising the process over the output (Toosi et al., 2021). As per IBM: "Artificial intelligence, or AI, is technology that enables computers and machines to simulate human intelligence and problem-solving capabilities" (IBM, 2023b). However, it is likely, if not expected, that the "AI" tools discussed herein, within the span of years or decades, may no longer be classified as AI by the general populous, just as with many algorithms in the past. As such, for the purposes of this research, it is beneficial to establish a situational definition, one which encapsulates what AI means to product designers at the moment this thesis is written.

Surveying WeLLDesign's team of eleven product design engineers, which constitute the primary beneficiaries of this research, a situational definition for AI was formulated. Unlike the schools of thought previously explored, this definition of AI is less concerned with elements of human intelligence and processes, instead prioritizing AI's ability to learn and iterate on existing data. The definition is as follows:

"Artificial Intelligence (AI) is the ability of a machine or program to learn from and assimilate data in order to generate an output relevant to a given input."

The definition places particular attention on the AI's ability to "learn" from data rather than simply process it as other, non-AI algorithms would.

As expressed in the introduction to this thesis, a detailed exploration of the inner workings of modern AI technologies is outside the scope of this research. It is, However, helpful to understand some of the fields more prominent concepts. Here, two concepts will be briefly explored: the basic workings of AI and the prominent typologies of AI.

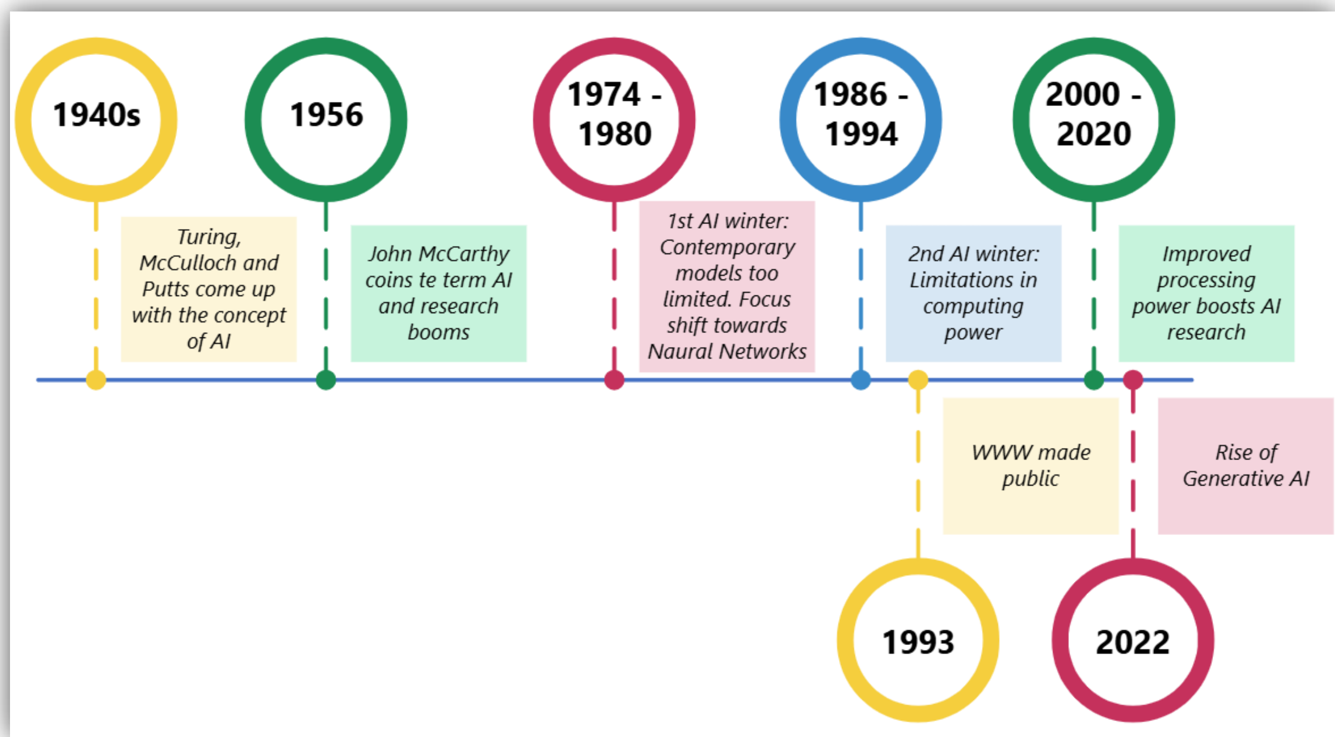


Figure 1: Timeline of AI development

AI Basics
Performing a cursory web-search to understand what AI is, one is presented with a multitude of acronyms such as ML, DL and neural networks. This can lead to confusion as it is often not immediately clear what these represent and how they fit within the realm of AI (Purohit, 2023). Here, these terms and concepts will be briefly explained and contextualized, providing the level of understanding of AI necessary to fully assimilate and benefit from what is discussed in this thesis.

Broadly speaking, AI is an umbrella term which covers a variety of algorithmic architectures. As seen in Figure 2, Machine Learning (ML) is a subset of AI and, in turn, Deel Learning (DL) is a subset of ML. This hierarchy of AI stems from the focus put on neural networks following the first AI winter. As such, while the terms ML and DL represent ways in which AI models are trained, the term neural network describes the underlying architecture of said models. (IBM Data and AI Team, 2023)

At their core, neural networks are algorithms which, as suggested by the name, imitate the way in which signals are passed between neurons in a human brain. Neural networks are made up of clusters or layers of artificial neurons (nodes), of which there are three distinct typologies: input nodes, hidden nodes, and output nodes. These nodes, which process a given data, are each assigned two values, a weight, which defined its influence on the output, and a threshold value for evaluating its output. When a node's data threshold is reached, it sends its output data to a node in the subsequent layer. This system of interconnecting node layers, allows data to be processed repeatedly and at high speeds, morphing from an input into an output. (IBM Data and AI Team, 2023)

Machine Learning typically leverages the neural network architecture, using a layup of (1) an input layer, (2) at least one hidden layer and, (3) an output layer. By presenting the neural network with pre-labelled input data as well as the corresponding pre-labelled output data, the algorithm repeatedly processes the input data though the three layers until its outcomes are able to match the given output data. This type of training, generally referred to as supervised learning, requires human intervention to provide accurately labelled data. (Delua, 2021; IBM Data and AI Team, 2023)

Deep Learning refers to ML models which have a neural network layup of more than 3 layers (Figure 3). By having additional hidden layers, DL models can be trained using both unlabelled and labelled data. The advantage of such a system is that it negates the need for investment into structured and labelled data, instead, during training, the algorithm is capable of parsing large volumes of raw data. This type of AI training, called unsupervised learning, relies on the neural networks ability to discover patterns in the raw data. These patterns, in the form of the models output, is then validated without human intervention, with the process repeating until the output is repeatedly accurate. (Delua, 2021; IBM Data and AI Team, 2023)

These three concepts represent the "ability of a machine or program to learn from and assimilate data" expressed in this thesis's working definition of AI.

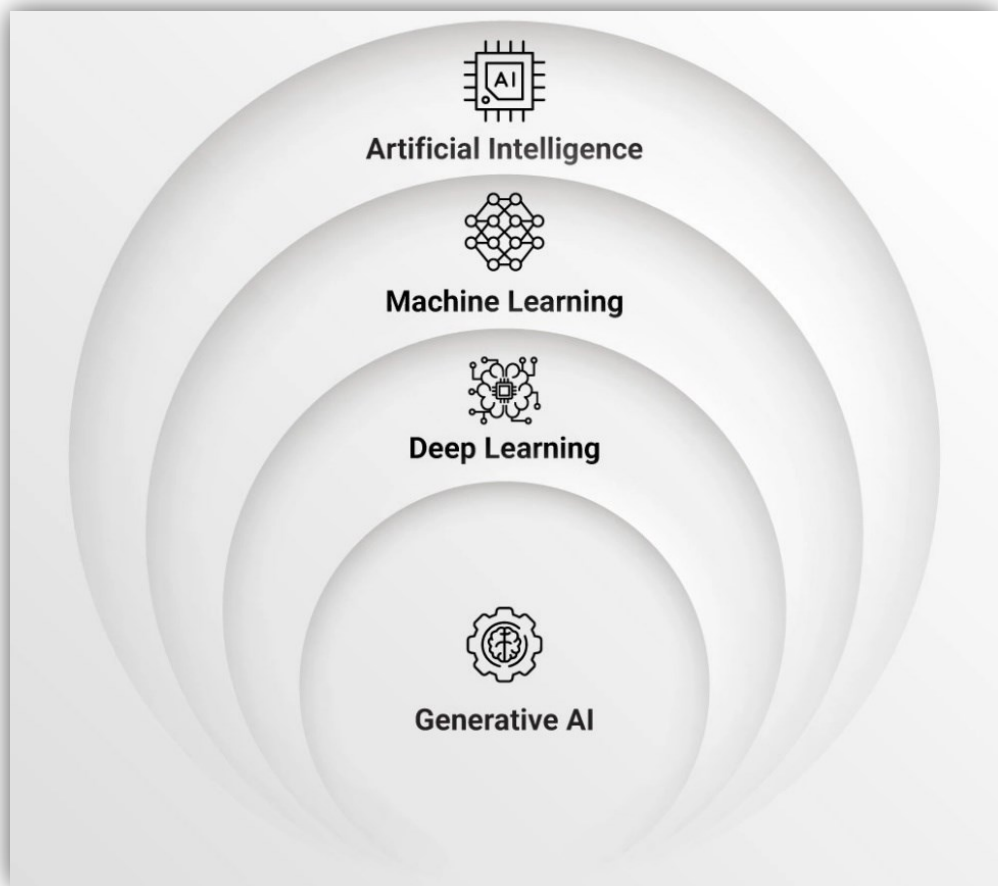


Figure 2: Visual contextualization of the relation between Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL) and Generative AI (GenAI) (IBM Data and AI Team, 2023)

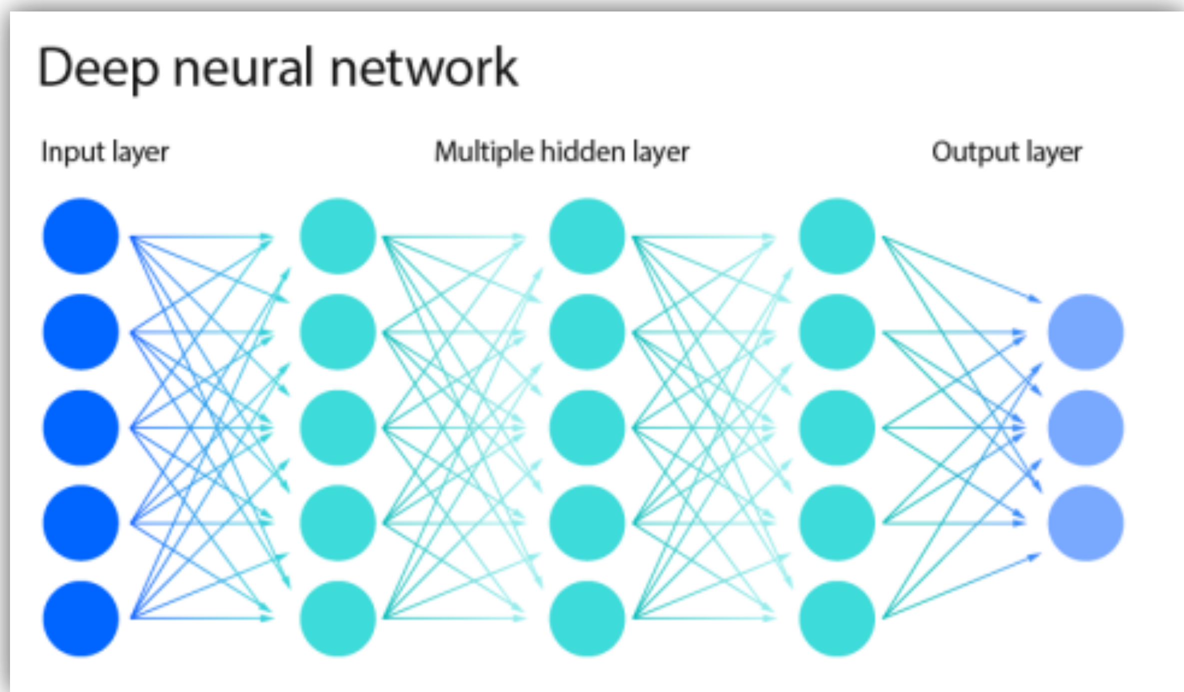


Figure 3: Visualization of a Deep Neural Network as presented by IBM (IBM Data and AI Team, 2023)

AI typologies
Defining the types of AI which exist is a challenging task as AI can be categorized based on a variety of factors: capability, functionality and, output.

When AI is categorized by capability, the focus is placed on the scope of a given AI algorithm. That is to say, the extent to which they are able to interact with data. There are three such typologies: Artificial Narrow AI, General AI and Super AI. Artificial Narrow AI, commonly referred to as Weak AI, refers to AI algorithms which are trained to perform a singular task and is unable to expand beyond that mandate. By contrast, General AI, also known as Artificial General Intelligence (AGI), and Super AI, are not bound by any given mandate and are able to grow and learn to perform new tasks without human intervention. Of these typologies, only Weak AI has been achieved, with AGI and Super AI remaining purely theoretical. (IBM Data and AI Team, 2024)

Classification by functionality aims to instead differentiate AI algorithms based on their ability to retain data. There exist four types, the latter two of which are, once again, purely theoretical: Reactive Machine AI, Limited Memory AI, Theory-of-Mind AI and, Self-Aware AI. Reactive Machine AI, as the name suggests, is only able to operate on currently available data and is unable to access or recall past outputs, examples of these include chess AIs and Netflix's recommendation algorithm. By contrast, Limited Memory AI is able to recall past outcomes, determining outcomes based on both current and past information. This is exemplified by tools such as ChatGPT which is able to have conversational awareness by referencing past prompts and responses in a given conversation. (IBM Data and AI Team, 2024)

Lastly, classification of AI by task, clusters AI's based on the real-world, tangible tasks they perform. It is this classification which is most relevant to this thesis's working definition as it outlines the expected output an AI can generate. Unlike the previous classifications, which define three to four typologies each, AI task typologies are numerous and varied, with some AI tools belonging to multiple typologies. However, examples include: Generative AI, Data Analysis AI, Computer Vision AI and Recommendation AI. Furthermore, sub categories can exist, with typologies such as Generative AI incorporating text-to-text, text-to-image, image-to-image, etc.. An example of this classification of AI is seen in Table 1, where AI task typologies are listed alongside example tools.

Diffusion of AI Across Industries
The vast diversity in AI output types and functionalities has allowed Weak AI to permeate virtually all modern industries. While, as seen with Generative AI in the art industry, introduction and development of AI can at times be disruptive to an industry, it's effects, or even involvement, are not always so obvious. An example of this is Netflix's recommendation algorithm which, while often unnoticed by users, is a powerful AI which has often been touted by industry experts as a primary driver behind the platform's success (SA, 2023). Such examples are not uncommon, with users often relying on tools which they are unaware are powered by AI systems. Because of this, AI systems have been primarily adopted in the Banking, Retail, Manufacturing and Healthcare industries, with their investment into AI applications predicted to grow by 66 billion dollars by 2026 (Jyoti & Kuppuswamy, 2023) (Figure 4). By contrast, the introduction of AI into creative Industries, including product design, is novel and underdeveloped.

Table 1: AI Categorization by Task

Task	Potential Fields	Example Implementations and Systems
Content Generation	Text generation; Translation; Image generation; Summarization.	Midjourney, ChatGPT, Copilot
Data Analytics	Detecting errors; Pattern recognition; Visualization of data; Prediction.	IBM Whatson
Optimization	Allocating Resources; Scheduling; Supply chain optimization.	IBM CPLEX
Recommendation	Content delivery; Product recommendations.	Netflix's Suggestion Algorithm
Computer Vision	Facial recognition; Object detection; Imaging.	Google Vision AI
Natural Language Processing	Text analysis; Sentiment analysis.	Hugging Face AI
Autonomous Systems	Automotive automation.	Tesla Autopilot
Gaming	Non-playable characters.	Nity ML-Agents

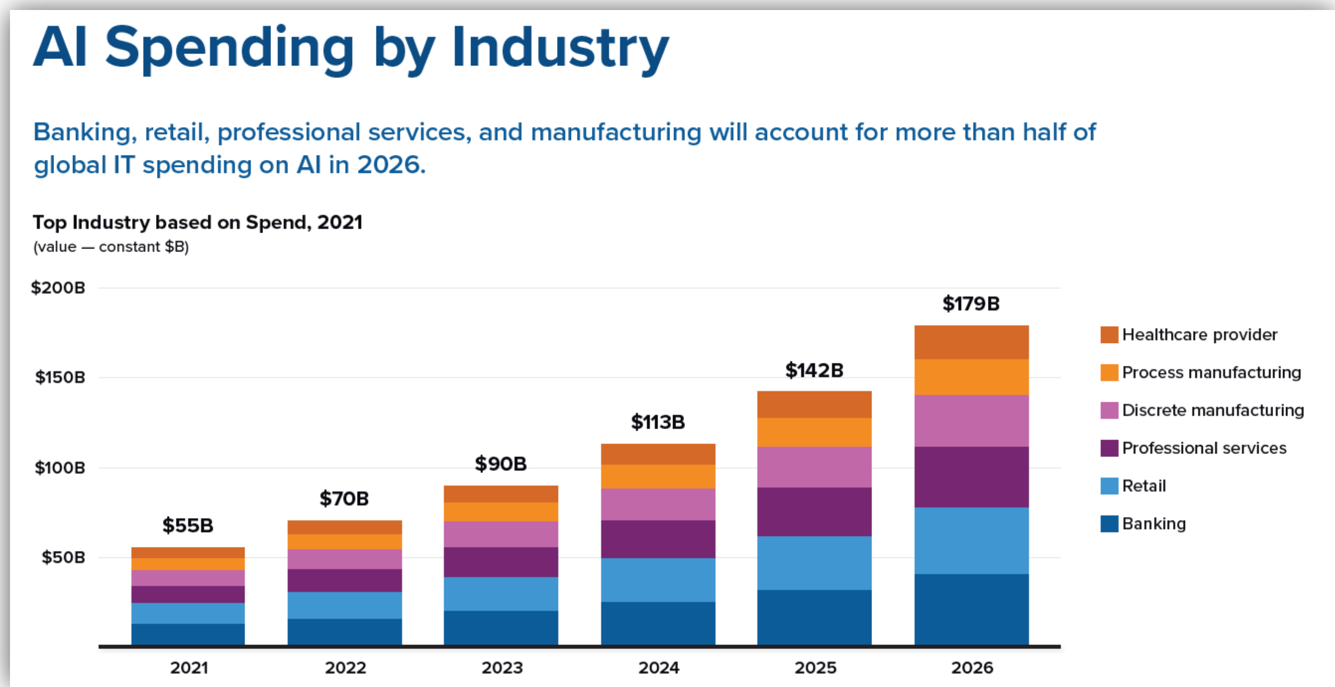
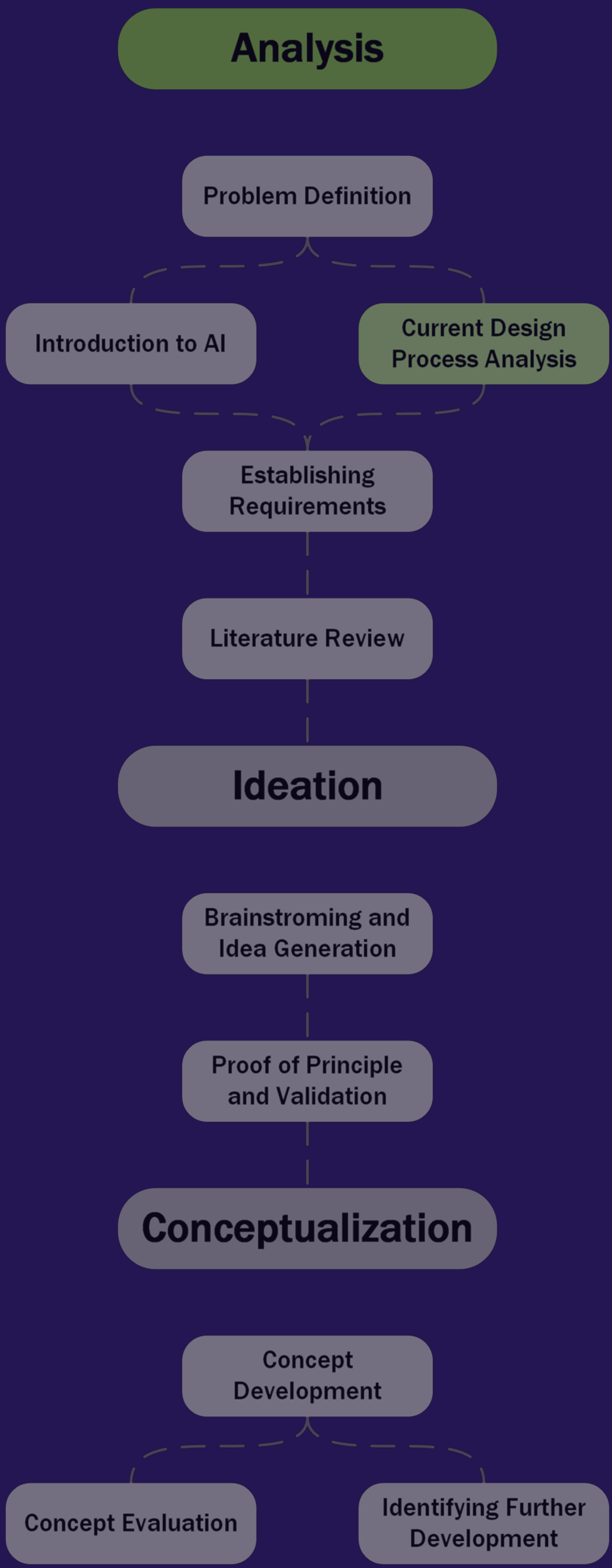


Figure 4: AI investment predictions 2021-2026 by industry (Jyoti & Kuppuswamy, 2023)

3. Introduction to WeLLDesign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History

Founded in 1979 by designers Mathijs van Dijk and Arthur Eger, WeLLDesign has a long history as a Dutch design agency. It has focused on all stages of the product development process, from market research and ideation to production and commercialization, collaborating with local and multinational clients alike to bring products to life. Notable examples include: the Royal Flora Holland flower stand used by florists worldwide, Internal engineering for the Senseo coffee machine and the M&G Skyline.

The company now employs 8 full-time designers who's expertise complement each other, creating a strong team able to undertake a multitude of projects and challenges. In recent years, with the advent of 3D printing and other rapid prototyping techniques, WeLLDesign has set up an impressive in-house prototyping workshop allowing them to deliver faster and better results. Now, amid the boon of AI, WeLLDesign is interested in staying on the leading edge and hope to develop a future proof AI integration methodology to further optimize their offerings and to allow the designers to focus on what they do best: design.

The WeLLDesign process

Throughout this collaboration with WeLLDesign, there have been several revisions to the company's design process. These changes were linked to a recent optimization and modernization effort. As a result of this restructuring, WeLLDesign's process moved from a 10 phase process (at the time the collaboration started)(Figure 5), to a 5 phase process (approximately 2 months into the collaboration) and finally to a 6 phase process (at the time of writing)(Figure 6). Despite the changes, the core workings of WeLLDesign's process remained the same, following a linear, yet iterative, stage-gate structure reminiscent of that proposed by Ullman. With clearly defined, yet interconnected, phases which each end with a refinement of the project's documentation and planning (Ullman, 2010)(Figure 7). This structure provides WeLLDesign enough division between phases to offer clients modular and customizable project plans, while retaining the interconnectedness required to perform iterative refinement tasks.

Along with these changes to the overall phase structure, which saw the merging of different phases into fewer, more meaningful phases, a clear list of expected design tasks was established. Here, the focus was on streamlining WeLLDesign's process through standardization of phases and related tasks to better align the designer's work with the needs of perspective clients. Using this structured list of design tasks, the designers are able to clearly outline the scope of a new project while drafting a project proposal for the client, assigning only relevant tasks to a time budget and reducing the likelihood of performing unneeded or undesired tasks. This may seem to add rigidity to project planning, restricting designers to predefined tasks, however, that is not necessarily the case. WeLLDesign prevents the undesired rigidity in two ways. Firstly, it plans project on a per-phase basis, only defining the tasks relevant to an ongoing phase. Secondly, in line with the Ullman framework, it establishes clear moments for the planning to be revised and updated, allowing both the designers and the clients to request course correction where needed.

This flexibility has allowed WeLLDesign to offer its services to a broad variety of companies, working on different stages of the design process where needed and quickly adapting to changes in client needs.

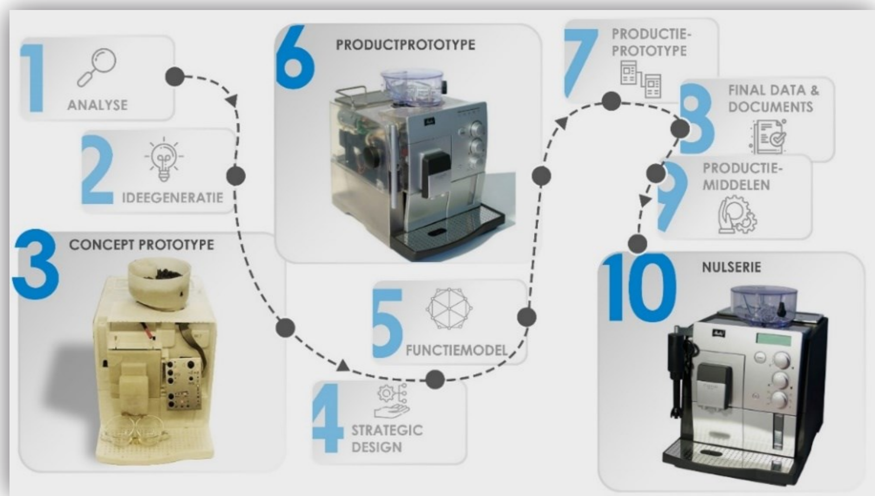


Figure 5: The old, 10 phase, WeLLDesign process

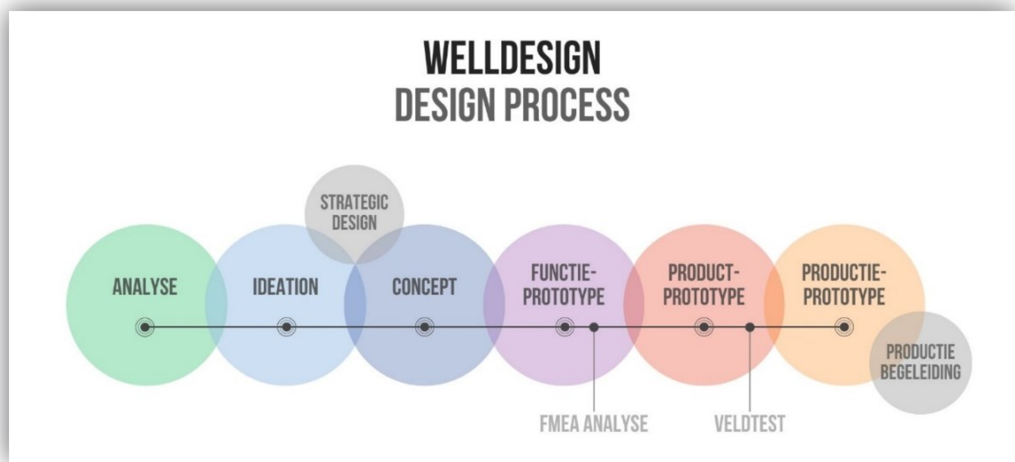


Figure 6: The new, 6 phase, WeLLDesign process

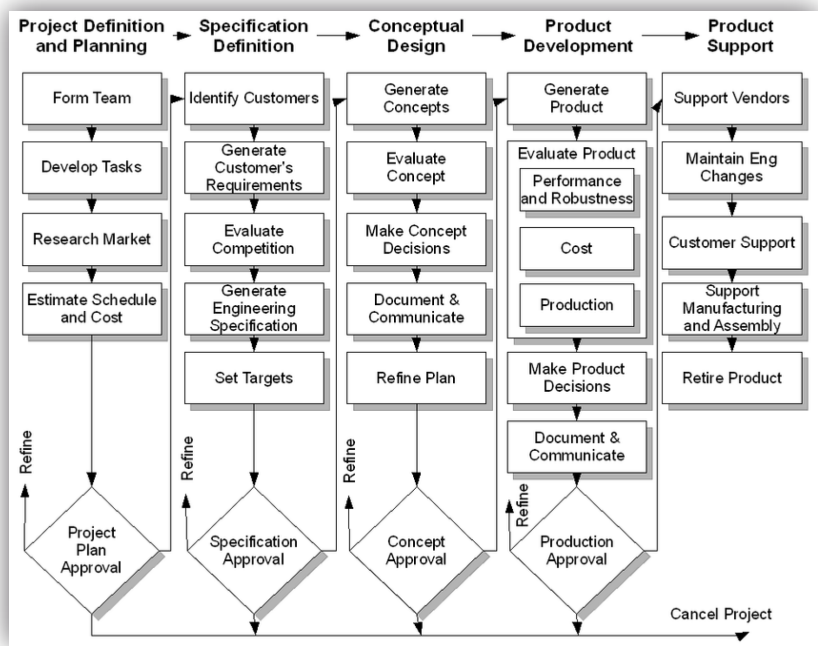


Figure 7: The Ullman process for mechanical design as presented by Nieberding (Nieberding, 2010)

Over the past 40 years, industries have collapsed, others have emerged and many have greatly changed. For WeLLDesign, surviving these changes has meant being able to adapt to current trends and client needs. This manifests as changes in the company's involvement with different phases of the design process. This has in the past resulted in WeLLDesign primarily focusing on the most commonly requested design phases rather than maintaining an even distribution of projects across the whole design process. An examination of 42 projects carried out by WeLLDesign since 2010was performed, represented graphically in Figure 8, to understand the company's current distribution of focus. In this examination, three additional pseudo-phases are included: Market Research, Acquisition and, Project Management. In the later 5 and 6 phase development processes, Market research and Acquisition activities were incorporated in the Analysis and Ideation phases. Project Management represented a series of overarching and indirect consulting activities, primarily aimed at clients seeking aid in structuring internal R&D projects. These consulting activities were later split into the optional Strategic Design and Production Guidance sub-phases seen in Figure 6.

As shown in Figure 8, WeLLDesign has in recent years focused on earlier stages of the design process, from Analysis to Concept Prototyping. This skewed focus is likely driven by the widespread off-shore relocation of R&D activities by companies in efforts to maximise their global value chains (P. Rodgers et al., 2019). This trend towards R&D offshoring has primarily affected less innovative and more repetitive design activities, resulting in concepts which are first developed locally, and later outsources to developing countries for lower development and production cost (P. Rodgers et al., 2019). For WeLLDesign, this has meant fewer requests for projects at the later stages of the development process. However, with the EU's post-Covid-19 push towards value chain reshoring, due to growing geopolitical concerns, it is likely that, in the near future, demand for late phase projects will increase(Pegoraro et al., 2022; Raza et al., 2021). For WeLLDesign, it is critical that, when this shift towards reshoring occurs, the company be ready. By leveraging AI in its methodology, to minimize time spent on time-inefficient task, the company would be able to refocus on its late phase offerings without sacrificing its performance in the earlier stages of the design process.

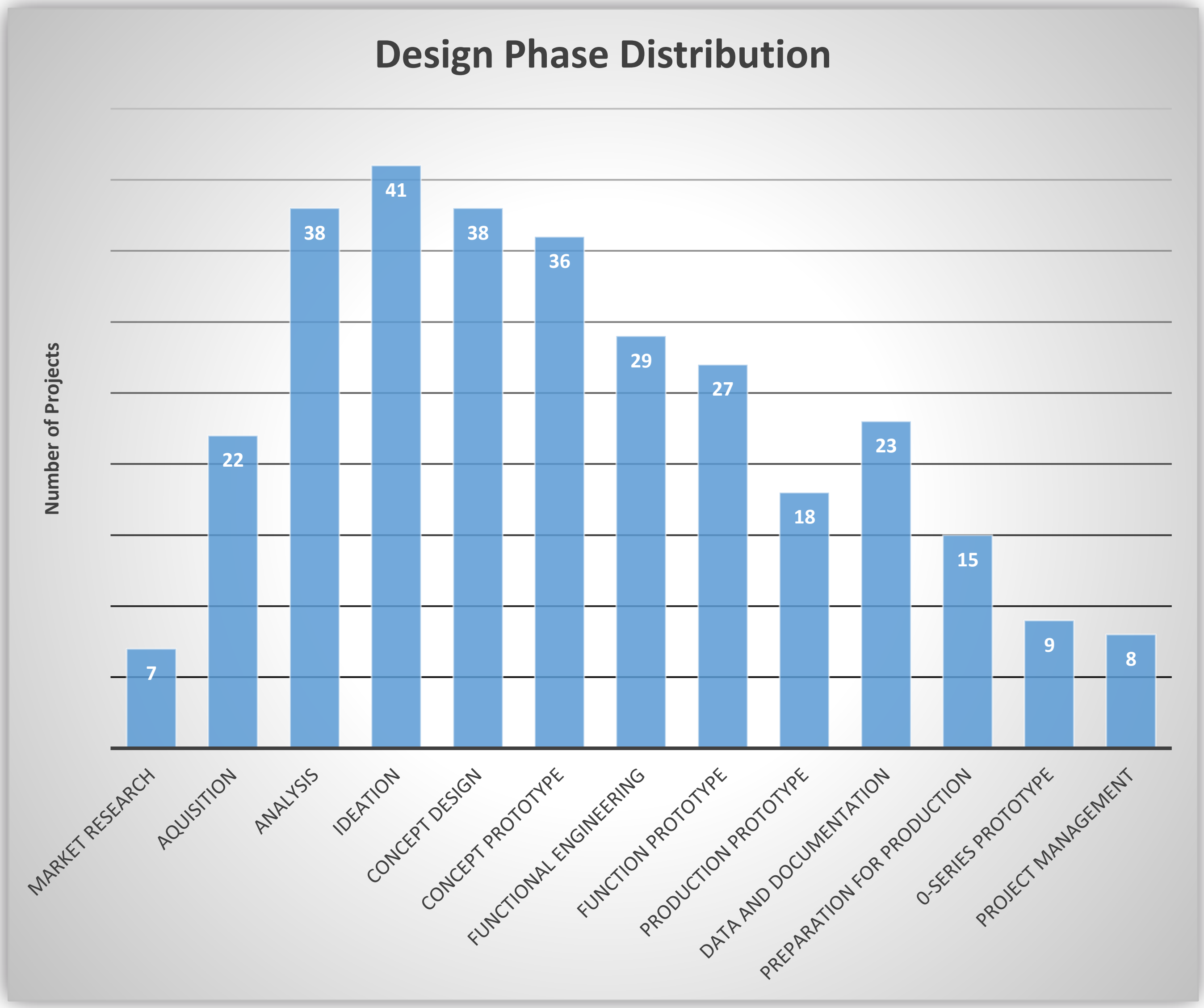
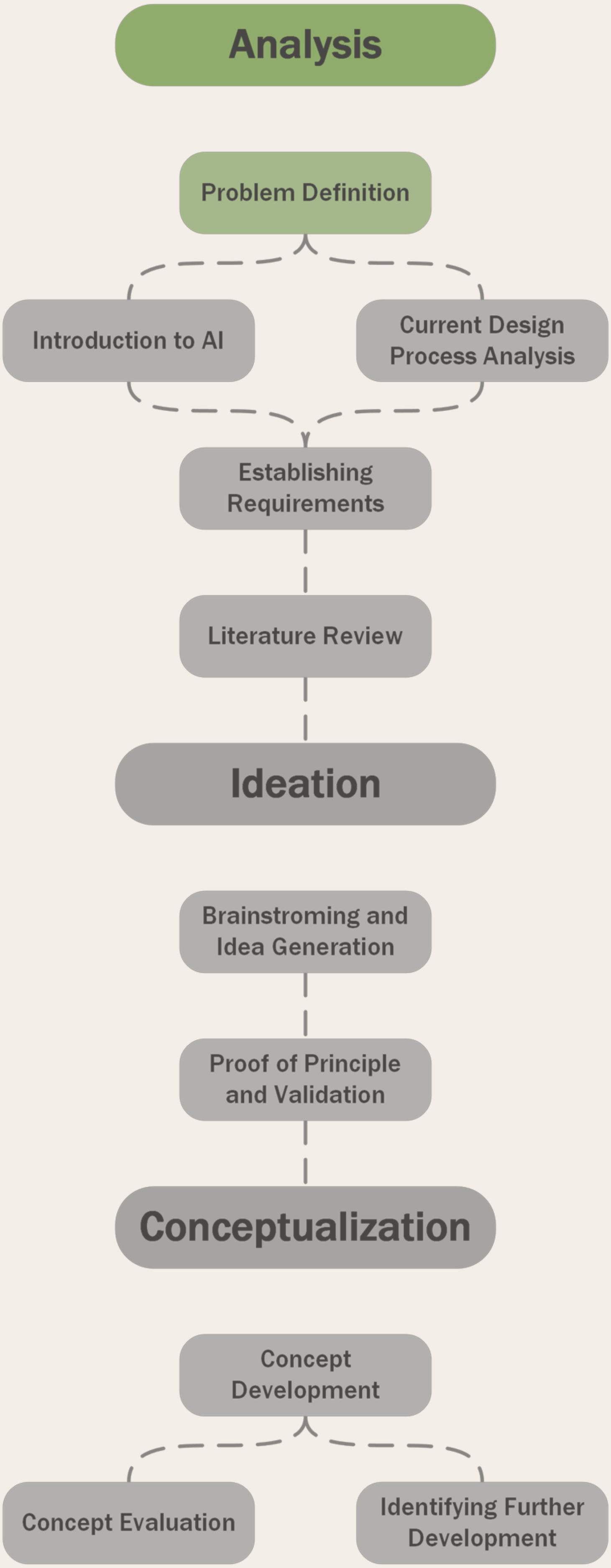


Figure 8: Project phase distribution for WeLLDesign projects (2010 - 2024) based on the original 10 phase process and accounting for additional 'Market Research', 'Acquisition' and 'Project Management' phases.

4. AI Expectations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Recent developments in AI applications, particularly with the rise of generative AI, have generated great interest. However, some experts warn that, lest expectations are tempered and realistic, the industry may inevitably head into a third winter (Toosi et al., 2021). The need for realistic expectations does not only cover the technicalities of what AI is able to accomplish, but must also consider the feasibility of how users and industries interact with a given tool. This chapter explores these concepts, focusing on internal WeLLDesign expectations for AI, and subsequently extrapolating these into more holistic, industry wide expectations.

Internal Expectations

Assessing the internal expectations for AI at WeLLDesign required investigation at different layers of the company's structure: at the leadership layer and, at the engineer/employee layer.

Leadership expectations

The WeLLDesign management ultimately decides how and when AI systems are purchased and implemented. As such, early in the research, a brainstorming session was held to explore potential avenues for AI implementation. The session was divided into three sections: exploring basic requirements, exploring critical areas for AI implementation, and establishing integration timeframes.

The basic requirements discussed during the brainstorming primarily focused on establishing limitations and safeguards. Importance was given to the designers, ensuring they are not removed from the critical design tasks and on the prevention of alienation and loss of enjoyment. As such, it was established that AI implementation should be limited to reducing and streamlining time-sink tasks. Here, time-sink tasks were defined as tasks or activities which require a disproportionate time commitment or effort relative to their complexity or importance, taking away time from more critical design tasks which require a human touch. In essence, streamlining time-intensive processes to allow designers to focus on design tasks which they can enjoy more. Throughout the duration of this research, as all parties involved developed a growing understanding of AI, these requirements were updated, forming the basis for the research requirements presented later in this chapter.

Once the focus was set to streamlining time-sinks, the leadership team generated a list of potential uses for AI which they felt could benefit the design process. This list can be found in Appendix A. The ideas varied in complexity and feasibility, resulting in the establishment of 3 timeframes around which to structure research: "Now", "Tomorrow" and "In-the-future". "Now" refers to applications of AI which can be directly implemented in the design process in a short timeframe and with minimal investments. Conversely, "Tomorrow" refers to those which rely on more complex or emerging AI technologies which would require larger investments and longer implementation times. Lastly, "In-the-future" refers to hypothetical implementations which might benefit the design process but are yet to be explored or developed to a feasible level. By grouping AI implementation ideas within these categories it is possible to temper expectations, creating a shared understanding of the timeframe in which any given idea becomes feasible.

Employee Expectations

A survey of WeLLDesign's, at the time, 11 designers, was used to gauge the employee experience and expectations for AI integration. The survey, comprised of five sections relevant to different concepts discussed in this thesis, can be found in Appendix B.

Exploring the designers previous interactions with AI as a design tool, only 4 of the 11 respondents signalled they had previously used AI in the design process, particularly for ideation tasks. The 4 further indicated they had only used two tool categories: Large Language Model (LLM) chat-bots, such as ChatGPT, and, image generators. Rating the complexity of the tools on a 1 (not complex) to 10 (very complex) scale, the designer's responses varied, averaging out to a 5.25 rating. Evaluating how the use of AI affected their work, designers praised increased efficiency and inspiration potential during Ideation, but highlighted issues with consistency, complexity and quality of results.

Regardless of the mixed experiences with AI, all employees indicated that they believed there is space for AI in the design process. As shown by Figure 9, asked which phases they expected to benefit from AI the most, respondents focused on the initial stages of the design process, with a focus on ideation, and largely dismissed AI integration in the later, more technical phases. In outlining which tasks they would like to perform using AI, a full consensus was found around idea generation and visualization, with a majority also interested in AI for research. This was in line with the teams interest into specific AI tool typologies, with all 11 designers signalling interest in image generators, followed by text generators and smart assistant tools which sparked the interest of 6 designers each. Asked why certain tasks where met with less enthusiasm for AI integration, designers aired concerns regarding reliability and trust in the output as well as the uncertainty of how an output is derived. Overall, while only 4 designers stated themselves to be outwardly concerned about the integration of AI in their workflow, all the respondents shared some level of concern, focusing primarily on: client acceptance, IP and copywrite issues, data security, tool complexity, reduced control over outputs and, risks for overdependence and loss of critical design skills.

Additionally, the designers were probed regarding the potential use of enterprise grade AI compared to consumer grade AI. Enterprise AI tools, which were defined as more expensive and complex AI tools which offer highly specialized solutions, such as IBM's Watson, were met with scepticism, with concerns over the high overhead costs and integration times, but excitement for potential uses in the future. Consumer grade tools, defined as less specialized tools such as ChatGPT, which can be immediately implemented without significant financial investments, were instead met with enthusiasm, with all 11 designers believing them to be beneficial to the current design process.

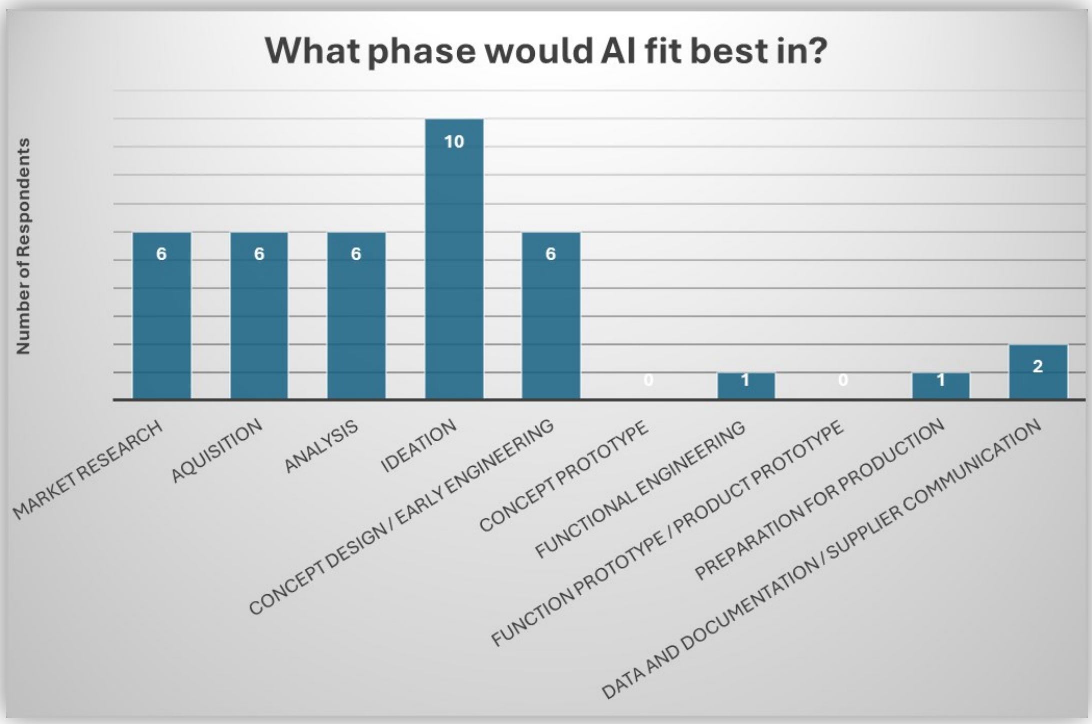


Figure 9: WeLLDesign employee expectations for which phases would benefit most from AI integration

External Expectations

Taking WeLLDesign's internal expectations as a basis to understand the broader expectations of the target industry, six core concepts emerged: Sustainability, Investments, Complexity, Explainability, Data Security and Client Acceptance.

Repeatedly defined by WeLLDesign as a core requirement for AI integration, sustainability is an important factor to consider when introducing AI to the design process. Here sustainability is defined by its 3 pillars: People, Planet and Profit. Specifically, interest is given to the balance between the People and Profit pillars. Design agencies looking to adopt AI design methods do so to increase efficiency and reduce redundancies in the design process, in an attempt to stay competitive in an industry plagued by constantly shortening development cycles and increased product complexity (Berisha & Lobov, 2021; Damgaard, 2023; Rane et al., 2023; Rosenthal & Niggemann, 2022; Sharma, 2023; Wu, 2023). Thus, any implementation of AI methodologies must result in tangible optimizations which either decrease development times or increase output quality. This however has to be balanced with employee retention as, without the designer to make critical design decisions, the process cannot be successful. For this reason, it is critical to implement AI in such a way that is supportive rather than alienating for the designer, reducing and optimizing undesired tasks while enhancing enjoyment for critical ones.

Relevant to the profit sustainability considerations, design professionals and agencies must weigh the potential benefits of an AI system with its set-up costs. Here, costs refers to both financial overhead and set-up/development times. Financial overhead must fit within the budget available to the individual design agency or professional and must result in a net gain through quality or productivity improvements. Similarly, set-up and development times must be consistent with the user's needs, as such, enterprise tools may be appropriate for "Tomorrow" and "In-the-future" implementation timeframes, while existing consumer AI may be directly suitable for shorter "Now" implementation timeframes.

Driving factors in discouraging designers from using AI, complexity and explainability are crucial factors which determine the success of an AI implementation. While similar, these two concepts deal with two different ends of human-AI interaction. Complexity refers to the ease of use of a given AI tool, the so called front-end of the system. For WeLLDesign, the complexity of AI tools, and the learning curve required to efficiently use them, was of clear concern. Explainability concerns the back-end of the interaction, that is, how easily a user can understand why an AI produced a given output. Due to the neural network architecture of modern AI systems, it is often impossible to accurately track how training biases, node interactions and user parameters affect how an AI reaches a result (IBM, 2023a). Lack of AI explainability makes it hard, if not impossible to fully and repeatably control an AI tools output, a concern raised by several WeLLDesign engineers. Recent studies, exploring the use of image generating AI in the design process, recognize these issues with complexity and explainability, with study participants expressing dissatisfaction over the inefficiency and lack of control over outputs (Lee & Lin, 2023; Marcus et al., 2022; Zhang et al., 2023). Similar conclusions were drawn by a group of Industrial Design students at Eindhoven University based on a survey sent to several Dutch design agencies (personal communication, April 22, 2024). It follows that, to maximise the successful implementation of AI in design activities, design agencies must adopt methodologies which minimise human-AI interaction complexity and maximise output explainability. Further, this strengthens the notion of AI as an assistive rather than substitutive tool, as, without trust in output logic, companies cannot rely on AI alone for critical tasks.

Data security, often omitted from research into AI design implementations, has long been a requirement for the introduction of new technologies in the professional design industry. That is, design professionals must ensure that confidential internal and client data is not accidentally mishandled. This covers existing data, such as design specifications and confidential data, but also new data, such as new intellectual properties. This presents an issue when integrating AI as, due to the low explainability, it is often impossible to directly track how input data is processed and handled by a service provider. Instead, AI systems are primarily governed by individual terms of service (ToS) and data privacy policies. Thus, design professionals must carefully consider their data privacy requirements before adopting any given AI system.

As highlighted by the concerns aired by WeLLDesign engineers, ensuring that clients react positively to AI implementations is an important factor guiding AI strategies for design professionals (Zhang et al., 2023). While little data is available to directly assess how potential clients may react, a report by Deloitte found that 72% of surveyed organizations are seeing growing trust in AI tools (Mittal et al., 2024). Despite the positive trend, Deloitte found that transparency in use and AI explainability remain leading factors in client acceptance of AI tools (Mittal et al., 2024). While this does not account for individual concerns on a client by client basis, it indicates that clients are open to the use of AI so long as methodologies are transparent and explainable.

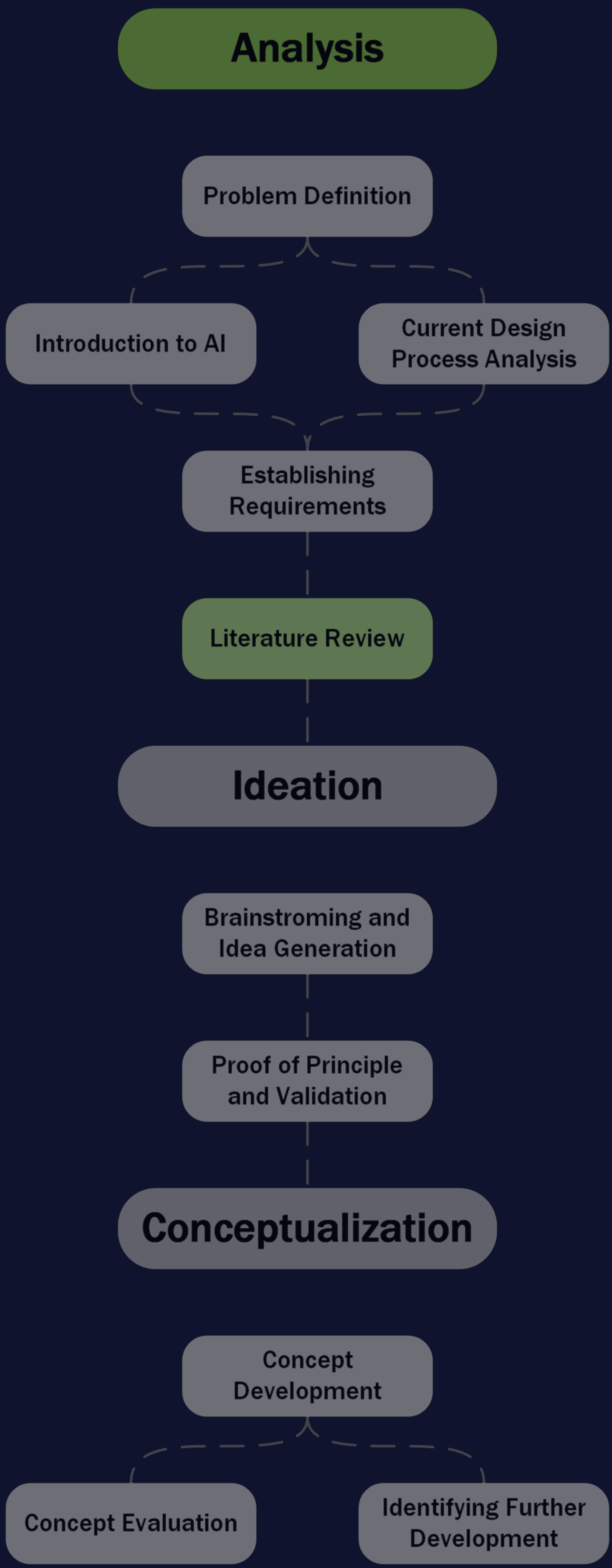
Methodology Requirements

Drawing from both internal and external expectations, Table 2 details a list of requirements set up to guide and assess the development of AI implementation methodologies.

Table 2: Methodology Requirements drawn from internal and external expectations

Concept	General Requirement	WeLLDesign specific Requirement
Sustainability	AI must be supportive rather than substitutive	
	AI methodology must increase efficiency and/or quality	Focus on streamlining time-sink tasks
	AI should not decrease the designers enjoyment of a given task	
Investments	AI methodologies must be financially feasible to implement	
	Implementation timelines must be in line with company needs	Focus on "Now" implementations
Complexity	Methodologies must be clear and tangible	
	Methodologies must have an acceptable learning curve	Learning curve must not negate financial benefit
Explainability	Methodologies should minimize reliance on "black-box" activities	Methodologies should include output refinement by user
	Outputs must be trusted by the user	
	Methodologies must lead to repeatable results	
Data Security	Selected AI tools must meet IP requirements for a given project	IP rights must be retained by WeLLDesign
	Selected AI tools must meet data privacy requirements for a given project	Does the AI train on / make public input/output data?
Client Acceptance	Client must be able to identify how and when AI is used	
Expandability	Methodologies must be able to adapt to changes in core design processes	
	Methodologies must be able to adapt to future AI systems and methods	

5. Exploring AI in Design Contexts


Analysis
Problem Definition
Introduction to AI
Current Design Process Analysis
Establishing Requirements
Literature Review
Ideation
Brainstroming and Idea Generation
Proof of Principle and Validation
Conceptualization
Concept Development
Concept Evaluation
Identifying Further Development

Now

Now tools are directly implementable, with little to no investment or additional development needed. Here, with the exception of image generating AI, there appears to be a distinct lack of academic research. By contrast, this area of AI and AI methodologies is thoroughly explored by online publications such as blogs, LinkedIn posts and company websites. This is likely due to academic research predominantly focusing on exploring hypothetical and early development systems, rather than on evaluating ready-for-market ones.

CAD/CAM and Simulation

AI algorithms have long been adopted by CAD/CAM (Computer Aided Design/Computer Aided Manufacturing) suites. Here AI is often used to power simulations, geometry and topology optimization and digital twinning. These capabilities have been predominantly used to optimize the more technical aspects of design engineering, such as with Neural Concept's NC platform, which, unveiled in 2024, is able to generate, simulate and optimize geometries based on a users' technical prompts (Neural Concept, 2024). These types of CAD/CAM AI systems are considered enterprise level tools as they are often purchased in the form of expensive tailor made software packages and require deep workflow integration. However, with the rise in interest around AI integrations, CAD/CAM providers SolidWorks and Autodesk have both started exploring solutions which can be implemented directly into existing program suites with minimal effort and learning curves.

In collaboration with Kartell and using Autodesk's AI capabilities, designer Philippe Starck made use of AI's simulation and generative capabilities to design the "A.I. Chair" (Figure 10). First presented at the 2019 Milan Design Week, this chair was described as the product of a years-long collaboration between Philippe Starck and Autodesk's AI team. Through the use of Autodesk's generative design tool, Starck was able to leverage AI to transform low fidelity ideas into optimised and aesthetic shapes with minimal additional creative input. (Neira, 2020)

In early 2023, SolidWorks unveiled the "Digital Assistant" for its cloud based CAD/CAM solutions. The design assistant was designed to reduce and automate repetitive time intensive tasks often encountered by designers during CAD modelling. It currently consists of the following four tools: Selection Helper, Mate Helper, Smart Mate and, Sketch Helper. The Selection Helper predicts and proposes selection options based on the user's currently selected features and the active modelling tool (Figure 11). Mate Helper evaluates an assembly and automatically suggests where new instances of existing components should be added. Smart Mate automatically suggests mating parameters when a component is placed in the proximity of another component (Figure 12). Lastly, Sketch Helper predicts what entities user needs to sketch next and makes relevant sketch suggestions. While these tools are currently only available for SolidWorks' web applications, it is likely that they will be integrated into future updates of the main SolidWorks Professional suite. (Pagliarini, 2023)

As the tools recently unveiled by SolidWorks and Autodesk are intended to be directly implemented in existing cad suites, they can be categorized as quasi-enterprise tools. Compared to their highly specialized enterprise counterparts, such quasi enterprise tools are more appropriate for direct implementation by smaller design agencies.

Figure 10: A.I. Chair by Phillippe Starck and Kartell (Kartell, n.d.)

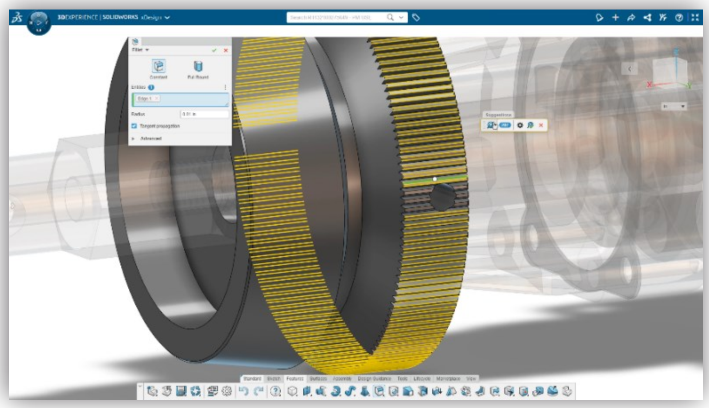


Figure 11: SolidWorks Selection Helper suggesting features to select for a filleting operation (Pagliarini, 2023).

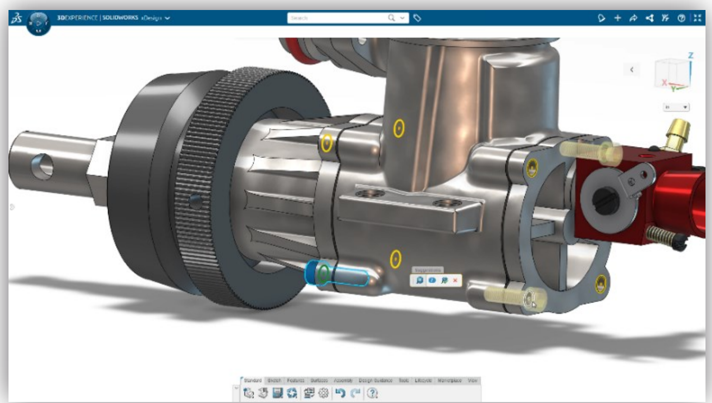


Figure 12: SolidWorks Smart Mate suggesting mating parameters and potential new mating instances (Kumar, 2023).

Generative AI

The current rise of Generative AI tools has sparked the interest of large companies and freelance designers alike, with a 2024 survey by AI company Weavely revealing only 11% of surveyed designers claim not using AI in their process. Particularly, the survey results showed designers' preference for chatbot and image generating AI, with 86% and 25% of designers claiming to have used ChatGPT and Midjourney, respectively, in design activities. While the statistical significance of Weavely's survey was not outlined and could not be independently verified, it's sample size of 393 surveyed designers offers an insight into the growing relationship between designers and AI in industry. (Weavely, 2024)

This phenomenon of generative AI in design is not limited to smaller design agencies. TATA ELXI, a subsidiary of TATA Group, has started integrating GenAI tools in its existing product design process. Designers at TATA ELXI presented an updated version of their ideation and concept development timeline, introducing GenAI tools in a non-disruptive manner. Here, rather than completely overhauling the design process to render it AI centric, TATA ELXI elected to introduce tools such as ChatGPT and Midjourney as design-assistants to support the designer centric workflow (Figure 13). The company claims that the updated timeline has resulted two times faster development. (Nimbalkar, 2024)

In 2023, Board of Innovation (BOI), a strategy and innovation consultancy aimed at design professionals, unveiled its "AI innovation Sprints", a three day AI cantered framework for kickstarting product development (Figure 14). Here, AI is again proposed as a "co-pilot" which works alongside the designer. BOI's framework plays on the ability of different GenAI tools to generate and validate "100s of ideas" in short periods of time. Throughout the sprint, GenAI is used for tasks ranging from process planning and market/consumer analysis, to generating ideas and performing end-user interviews (Decuypere, 2023). The BOI website claims for this framework to have already been implemented by companies such as TATA Consumer Products, PepsiCo and Siemens (Board of Innovation, 2023).

In 1999, Rodgers et al. explored the use of AI as a knowledge based system (KBS) to support designers in finding and implementing design knowledge, particularly in the early stages of conceptual CAD design. This system was built on an earlier CADET (Computer-Aided Design Evaluation Tool) system, modified to dynamically adapt to new and changing design knowledge in development teams. Dubbed WebCADET, the envision system made use of World Wide Web functionality to act as a repository for (Brisco et al., 2023; Lee & Chiu, 2023; Lee & Lin, 2023; Liu & Hu, 2023; Yin et al., 2023; Zhang et al., 2023)rule based design knowledge, allowing designers to access domain specific knowledge for a given task or product category (P. A. Rodgers et al., 1999). While no evidence could be found that WebCADET has been further developed or adopted at large, similar capabilities are now found in upcoming GenAI tools such as Leo™, a ChatGPT powered chatbot trained on design domain knowledge.

Image Generators

Relative to other GenAI tools, the use of readily available image generators in design processes has been the focus of much academic research.

In 2023, Liu & Hu published their research into the use of open source image generator Stable Diffusion (SD) in the design process. They found AI image generation to be particularly adept at supporting early ideation and conceptualization tasks. In their research, Liu & Hu experimented with using SD for intent mapping, sketch and shape alterations and, style transfer. By using progressively more detailed prompt inputs, they were able to create a clear progression in generated images which allows designers to show the thought process behind an AI generated design (intent mapping). (Liu & Hu, 2023)

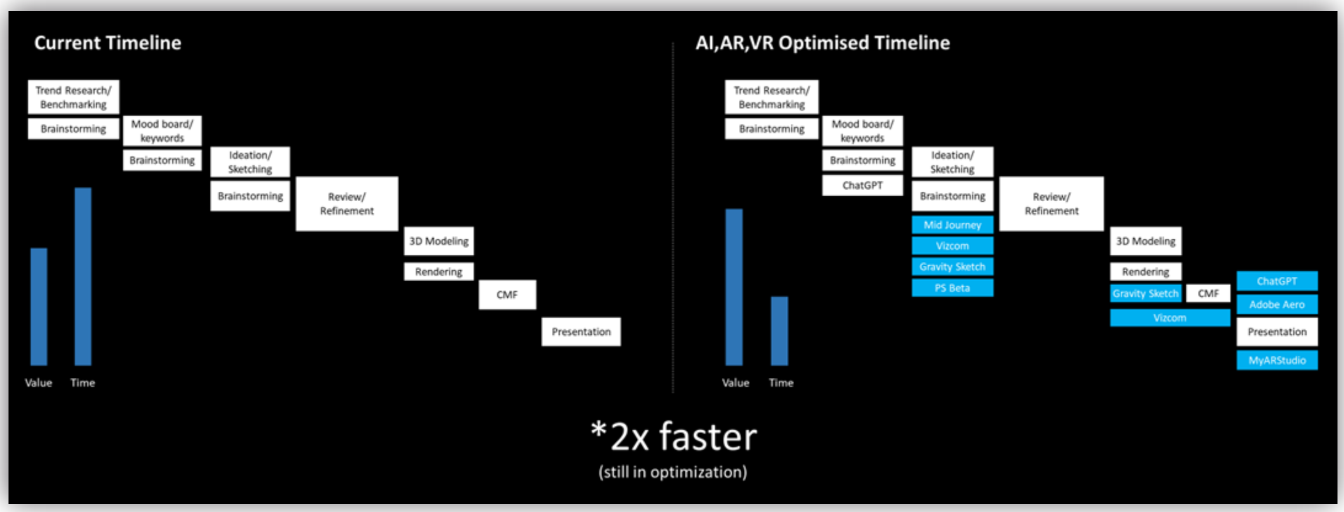


Figure 13: Non-AI (Left) and AI (Right) based development timeline by TATA ELXI (Nimbalkar, 2024)

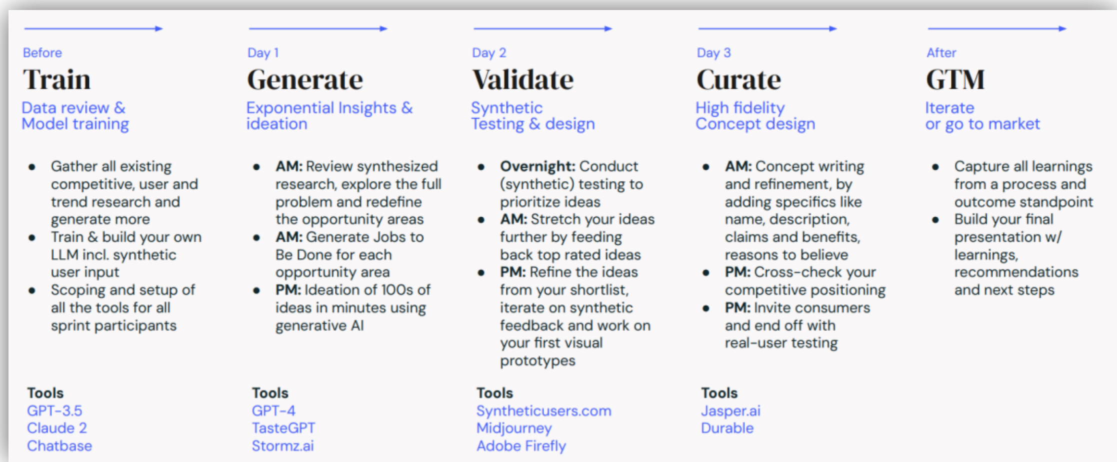


Figure 14: The AI Innovation Sprint agenda as proposed by BOI (Decuypere, 2023).

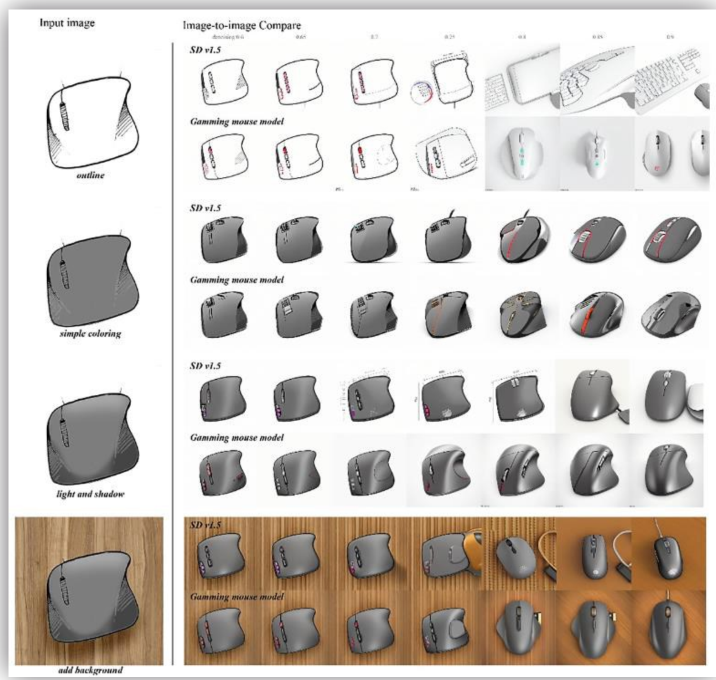


Figure 15: Input sketch variations generated using Stable Diffusion by Liu & Hu (Liu & Hu, 2023).

Leveraging SD's option for image-to-image generation, Liu & Hu were able to quickly and efficiently generate many design variations based on a single input sketch. This was done by modifying the AI's input adherence value and allowing it to deviate further from the original design (Figure 15)(Liu & Hu, 2023). Less success was found with style transfer activities, with SD succeeding in generating the intended shapes but failing to incorporate the intended style (Liu & Hu, 2023). Failure with style transfer was also noted by Lee & Lin in a separate research into the use of OpenAI's Dall-E image generating tool, with both papers pointing at how AI parses prompts as the leading cause (Lee & Lin, 2023; Liu & Hu, 2023). Specifically, Lee & Lin found that the object classifier portion of the prompt has a greater effect on the output than the style classifier (Lee & Lin, 2023). All three use cases explored by Liu & Hu saw improvements in outputs when the AI was fine-tuned to a specific subject using relevant public images (Liu & Hu, 2023).

Beyond ideation and conceptualization tasks, Liu & Hu further explored the use of SD in product rendering. To retain greater control and output coherence they proposed the use of screenshots of a blank CAD model of a chair, viewed from multiple angles, to train the AI model. This technique allowed the researchers to reach high object fidelity in the generated renders, while also modifying attributes such as colours and materials. Liu & Hu however pointed out that the quality of the renders, was not appropriate for client or product renders, and were instead more appropriate for fast internal visualization before time is invested in professional renders. (Liu & Hu, 2023)

Studies by Lee & Chiu and Yin et al. found the use of image AI as a visual stimulant during brainstorming and ideation to have positive results. Participants in the studies reported reduced design fixation by prompting AI to generate relevant but abstract shapes. Further, participants believed AI to improve co-design by providing a way for participants with sub-par design skills to adequately express their ideas in multidisciplinary groups. (Lee & Chiu, 2023; Yin et al., 2023)

Several papers also discuss the shortcomings of currently available AI tools, particularly: training data, output volatility, ease of use and, perceived creativity. Papers by Zhang et al. and Brisco et al. highlight that widely available AI tools are not sufficiently trained on design domain terminology and data, limiting the usability of said tools in a professional design environment (Brisco et al., 2023; Zhang et al., 2023). Liu & Hu, Yin et al. and Zhang et al., al found the volatility and lack of control over the AI's outputs to be detrimental for designers in professional environments, relegating the use of such tools to earlier ideation stages rather than later product visualization activities (Liu & Hu, 2023; Yin et al., 2023; Zhang et al., 2023). Affected by the issues with volatility, both Lee & Lin and Zhang et al. expressed dissatisfaction with the ease of use of AI tools in the product design domain, citing the required prompt complexity as a limiting factor in adoptability by design professionals (Lee & Lin, 2023; Zhang et al., 2023). Lastly, as generative AI generates average representations of its training dataset, Brisco et al. and Yin et al. each expressed concern for a potential increase in design biased and derivative designs (Brisco et al., 2023; Yin et al., 2023).

Tomorrow

Tomorrow tools, which are in development but require more time and investment before being suitable for widespread adoption. Withing this timeframe, academic research into AI applications in design is plentiful.

End-User Data Analytics

To deal with increased demand for customization and shortening product lifecycles, AI data analytics tools have gained traction in the product design industry. Particular focus has been given to AI systems which allow designers to more efficiently adapt to dynamic consumer expectations (Shaik Vadla et al., 2024).

Such use of AI has already emerged in industry. A 2023 Medium article by Martina Sartor, a principal product designer for AI company BrieflyAI, outlines how large data AI systems are being used to parse large amounts of consumer data to gain user insight and predict valuable UI/UX design decisions (Sartor, 2023). Similarly, a blog post by AI company Neural Concept, highlighted trends in healthcare and fashion industries where AI systems are used to examine large amounts of medical and fashion data (respectively), to identify core design requirements and needs (Neural Concept, 2024).

In academia, these design focused analytics tools are also gaining attention. Research by Shaik Vadla et al. explored the use and development of an AI driven sentiment analysis tool aimed at providing designers with data driven insights for product development. The study leveraged Google's BERT (Bidirectional Encoder Representation from Transformers) and T5 (Text-to-Text Transfer Transformer) models to automate the traditionally labour intensive process of acquiring and processing consumer expectations to extract tangible development requirements. Drawing from public and plentiful Amazon product reviews, Shaik Vadla et al.'s system was able to predict and correctly classify core design aspects and sentiments with a 91-92% accuracy. While this accuracy was achieved by training the models on domain specific keywords and concepts for eco-friendly products, Shaik Vadla et al. envision that this system may eventually provide designers with a search engine for consumer insights for any product category (Shaik Vadla et al., 2024).

Technical Development Frameworks

Beyond the realm of end user analytics, research into AI systems for design have also focused on improving technical product development capabilities.

In 2007, Chin et al. presented EPDS-1 (Expert Product Development System 1), a Failure Mode and Effects Analysis (FMEA) tool powered by fuzzy logic. EPDS-1 aimed to leverage AI architectures to assist designers in evaluating their designs through FMEA. Here, Chin et al. aimed to minimize the uncertainties encountered when performing an FMEA at conceptual stages of the design process; such as determining probabilities of failure events and predicting the interrelationship between different components and failure methods. To achieve this, EPDS-1 relied on fuzzy logic, a subfield of AI research which mathematically introduces uncertainty and vagueness into algorithmic calculations to mimic real-world uncertainties and externalities. A prototype of this system was successfully applied during the development of a printer cartridge driver (Chin et al., 2008). While the EPDS-1 framework appears not to have been further developed, it validated the use of Fuzzy logic in AI solutions as a surrogate for real-life design uncertainties.

Focusing on the use of AI in CAD applications, Krahe et al. explored the use of AI to leverage knowledge based engineering (KBE) to streamline the CAD modelling process. Here, ML methods would be used to process implicit information from a CAD component's model tree, which acts as a log of the designers modelling approach, and propose ‘next-steps’. The researchers were able to achieve 72% proposal accuracy with such a model when trained on knowledge for the relevant component. Krahe et al. highlighted that this level of accuracy is subject to fluctuation as a suggestion given by the AI may not be the only viable next step. The researchers have indicated interest in further development of this system, aiming to broaden the scope of the predictions and to implement visual representations of the AI suggestions through alterations to a given 3D geometry. (Krahe et al., 2019)

Early Development GenAI Tools
Beyond the realm of academia, since the emergence of GenAI, several industry newcomers have poised themselves to release a slew of AI tools aimed at design and engineering. While still in development and pre-release betas, these tools promise functionalities which could streamline time intensive processes in product development, particularly with CAD related tasks.

The web based application Leo™, mentioned earlier in this chapter, is currently in the development of a text-to-parametric CAD function, which would allow users to quickly generate modifiable parametric CAD models based on a textual input. The core of this technology is a new AI model being developed by the Leo™ team, which they have dubbed the Large Mechanical Model (LMM), which is allegedly able to generate CAD data (Figure 16). At the time of writing, this functionality is still in private beta. (Leo™, 2024)

French company Spare Parts 3D has instead focused on using AI to automatically convert technical drawings into parametric CAD models. The tool, named Theia, aims at reducing the amount of time spent by engineers to read, understand and convert technical drawings into 3D models (Figure 17). The company has not shared detail around the technical working of this software, which is still in beta testing (Spare Parts 3D, 2024). Similarly, independent developer Lucas Crupi is working on a SolidWorks compatible AI plug-in called FabrAIcate, which would allow users to convert 3D models into detailed and precise technical drawings (Lucas Crupi, 2024). The continued development of these two tools would likely be greatly beneficial for efficiency as designers are often required to provide manufacturers with technical drawings and, often spend valuable time modelling stock components to insert into their design.

The State of the Art
This chapter has outlined the state of the art for both current applications of AI in the design industry, and emerging ones. It is evident that, along with established implementations of AI in data analytics and simulation, great interest has been shown towards GenAI tools. Here, Chatbots and image generators, such as ChatGPT and Stable Diffusion, have already entered the industry in assistive capacities, while parametric CAD and KBE/KBS systems are being actively developed. There is however a distinct shortage of overarching methodology, with industry and academia focusing instead on defining how to apply individual systems over limited scopes. Thus, the concepts explored in this chapter, along with the requirements and industry needs defined in Chapter 4, were used to bolster the development of the methodologies proposed in subsequent chapters.

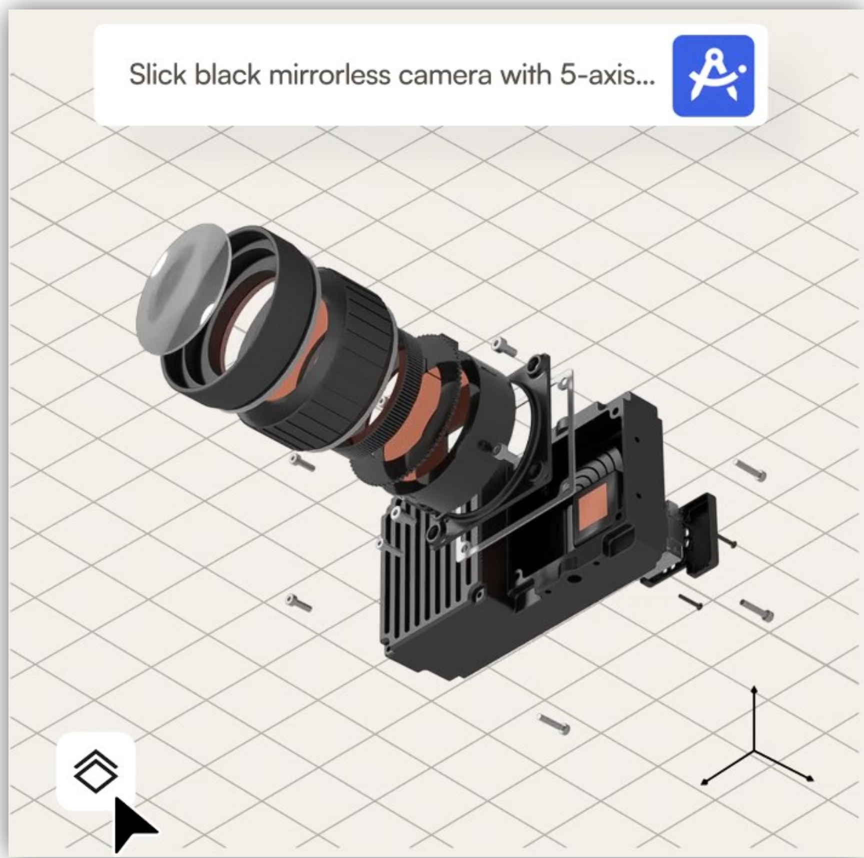


Figure 16: Promotional visual of parametric CAD AI tool by Leo™ (Leo™, 2024)

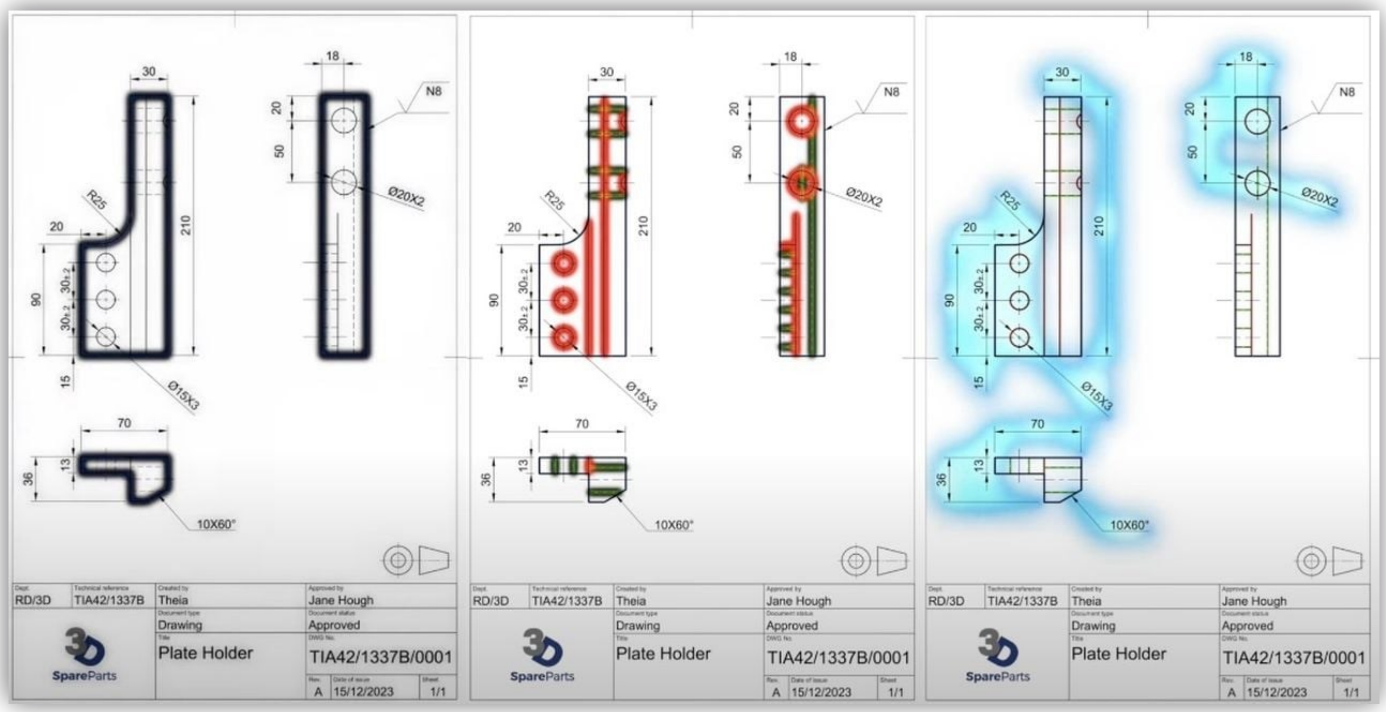
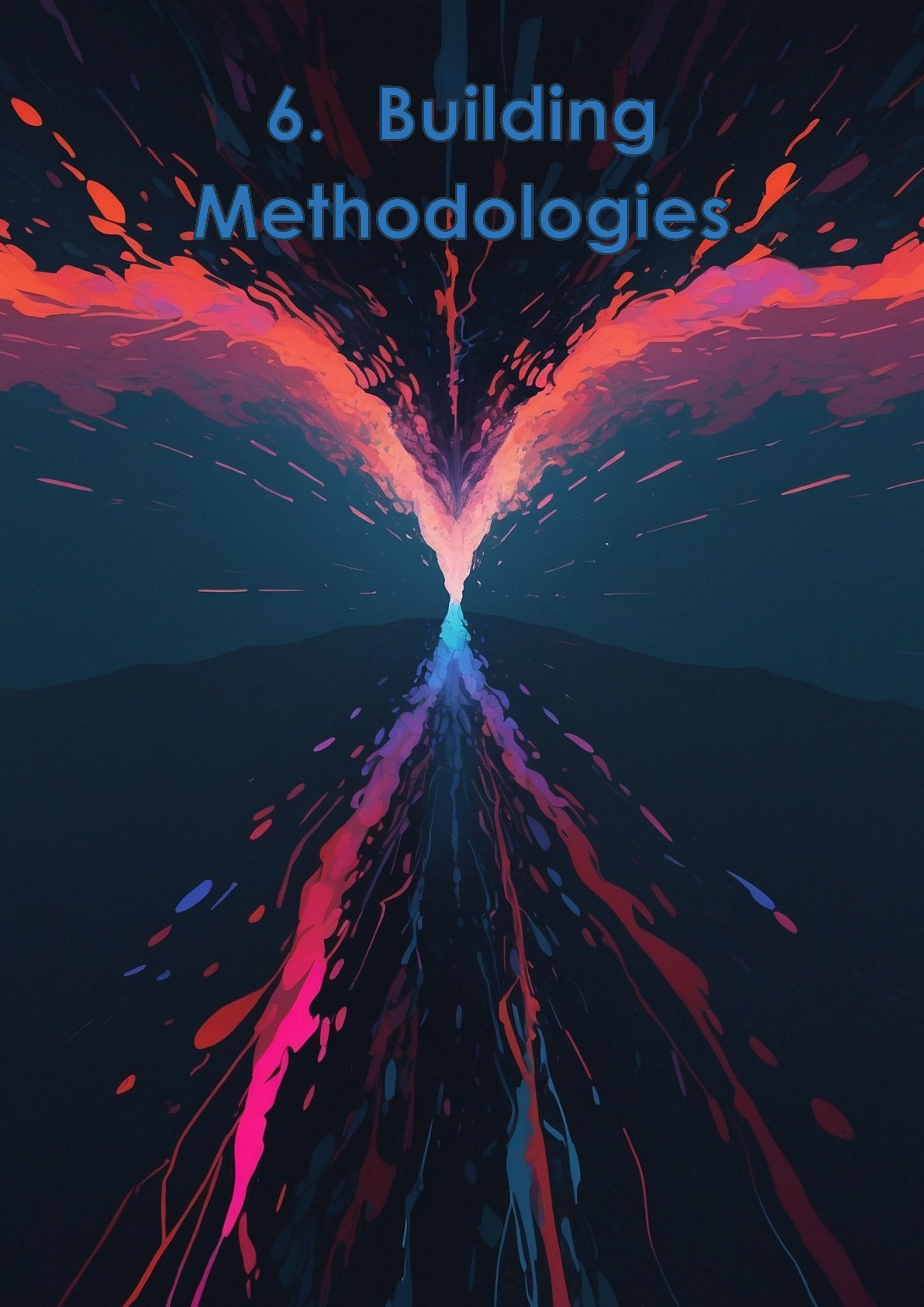
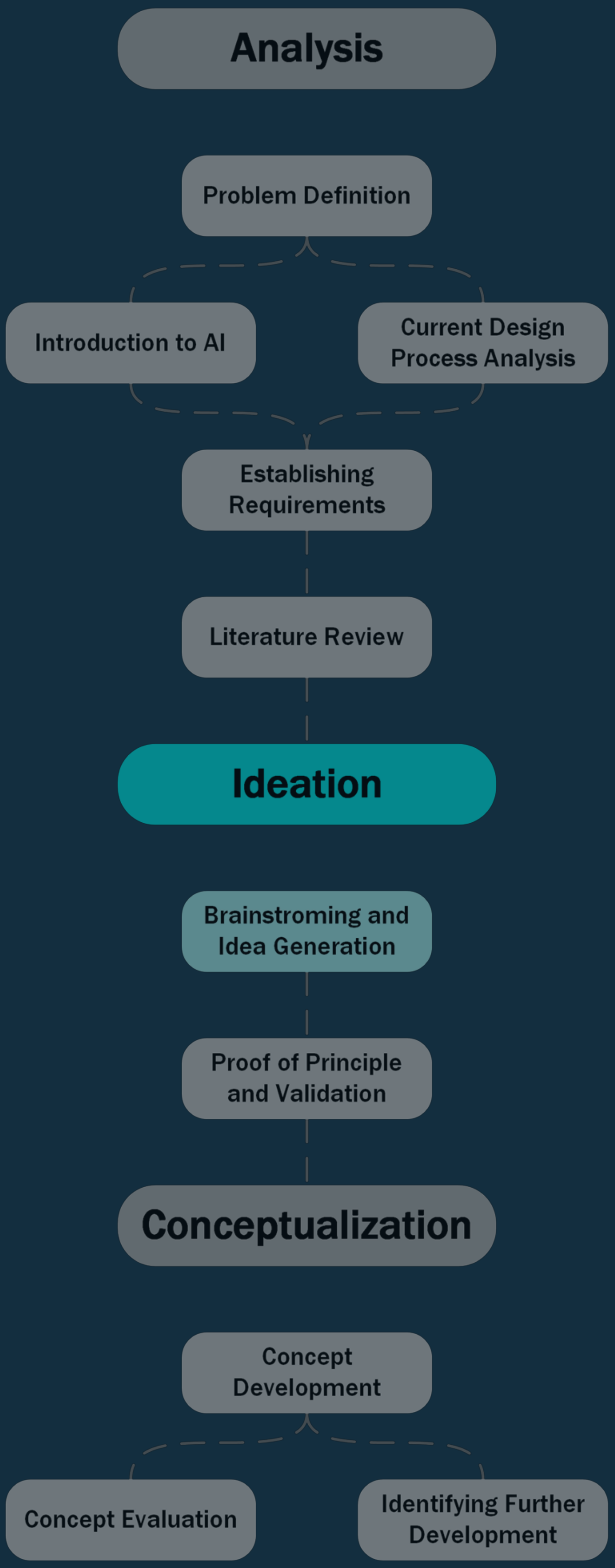


Figure 17: Visualization of Spare Parts 3D's Theia tool analysing a technical drawing before conversion to a CAD part (Stevenson, 2024)

6. Building Methodologies




Analysis
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Concept Development
Concept Evaluation
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Design Process Time-Sinks

To identify the area of the design process which would most benefit from AI integration, the WeLLDesign design process was closely examined to identity time-sinks. At the time of this exploration, the company was operating on its original 10 phase development process. In consultation with senior designers at WeLLDesign, a list of 69 design tasks, often associated with each phase, was compiled. This list, found in full in Appendix C, was used to identify WeLLDesign's time-sinks. An internal survey was performed, asking WeLLDesign employees to rate the extent to which these tasks, listed by phase, were considered as time-sinks. This survey, filled in by nine professional designers, provided an useful insight but was unable to account for two important factors: phase frequency, and phase magnitude.

Phase frequency refers to how often designers are involved in a given phase and, subsequently, its related tasks. On the other hand, phase magnitude is the measure of how much of a projects time budget is assigned to a given phase. Failure to account for these two factors would have led to inaccurate inferences about which tasks require optimization, potentially prioritising infrequent and low magnitude tasks with a high time-sink ratings over frequent, high magnitude tasks with lower time-sink ratings. To account for these factors, the author applied two sets of weighted multipliers (Table 3) to the initial survey results: frequency and magnitude. The frequency multipliers were extrapolated from the 10 year project retrospective presented in chapter 3 (Figure 8), with each design phase being assigned a value representing the percentage of projects in which they were undertaken. The magnitude multipliers were instead derived from a second internal survey, in which designers were asked to rate each design phase on a scale from 1 to 10, with 1 representing a phase which makes up a near negligible portion of the average projects time budget, and 10 representing on which makes up a significant portion. These multipliers were applied to each tasks rating to calculate a weighted rating.

The tasks were subsequently ranked based on the weighted rating, with higher ratings indicating greater time-sinks to be optimized. Here, some previously highly ranked tasks from Project Management, Preparation for Production and Market Research dropped in the ranking. Conversely, previously mid-rank tasks in the Concept Design phase climbed the rankings. The top 15 (orange) and bottom 15 (green) tasks are shown graphically in Figure 18. Out of the 30 top rated time-sinks; 7 focused on document creation, 6 on technical development, 5 on planning, 5 on sketching and visualizing ideas, 3 on research, 3 on sourcing and 2 on other tasks.

Presented with these results, WeLLDesign management indicated that AI integration should be avoided for financial or planning tasks such as budget and time estimations. This decision was driven by issues with AI explainability. Here, explainability can be viewed as a subjective requirement, affecting tasks differently based on the level of understanding required for a designer to trust a given output. With financial and planning tasks, which produce high-risk quantitative outputs directly affecting the success of a development project, any AI tool is required to be highly explainable, allowing designers to properly identify and explain to clients how and why a decision was made. Inversely, tasks such as image generation, which generate relatively low-impact qualitative outputs, the threshold for acceptable explainability is low, increasing the number of acceptable AI implementations. Along with the complete avoidance of AI for financial and planning tasks, WeLLDesign leadership further stressed the importance of human oversight and review of AI outputs, particularly in technical development.

Table 3: Per-phase weight multipliers for identifying time-sink tasks

Phase	Frequency weight	Magnitude weight	Resultant weight
Project Management	1	3.75	3.75
Data & Documentation	1	4.75	4.75
Market Research	0.167	3.38	0.56
Acquisition	0.524	5.5	2.88
Analysis	0.905	5.13	4.64
Ideation	0.976	5.25	5.12
Concept Design & Early Engineering	0.905	6.25	5.66
Concept Prototyping	0.857	6.75	5.78
Functional Engineering	0.69	7.38	5.09
Product Prototype	0.643	7.38	4.75
Preparation for Production	0.357	7.38	2.63
Production Prototype	0.429	6.63	2.84

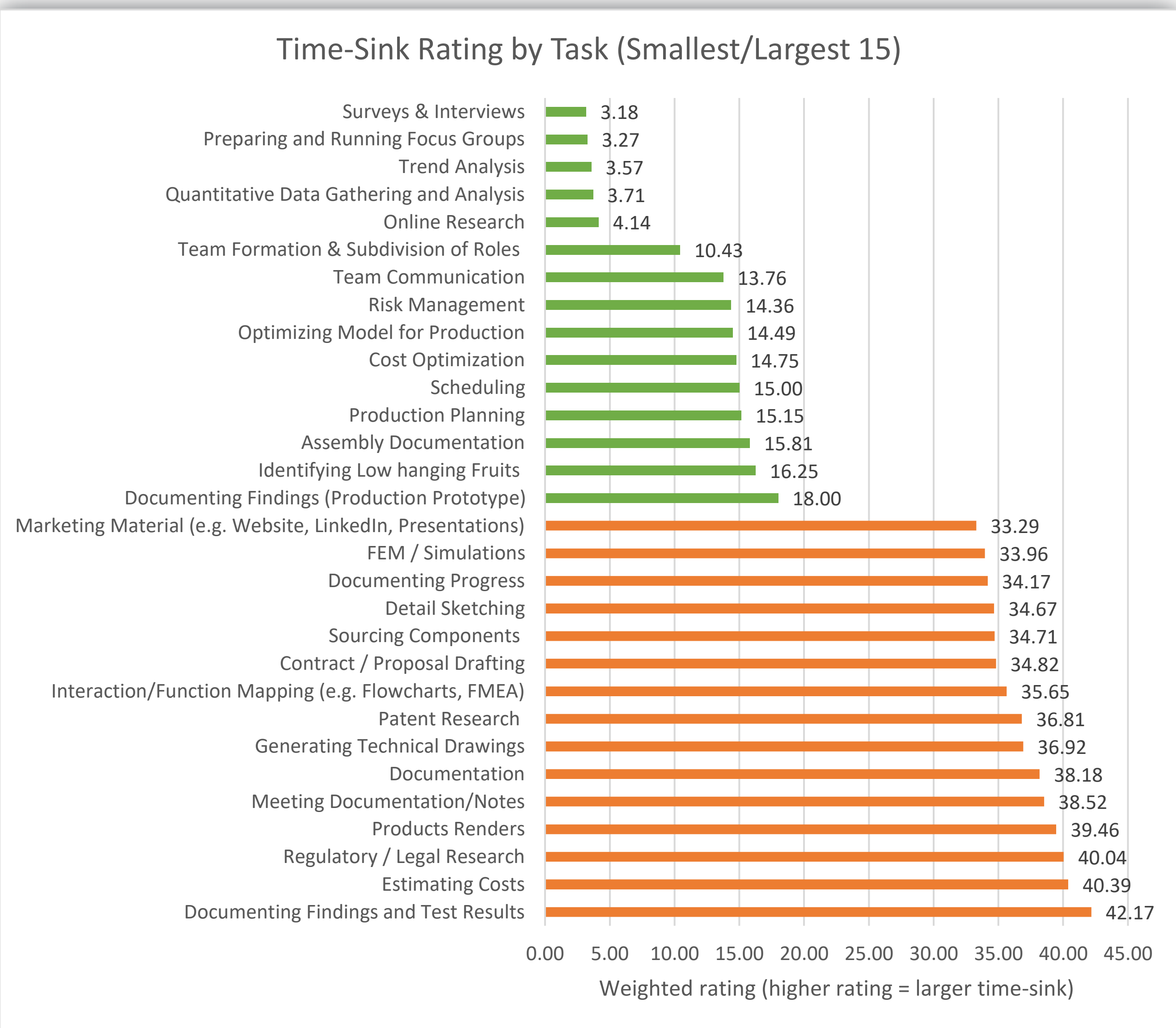


Figure 18: Largest 15 (orange) and smallest 15 (green) design time-sinks ranked by weighted rating

Task Categorization

As previously mentioned, throughout the duration of this research, WeLLDesign's design process was updated. While this update most notably reduced the number of phases from 10 to 6, it also led to the development of a standardized list of phase specific tasks. This change was announced immediately following the ranking process, resulting in differences between the tasks used for ranking and the newly established tasks. Despite these differences, it was possible to map the most relevant time-sinks onto the new standardized tasks, as shown in Figure 19. Here, AI compatible tasks are marked with what is broadly recognized as the symbol for AI: ✨ (Shah, 2024).

This change in design process and tasks highlights an inherent issue with designing AI methodologies around specific tasks or phases: adaptability. While the differences were minimal to the point where successful mapping was possible, it is not granted that future changes will offer similar adaptability. Thus a categorization system to minimize this dependency was introduced. In a previous work, the author proposed a development process framework, adapted from Liu & Hu's 4 stage design process, aimed at maximising AI potential by applying AI systems to classes of activities rather than to predefined tasks (Liu & Hu, 2023; Serra, 2024). To adapt this process framework into a meaningful categorization framework, the individual stages were divided into independent task categories, no longer representing a process flow, but rather standalone categories in which design tasks can be subdivided. Shown in Figure 20, a total of 5 categories were derived: Planning and Documentation, Ideation and Conceptualization, Validation and Development, Visualization and Contextualization and, Manufacturing and Logistics.

The Planning and Documentation category represents all tasks for which the output is the creation of a document, ranging from simple meeting notes (minutes) to detailed project proposals.

Ideation and Conceptualization tasks are those which aid the process of identifying ideas or concepts relevant to the development goals. These include tasks such as brainstorming sessions, problem analysis and general research.

Tasks in the Validation and Development category are primarily engineering tasks aimed at developing ideas or concepts into workable solutions. Multidisciplinary communication, CAD, prototyping and testing all fit within this category.

Visualization and Contextualization refers to any task whose output is a visual representation of an idea or concept, from sketch ideation to product renders.

Lastly, Manufacturing and Logistics tasks focus on ensuring a design is appropriate for production. Common tasks include sourcing of materials and components, as well as communication with manufacturers and planning for assembly.

By structuring AI implementation frameworks and methodologies around these task categories rather than for individual tasks, the frameworks become highly adaptable and expandable. That is, such AI methodologies can be implemented with any given development process, with no alterations to the core flow of tasks, by simply identifying which category the relevant asks belong to. Because of this, the methodologies become largely unaffected by changes in an individual's design process. This concept further applies in the inverse, as changes to the AI methodologies, driven by developments in AI technologies, do not directly impact the structure of any given development process.

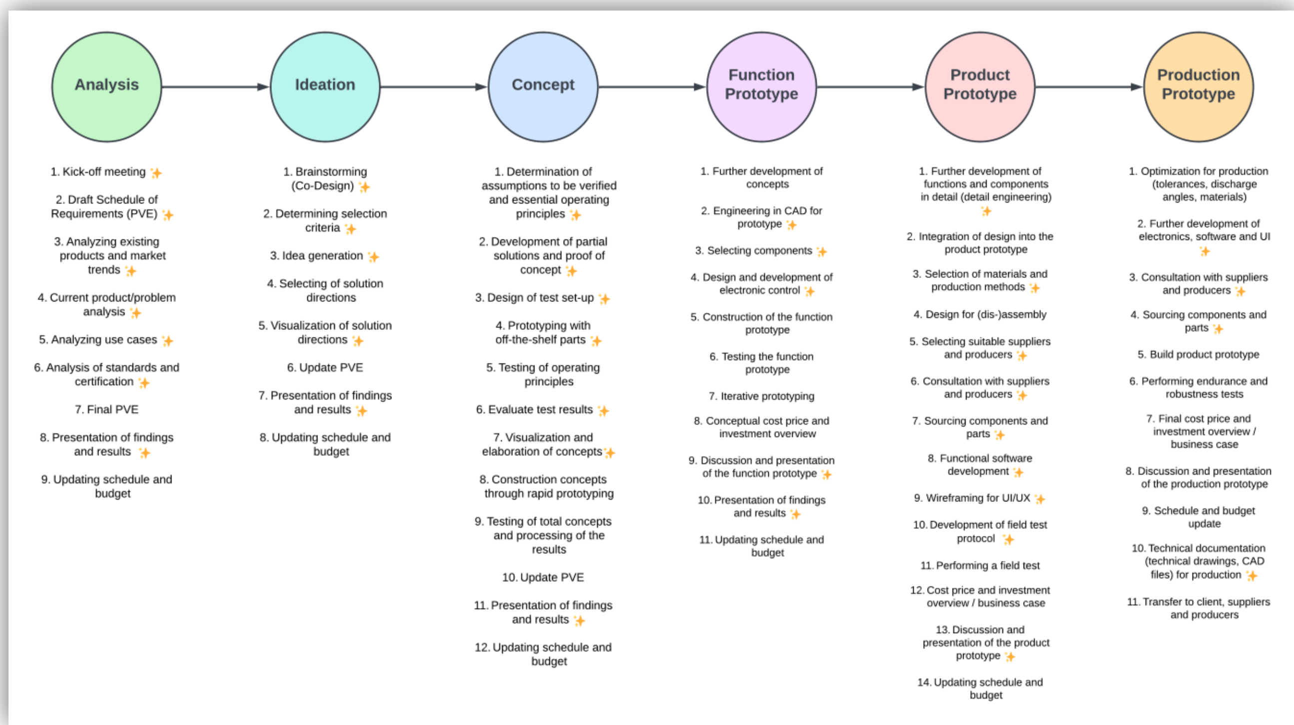


Figure 19: AI compatible tasks (✨) mapped onto WeLLDesign's new 6-phase process

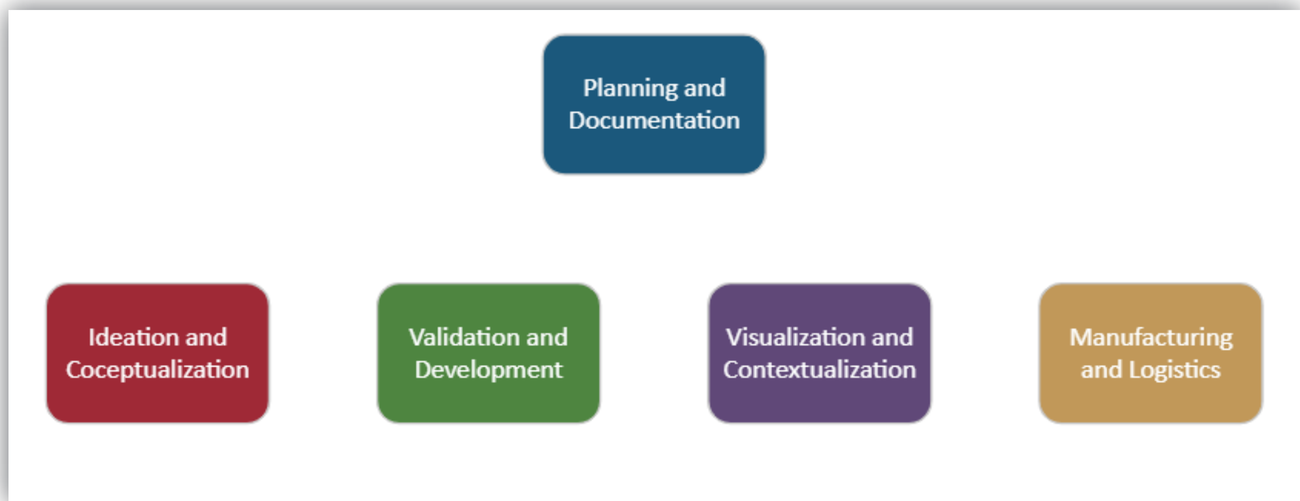


Figure 20: The 5 Task Categories

Drafting WeLL-AI Methodologies

To guide the ideation process, and to benefit from the previously discussed adaptability of task categorization, AI relevant tasks from WeLLDesign's six phase design process were categorized. As shown in Figure 21, The tasks were further grouped into sub-categories. Here, the intent was to further allow individual methodologies to cover multiple tasks by identifying groups of tasks with similar outputs. In total, 13 potential sub-categories were identified, these are outlined in Table 4.

For each sub-category, leveraging past design experience and literature insights, a matching methodology was ideated. Through this process, 14 draft methodologies were proposed, with Visualization 2 being split into "a" and "b". These 14 proposals, in the form of process flowcharts to make them easy to follow and apply, can be found in Appendix D. The process through which the Visualization 1 methodology was drafted acts as a well-rounded exemplar of the ideation process undertaken to ideate on all 14 methodologies.

Table 4: Draft Task Sub-Categories

Sub-Category	Description
Documentation 1	Presentation of finding and of prototype
Documentation 2	Document creation
Documentation 3	Note Taking
Documentation 4	Emailing and communication
Ideation 1	Kick-off and brainstorming
Ideation 2	Analysis and research
Development 1	Designing test set-ups
Development 2	Prototyping with off-the-shelf components
Development 3	Multidisciplinary co-development
Development 4	Interaction and function mapping
Visualization 1	Visualizing initial solution directions
Visualization 2	Rendering
Manufacturing 1	Process / material / manufacturer selection

Figure 21: Draft categorization of WeLLDesign's AI compatible tasks

Drafting Methodologies: Visualization 1

The first step in structuring each methodology draft was to identify how a given sub-category of tasks is usually approached by designers. Here, the author leveraged five years of design domain education, mixed with two years of practical industry experience and an intimate knowledge of WeLLDesign's processes, to define the basic building blocks of each methodology. In the case of Visualization 1 tasks, which focus on early stage design sketching for ideation, these building blocks included: previously defined solution directions, low fidelity sketching, shape studies and sketch refinement.

These building blocks were cross referenced with literature, identifying relevant past AI integrations. For Visualization 1, inspiration was found in Liu & Hu's use of image generating AI for shape variation and style transfer for iteration and visual stimulation (Liu & Hu, 2023). Combining this with Lee and Chiu's further assertions of the benefits of image AI for less skilled sketchers, the idea of a methodology in which AI is leveraged to help designers quickly generate higher quality sketch variations was introduced (Lee & Chiu, 2023; Liu & Hu, 2023). Here, in contrast to Liu & Hu's work, which separated the use of text prompts (style transfer) and image guidance (sketch variations), the two prompting techniques were combined to retain greater control over the outputs. By doing so, designers could input both a guidance image, and a style transfer prompt, to output large numbers of tailored sketch variations.

Lastly, the requirements set in chapter 4 were considered and applied. With Image generation activities, sustainability and data security requirements were of particular importance. Within WeLLDesign, sketching activities were found to be of particularly enjoyable for the team. Thus, the methodology was made to account for designer centric activities such as initial sketching, shape studies and manual sketch detailing and refinement. The inclusion of these activities was further bolstered by concerns over IP retention, as ensuring ownership of the final design is essential in professional environments. For this, by ensuring that AI is only applied on designer made sketches, the risk of accidentally infringing on existing design IPs is limited. Further, by using the AI's outputs as inspiration for shape studies and manual refinement, and setting the AI to only output basic, monochromatic line sketches, designers are more likely to meaningfully deviate from derivative designs in such a way that no IP infringement occurs.

These concepts were then combined into meaningful methodology frameworks, in the form of flowcharts, to guide design engineers through the process of implementing AI in a given sub-category of tasks. As such, the Visualization 1 methodology (Figure 22) presents the following workflow:

1. Drawing from previous project data, a designer makes basic, black and white, ideation sketches
2. The sketches are uploaded to an image generating AI as image guidance for the output
3. The designer establishes a prompt, outlining the subject/object and the desired style or feature
4. The designer uses AI to generate relevant sketch variations, updating prompt and image guidance between generations
5. Sketch variations are used by the designer as inspiration for shape studies and detailing
6. The designer's final sketches are presented and/or stored in project documentation for later use.

In the framework, as presented in Figure 22, solid lines represent the main process flow, while dotted lines were used to symbolize either a transfer of data or a recursion in the process. Grey elements were used to represent additional, optional activities, such as the use of AI to upscale and detail individual sketches.

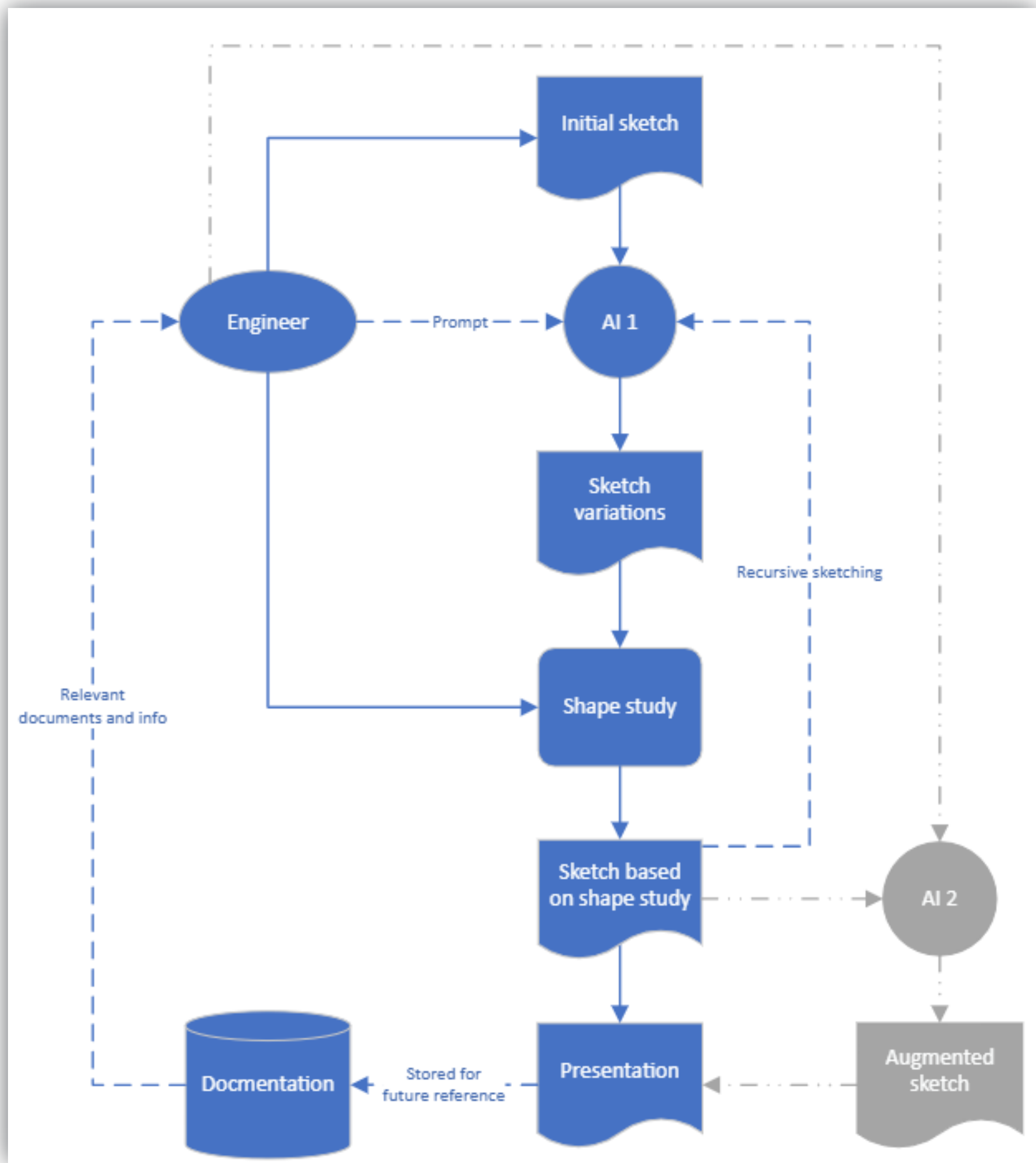
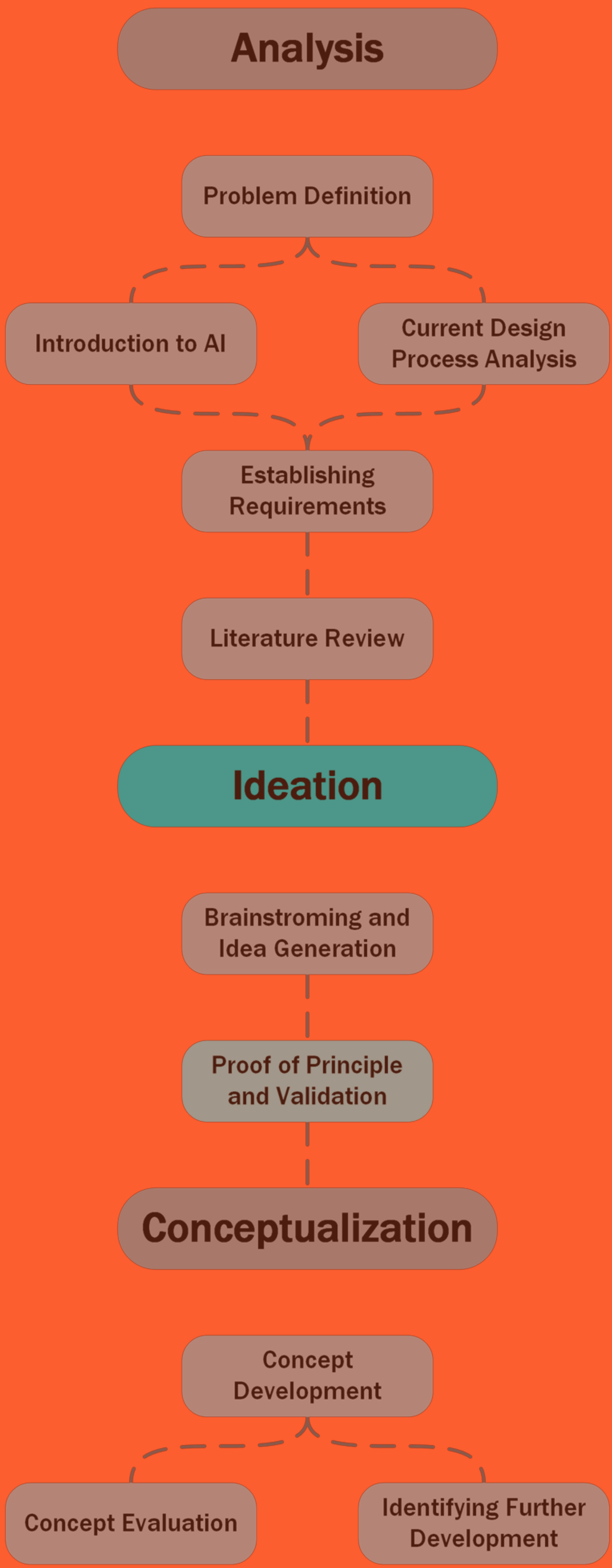


Figure 22: Draft AI Methodology - Visualization 1

7. Case Study Implementation


Analysis
Problem Definition
Introduction to AI
Current Design Process Analysis
Establishing Requirements
Literature Review
Ideation
Brainstroming and Idea Generation
Proof of Principle and Validation
Conceptualization
Concept Development
Concept Evaluation
Identifying Further Development

Of the 14 draft methodologies, 9 were applied to evaluate their efficacy and to identify strengths and weaknesses. Throughout these implementations, where possible, a quantitative evaluation of the methodologies effects on efficiency were conducted through thorough time tracking. Simultaneously, qualitative observations regarding factors such as ease of use, bottlenecks and process strengths were recorded.

To ensure the reliability of the qualitative evaluation, a project, based on a hypothetical product class, with WeLLDesign acting as the client, was carried out using the drafted methodologies. For this, expert WeLLDesign engineers outlined a project plan, defining relevant tasks to be performed and their associated time budget. This time budget was based on the expected time required to perform the tasks without AI in a professional design environment. To accurately simulate real life professional scenarios, where WeLLDesign engineers work within a known time budget, the author was presented with both the selected task and their associated time budget. Throughout the duration of this activity, the author precisely logged the time spent on each task using a digital timer to emulate the internal time logging system used by WeLLDesign.

The implementation project revolved around the design of a hanging lamp with sound absorbent properties, focusing specifically on the Analysis, Ideation and Concept phases of development. The end outputs of this case study project were a developed concept design (Figure 23) and a workable testing plan for determining the design's sound absorption qualities. While this case study does not represent an active, ongoing or strictly confidential project at WeLLDesign, this chapter will share limited technical information on the exact workings and context of the product being developed. Focus is instead given to evaluating the tangible impact of using the draft AI methodologies. The full list of tasks, along with the relevant time budgets and the logged development times can be found in Appendix E.

Figure 23: Context render of the hanging lamp concept developed for the implementation case study

Documentation 1

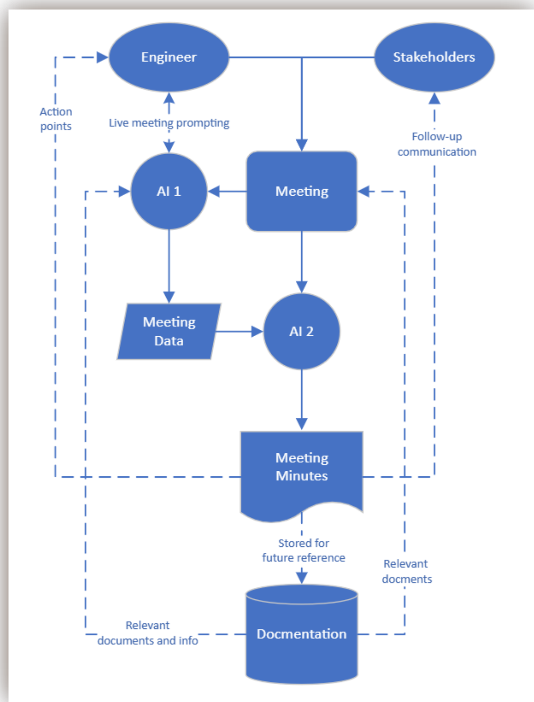


Figure 24: Draft AI Methodology - Documentation 1

Use Case and Observations:
The Documentation 1 methodology was applied during a client presentation at the end of the Analysis phase. Here, Copilot for Teams was used to serve as both "AI 1" and "AI 2" as it offers both live-meeting prompting and post-meeting summary functions. Following the methodology, the author was able to fully immerse in the meeting without needing to frequently pause to take meeting notes. Live-meeting prompting, which allows participants to query the AI about meeting insight or relevant documents during the meeting itself, was not used, suggesting that, while a potentially useful addition, it may not be applicable to all meeting scenarios. Following the meeting, it was observed that the notes (minutes) generated by the AI, which records and transcribed the meeting to use as an input, were not sufficiently detailed or structured to be sent to external stakeholders (clients) directly. Instead, the author found success in manually copying the AI minutes into a Word document and refining the output, using key words and concepts, noted on a post-it during the meeting, to prompt the AI into providing higher levels of details.

The structure of the flowchart itself was found to be, at times, convoluted and hard to follow, with no clear distinction between AI and non-AI functions and processes. Because of this, it was not immediately clear how the user should interact with the AI and, importantly, what data or information they must provide. This was particularly true for processes around AI 1

Effect on Efficiency:
Presentation of findings and results: 1.7% increase in efficiency (from 2 hours to 1 hour 58 minutes)

Quantitatively, evaluating this methodology purely on the basis of time saved, it would appear the introduction of AI during meetings as a note taking tool did not meaningfully affect efficiency. However, this fails to account for the fact that, with a scheduled meeting, participants will make full use of the scheduled time. When evaluated qualitatively, the use of AI allowed the participants to focus fully on the meeting, allowing for a greater breadth and depth of topics to be discussed within the same timeframe.

Documentation 2

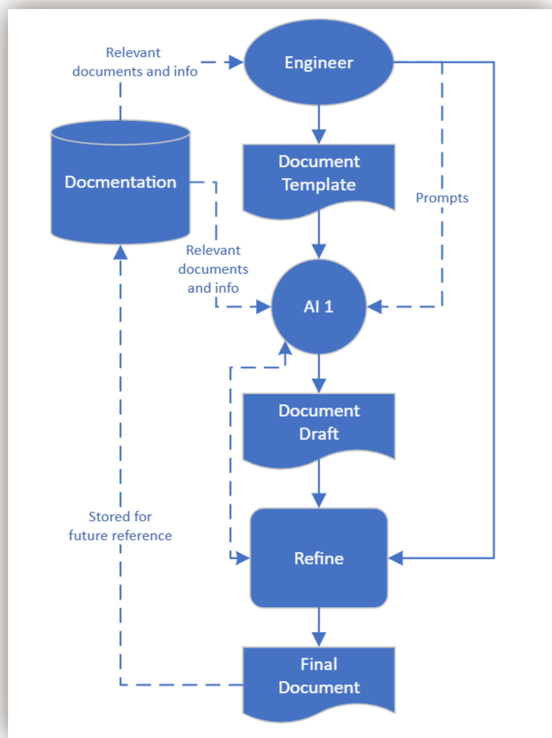


Figure 25: Draft AI Methodology - Documentation 2

Use Case and Observations:
Within the case-study, this framework was used to prepare the PowerPoint slides used to present the findings from the Analysis phase to the client. Here, Microsoft's Copilot for PowerPoint was used to generate relevant slides based on a text file containing all the analysis' research notes. This did not provide workable results pointing to two limitations: inability of the AI to build off a document template and, a lack of detail in the AI's output. Due to its currently limited capabilities, Copilot for PowerPoint could only be prompted to generate whole presentations from existing documents, without the option for the user to leverage the AI to refine individual slides or texts.

To confirm whether these limitations were specific to presentation drafting, a separate test was performed, using Copilot for Word to draft a hypothetical project plan based on WeLLDesign's standard template. Here, the author encountered better results as the AI could be prompted to generate and refine individual portions of text.

Ultimately, for the case study, Copilot, along with ChatGPT, was used as a tool to generate structure suggestions based on the notes, rather than to draft the presentation's content. Thus, contrary to the draft methodology, AI was used to indirectly, rather than directly, draft documents, with the user acting as a buffer between the AI generated content and the drafted document.

Effect on Efficiency:
Presentation of findings and results: 9% increase in efficiency (from 4 hours to 3 hours 39 minutes)

Despite the bottlenecks present in the draft methodology, the shift to using AI as an indirect assistive tool allowed for an increase in the author's efficiency, as the author was able to quickly identify a relevant presentation structure based on the research notes.

Ideation 1

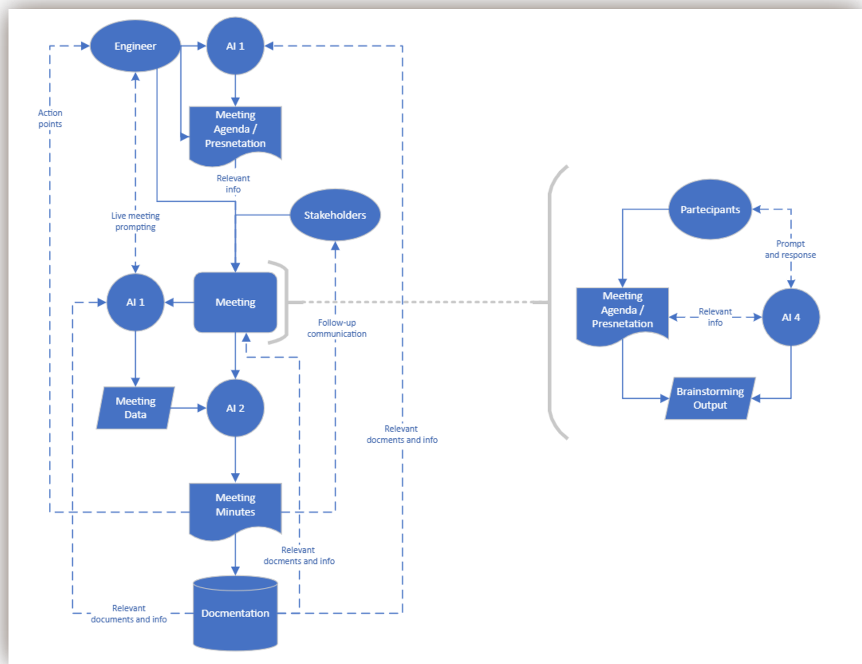


Figure 26: Draft AI Methodology - Ideation 1

Use Case and Observations:
The Ideation 2 framework was applied to two separate case-study tasks: the initial project kick-off and, the initial brainstorming during the ideation phase. Upon implementation, it became evident that the proposed methodology was plagued by redundancies, unnecessary processes and a lack of detail regarding the interaction between user and AI.

The author observed that, when applied to the initial project kick-off, the successful aspects of the methodology shared distinct similarities to the processes described by Documentation 1 and Ideation 2, benefitting from the AI's ability to summarize meetings and documents (respectively).

The author was able to implement AI in brainstorming activities by using insights from project documentation as inputs for both Board of Innovation's AI tools and ChatGPT, successfully identifying potential target groups, product ideas, design directions, market trends and product-user interactions. However, this was found to be a more complex user-AI interaction than that presented around "AI 4" in Figure 26, requiring users to identify key-words and concepts, prepare detailed prompts and, discuss and refine outputs into meaningful information. Furthermore, the proposed framework assumed brainstorming activities to only occur in meetings or groups, precluding use in independent brainstorming contexts.

Efficiency:
Project kick-off: 40% increase in efficiency (from 1 hour to 35 minutes)

Not only was the use of AI able to reduce the time needed for the author to familiarize himself with the project by rapidly and accurately summarizing existing documents, it also increased the likelihood of the user identifying details which could have otherwise been lost in documentation.

Brainstorming: 14% increase in efficiency (from 4 hours to 3 hours 28 minutes)

Similarly, the use of AI for brainstorming both reduced the time spent on the task, and presented the author with ideas or concepts which would have otherwise not been considered or thought of, allowing for a greater depth of ideation.

Ideation 2 & Manufacturing 1

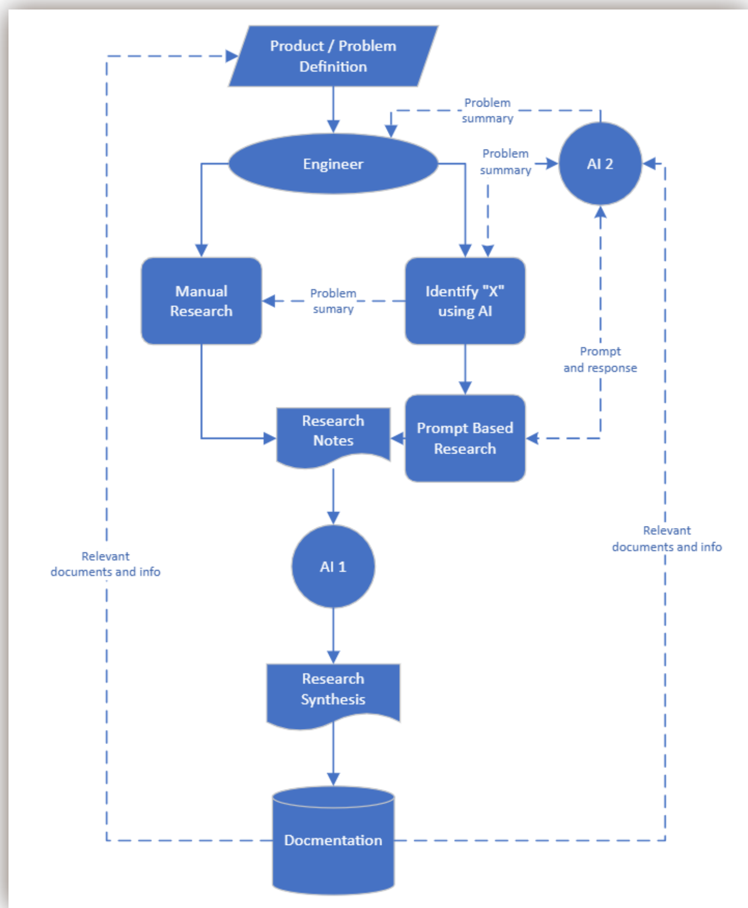


Figure 27: Draft AI Methodology - Ideation 2

Use Case and Observations:
Revolving around similar uses of AI as research and analysis tools, Ideation 2 and Manufacturing 1 were the two most successful draft methodologies in the case-study implementation.

Ideation 2 was applied to tasks such as: drafting PVE (schedule of requirements), analysing standard, market trends, patents and use cases and, to identify potential selection criteria during ideation. Here, an important step, in ensuring successful use of AI, was the user's ability to identify the topic of research and transfer it into functional prompts for the AI. This was represented in the methodology by a manual research process, working in parallel with a logic loop which leveraged "AI 2" to help the user to first identify a problem summary and subsequently perform AI based research. It was found that, while the methodology accurately represents the way in which AI can be leveraged in research and analysis tasks, its flowchart representation (Figure 27) remains hard to follow and lacks a detailed overview of the internal workings of the "Prompt Based Research" process. Further, the use of "AI 1" to generate a research synthesis document, was found to be redundant, with raw research notes providing a greater breath of knowledge for later use as project documentation for other tasks and methodologies.

Manufacturing 1 provided a similar experience when applied in the development of partial concept solutions to identify potential production methods, materials and components. However, in contrast to Ideation 2, which was presented with a convoluted flowchart, Manufacturing 1 was presented as a slim process, depicting AI as a secondary research tool and prioritizing manual research. This representation was found to be an oversimplification of a process which, when put into practice, more directly mimicked the balance between manual and prompt-based research of Ideation 2.

Efficiency:

Draft PVE: 3% decrease in efficiency (from 3 hours to 3 hours 5 minutes)

Marking the first instance of one of the proposed methodologies resulting in a decrease in efficiency, however minimal, applying Ideation 2 in defining design requirements highlighted the volatility of AI use. Here, the author encountered difficulty in formulating prompts which would results in actionable outputs, leading to repeated attempts. While ultimately generating the desired outputs, this came at the cost of an increase of time spent on the task. This can be partially attributed to a learning curve, with this implementation representing the authors first use of this methodology. This pitfall signals the importance of remaining cognisant of whether, when initial prompting does not succeed, it is worth it to continue. Nonetheless, the use of AI for document summaries was found to be particularly helpful, allowing the designer to quickly identify relevant standards and regulations and, to parse through them with little time and financial investments. It can therefore be observed that, of the two activities, the one which leveraged AI as an primarily assistive tool for summarizing documents, rather than for generating content, was most successful. This strengthened the idea of assistive AI.

Analysis: 43% increase in efficiency (from 16 hours to 9 hours 10 minutes)

In stark contrast to the decrease in efficiency seen with drafting a PVA, the use of the methodology in the aforementioned analysis tasks significantly improved process efficiency. Here, balance between manual and prompt-based research was found to be of critical importance. Particularly, the use of AI as a research assistant to build on and broaden the users knowledge based on inputs form manual research. ChatGPT, as "AI 2", was prompted based off the users initial project knowledge, with the outputs being subsequently used to guide manual research and as inspiration for progressively detailed prompts. This interaction culminated with the use of a well-structured prompt for the fast processing of more than 20 web-shop listings, to extract specific details such as prices, features and materials. To confirm whether the significant time decrease was the result of sub-par or underdeveloped research, the research notes were presented to an expert WeLLDesign engineer, with years of relevant professional experience. The expert concluded that, not only was the scope of the research appropriate, but the quality and depth of information surpassed what is typically expected of such an analysis.

Selection criteria: 23% increase in efficiency (from 1 hour to 46 minutes)

Building off the learning curve experienced with the application of Ideation 2 in drafting requirements, the author was able to more efficiently leverage ChatGPT to identify potential design direction selection criteria. The AI's ability to process existing documents was once again of particular use, allowing for the user to upload contextual information and requirements, guiding the AI towards actionable outputs. Here, the importance of user refinement was highlighted, as the outputs, despite being relevant and actionable, required rewording and restructuring before they could be applied as selection criteria.

Partial Solutions: 16% increase in efficiency (from 16 hours to 13 hours 26 minutes)

Leveraging both the Ideation 2 and Manufacturing 1 methodologies, the use of AI for developing the selected ideas into viable concepts presented a series of quantitative benefits along with the increase in efficiency. Applying Ideation 2 for in-the-moment research, the author was able to identify and resolve development and contextual questions or assumptions which would have otherwise gone unnoticed. Similarly, Manufacturing 1 allowed the user to identify unfamiliar production processes and stock components using natural language prompts. This ability to use natural language prompts was particularly helpful, as it allowed the author to describe specific processes or components without knowing the official, technical, nomenclature typically required for conventional research.

Development 1

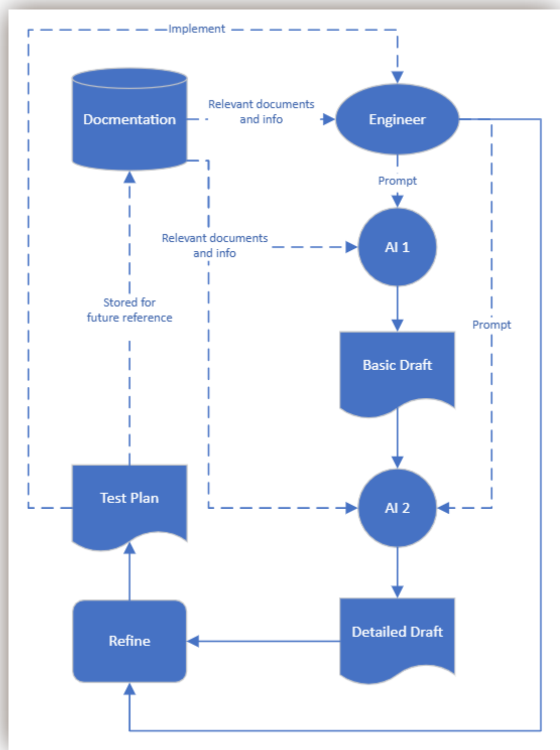


Figure 28: Draft AI Methodology - Development 1

Use Case and Observations:
Despite its flowchart representation lacking a clear progression for the user to follow, the core concepts presented by Development 1 proved to be successful in optimizing the test-setup design process. The use of ChatGPT, as "AI 2", to quickly and accurately process information form regulations and standards, made it easy to find and add relevant detail to basic test plan drafts. Here however, the AI's ability to provide insight and details about relevant standards, even those typically only accessible through an expensive purchase, renders the user refinement step all the more important. While the insight provided allows the designer to create proposals for testing plans at low investment costs, once approval is received, the designer must gain direct access to the relevant standards and refine the plan accordingly. Lastly, the split between "AI 1"and "AI 2" was found to be redundant, as both systems were intended to serve a similar function.

Efficiency:
Design test setup: 25% increase in efficiency (from 4 hours to 3 hours 1 minute)

Both quantitatively, with a 25% increase in efficiency, and qualitatively, by providing otherwise hard to access information, the Development 1 methodology showed potential for positively impacting the design process.

Development 4

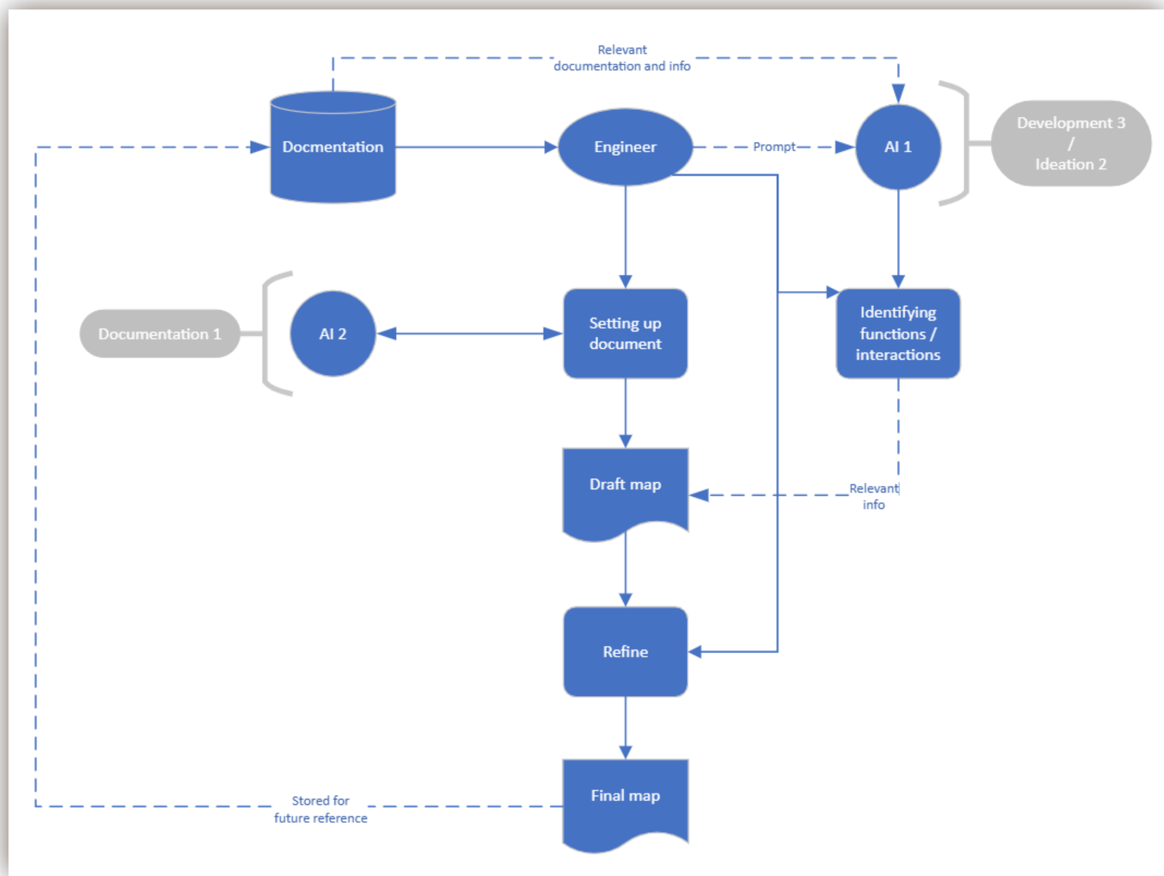


Figure 29: Draft AI Methodology - Development 4

Use Case and Observations:
Despite successfully using ChatGPT to identify potential operating principles and functional assumptions for each design idea, the Development 4 methodology was found to be hard to follow. That is, the flowchart representation included several non-core steps which greatly complicated the methodology with no added benefit. As such, implementation focused predominantly on the interaction between the user and "AI 1", with the use of contextual documents and prompts driving the implementation's success. Once again, the user refinement step was essential in converting the raw AI outputs into viable information to guide product development.

Efficiency:
Identify assumptions / operating principles: 13% increase in efficiency (from 1 hour to 52 minutes)

Despite initial difficulties with prompt refinement, the implementation resulted in a net, increase in efficiency. From a qualitative standpoint however, it is to be noted that the level of user refinement required for identifying assumptions and potential operating principles was likely lower than that required for more influential mapping such as FMEAs. That is, while assumptions and operating principles serve as inspiration to guide early development processes, FMEA like tasks require more concrete, exact and explainable outputs as they greatly affect decision making. Hence, the time spend by a user in refining the AI's output may increase for other tasks, affecting the methodology's efficiency.

Visualization 1

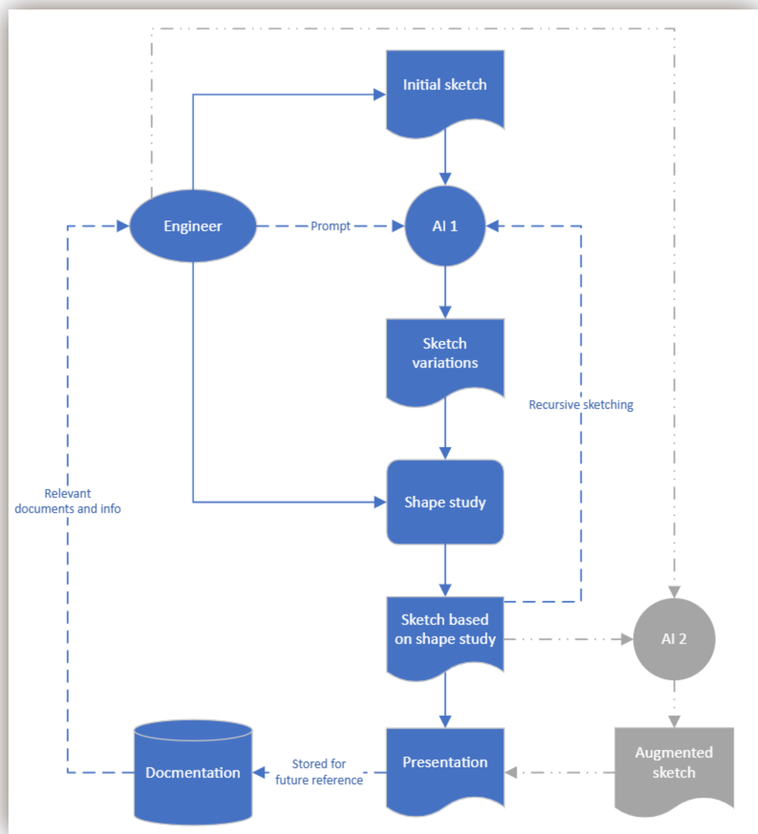


Figure 30: Draft AI Methodology - Visualization 1

Use Case and Observations:
Representing the greatest decrease in efficiency posed by the draft methodologies, use of AI (LeonardoAI) to generate ideation visualizations was filled with issues. These issues however, do not stem from the core concepts outlined in Visualization 1, but rather with the complexity and limitations of image generation AI tools. Within the context of the case-study, the author used a series of low-detail, black and white ideation sketches as image guidance inputs, paired with detailed style and feature prompts, to generate sketch variations (Figure 31). This was however broadly unsuccessful, leading the author down a time consuming path of prompt iteration which was ultimately fruitless, with often unintelligible outputs. By contrast, when the same methodology was applied to a different subject, a rain barrel, fast and meaningful sketch variations were successfully generated and applied to a shape study (Figure 32). This dissonance may be due to the way the AI parses prompts, and its training dataset, with certain key-words and subjects being easier for the AI to process and recognize than others. This hypothesis aligns with observations made by both Lee & Lin and Liu & Hu, who found AI image generators often struggle to accurately parse specific concepts or classifiers (Lee & Lin, 2023; Liu & Hu, 2023).

Efficiency:
Idea generation and visualization: 37% decrease (from 5 hours to 6 hours 52 minutes)

In the case-study implementation, efficiency was affected both in terms of time and in terms of the tasks output quality, with the AI generating few, if any, meaningful sketch variations. Despite these downfalls, the rain barrel example showed the methodology's potential. Thus, it is likely that, by introducing flowchart elements outlining the prompting process, and by making early evaluations of the AI's contextual success, the methodology could result in increases in efficiency.

Figure 31: Basic sketch of a handing lamp design (left) and some of its AI generated variations (right), generated using LeonardoAI

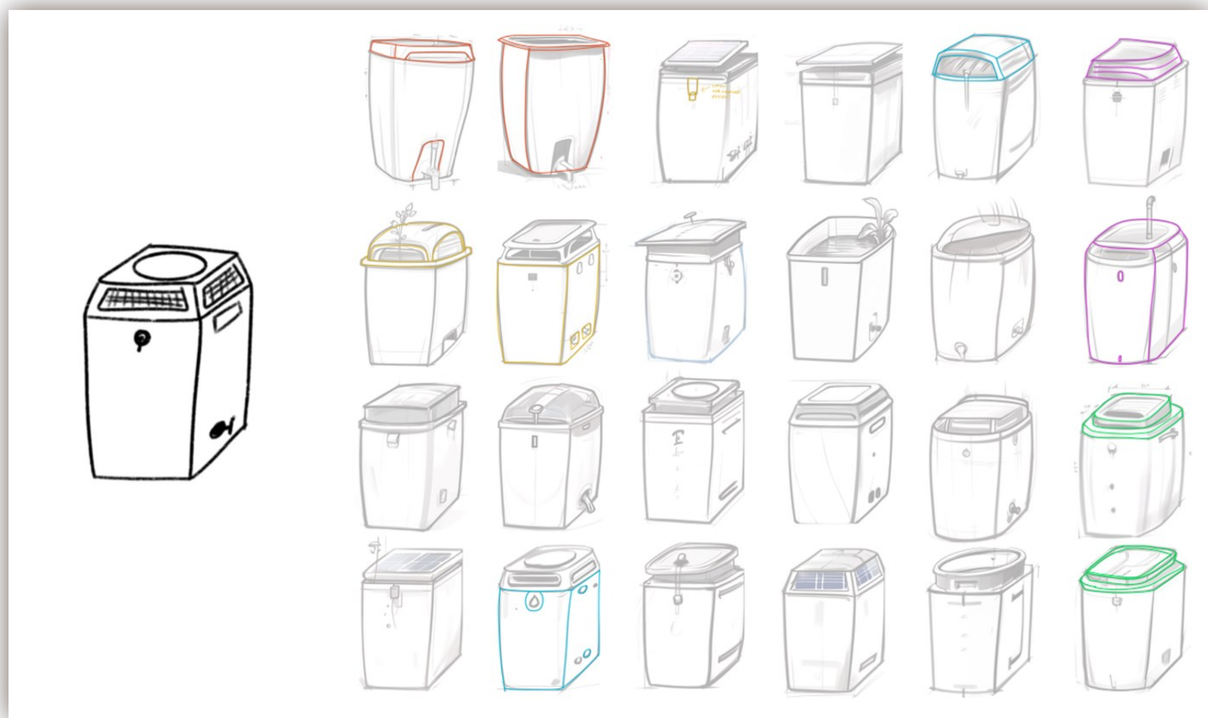


Figure 32: Basic sketch of a rain barrel (left) and its AI generated variations used for a shape study (right), generated using LeonardoAI

Visualization 2

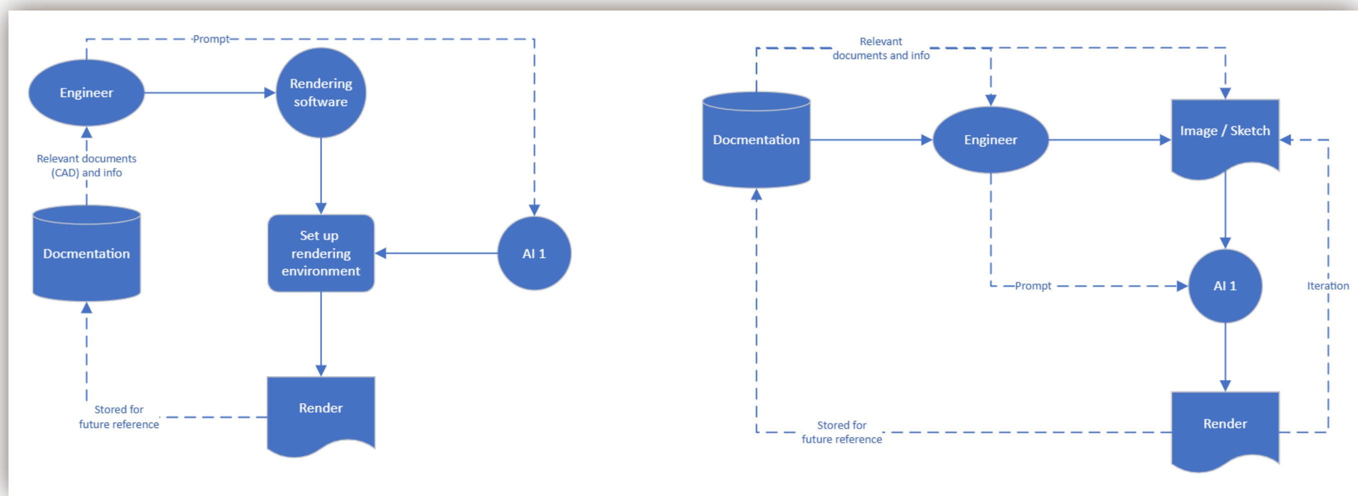


Figure 33: Draft AI Methodology - Visualization 2.a (Left) & 2.b (Right)

Use Case and Observations:
Following the precedent set by Visualization 1, the use of the Visualization 2 methodologies to generate renders was largely unsuccessful. Here, the methodology flowcharts were clear and simple to follow, however, the core substitutive processes were found to be non-conductive to usable product renders. This was particularly true for Visualization 2.b, where the AI tools did not provide sufficient control over the generated output. This manifested in 2 ways: shape inconsistencies, with the AI altering core geometries, and, prompt adherence, with the AI prioritizing some elements over others. For Visualization 2.a, the methodology was limited by a lack of broadly available and reliable AI plug-ins for professional rendering software. While some plug-ins were found for the Blender software, the author was unable to implement them, either due to outdated documentation, or due to data privacy limitations. Ultimately, the author found success by combining aspects of the two methodologies, using Blender to generate conventional renders (Figure 34), and Photoshop's AI powered Generative Fill to add details to the render (Figure 35), relegating the use of AI from substitutive to assistive.

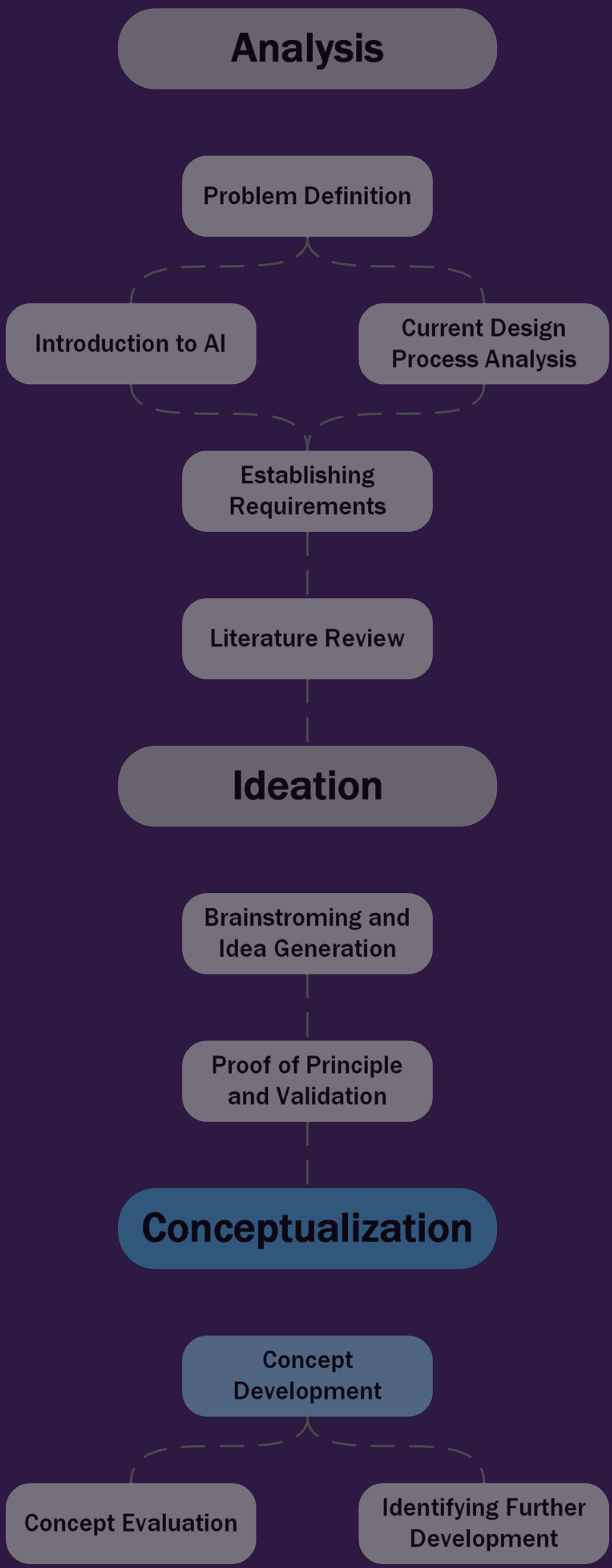
Efficiency:
Renders: 6% decrease in efficiency (from 8 hours to 8 hours 30 minutes)

Despite initial time-sinks caused by trying to set up and use the AI tools as proposed by the methodologies, the switch to using AI to add details to existing renders showed promise in improving efficiency. This approach allowed the author to focus on making good looking renders without needing to set up the time consuming and detailed environments or elements which could later be added with AI.

Figure 34: simple hanging lamp render made using Blender, no AI augmentation

Figure 35: Hanging lamp render with AI generated elements (TV and whiteboard), using Photoshop's Generative Fill

8. Revision


Analysis
Problem Definition
Introduction to AI
Current Design Process Analysis
Establishing Requirements
Literature Review
Ideation
Brainstroming and Idea Generation
Proof of Principle and Validation
Conceptualization
Concept Development
Concept Evaluation
Identifying Further Development

Building on the observations from applying the draft methodologies in the case study project, the proposals were revised and restructured into eight improved concept methodologies for WeLLDesign to implement (Appendix F). Here, green is used to indicate AI specific processes, grey for optional processes, solid lines to indicate process flows and, dotted lines to indicate flows of data and information. These aesthetic changes serve to increase legibility and ease-of-use.

Documentation 1: Meetings and Minutes
A direct upgrade to the original Documentation 1 draft, the updated Documentation 1 methodology streamlines the proposed workflow. Here, a single AI is adopted to serve both in-meeting and post-meeting functions. This AI is made a central, yet primarily passive component of the methodology's workflow, able to perform its core note-taking functions with minimal user intervention. Despite the primarily passive implementation of AI, the methodology outlines active in- and post-meeting interactions between the user and the AI. It instructs users to take note of important meeting key-words and concepts to use as prompt components when asking the AI for detailed meeting summaries. Lastly, a user refinement step was introduced to convert the AI's output into reliable and usable information. For its ability to parse relevant documents, translate, record and transcribe meetings and generate detailed summaries, Microsoft's Copilot for Teams AI system is recommended as "AI 1".

Documentation 2: Document Creation
Drawing on the weaknesses of its predecessor, the new Documentation 2 methodology focuses on the importance of using AI as an assistive tool in document creation. As such, two separate AI interactions are outlined at different stages of document creation. The first sees AI tools used by the designer to suggest how a document should be structured, defining chapters and concepts for the user to develop further. The second involved AI as a content editor after the user has established a document draft, suggesting edits to the user's content, tone and wording. The methodology is again capped with a user refinement step, ensuring a buffer between the AI generated content and the final document. For both interactions, given the currently available AI tools, the use of ChatGPT and Microsoft's Copilot for Word is recommended.

Ideation 1: Brainstorming
A major shift from its original form, the updated Ideation 1 methodology refocuses on specific brainstorming activities rather than on meeting procedures as its predecessor did. Here, the onus is placed on the user to select which type of brainstorming activity is most relevant, with the methodology being largely unaffected by whether the activity is performed by one or more users. While, currently, only 2 brainstorming activities are explored in detail, they both follow a similar structure, requiring the user to interact with the AI systems based on identifiable key-words and concepts, and ultimately requiring output refinement by the user. As such, it is possible, in the future, to adapt this basic structure to additional brainstorming activities. For visual stimulation activities, proven by Lee & Chiu to benefit from the use of AI, image generation tools such as LeonardoAI and Ball-e are recommended (Lee & Chiu, 2023). ChatGPT and Board of Innovation's AI tools are instead recommended for problem definition tasks.

Ideation 2: Analysis and Research
Maintaining the core structure of its draft, the concept Ideation 2 methodology provides more details into how prompt-based research should be structured. Here, the core building blocks of a successful prompt are presented to inform the user of which data they must provide the AI. Additionally, further importance is given to refinement, not only of the AI's output, but also of the user's prompt, improving the balance between user and AI and allowing for progressively more detailed research. Here, ChatGPT is suggested for all web-based research, while Microsoft's Copilot is recommended for internal document summaries.

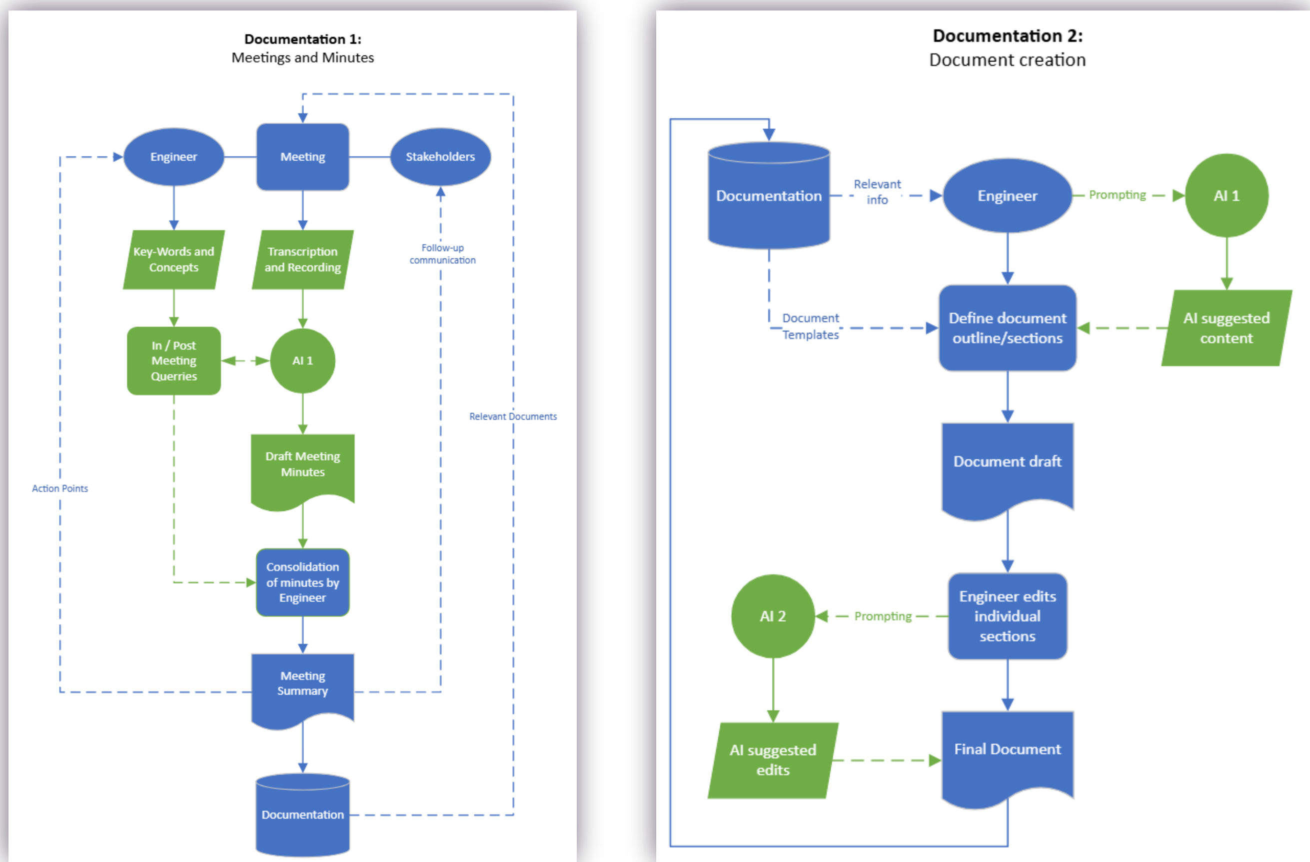


Figure 36: Concept Methodologies - Doucmentation 1 (Left), Doucmentation 2 (Right)

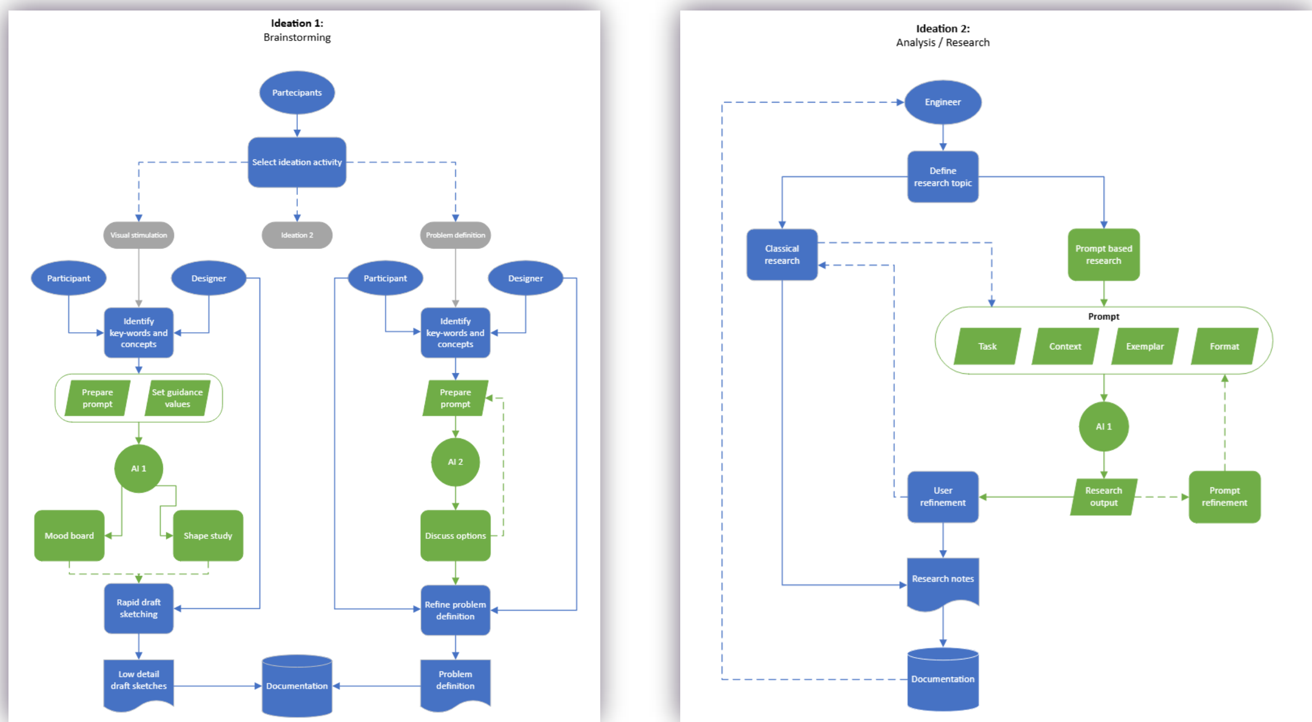


Figure 37: Concept Methodologies: Ideation 1 (Left), Ideation 2 (Right)

Development 1: Development Activities
Inspired by the updated structure of Ideation 1, the new Development 1 concept framework not only improves on its predecessor, but also integrates the former Development 3 and 4 drafts into a simple to follow workflow. This merger was possible as each of the three activities was found to benefit from similar uses of AI, namely, as a research and development partner. Here, the user must define the development scope and outline the activity's structure before AI is introduced. This is done to ensure the user is able to properly outline the context and activity which the AI must operate in. Unlike the original Development frameworks, the new concept does not focus on generating a finalized document or plan, but rather on how AI is leveraged by the user to progress the relevant development activity. For their ability to provide detailed engineering knowledge in a natural language format, the ChatGPT and Leo™ AI tools are currently recommended.

Manufacturing 1: Sourcing and Selection
Given the workflow similarities observed during the case study implementation, the Manufacturing 1 methodology was updated to mirror the new Ideation 2 concept. Here, the only tangible differences between the two concepts are the users focus, the prompt structure, and the final output. Rather than defining a research topic, the user is instructed to define sourcing parameters, that is, identifying the specific functions or properties the object of the research must satisfy. Defining these parameters is essential for proper prompt formulation, guiding the AI towards relevant outputs. Lastly, following user refinement in the form of selection, bill of materials (BOM) or other such sourcing document is developed rather than detailed research notes. Similarly to Ideation 2, the proposed AI tools consist of ChatGPT, for its access to online information, and Microsoft's Copilot, for its ability to parse internal documents and communications with suppliers.

Visualization 1: Ideation Sketching
Expanding on the user-AI interaction required to successfully implement image generating AI tools in ideation sketching, the updated Visualization 1 concept focuses on two factors: the inclusion of a "go/no-go" decision, and the fleshing out of relevant image generation parameters. The inclusion of a "go/no-go" decision serves to avoid potential users spiralling into time-inefficient and recursive prompting when AI is repeatedly unable to generate meaningful results. Further, by outlining which input parameters, such as guidance values and prompts, affect the AI's output, the methodology's learning curve is reduced. These changes highlight the importance of the users ability to critically asses the activity's success and to respond appropriately, either by adjusting relevant input parameters, or by making an early decision to forgo the use of AI. Powered by Stable Diffusion's open source architecture, and thus offering greater control over input parameters compared to its competitors, LeonardoAI's image generator is recommended for use with this methodology.

Visualization 2: Concept Renders
Having identified the unreliability of AI image generators in generating accurate, controllable and repeatable product renders, the Visualization 2 methodology was reshaped to focus on the interaction between traditional rendering methods and AI augmentations. Following the process ultimately used during the case study implementation, the updated framework instructs users to use traditional rendering to generate basic renders, which are later augmented by the using AI. Here, the methodology outlines input parameters which the user may consider while using AI to add details to a renders. For its simplicity use, and integration into a commonly used software suite, Adobe Photoshop's Generative Fill tool is recommended for prompt based detailing. Additionally, users may choose to leverage Vizcom's live canvas editing features, which allow users to highlight, sketch, and introduce reference images on top of an existing image as inputs to generate real time modifications.

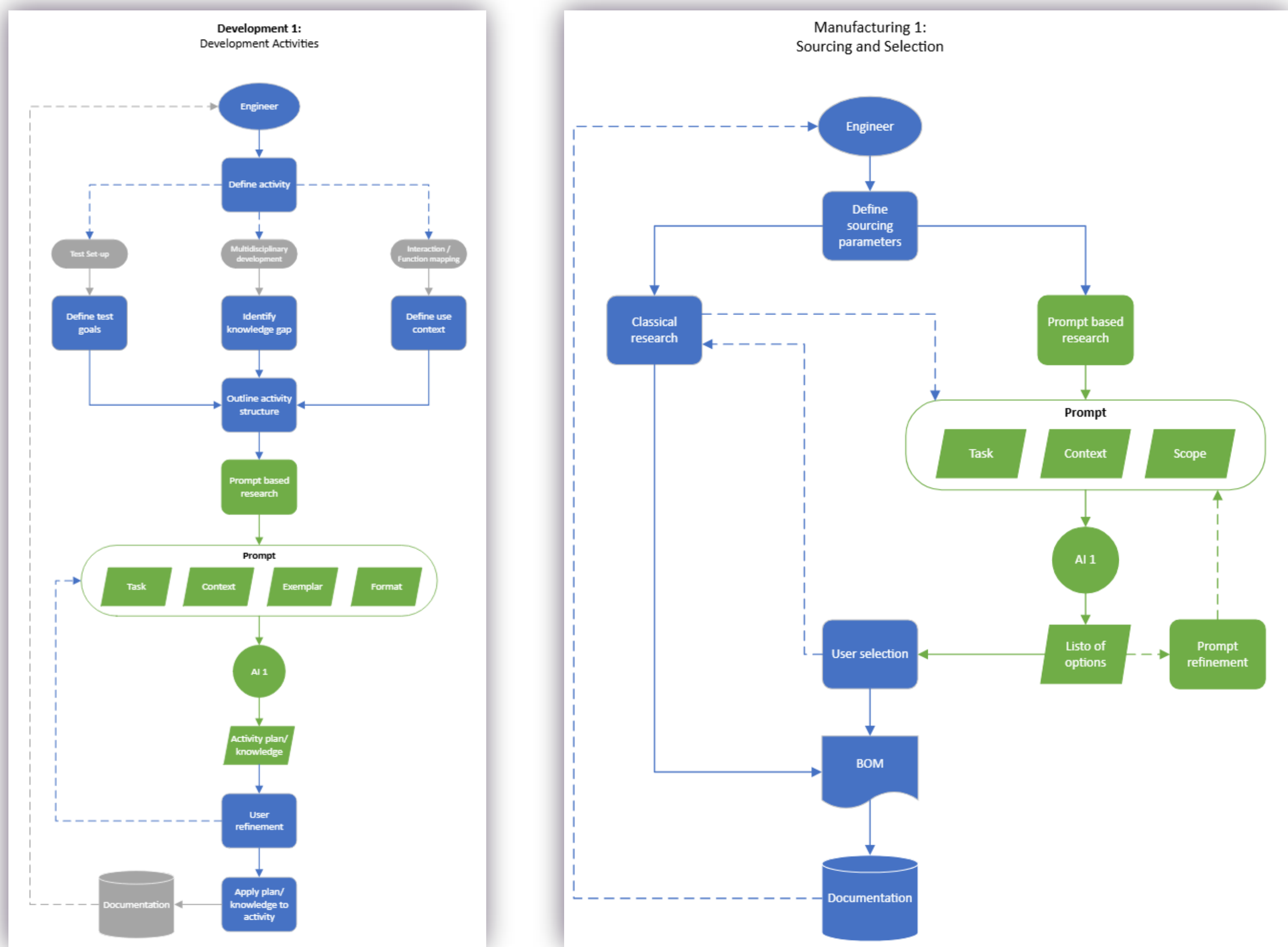


Figure 38: Concept Methodologies: Development 1 (Left), Manufacturing 1 (Right)

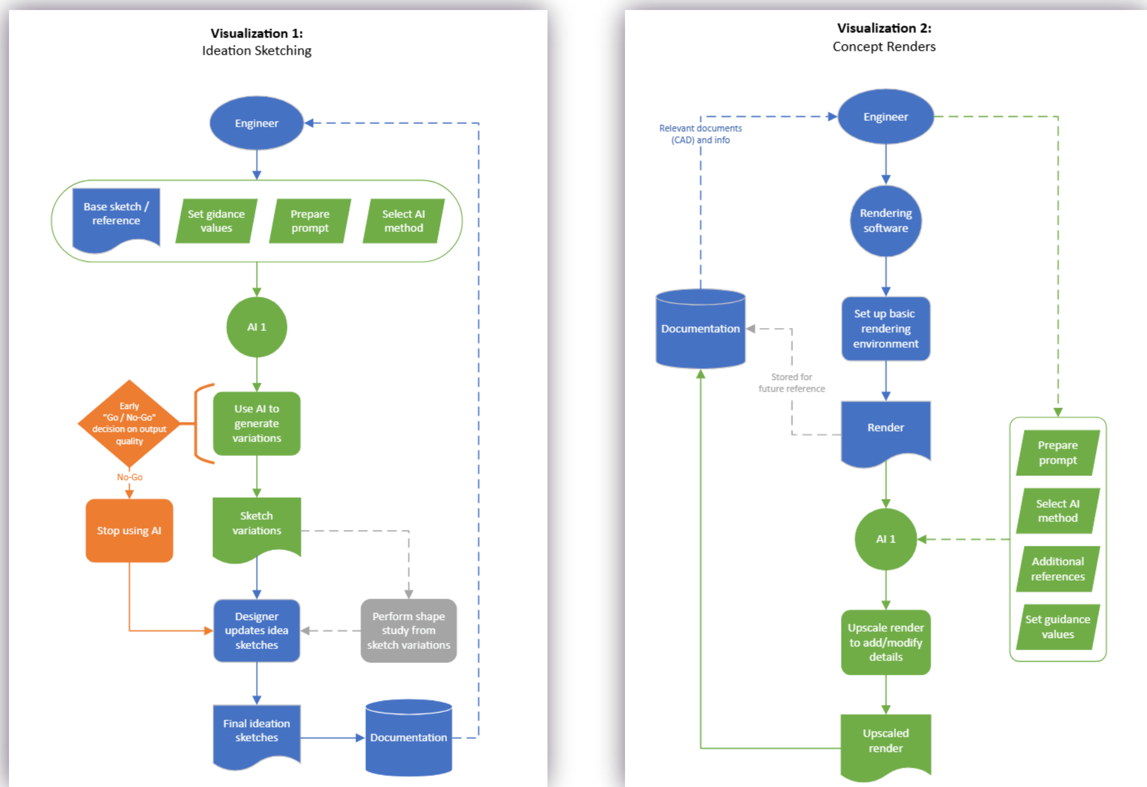
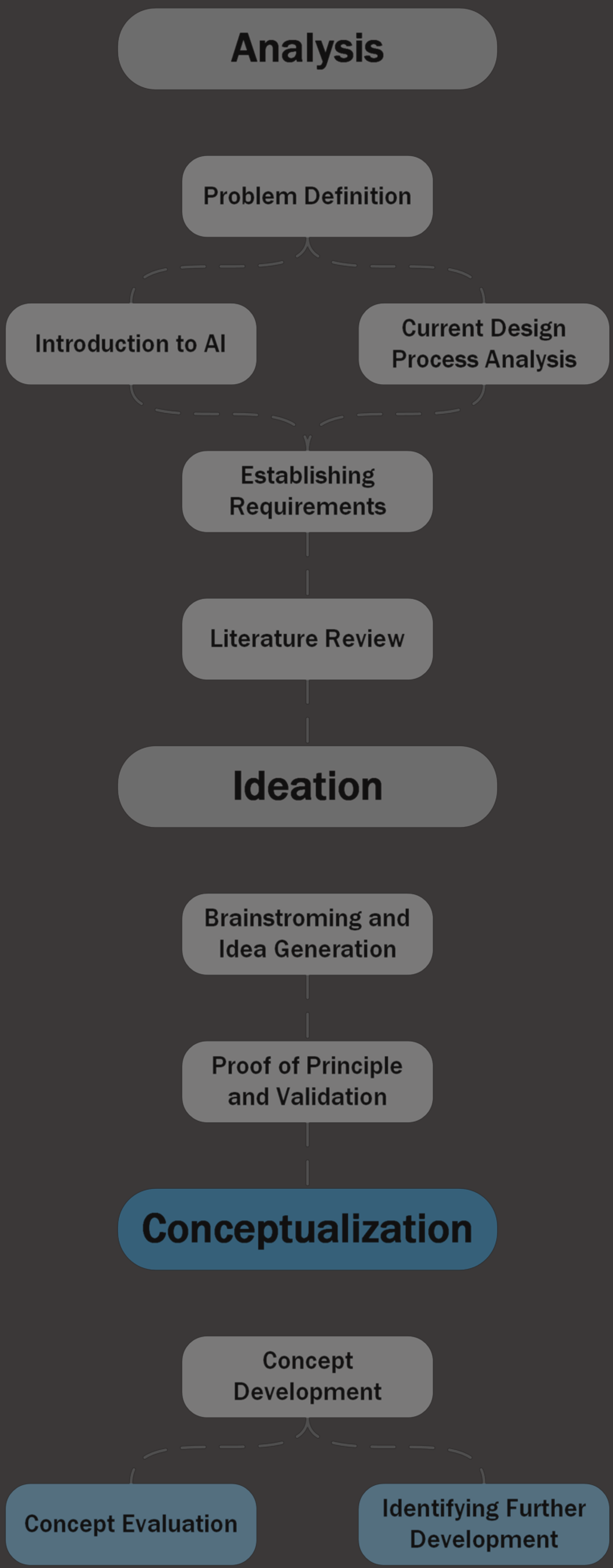


Figure 39: Concept Methodologies: Visualization 1 (Left), Visualization 2 (Right)

9. Discussion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Proof of Principle and Validation
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Concept Development
Concept Evaluation
Identifying Further Development

Culminating in 8 methodology concepts, this collaboration with WeLLDesign has laid the groundwork for tangible academic exploration of the potential of AI systems in minimizing and streamlining design time-sinks. The tangibility of these findings can be attributed to the inside-out approach taken by the author, grounding decision making into the actual and current needs of an established design agency as a conduit for the broader industry. Thus, the outcome of this research not only impacts WeLLDesign, but affects the way AI is further explored and integrated into the design domain, both at the academic and professional levels.

Impact for WeLLDesign

As the primary benefactor of this research, evaluating the results through the needs of WeLLDesign provides crucial insight into its real-world ramifications and potential. That is, by Introducing concepts often ignored in academic exploration, such as data privacy requirements and non-controlled environments.

Implementation Takeaways

Drafted by expert designers with years of industry experience, the realistic case-study proposed by the company was a vital components of this research. One through which the author not only identified strengths and shortcomings for the original methodology drafts, but also qualitatively and quantitatively evaluated their effect on the design process. Notably, this highlighted the importance of clearly defining the interaction between the user and the AI as assistive. In fact, it was the methodologies which most relied on AI to replace designer involvement in core processes which benefited the least from AI integration. Especially evident with the slips in efficiency seen in Visualization activities, where AI was used in a more substitutive manner, overreliance on AI can have detrimental quantitative effects.

The negative ramifications of AI overreliance is however not limited to quantifiable effects on efficiency, it also risks affecting the quality of work performed by professionals who are not cognisant of AI's pitfalls and inaccuracies. This spurred the redesign of the methodologies to include important user refinement steps and to better outline the data a user must provide to maximise the AI's potential.

Quantitatively, as shown in Figure 40, the greatest improvements in efficiency were seen in research focused tasks where AI was used in parallel to traditional research methods as an assistive tool. This also highlights the particular adeptness of current AI tools at analysing, synthesising and presenting valuable textual information.

Overall, the use of AI in the case study resulted in a 15% increase in efficiency and reduction in development costs. This figure is especially significant for WeLLDesign as it signals that the use of these AI methodologies may give it a competitive edge as it's designers are able to perform more efficiently, and thus incur lower development costs for clients.

Introducing AI Tools

For WeLLDesign, beyond the development of eight methodology concepts for future integration and refinement, this partnership and case study resulted in the immediate introduction of two AI Tools: ChatGPT and, Copilot for Microsoft 365.

ChatGPT was introduced as a companywide tool, with shared access for all team members. The use of this tool was evaluated with an internal survey filled in by six active team members, five of which reported frequent, weekly use. The findings of this evaluation aligned with the author's experience during the case study implementation, with the designers expressing satisfaction with the tools efficiency but reiterating the importance of a user refinement step to ensure output accuracy.

Copilot for Microsoft 365, due to its required yearly subscription commitment, was instead implemented as a pilot, with the author and company supervisor using it in daily design tasks. Copilot was successfully applied as outlined by the Documentation 1 & 2, Ideation 2 and Manufacturing 1 concept methodologies. Satisfying the "1 hour saved per month" requirement set by the management team to evaluate whether to proceed with a team wide implementation.

These tools were selected, not only for the functions they offer, but as they align with the basic data security requirements of the company, wherein, no data is made public or used for training, and all IP is retained by the user.

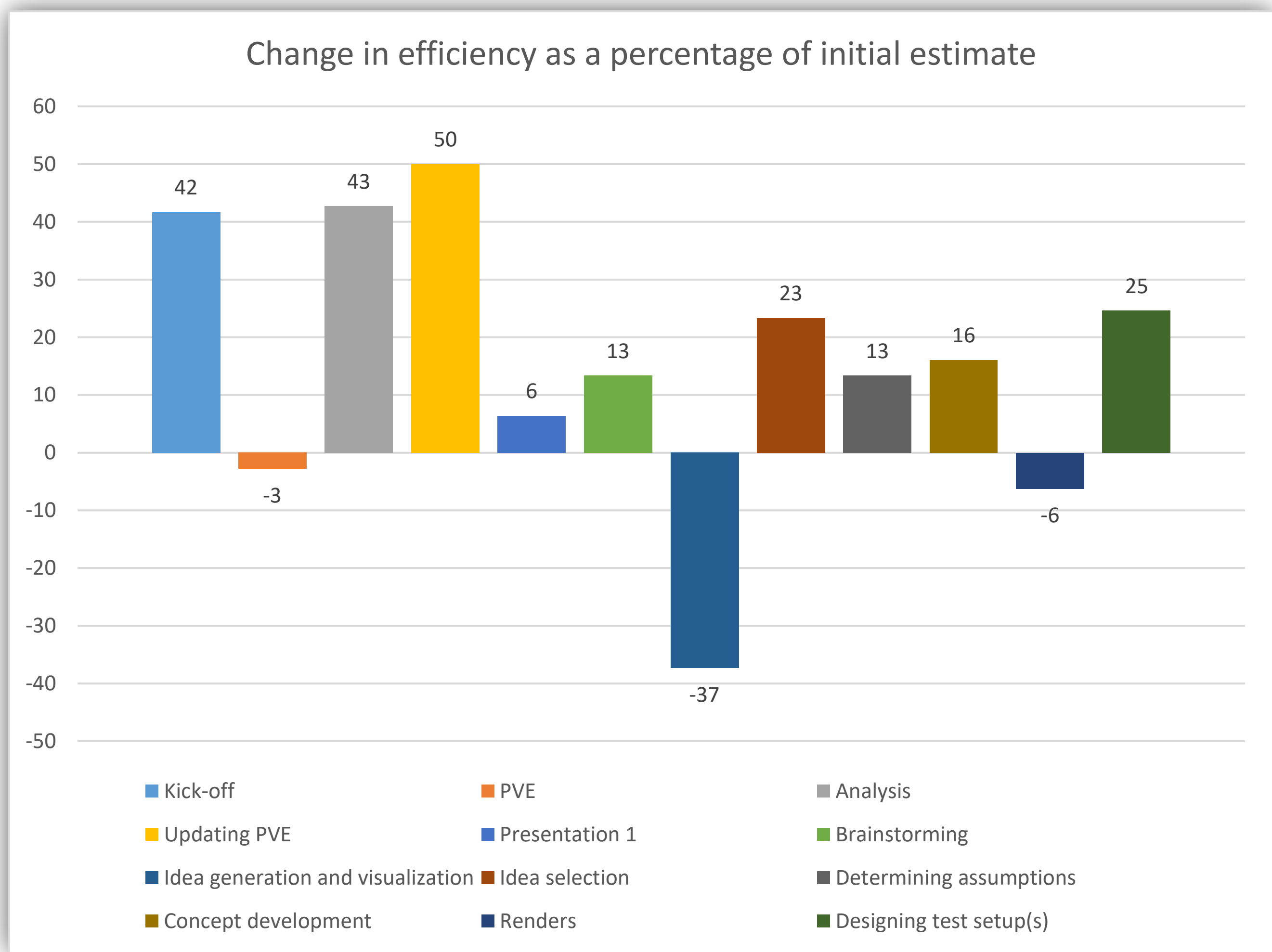

Figure 40: Effect of AI implementation on the efficiency of each relevant task as a percentage of budgeted time

Impact on the Industry

While designed primarily for implementation at WeLLDesign, the proposed methodology concepts are based on core concepts applicable to the industry as a whole. By tailoring these methodologies and applying these core concepts to their specific needs, design agencies and industry professionals alike can benefit from the efficiency improvements offered by AI.

Optimization and Reshoring

As previously discussed in this thesis, research and development offshoring trends have tightened the market in which local design agencies operate. Because of this, local design professionals not only compete with each other, but also face mounting competition by large foreign development companies and manufacturers who are able to offer lower rates. As hypothesised early in this thesis, and exemplified by the successful cost reduction from this thesis's case study implementation, AI offers an avenue for these local designers to increase their competitiveness in the market. If the 15% efficiency gains seen in the case study are proven to be repeatable for larger projects, such AI driven cost reductions are likely to push the industry towards a reshoring of key R&D activities. These cost reductions may lead to the re-establishment of internal R&D departments for some large multinationals and an increase in local development collaborations for smaller companies. These collaborations are likely to favour design agencies which successfully leverage AI to reduce development costs. This has a positive effect on the profit pillar of sustainability, improving the ability of small agencies to stay in business and creating demand for further research and development of design focused AI tools. In reference to the requirements set in Table 2, the methodologies satisfy the efficiency requirements.

Methodology Adaptability

Throughout the later stages of this research, the focus has been on developing methodologies for direct implementation. As defined by this thesis, this fits the "Now" timeframe, making use of low investment, commercially available AI systems. This, however, does not present a limitation. Indeed, the methodologies are designed to be highly adaptable, both to changes in available technologies and changes in design processes. This adaptability is especially advantageous in this early stage of AI's incursion in the design domain, allowing design professionals to invest time into implementing AI methodologies "Now" without worrying about significant changes "Tomorrow". This concept extends further, with the use of task categories and subcategories making it possible to introduce new, previously unthought of methodologies "In-the-Future". Thus, the propositions satisfy both the expandability and investment requirements, adapting to the implementer's needs.

Human-AI Interaction

The interaction between humans and AI has been a focal point of recent AI developments, with some seeing the technology as substitutive and others seeing it as supportive. This is true also for the use of AI in the design engineering domain, WeLLDesign, as an example, stressed the importance of developing methodologies which leverage AI as an assistant rather than to replace the designer's involvement in core tasks. This concept of assistive AI was foundational to this thesis's research, not only to avoid alienating designers, but also to make up for the current shortcomings of AI technologies. Current AI systems are not perfect, with issues of low explainability, low control over the outputs and, with GenAI, the tendency to misrepresent or make up information. While most evident when applying the AI to Visualization tasks in the case study, these issues are present in all manner of AI applications. The proposed methodologies tackle this issue by outlining the critical human-AI interactions which allow the user to better control and revise the AI's outputs. This sets an important precedent for the industry, outlining the importance of avoiding overreliance on AI systems, and ensuring designers stay involved in core development activities. This thesis, by already framing AI as an assistant rather than an usurper, stives to strengthen the people pillar of AI's sustainability in design domains. This precedent, if adopted, will play a role in protecting designers, as it is likely that AI systems will, in the future, achieve the level of accuracy and explainability required for core design tasks.

Data Privacy and Intellectual Property

As previously argued, in the field of AI for design processes, academia often neglects important factors such as data security and intellectual property (IP) retention, factors which often dictate whether professionals will adopt a given system into their workflow. When these are considered, such as by Liu & Hu, it is from the perspective of potential issues with an AI's original dataset (Liu & Hu, 2023). While that issue is important, it does not account for other factors, such as commercial-use of software, ownership of input and output and, data privacy. The current lack of legal precedent has allowed the AI industry to self-regulate through language embedded into individual terms of service agreements (ToS). To complicate the matter further, when it comes to data privacy, not all tasks and projects are equal. Some may require stringent data handling while others may be altogether unburdened by confidentiality. It is thus possible, if not likely, that the same methodology, applied to the same task, in different projects, may require the use of two different AI tools. The adaptability of the proposed methodologies accounts for this by using placeholders (e.g. "AI 1") rather than by defining specific tools. Because of this, potential users are free to select tools tailored to their specific data and IP needs, satisfying the data security requirements set early in this report.

Limitations and Future Outlook

Despite the overall success of this research and collaboration, the author acknowledges some limitations which require further attention if AI is to be implemented at a broader scale in the industrial design industry.

First and foremost, as outlined in the introductory chapters, the outputs of this research are but concepts. Concepts developed through iterative ideation, literature backing and testing, but concepts none the less. The purpose of these was to provide WeLLDesign, and by consequence the industry at large, an entry way into AI implementation. However, to cement themselves as industry standard methodologies, further cycles of testing and iteration are needed, involving multiple designers with a broad range of industry experience and fields of expertise within product development. By doing so, it would be possible to define the effect user experience has on the methodology's success. This was not possible within the timeline of this collaboration, as the concepts required validation in a hypothetical case study project before implementation in ongoing projects for paying clients. A future collaboration between the author and WeLLDesign is planned to oversee the future implementation and development of the concepts.

Limitations were also present in the case study implementation, that is: project scope and the inherent volatility in project planning. The case-study was limited in scope, covering only the initial Analysis, Ideation and Concep phases of WeLLDesign's development process. As such, the author was unable to validate the effect of the AI methodologies at later stages of the design process. While this aligns with the idea of streamlining WeLLDesign's more frequent early design and engineering task in order to focus more time on the potential reshoring of the later stages of the design process, the author hopes for further implementations for all development stages. Further, project planning is not an exact science, and is greatly affected by experience, unexpected externalities and project complexity. Thus, while the case study acts as a valuable baseline for concept development, further validation of the methodologies efficiency will be required.

The planned collaboration with WeLLDesign offers promising opportunities for the further development of tangible AI methodologies at this crucial stage in the diffusion of AI.

10. Conclusion

Culminating in eight concept methodologies for AI integration, this thesis, and the associated research, has outlined the core principles, opportunities, challenges and knowledge gaps present in the field of AI for industrial design. Most importantly, it has outlined, through testing and revision, the extent to which AI can be leveraged to increase process efficiency.

With a focus on small to medium design agencies and freelance professionals, the early chapters drew on a mixture of academic publications, consultant reports and informal web-content, to understand the current state of the art. By doing so, this thesis lays the groundwork for bridging the gaps between industry and academia, taking an academic approach to addressing tangible industry needs. Here, the requirements most likely to produce successful AI methodologies were extrapolated, drawing focus to issues of AI explainability, sustainability, complexity, expandability, data security, client acceptance and, implementation investments.

Acting as a proof of principle, the case study implementation demonstrated the importance of treating AI as a supportive rather than substitutive tool, outlining the accuracy and complexity pitfalls which occur with AI overreliance. Resulting in a 15% development time and cost reduction over the Analysis, Ideation and Conceptualization phases. At a more granular level, the most meaningful efficiency improvements, both qualitative and quantitative, were observed in methodologies which implemented AI as an assistive tool. Such methodologies included the original drafts for: Documentation 1, Ideation 1 & 2, Development 1 and Manufacturing 1. Of these the use of Ideation 2 in analysis tasks was the most successful, with a 43% efficiency increase. Conversely, methodologies which place AI in more substitutive roles, directly performing significant portions of core design activities, were found to decrease process efficiency. This is particularly observable with the original Visualization 1 draft, where overreliance on AI to generate sketch variations resulted in both a 37% efficiency decrease and unusable outputs. It was thus concluded that AI is best suited to offer increased efficiency when used in an assistive manner. This conclusion was reflected in the updated methodologies, which better outline the interactions between designer and AI, ensuring the designer is always in control of the design activity. Here, methodologies were drafted to include critical user refinement steps, creating a buffer between the AI's output and the end product to preserve the logical flow of design decisions. The interaction was further fleshed out to address complexity, clearly outlining the required transfer of knowledge and information between user and AI to maximise control over the output. These concepts, while not affecting the explainability of individual AI tools, lay the groundwork for explainable AI methodologies.

Expandability was successfully implemented through the subdivision of tasks into categories and sub categories, such that individual methodologies can be applied to a multitude of tasks and design processes. The concept was further extended to address data security, by outlining the inputs and outputs of the desired AI systems without defining any one tool, ensuring users have the freedom to select tools with project appropriate ToS.

This research produced eight concept methodologies, covering four task categories: Documentation and Planning, Ideation and Conceptualization, Validation and Development, Visualization and Contextualization and, Manufacturing and Logistics. Ultimately, while the proposed methodologies require further testing and development, they offer both industry and academia a solid and provable basepoint on which to expand.

Thus, in addressing the core question behind this research, it is concluded that AI is uniquely positioned to minimize and streamline time-sink tasks. That is, in so far as it is used as an assistive technology, not to fully replace core design activities, but rather to facilitate trivial, repetitive, and data intensive tasks.

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A mia mamma, Alessandra, che non mi ha mai duditato. Che, nei momeni piu difficili, in un sistema dove un bambion dislessico come me non srebbe mai arrivato dove sono ora, non ti sei mai arresa e hai sempre lottato per me. Ti ringrazzio per tutto quello che hai fatto per me e per tutti gl'altri ragazzi ICM che, grazzie a té, sono riusciti a sorpassare gl'anni piu difficili della loro educazzione. Grazzie per tutto, non c'é l'avrei fatta sensa di té.

Infine, all nonno babbo dedico questa tesi. Non sei qui per chiamarmi ingegnere ma spero tu sia orgolgioso quanto ci guardi dall'alto.

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Appendix A: List of Potential AI Uses

Idea	Timeframe
Generating quotes	Today
Idea generation based on specific factors	Today
Planning	Today
Generating activity guidelines	Today
Research	Today
Automated conformity checks	Today
Generating selection criteria for ideation	Today
Cost estimations	Today
Concept evaluation	Today
Trend analysis	Today
Design review	Today
Coding	Today
Electronics	Today
Sourcing	Today
Generating test protocols	Today
Identify market opportunities	Today
Identifying exit strategy	Today
Competitor research	Today
Brand identity / shape conformity	Today
Design modification	Today
Analysis tools	Tomorrow
Live sketch modification	Tomorrow
Draft CAD generator	Tomorrow
Process selection	Tomorrow
Material selection	Tomorrow
Test result analysis/prediction	Tomorrow
Identifying perspective clients/partners	Tomorrow
Combining form and mechanical design	Tomorrow
True creativity	In the Future

Appendix B: Internal AI Survey

Integrating AI in our Design Process

Hi Team,

For my thesis I want to get everyone's opinion on if, how and where AI can fit in our design process. It would be great if you could spare 10 minutes to fill out this survey, that time can be folded in with whichever project you are working on. If it takes longer than 15 minutes to fill in the survey, you can log it as WeLLDesing Indirect on TimeChimp.

The replies are fully anonymous so feel free to share any concerns or comments about this topic in the last 2 sections of the survey.

If you have any questions or related comments let me know.

Thank you for your time.

AI Litteracy

In this section you will answer questions aimed at better understanding the team's knowledge of AI and AI tools.

1. How would you personally define artificial intelligence (AI)? (in general, not only in our industry)

2. When you hear "AI", what do you typically associate it with?

- ☐ Chat bots (e.g. ChatGPT, customer support chat)
- ☐ Image generators
- ☐ Suggestion algorithms (e.g. YouTube and Instagram)
- ☐ Game bots (e.g. chess computers)
- ☐ Optimization (e.g. plant optimization, financial optimization)
- ☐ Smart assistants (e.g. Alexa, Siri)
- ☐ Other

3. Do you try to keep up to date on developing AI trends?

- ○ Yes
- ○ No

4. If yes, how do you keep up to date?

- ☐ News articles
- ☐ Linked-In
- ☐ Social Media
- ☐ Word-of-mouth
- ☐ Other

Past Experiences with AI in Design

In this section we explore what AI tools or processes the team has already used in projects.

5. Have you used any AI tools in the design process before?

- ◯ Yes
- ◯ No

6. What tools have you used?

- ☐ ChatGPT
- ☐ Image generators (e.g. Dall-e, Midjourney, Stable Diffusion)
- ☐ Optimization tools (e.g. Schedule planers, Finance AI)
- ☐ Search optimizers (e.g. Microsoft CoPilot)
- ☐ Image-to-CAD
- ☐ CAD optimization (Generative design and topology optimization)
- ☐ Other

7. In which stages of the design process?

- ☐ Market Research
- ☐ Aquisition
- ☐ Analysis
- ☐ Ideation
- ☐ Concept Design / Early Engineering
- ☐ Concept Prototype
- ☐ Functional Engineering
- ☐ Function Prototype / Product prototype
- ☐ Preparation for Production
- ☐ Data and Documentation / Supplier Communication

8. How complex was it to use the tools?

1	2	3	4	5	6	7	8	9	10

9. Did the results meet your expectations?

1	2	3	4	5	6	7	8	9	10

10. In what POSITIVE ways did the tools affect your work?

- ☐ Increased efficiency
- ☐ Better inspiration
- ☐ Increased consistency
- ☐ N/A
- ☐ Other

11. In what NEGATIVE ways did the tools affect your work?

- ☐ Decreased efficiency
- ☐ Sub-par results
- ☐ Reduced consistency
- ☐ Complexity
- ☐ N/A
- ☐ Other

12. How would you rate your overall experience with these tools?

1	2	3	4	5	6	7	8	9	10

13. Why not?

- ☐ Have not had the need to
- ☐ Too complex/inconvenient
- ☐ Did not know where to start
- ☐ Distrust
- ☐ Tools were behind a paywall (transaction needed)
- ☐ Other

Evaluating our Design Process

In this section we will evaluate our design process to identify strength, shortcomings and areas of improvement.

14. Which phases of the design process are you most involved in?

- ☐ Market Research
- ☐ Aquisition
- ☐ Analysis
- ☐ Ideation
- ☐ Concept Design / Early Engineering
- ☐ Concept Prototype
- ☐ Functional Engineering
- ☐ Function Prototype / Product Prototype
- ☐ Preparation for Production
- ☐ Data and Documentation / Supplier Communication

15. Which tasks/phases of the design process do you consider to be the biggest "time sinks"?

- ☐ Market Research
- ☐ Aquisition
- ☐ Analysis
- ☐ Ideation
- ☐ Concept Design / Early Engineering
- ☐ Concept Prototype
- ☐ Functional Engineering
- ☐ Function Prototype / Product Prototype
- ☐ Preparation for Production
- ☐ Data and Documentation / Supplier Communication

16. Rank the following design tasks/phases based on how prepared WeLLDesign is to accomplish them. (Top = Most Prepared)

- Market Research
- Aquisition
- Analysis
- Ideation
- Concept Design / Early Engineering
- Concept Prototype
- Functional Engineering
- Function Prototype / Product Prototype
- Preparation for Production
- Data and Documentation / Supplier Communication

17. Rank the following design tasks/phases based on personal enjoyment/satisfaction with the task.

- Market Research
- Aquisition
- Analysis
- Ideation
- Concept Design / Early Engineering
- Concept Prototype
- Functional Engineering
- Function Prototype / Product Prototype
- Preparation for Production
- Data and Documentation / Supplier Communication

AI in our Design Process

In this section we explore what your expectations for AI in the design process are.

18. Do you believe there is space for AI in our design process?

- ◯ Yes
- ◯ No
- ◯ Other

19. Where in our design process would AI fit best?

- ☐ Market Research
- ☐ Aquisition
- ☐ Analysis
- ☐ Ideation
- ☐ Concept Design / Early Engineering
- ☐ Concept Prototype
- ☐ Functional Engineering
- ☐ Function Prototype / Product Prototype
- ☐ Preparation for Production
- ☐ Data and Documentation / Supplier Communication

20. Enterprize grade AI refers to custom systems designed for a specific industry or even company. These are more expensive and complex to set up but offer highly specialized solutions for process optimization and analysis (e.g. IBM Watson). Do you think WeLLDesign would benefit from such tools?

- ◯ Yes
- ◯ No
- ◯ Other

21. Consumer grade AI refers to more broadly available tools. These are relatively less expensive and simpler to implement but also less specialized/customized (e.g. ChatGPT, Dall-e). Do you think WeLLDesign would benefit from such tools?

- ◯ Yes
- ◯ No
- ◯ Other

22. What Tools would you be most interested in applying to our design process

- ☐ Text Generators
- ☐ Image Generators
- ☐ Finance Tools
- ☐ Planning Tools
- ☐ CAD Tools
- ☐ Smart Assistants
- ☐ Other

23. What tasks would you want to use AI for?

- ☐ Research (market, patent, regulations)
- ☐ Ideation (inspiration and sketch variations)
- ☐ Mechanical Design
- ☐ Visualization
- ☐ Electronics Design
- ☐ Coding
- ☐ Project Planning
- ☐ Other

24. Without limiting yourself to existing tools, are there any tools or applications you want to see developed in the future?

Concerns

In this section you can express any concerns you have with the prospect of using AI in our Design Process.

25. Are you concerned about integrating AI in our design process?

- Yes
- No

26. Do you think clients would be discouraged by the use of AI in our design process

- Yes
- No
- Other

27. What are some concerns you might have about the integration of AI in our design process?

Additional Comments

28. Feel free to leave any additional comments on the topic

Appendix C: List of Design Tasks

Task	Phase
Identifying Low hanging Fruits	Analysis
Feasibility Studies	Analysis
Identifying Target Groups and Personas	Analysis
Identifying Requirements	Analysis
General Research	Analysis
Documenting Findings	Analysis
Budget Estimations	Acquisition
Marketing Material (e.g. Website, LinkedIn, Presentations)	Acquisition
Contract / Proposal Drafting	Acquisition
Early CAD	Concept Design & Early Engineering
Evaluating Concepts	Concept Design & Early Engineering
Mechanical Ideation	Concept Design & Early Engineering
General Research	Concept Design & Early Engineering
Early Renders	Concept Design & Early Engineering
Multidisciplinary Collaboration (e.g. with Quant)	Concept Design & Early Engineering
Material Selection	Concept Design & Early Engineering
Detail Sketching	Concept Design & Early Engineering
Component Selection	Concept Design & Early Engineering

Documentation	Concept Design & Early Engineering
Estimating Costs	Concept Design & Early Engineering
Setting Up Testing Plans	Concept Prototyping
Sourcing Components	Concept Prototyping
Documenting Findings and Test Results	Concept Prototyping
Updating Project Plans	Data & Documentation
Writing Technical Reports	Data & Documentation
Writing Budget Reports	Data & Documentation
Preparing Presentations	Data & Documentation
Patent Research	Data & Documentation
Meeting Documentation/Notes	Data & Documentation
Regulatory / Legal Research	Data & Documentation
Mechanical Detailing	Functional Engineering
CAD Detailing	Functional Engineering
Component & Material Sourcing	Functional Engineering
Cost Estimations	Functional Engineering
Documenting Progress	Functional Engineering
FEM / Simulations	Functional Engineering
Generating Technical Drawings	Functional Engineering
Interaction/Function Mapping (e.g. Flowcharts, FMEA)	Functional Engineering
Products Renders	Functional Engineering
Evaluating Ideas	Ideation
Co-Ideation (with clients or users)	Ideation
Setting Up and Running Brainstorming Sessions	Ideation

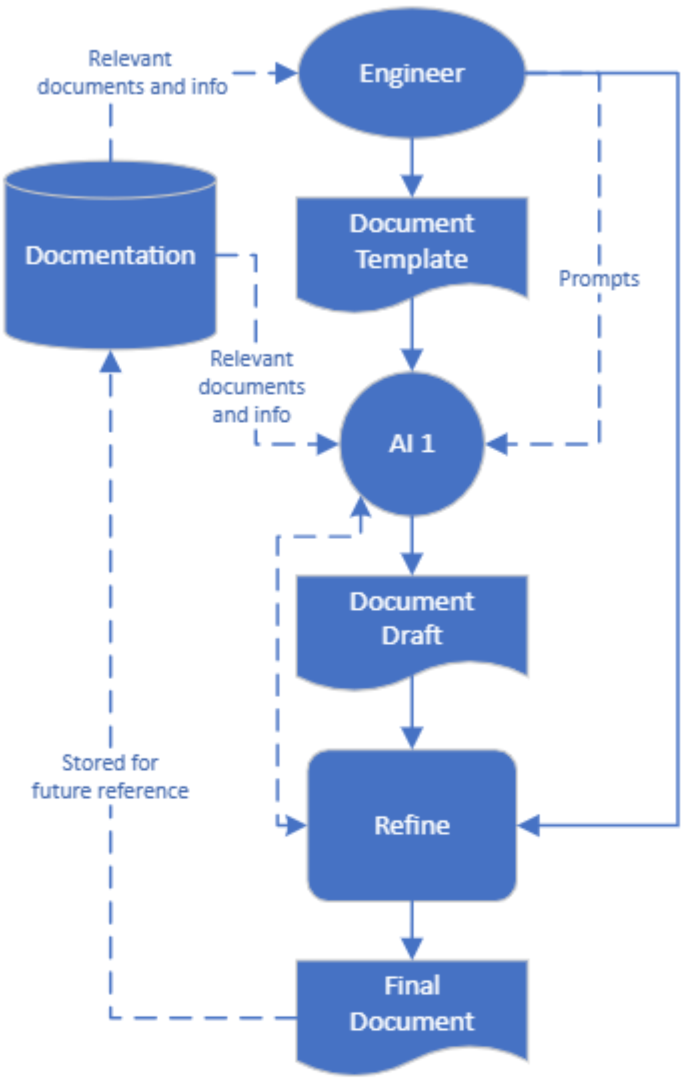
Sketching	Ideation
Mood Boarding	Ideation
Documenting Findings	Ideation
Trend Analysis	Market Research
Surveys & Interviews	Market Research
Preparing and Running Focus Groups	Market Research
Online Research	Market Research
Quantitative Data Gathering and Analysis	Market Research
Optimizing Model for Production	Preparation for Production
Cost Optimization	Preparation for Production
Production Planning	Preparation for Production
Assembly Documentation	Preparation for Production
BOM & Sourcing	Preparation for Production
Final Technical Drawings	Preparation for Production
Production Documentation	Preparation for Production
Supplier Communication	Preparation for Production
Sourcing Components	Product Prototype
Setting Up Testing Plans	Product Prototype
Documenting Findings and Test Results	Product Prototype
Documenting Findings	Production Prototype
Setting Up Test Plans	Production Prototype
Team Formation & Subdivision of Roles	Project Management
Team Communication	Project Management
Risk Management	Project Management

Scheduling	Project Management
Client Communication (Emails)	Project Management
Client Communication (Presentations & Documents)	Project Management

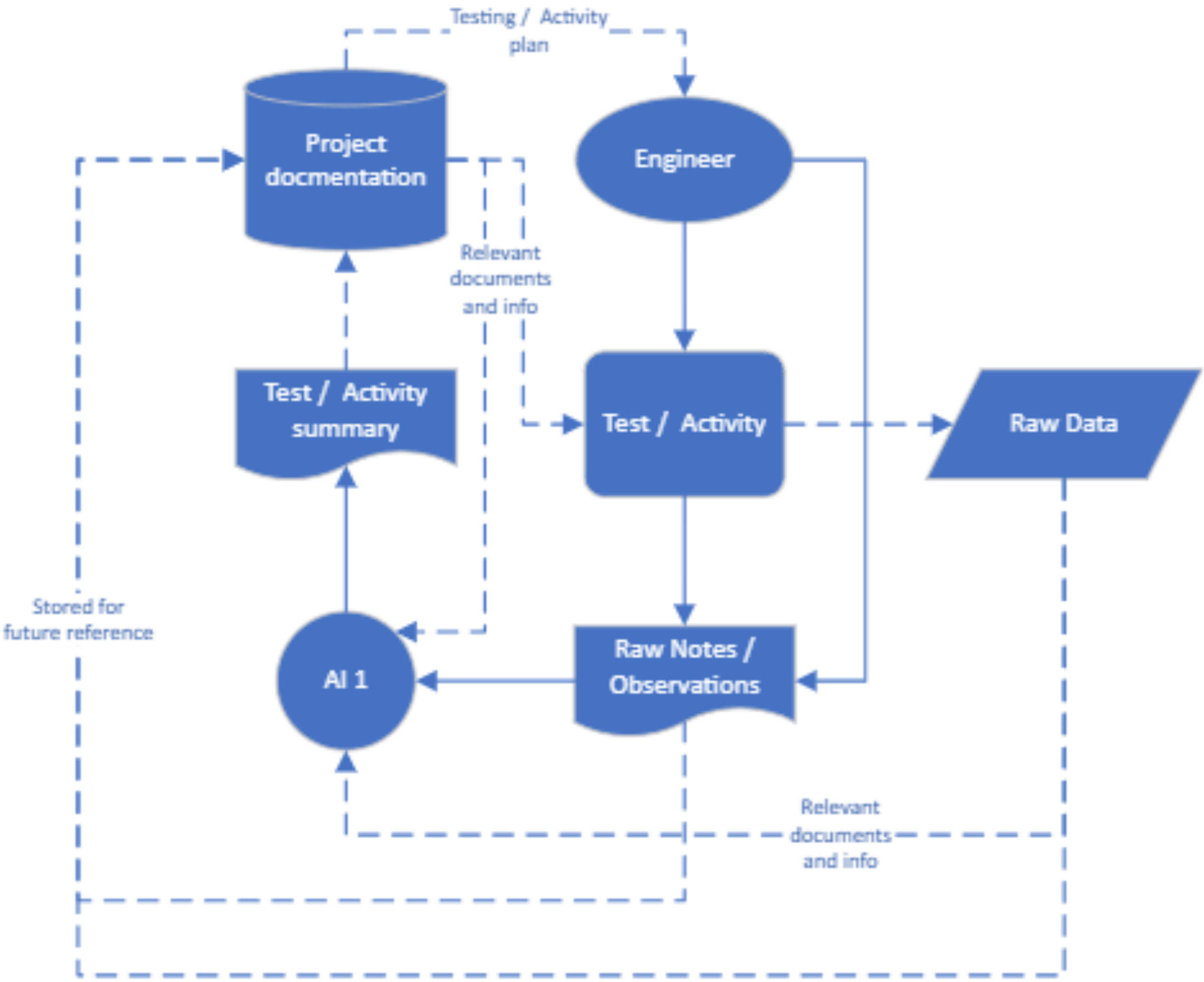
Appendix D: 14 Draft Methodologies

Documentation 1:
Presentation of findings and of prototype

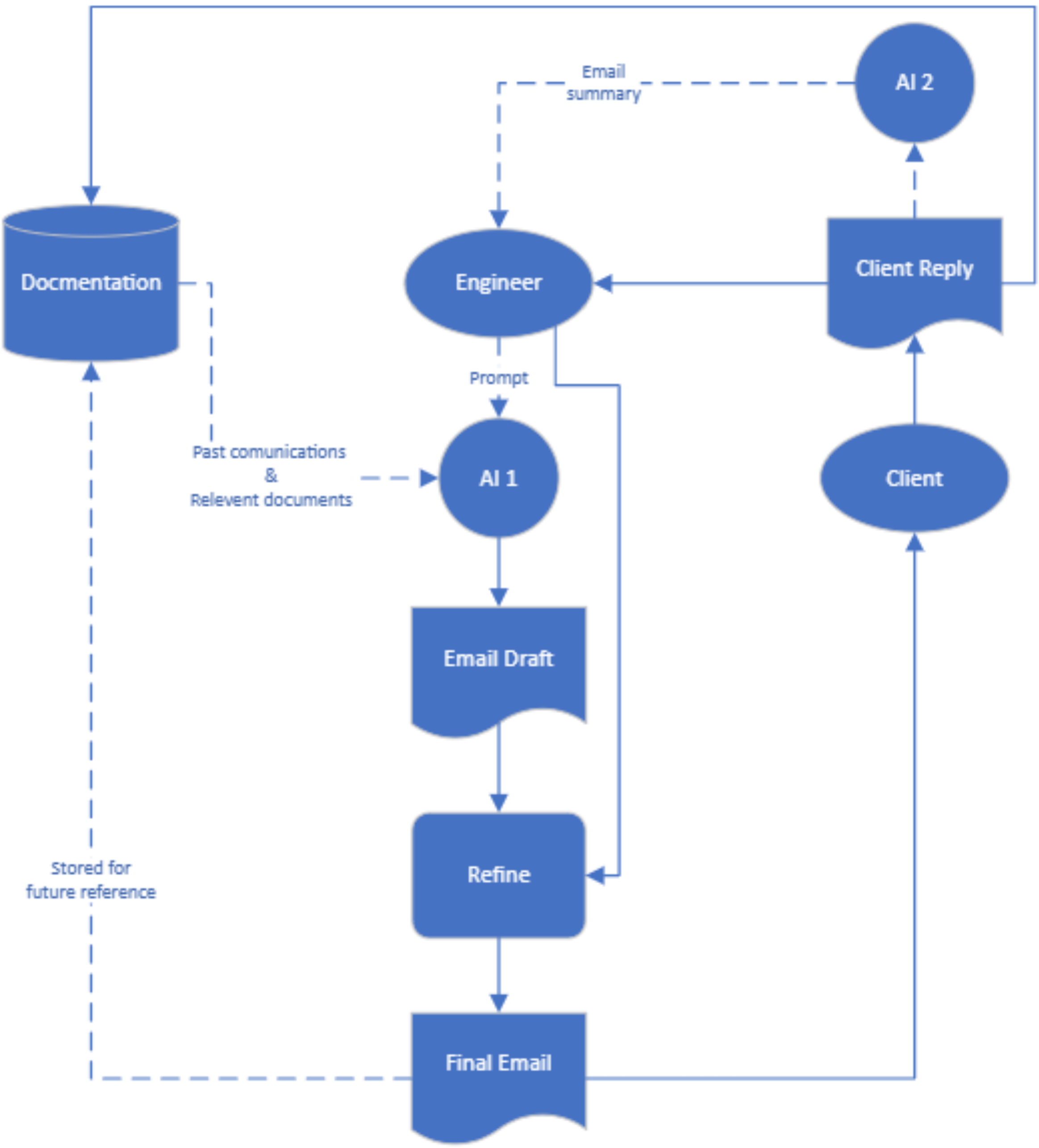
Documentation 2:
Document creation



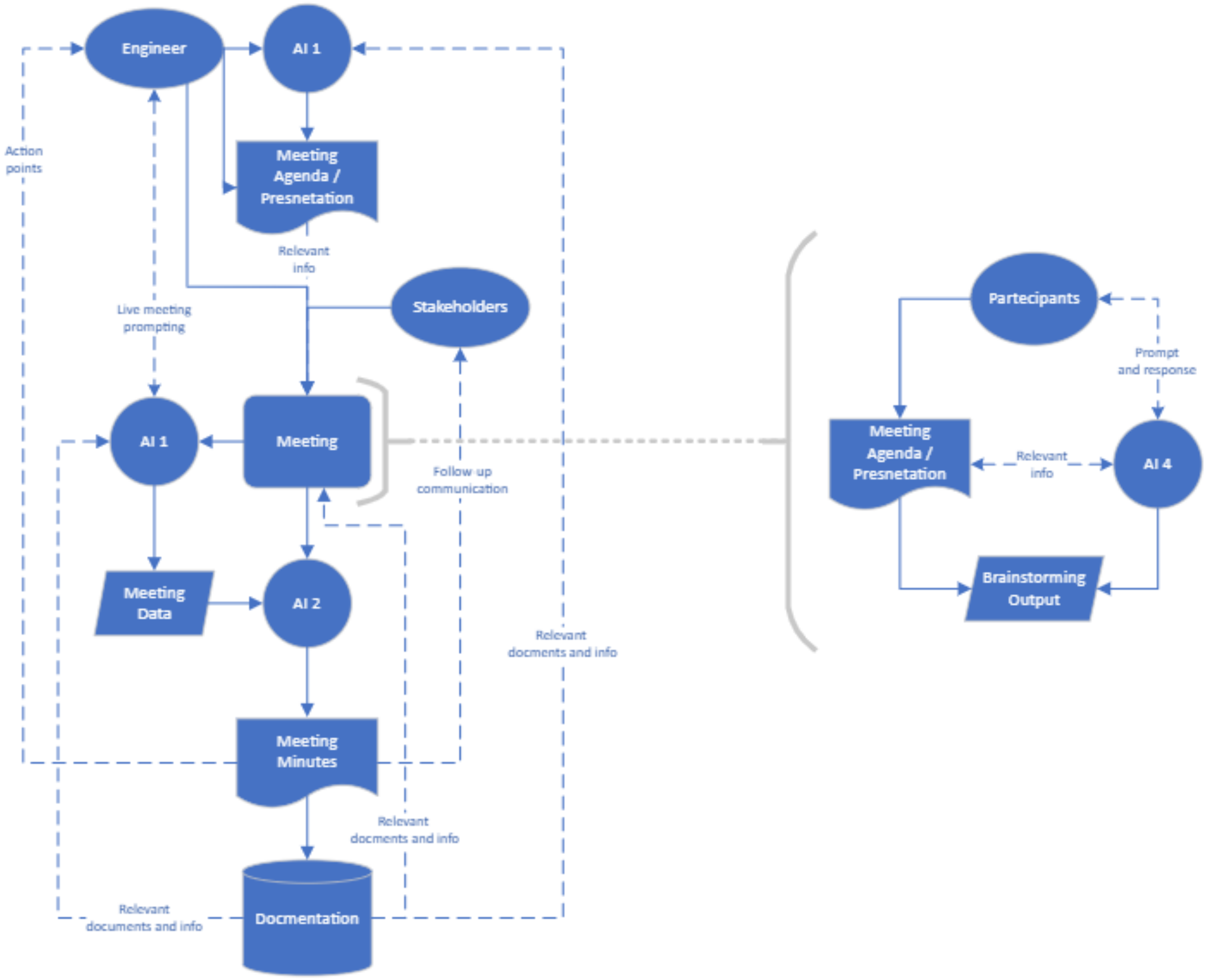
Documentation 3:
Note taking



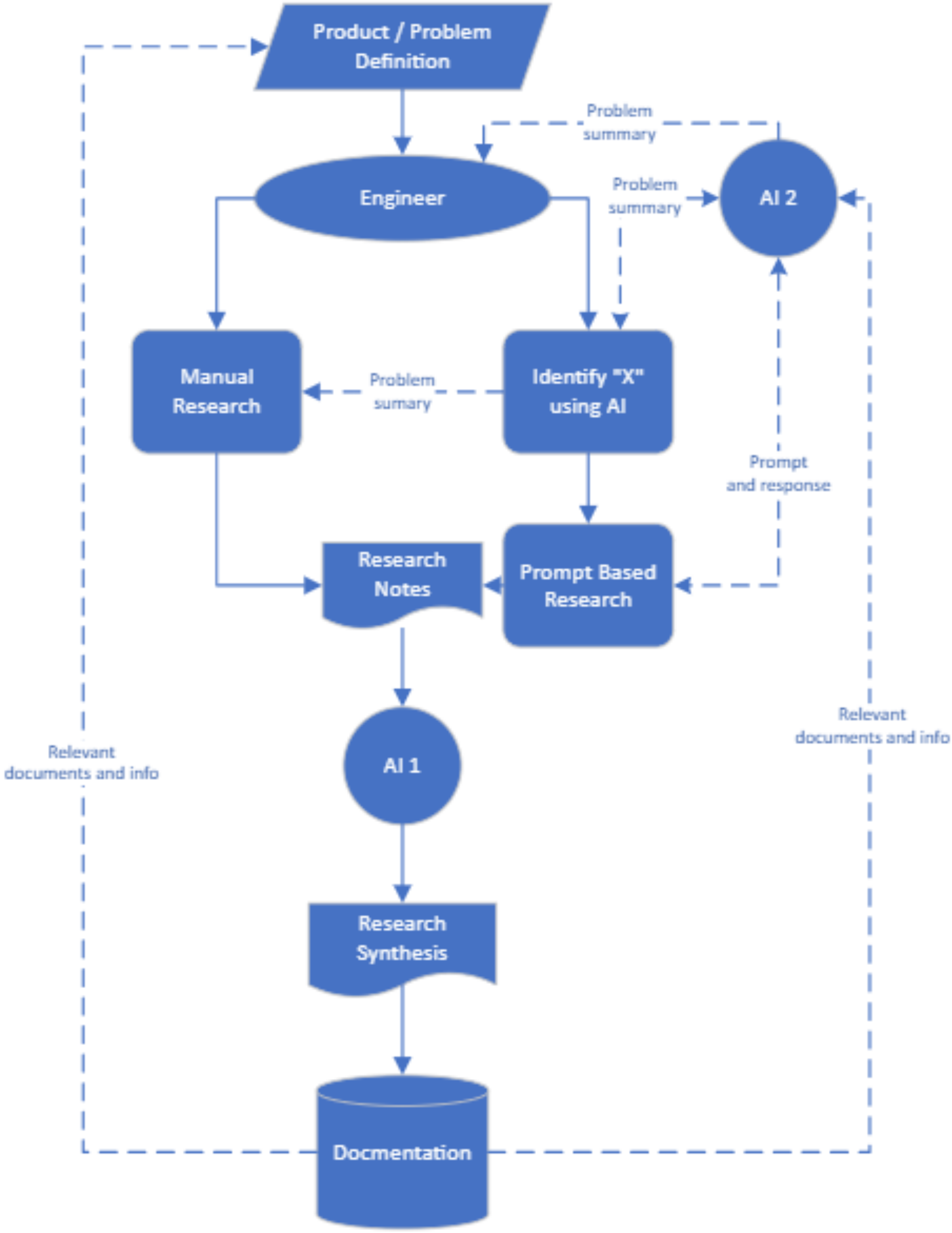
Documentation 4:
Email and communication



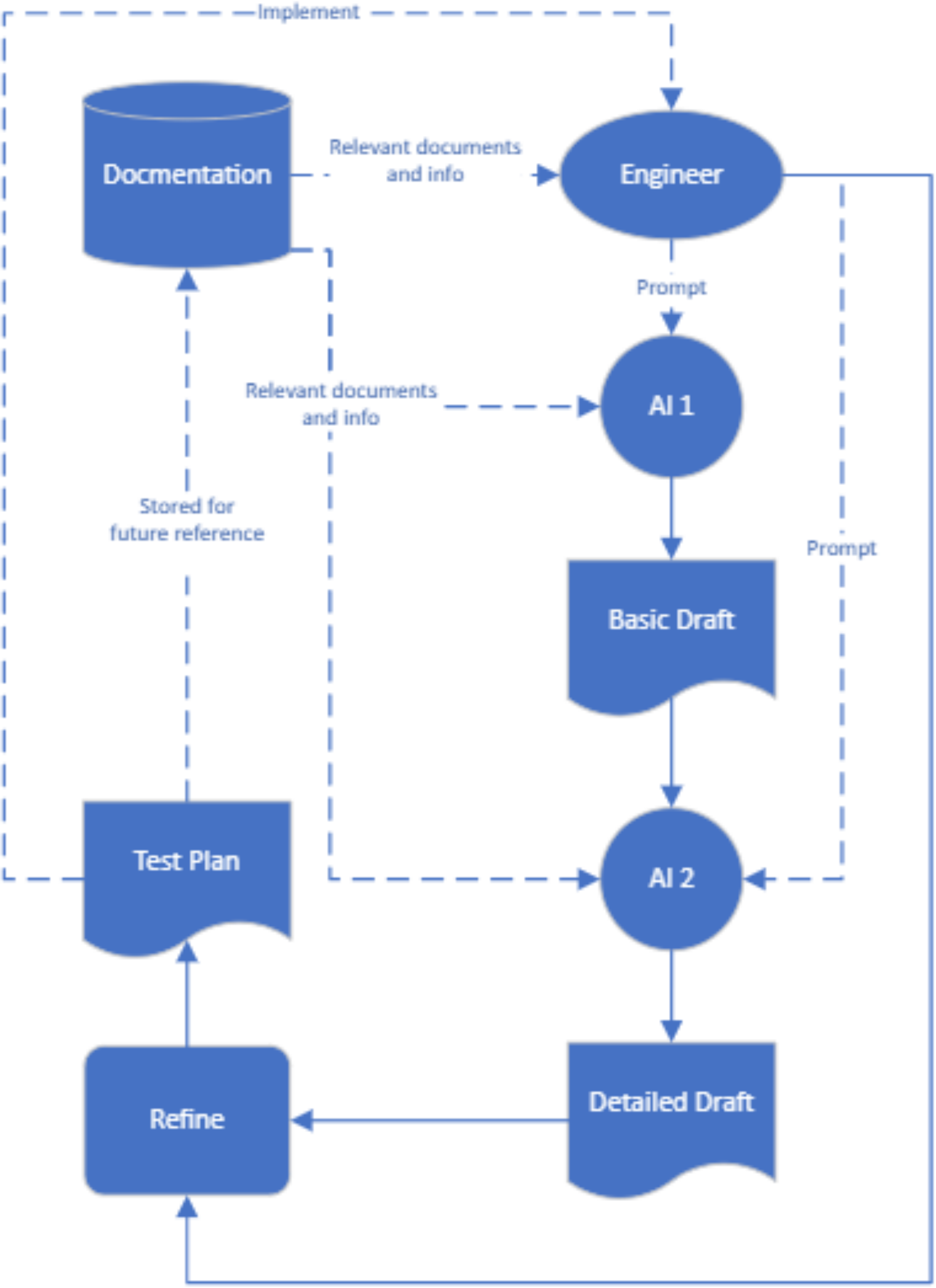
Ideation 1:
Kick-off and brainstorming



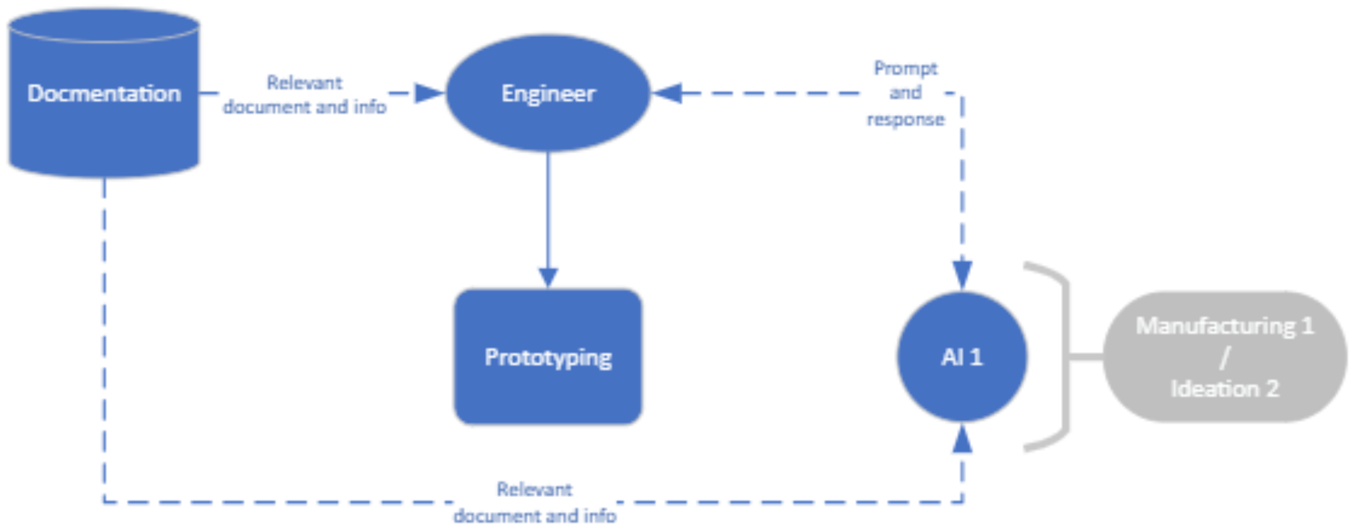
Ideation 2:
Analysis / Research



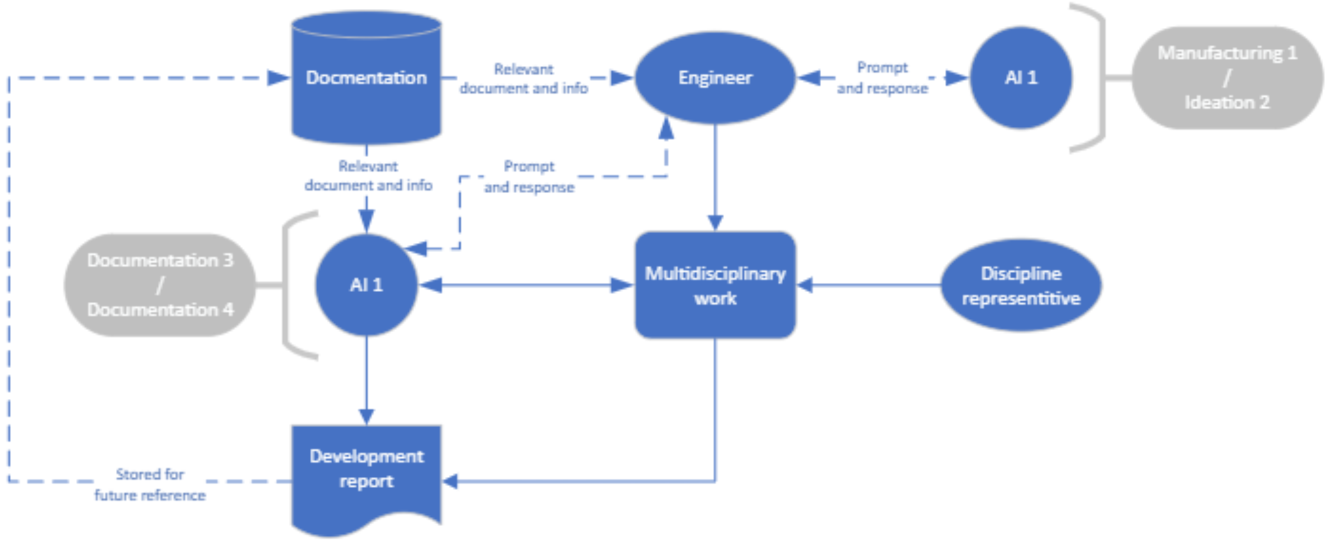
Development 1:
Setting-up tests



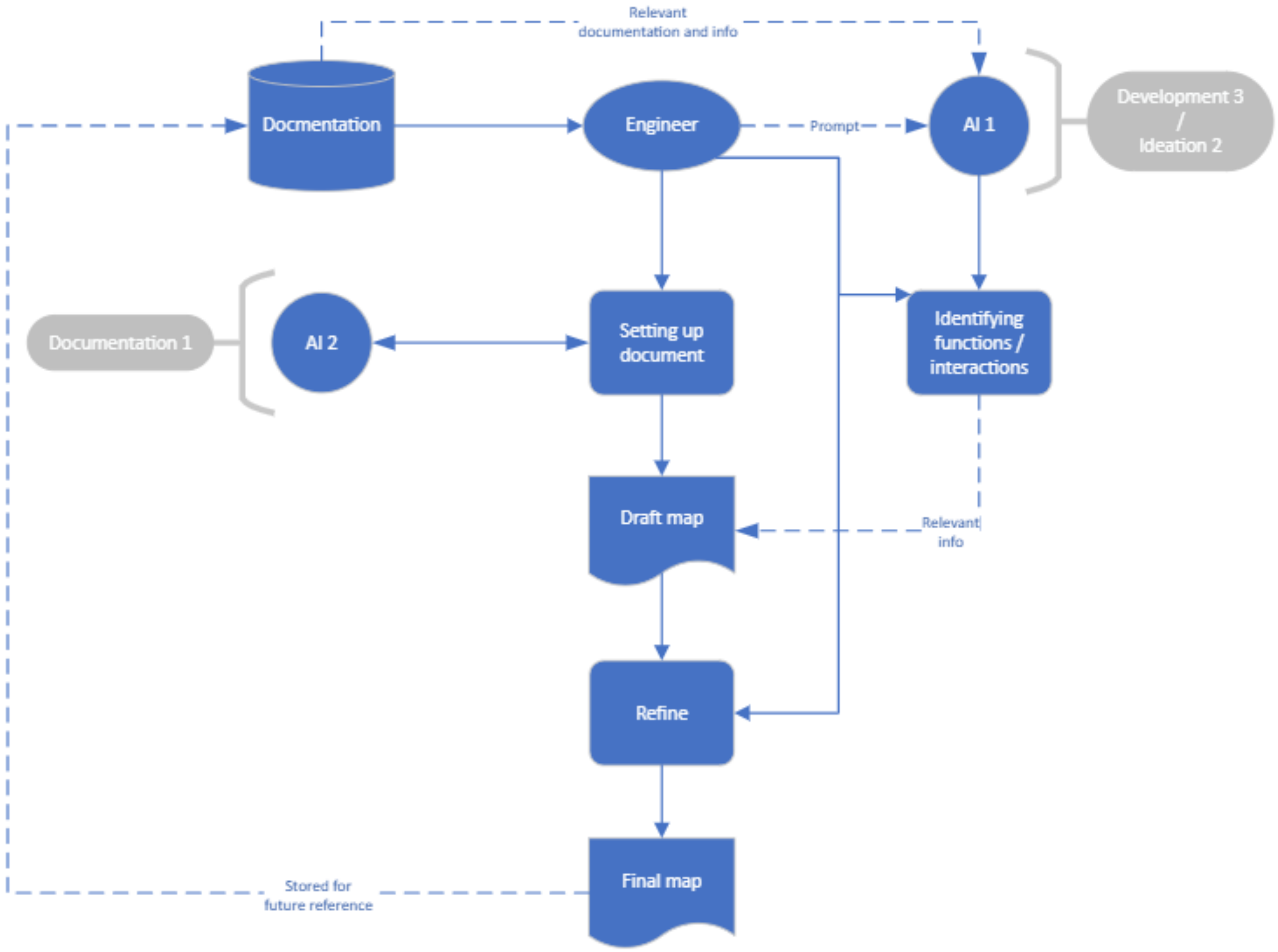
Development 2:
Prototyping with off-the-shelf components



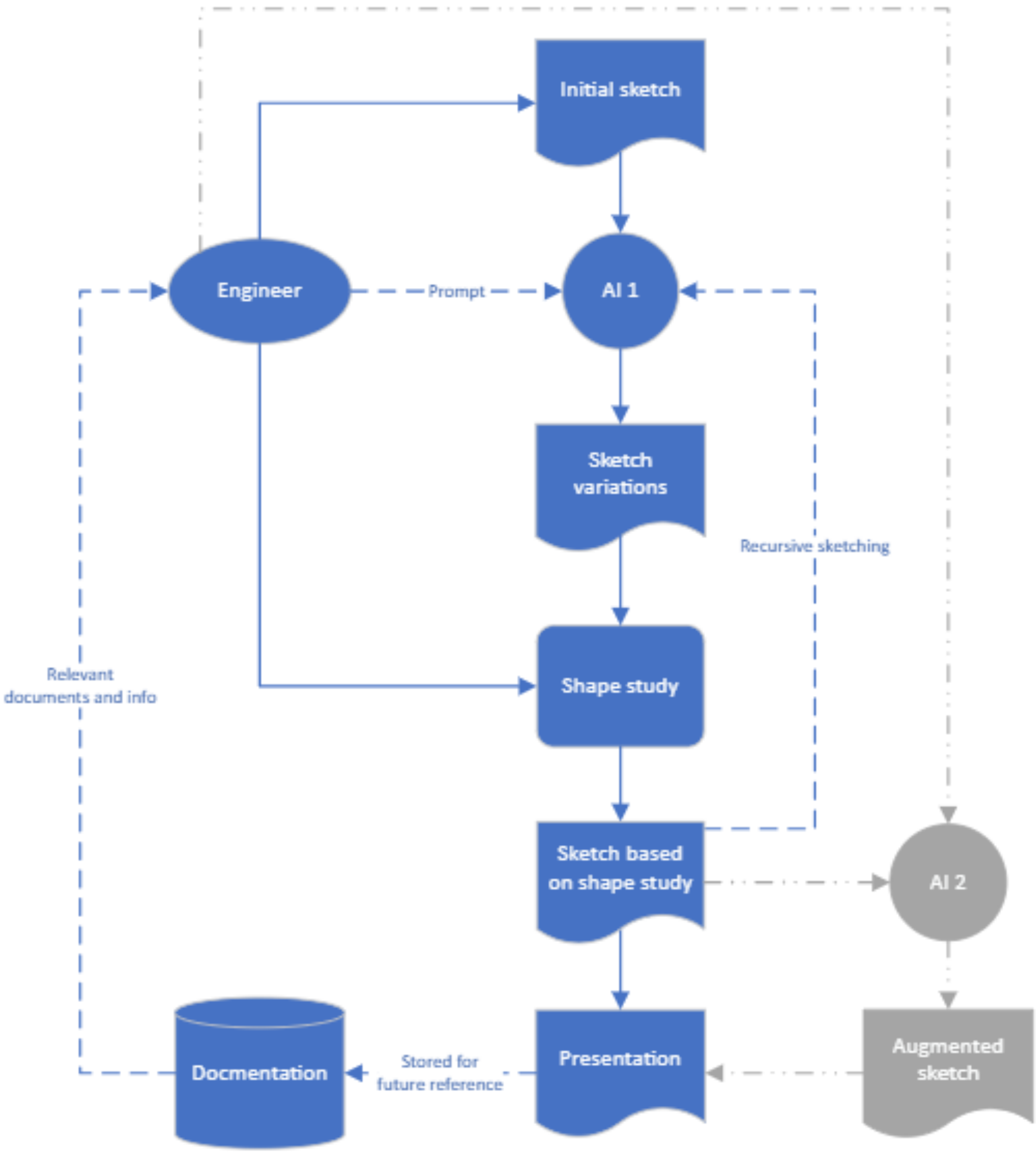
Development 3:
Multidisciplinary development



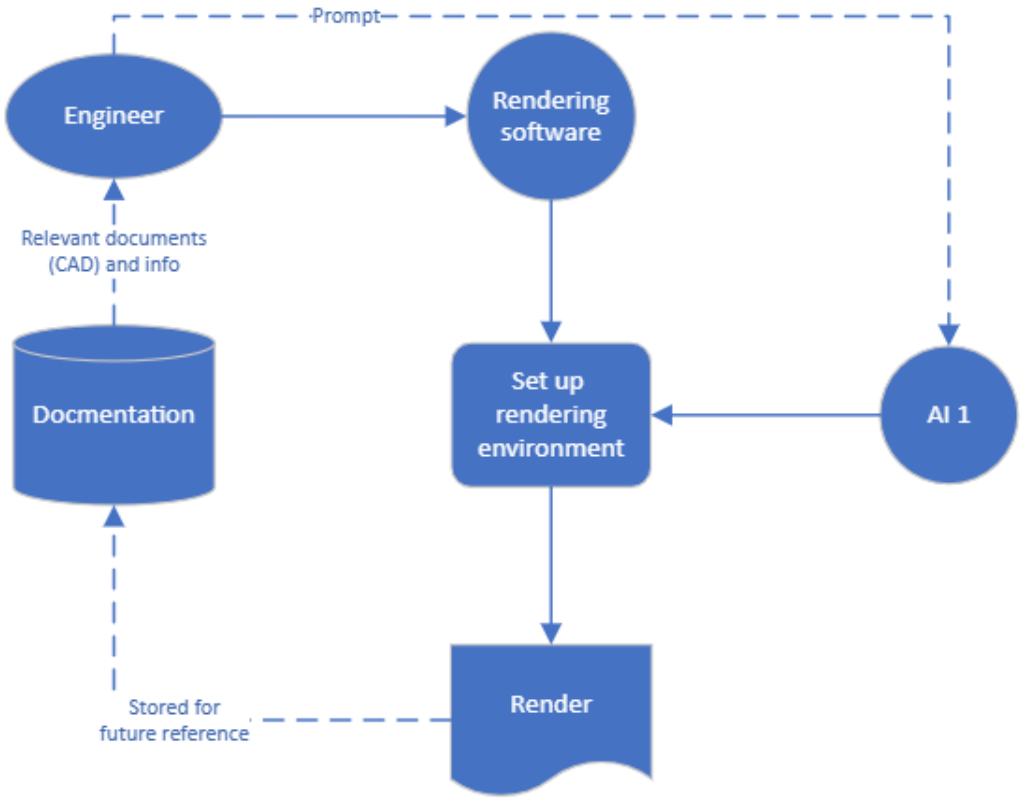
Development 4:
Interaction and function mapping



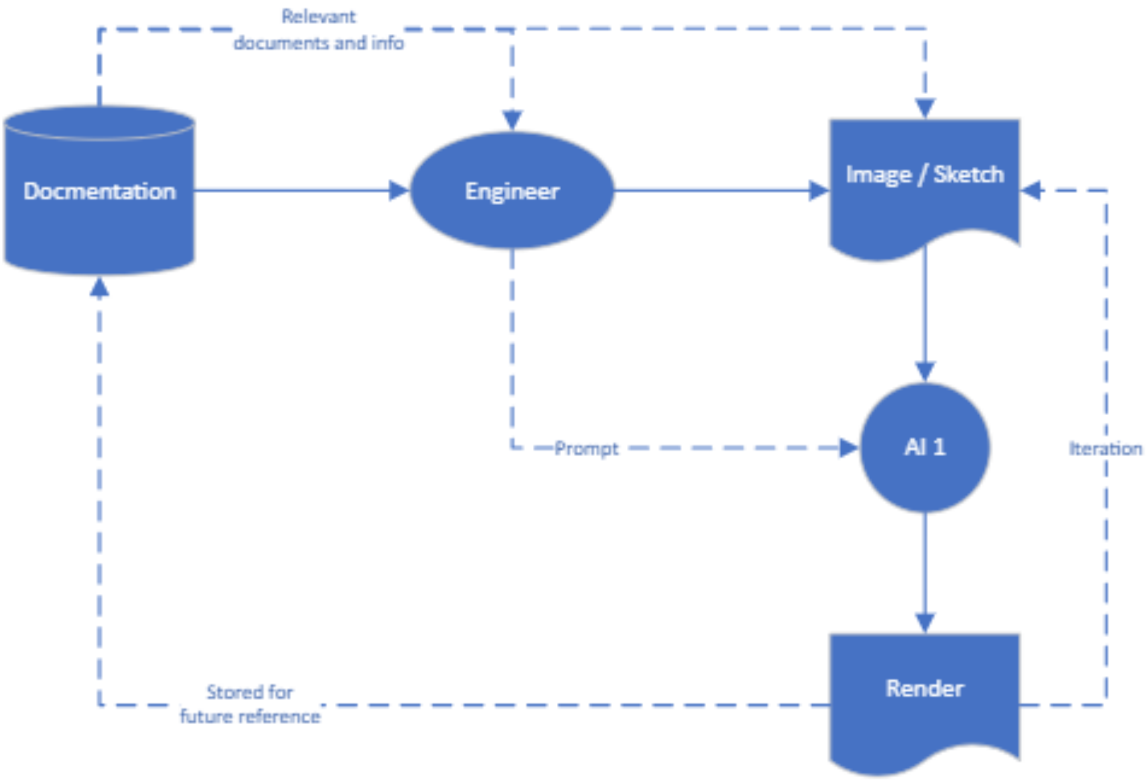
Visualization 1:
Solution directions (Ideation)



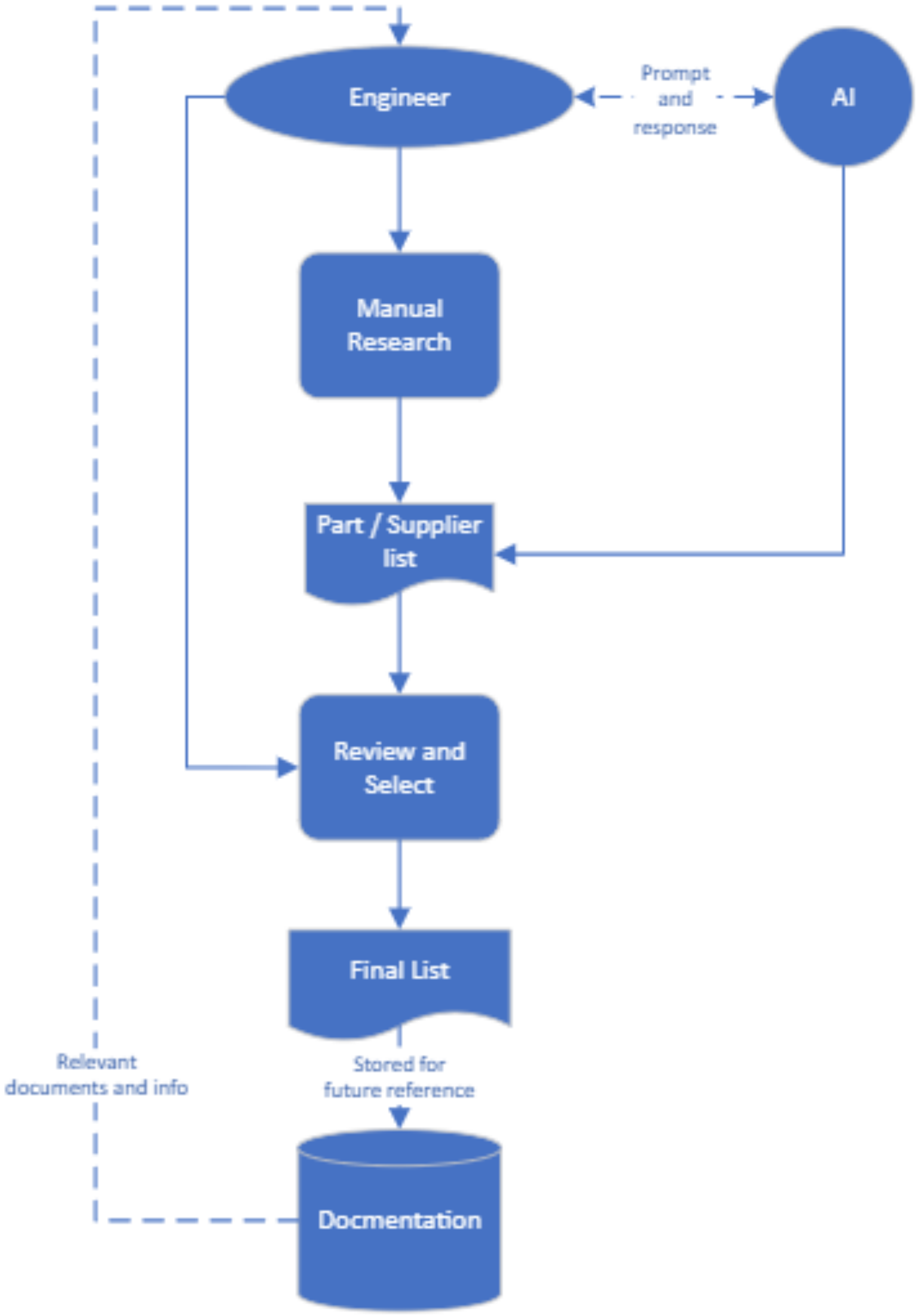
Visualization 2.a:
Concepts (renders)



Visualization 2.b:
Concepts (renders)



Manufacturing 1:
Selection



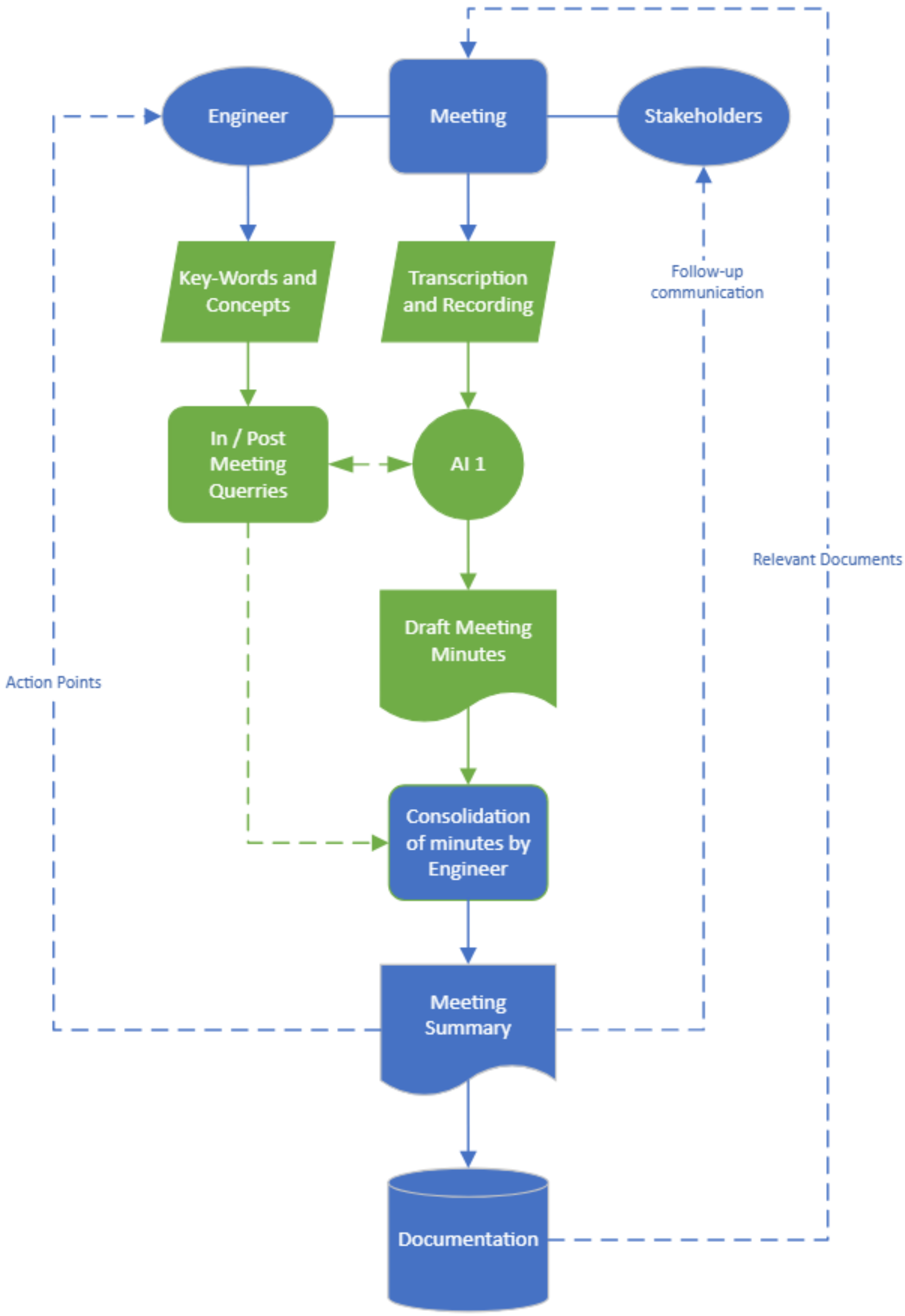
Appendix E: Case Study Tasks & Budget

Phase	Task	Estimate	Actual
Analysis	Kick-off meeting with client and relevant stakeholders	01:00	00:35
	Drawing up a draft Schedule of Requirements (PVE)	03:00	03:05
	Analyzing existing products on the market and trends through desk research and patent research	16:00	09:10
	In-depth analysis of the current product		
	Analyzing use cases		
	Analysis of standards and certification		
	Drawing up a final Schedule of Requirements (PVE)	01:00	00:30
	Presentation of findings and results	06:00	05:37
	Identification of follow-up actions		
	Updating schedule and budget	N/A	N/A
Concept	Brainstorming session with the WeLLDesign team and relevant stakeholders	04:00	03:28
	Idea generation and grouping ideas into meaningful combinations	05:00	06:52

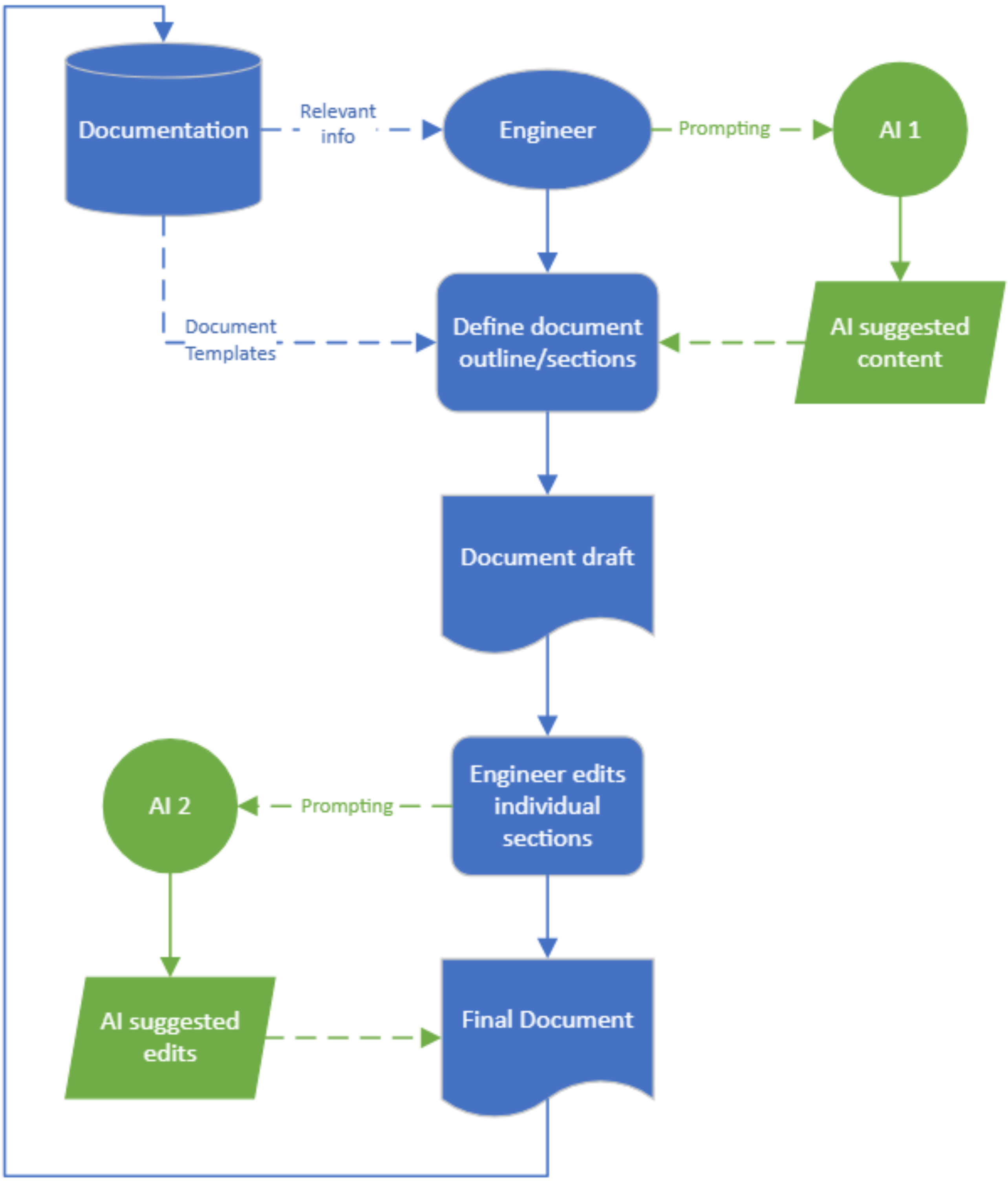
	Visualization of solution directions		
	Establishing selection criteria and selecting solutions	01:00	00:46
	Determining assumptions and essential operating principles to be verified	01:00	00:52
	Development of partial solutions and proof of concept	16:00	13:26
	Designing test setup(s)	04:00	03:01
	Prototyping partial solutions with off-the-shelf parts	N/A	N/A
	Testing operating principles in WeLLDesign workshop	N/A	N/A
	Evaluating test results	N/A	N/A
	Concept development based on findings	N/A	N/A
	Visualization and development of concepts with a focus on operation and design (Solidworks, Illustrator, Photoshop)	08:00	08:30
	Construction of 1 to 3 total concepts using rapid prototyping and available production techniques	N/A	N/A
	Testing total concepts and processing the results	N/A	N/A
	Update from the PVE	01:00	
	Presentation of findings and results	06:00	
	Determining follow-up actions	01:00	
	Updating planning and budget	N/A	N/A

Appendix F: Final Concept Methodologies

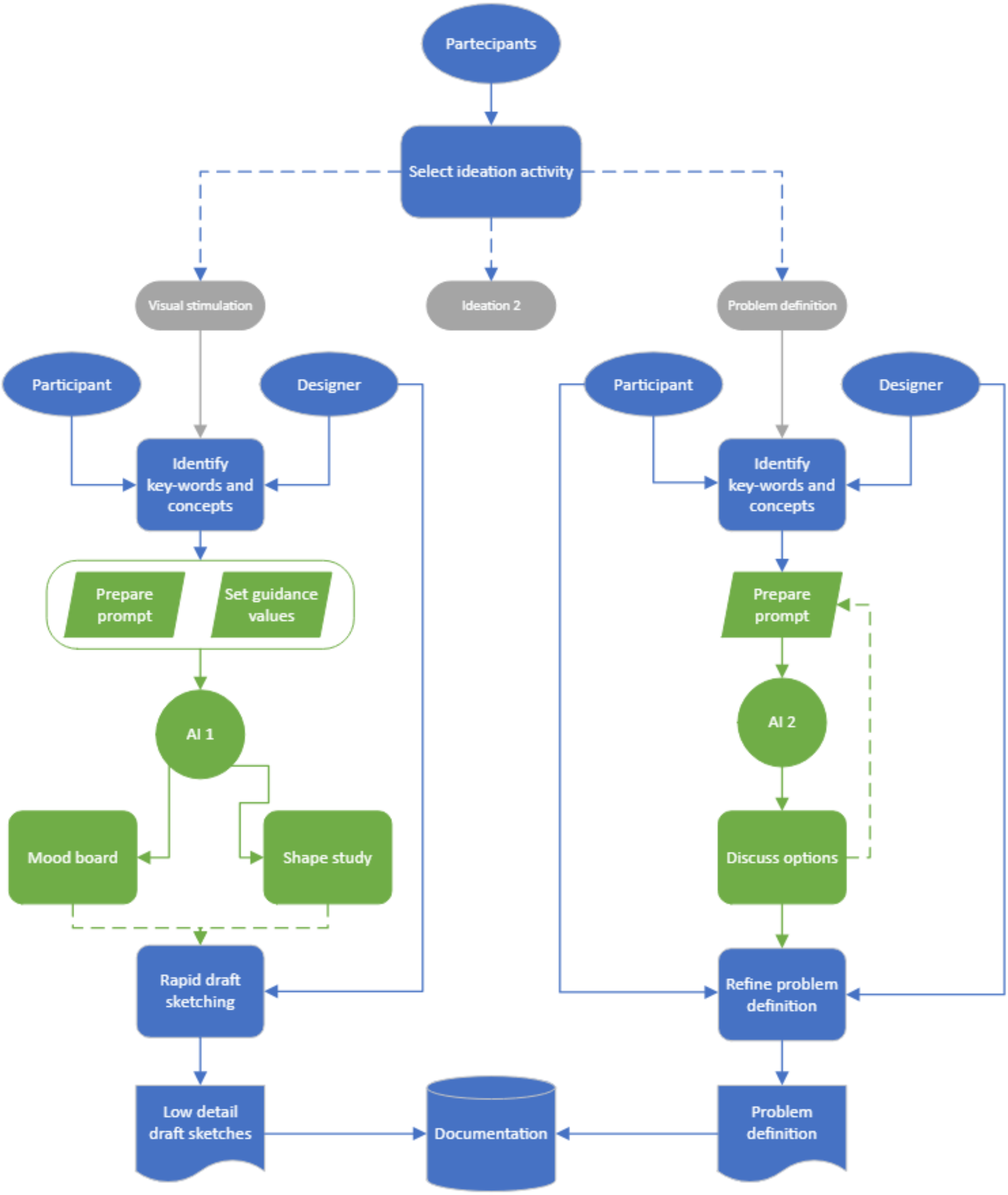
Documentation 1:
Meetings and Minutes



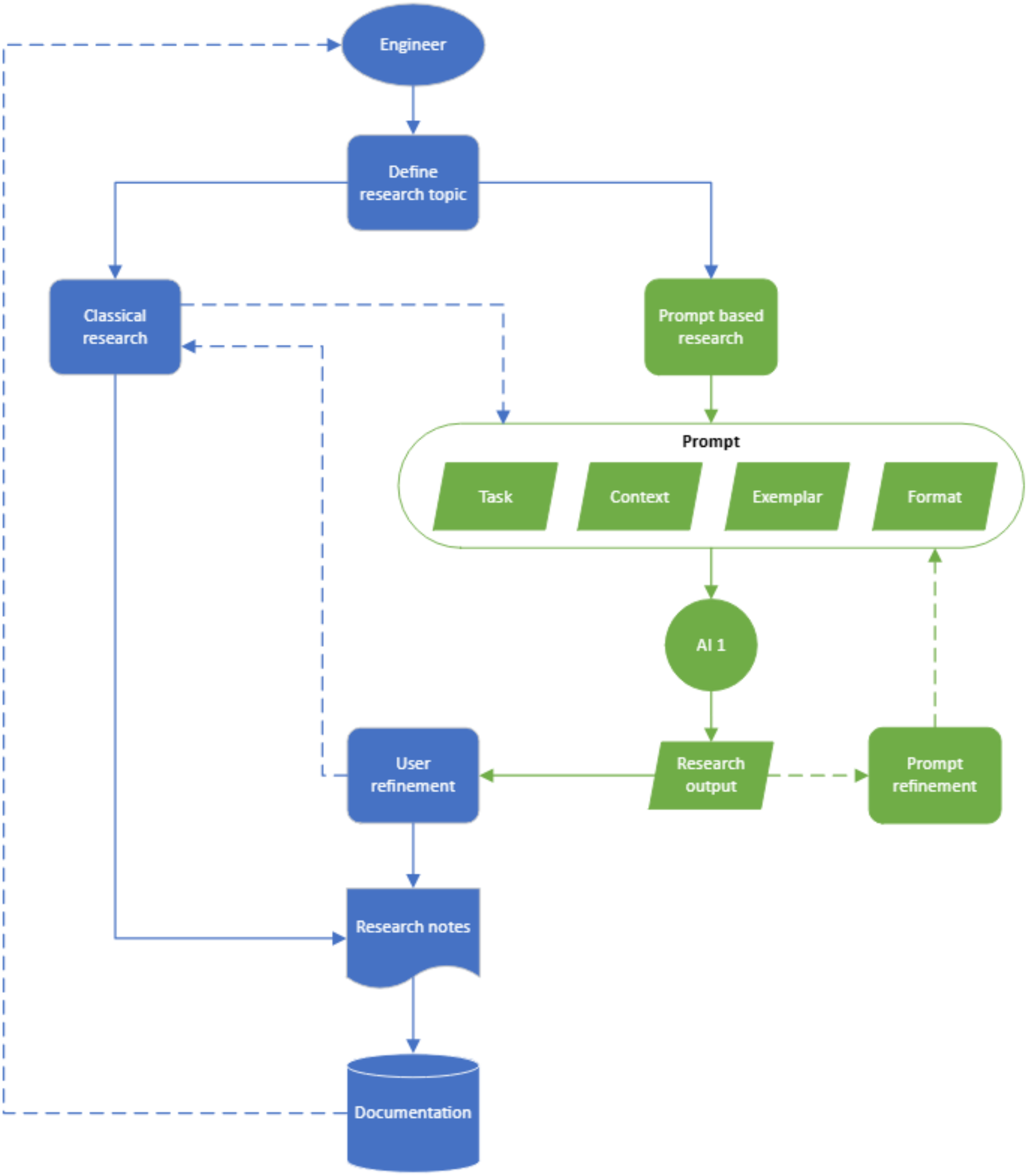
Documentation 2:
Document creation



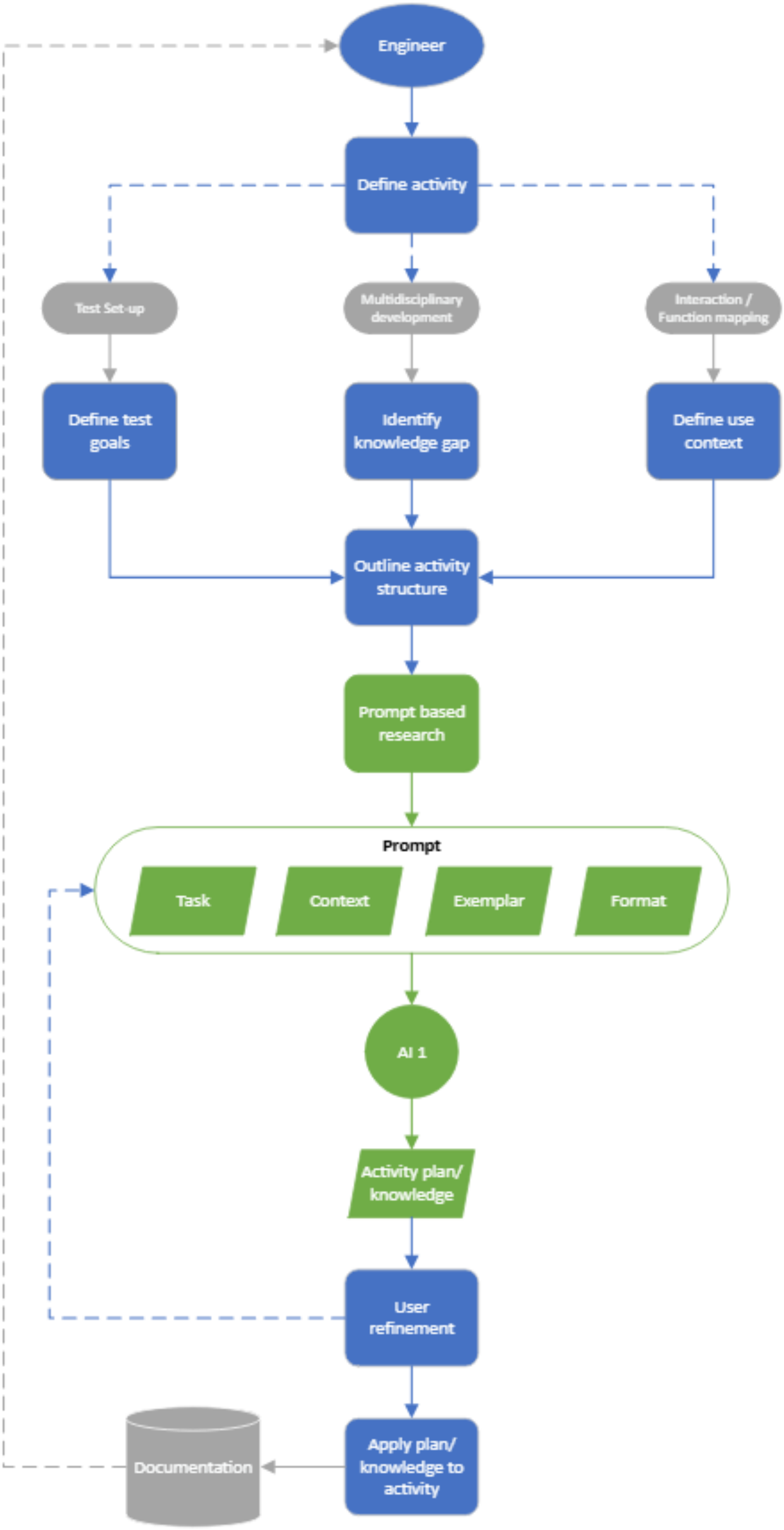
Ideation 1:
Brainstorming



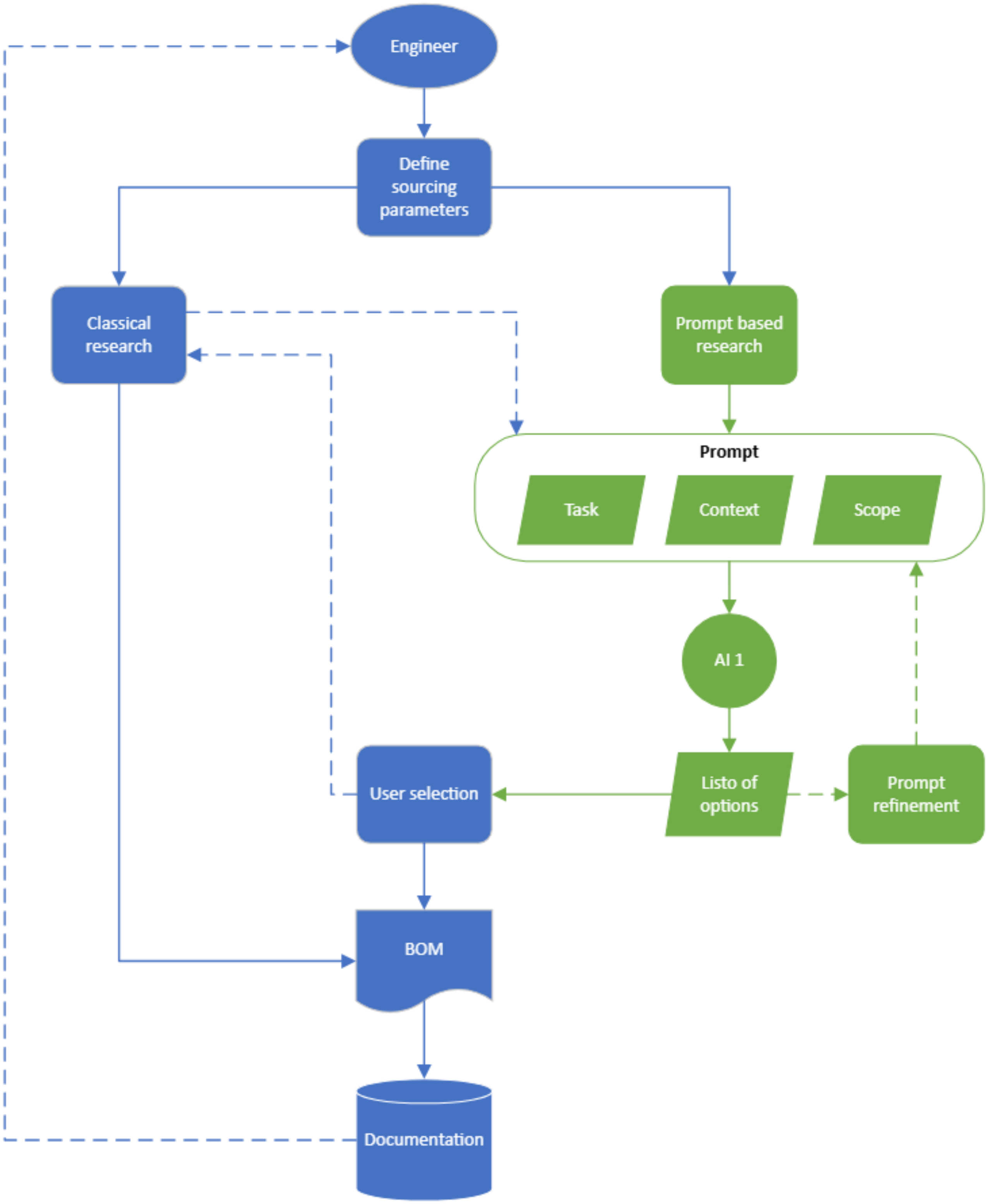
Ideation 2:
Analysis / Research



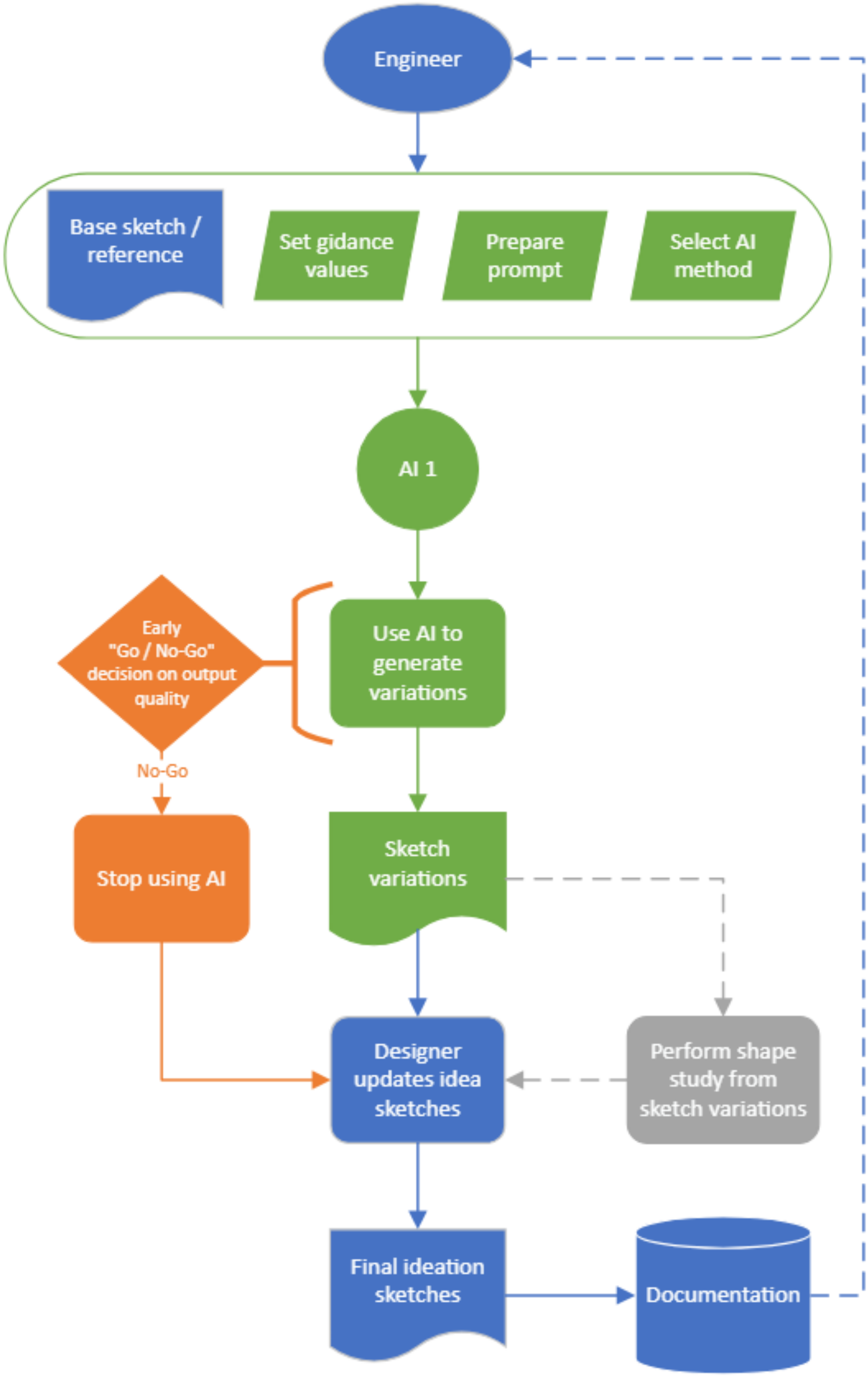
Development 1:
Development Activities



Manufacturing 1:
Sourcing and Selection



Visualization 1:
Ideation Sketching



Visualization 2:
Concept Renders