The development of a decision support tool to assist manufacturing SMEs during adoption and exploitation of novel manufacturing technologies.

By

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Abstract

The efficacy of manufacturing and industrialization activities for improving the economic growth of developing countries has been proven over the last 25 years in countries such as China and India. Participation in the manufacturing domain of lower-income developing counties is only possible if these countries prepare their operations for sustained growth and improvement. One mechanism that can support long-term growth, is the adoption and successful implementation of novel manufacturing technologies, however, it is a growth mechanism that is accompanied by considerable risk. Adopting unproven technologies can be extremely costly and does not necessarily guarantee significant operational or financial gain. Manufacturing small- to medium-sized enterprises (SMEs) in developing countries are therefore incentivised to reduce this adoption uncertainty by employing various analysis techniques.

This study aimed to help reduce the risk associated with novel manufacturing technology adoption, by developing a decision support tool that can support the decision-making of manufacturing SMEs during the technology adoption and exploitation process. To achieve this goal, the researcher identified four theoretical models within the realms of technology readiness, R&D risk assessment, external maturity, and internal operational maturity, and integrated them into an easy-to-use digital tool.

This study achieved its goal of developing such a decision support tool by completing three distinct design cycles. The first design cycle dealt with the initial tool creation and was largely supported by an extensive literature review. The review led to the identification of multiple relevant theoretical models on which various comparison and elimination activities were performed to select the final four models used in the decision support tool. Finally, the first design cycle also saw the initial iteration of a fully functioning digital interface for the tool.

The second design cycle dealt with further development and refinement of the decision support tool. The first refinement step was done by conducting multiple additional literature searches to analyse and refine various details of the existing models selected for use in the tool. This helped to align the tool to the contextual and theoretical requirements of this study. A second refinement step was completed which involved interviews with various industry and subject matter experts who could rate and comment on the details of the tool, thereby increasing the tool's efficacy in practical application.

The third design cycle dealt with the final validation of the newly developed decision support tool. The tool was validated by identifying and applying the tool to a manufacturing SME looking to implement a novel manufacturing technology. The validation stage found that the decision support tool developed in this study successfully fulfilled its purpose. The tool accurately reflected the development position of both the novel manufacturing technology and the SMEs' operational activities. The tool strengthened the decision-making capabilities of the SME and helped the SME with road-mapping activities. Lastly, the tool was useful not only for the analysis of a novel technology but also for the analysis of a novel manufacturing process encapsulating the technology. Ultimately, the tool was developed for use by the cemented tungsten carbide industry for decision support during the commercialization of cemented carbide additive manufacturing technologies.

Opsomming

Die doeltreffendheid van vervaardigings- en industrialisasie -aktiwiteite om die ekonomiese groei van ontwikkelende lande te verbeter, is die afgelope 25 jaar bewys in lande soos China en Indië. Deelname van laerinkomste ontwikkelende lande in die vervaardigingsdomein is slegs realisties indien dié lande hul bedrywighede voorberei vir volgehoue groei en verbetering. Een meganisme wat langtermyngroei kan ondersteun, is die aanvaarding en suksesvolle implementering van nuwe vervaardigingstegnologieë, maar dit is 'n meganisme wat gepaard gaan met groot risiko's. Die implimentering van onbewese tegnologie kan uiters duur wees en waarborg nie noodwendig beduidende bedryfs- of finansiële wins nie. Vervaardigings KMOs in ontwikkelende lande word dus aangemoedig om hierdie implementeringsonsekerheid te verminder deur 'n aantal ontledingstegnieke te gebruik.

Hierdie studie was daarop gemik om die risiko wat verband hou met die implementering van nuwe vervaardigingstegnologie te verminder, deur 'n hulpmiddel vir besluitneming te ontwikkel wat besluitneming van vervaardigings KMOs kan ondersteun tydens die aannemings- en implementeringsproses. Om hierdie doel te bereik, het die navorser vier teoretiese modelle geïdentifiseer binne die gebied van tegnologiese gereedheid, Navorsing & Ontwikkelings risiko-assessering, eksterne volwassenheid en interne operasionele volwassenheid, en dié modelle geïntegreer in 'n bruikbare digitale hulpmiddel.

Hierdie studie het sy doel bereik om so 'n besluitnemingshulpmiddel te ontwikkel deur drie verskillende ontwerpsiklusse te voltooi. Die eerste ontwerpsiklus het gehandel oor die aanvanklike ontwikkeling van gereedskap en is grootliks ondersteun deur 'n intensiewe literatuuroorsig. Die literatuuroorsig het gelei tot die identifisering van verskeie relevante teoretiese modelle waarop vergelykings- en eliminasie -aktiwiteite uitgevoer is om die finale vier modelle te kies. Laastens is die eerste iterasie van ŉ digitale koppelvlak vir die hulpmiddel voltooi tydens die eerste ontwerpsiklus.

Die tweede ontwerpsiklus het gehandel oor verdere ontwikkeling en verfyning van die besluitnemingshulpmiddel. Die eerste verfyningsstap is gedoen deur verskillende aspekte van die bestaande modelle wat gebruik is in die hulpmiddel, te ontleed en te verfyn deur verskeie addisionele literatuurondersoeke uit te voer. Dit het gehelp om die instrument aan te pas vir die kontekstuele en teoretiese vereistes van hierdie studie. 'n Tweede verfyningsstap is voltooi deur onderhoude met verskillende bedryfs- en vakdeskundiges, wat die besonderhede van die instrument kon beoordeel en kommentaar lewer, te voer en sodoende is die doeltreffendheid van die instrument in die praktiese toepassing verhoog.

Die derde ontwerpsiklus het gehandel oor die validering van die hulpmiddel. Die validering is gedoen deur 'n vervaardigings-KMO te identifiseer wat 'n nuwe vervaardigingstegnologie wil implementeer en die hulpmiddel kan gebruik. Dit is gevind tydens die valideringstadium dat die besluitnemingshulpmiddel wat in hierdie studie ontwikkel is, sy doel suksesvol bereik het. Die hulpmiddel het die posisie van die nuwe tegnologie en die KMO-aktiwiteite akkuraat weerspieël en het die besluitnemingsvermoëns van die KMO versterk. Die hulpmiddel het die KMO ook gehelp met padkaartaktiwiteite. Laastens was die instrument nie net nuttig vir die ontleding van 'n nuwe tegnologie nie, maar ook vir die ontleding van 'n nuwe vervaardigingsproses wat met die tegnologie gepaard gaan. Uiteindelik is die hulpmiddel ontwikkel vir gebruik deur die sement-wolframkarbied-industrie vir besluitondersteuning tydens die kommersialisering van sementkarbied-byvoegvervaardigingstegnologieë.

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I would like to thank my parents for their unwavering support and insightful advice.

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List of Abbreviations

DoD	Department of defence
MCRL	Manufacturing Capability Readiness Levels
TRL	Technology Readiness Level
SME	Small and Medium Sized Enterprise
MRL	Manufacturing Readiness Level
LVoD	Long Valley of Death
VoD	Valley of Death
TRRA	Technology Readiness and Risk Assessment
ROI	Return on Investment
ROE	Return on Equity
AM	Additive Manufacturing
SM	Smart Manufacturing
SRQ	Secondary Research Questions
IS	Information Systems
WSN	Wireless Sensor Network
CPS	Cyber Physical System
IoT	Internet of Things

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Chapter 1: Introduction

1.1 Background

Since the industrial revolution manufacturing has been, and will continue to be, one the most important industries in the world. It is in a constant state of evolution and improvement, forcing manufacturing enterprises to adapt and grow at a rapid rate (Dean Group, 2018). Strangely, however, it has been observed that since 1970, the manufacturing sector's value added and employment contribution to world GDP and employment, respectively, have not changed significantly (Haraguchi, Cheng and Smeets, 2017). This is a decline observed specifically in value added by manufacturing in developing countries and is attributed to a shift of manufacturing activities to a small number of populous countries, thus resulting in a concentration of manufacturing activities in very specific developing countries (Haraguchi, Cheng and Smeets, 2017). However, the efficacy of manufacturing and industrialization in improving economic growth of developing countries have been proven by the rapid and sustained growth observed over the last 25 years within the select developing countries that prioritised manufacturing. While these select countries have a hold on the manufacturing industry, they are quickly approaching a mature stage of industrialization, which could open the manufacturing market for lower-income developing countries (Haraguchi, Cheng and Smeets, 2017) (Krishna, 2021).

To exploit this shift in manufacturing activities, enterprises in developing countries need to prepare their operations for sustained growth and improvement. There are multiple mechanisms for growth within enterprises, however, this project will focus on creating and sustaining growth through the adoption of new manufacturing technologies by SMEs. If an enterprise can be the first to commercialise a new manufacturing technology, they are awarded the opportunity to out preform the conventional methods of their competitors, or insert themselves into a newly discovered market, which they can now help shape to their advantage (Mortara and Ford, 2012). This chance for success is, however, accompanied by immense risk, as the adoption of novel and unproven technologies require large financial and operational investment without a guarantee of any substantial improvement in performance and monetary gain. This problem is especially significant when enterprises do not understand why new technologies are needed and adopt them without a clear adoption strategy (Barwell, Stewart and Hoad, 2020). Enterprises are therefore incentivised to implement some analysis capabilities which can help them quantify and predict the possible risk of further technological development and implementation, while also improving road-mapping and strategic capabilities. Decision support is therefore required to help enterprises make sound investment and strategic decisions and can be provided by incorporating various theoretical models and analysis methods into a decision support tool. The following section will discuss such theoretical models.

1.1.1 Technological readiness and maturity

In 1995 NASA published a paper that neatly outlined nine technological readiness levels (TRL) and how these levels can be used as an analysis tool to determine the perceived level at which a new technology can be utilised (Mankins, 1995). This report proved to be the fundamental basis upon which various subsequent papers were built. The idea of readiness models was researched extensively in subsequent years with inter alia -Parasuraman publishing the 36-item Technological Readiness Index in 2000 (Parasuraman et al., 2015). Industries such as the automotive and IT industries also capitalised on the usefulness of readiness models by creating their own readiness assessment guides. The Automotive Technology Readiness Level guide (Williamson and Beasley, 2011) and the IT sustainability: IT readiness model (Molla et al., 2009), act as examples for corporate use of the models. The importance of these models was clear and constant improvement of existing models became commonplace.

These models are used as tools to conceptualize and quantify the position of a process, technology or organisation within its lifecycle. The ability of an enterprise to understand their position relative to their milestones could set them apart from their competitors. Besides creating a more accurate understanding of the operational landscape, it also allows for the methodical development of plans and standard practices to ensure continuous development and growth is achieved sustainably.

1.1.2 The Long Valley of Death

The term “Valley of death” is frequently used in the manufacturing realm to describe the gap between academic innovation and market commercialisation of a new technology. The gap represents a phase during innovation development where academic funding and interest for further development has been exhausted but the development is not yet significant enough to attract commercial involvement in the project. In many cases, this gap can prevent potentially lucrative and innovative technologies from ever reaching commercial use. Luckily, the importance of proper planning and support during this phase is well understood. So well, in fact, that the UK government established the High Value Manufacturing Catapult. This is a network of manufacturing innovation centres that work together to overcome the valley of death. Their aim being to bridge the gap by providing enterprises with expert research, advice and guidance (CATAPULT High Value Manufacturing, 2021).

In their 2017 paper, Ward et al. argues that overlapping the “Valley of Death”, is a “Long Valley of Death” (Ward *et al.*, 2017). They suggest that most institutions view the valley of death as a Manufacturing Readiness Level (MRL) issue, specifically the transition between MRL 4 and 6 where, in reality, the true problem starts even earlier and concludes later down the innovation timeline. The implication of the LVoD is that enterprises will have to consider potential influencing factors from much earlier in the innovation timeline while also being aware of extended periods of required support after development. Ward et al. also believe that in addition to issue of readiness, enterprises should consider specific maturity dimensions which can drastically influence the perceived risk of the project. This concept will be explored extensively in Chapter 2. By understanding the obstacles associated with the LVoD, an enterprise can tailor its decision making accordingly. Ideally, the LVoD concept must be combined with a maturity model to communicate the position of the various LVoD influencing factors within the implementation roadmap.

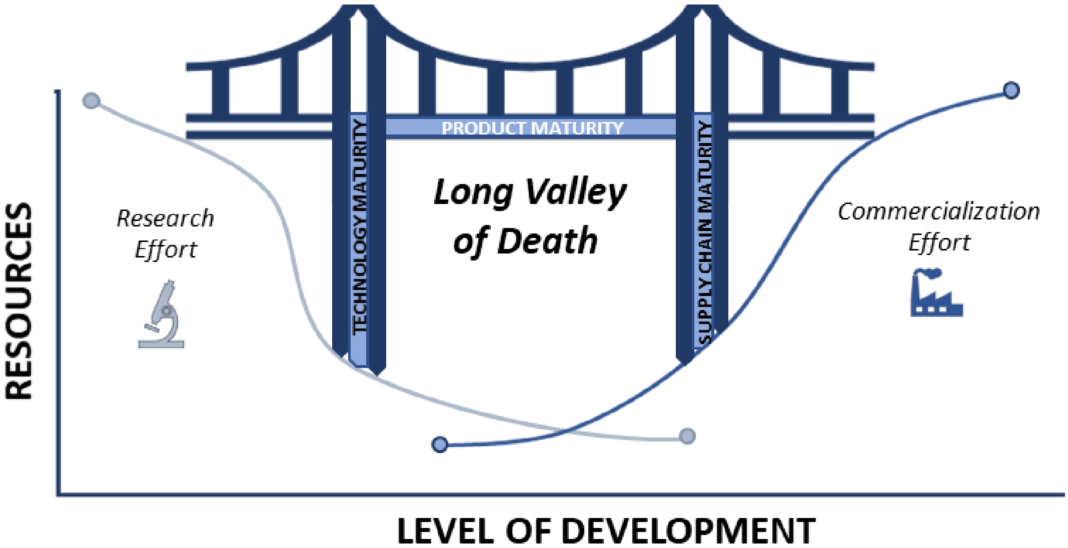


Figure 1-1: *Long Valley of Death example*

1.2 Problem statement

The adoption and implementation of new technologies within an enterprise or industry is usually an iterative process that requires proper planning and performance tracking (Barwell, Stewart and Hoad, 2020). Knowing at what phase of technology implementation an enterprise is, as well as the steps required to realise full technological capability, can be of value to both company management and stakeholders. Theoretical frameworks such as technological readiness indexes and maturity models are known tools used for quantifying the capability- and development phases of newly implemented technologies. (Mankins 1995). These frameworks analyse and rank predetermined criteria applicable to specific technologies, enterprises, or industries to provide a sense of the implementation stage and development requirements of the technology (Proença & Borbinha, 2016). Most of these models, however, can only analyse either the pre-implementation stage or post-implementation stages of technology. They do not function optimally during the transitional stages of technology implementation.

The preliminary investigation suggests that the transition of novel proof-of-concept manufacturing technologies to commercial application is associated with high market failure rates (Ellwood, Williams and Egan, 2020). Enterprises seeking to adopt novel third party manufacturing technologies, therefore, need a decision support framework to assist with the quantification of various risk factors in order to make an informed decision around future technology adoption and company policies. This tool must consider influencing factors external to the enterprises as well as internal operational factors. It is hypothesised that such a decision support tool can be created integrating various applicable maturity and readiness models and adjusting the different dimensions to fit the specific needs of the industry.

1.3 Motivation

In 2012 the U.S.A Department of Defence (DOD) published the Manufacturing Readiness Level Deskbook. In the Deskbook they site the decline of readiness and maturity reviews, especially within the manufacturing industry, as a potential cause for a sharp increase in manufacturing-related impacts on costs and schedule slips of DOD acquisition programs *(OSD and MRL Working Group, 2012).* Maturity and readiness reviews are therefore paramount to the successful implementation of new technologies and systems within industries. Subsequently, industries started realising the value of these reviews and started adapting, creating and combining previous work on these subjects to fit the specific needs of their industry. One such example was the creation of Manufacturing Capability Readiness Levels (MCRL) by Rolls Royce to improve manufacturing capabilities of their industry (Ward and Winton, 2007). Rolls Royce representatives would continue to improve on the MCRL till, in 2017, a paper entitled "*Three dimensions of maturity required to achieve future state, technology enabled manufacturing supply chains*" was published (Ward et al., 2017). This paper utilises the authors specialist knowledge of MCRL to finally address the issue of "The valley of death" from a manufacturing technology standpoint and, subsequently, create the concept of "The Long Valley of Death". For developing countries this valley can be especially difficult to cross not only due to financial restrictions but also as a result of lower labour skill, which greatly reduces the ability to adopt innovative and advanced technologies (Coulibaly and Foda, 2020). However, countries such as South Africa, is classified as a developing country with an upper-middle income (ESARO UNFPA, 2019). Such an upper-middle income developing country has a noticeable advantage over low-income developing countries in terms of future manufacturing capability development, in that they possess the resources to invest in technology-led manufacturing while retaining a competitive advantage for price and cost (Coulibaly and Foda, 2020). For these upper-middle income counties it could be extremely beneficial to investigate the opportunities presented by manufacturing technology adoption.

Even though the concept of The Long Valley of Death has been established, the model developed by Ward mostly focuses on external considerations and, while valuable, is too rudimentary to be used as a proper predictive tool (Ward et al., 2017). The literature, however, is rife with manufacturing maturity models that can be used to analyse internal maturity and thus help with the prediction of internal manufacturing success. Extensive work was done by Mittal to create a toolbox system for improving smart manufacturing in manufacturing SME's (Mittal et al., 2018). Their model, however, focuses only on considerations of a manufacturing enterprise's internal operations, therefore ignoring the external influences of the Long Valley of Death. Therein lies the motivation of this thesis: In order to create a truly holistic view that can facilitate crossing the Long Valley of Death while also improving internal maturity and operations, one must marry the different concepts of readiness, maturity and LVoD into one useful stepwise tool. The tool must help SMEs identify a novel technology, analyse the external considerations and the risk involved in pursuing technological adoption and finally allow for the analysis of internal maturity as a predictor of internal adoption and integration success.

1.4 Research Gap Identification

The motivation for this project originated from the need expressed by the DSI-NRF Centre of Excellence in Strong Materials for research contributions in the field of additive manufacturing (AM) of cemented tungsten carbide. This led to the publication of a scoping review which proposed and then analysed the possibility of creating maturity and readiness models specifically for cemented carbide additive manufacturing technologies (Burger, Grobbelaar and Sacks, 2020). The scoping review identified four critical papers in the field of maturity model development steps, and an additional five critical papers in the field of industry 4.0 manufacturing specific maturity models. The scoping review also provided the first introduction to the SM^{3}E model proposed by Mittal (2018), a model which is used extensively in this project, with the hope of building a new maturity model which could guide future development efforts of cemented carbide additive manufacturing.

Additionally, the scoping review also contained literature searches surrounding viable cemented carbide additive manufacturing technologies (Burger, Grobbelaar and Sacks, 2020). Further investigation of the literature surrounding these technologies revealed that most of the technologies are, at the time of writing this thesis, mainly in the academic research and development phase, with limited commercialisation efforts. As the cemented carbide additive manufacturing commercial sector was found to be in its infancy stage, creating a maturity model was deemed unrealistic. Additionally, simply developing a technology maturity model would not have sufficient academic merit as there are [1]many similar models already available and [2]the uncertainty surrounding the cemented carbide AM technology development could result in an unreliable model. None of the existing models addressed the relevant questions all the way from technology development, through adoption, to implementation. Instead, each model focussed on a specific phase of the technology's lifecycle. The realisation quickly became that the limiting factor to the original scoping review project proposal was the uncertainty and lack of information associated with the development and adoption process of novel manufacturing technologies. Therefore, instead of developing a model to address a single area of technology adoption, combining different models, each addressing a unique problem of technology adoption, into a tool could provide far more insight into the development and adoption processes.

Following the new approach, the search terms for the literature gap identification was adjusted to include frameworks and models which deal with the analysis of novel, proof-of-concept technology development and adoption. These new search terms lead to the identification of the Long Valley of Death, and the relevant dimensions which influence successful technology development, adoption and exploitation. From this literature analysis, the focus of this thesis became the development of a decision support tool that can assist with technology innovation and adoption. Such a tool would not only be extremely useful for a variety of manufacturing technologies and enterprises, but it would be directly applicable to the cemented carbide additive manufacturing industry since the majority of the viable cemented carbide AM technologies will soon enter the Long Valley of Death phase of commercialisation. The proposed decision support tool can therefore support future development activities in the cemented carbide AM industry, thus satisfying the requirements of the DSI-NRF. While there could be private enterprises who currently use decision support tools for similar purposes as the tool developed in this project, no such tools were found to be available in the public domain. This project, therefore, not only developed a useable and applicable tool, but also provides the public academic sphere with the necessary guidelines for development and use of future tools.

1.5 Research Questions and Objectives

The problem statement gives rise to certain research questions. There is a main research question which contains four distinct concepts. Each of these concepts give rise to secondary research questions. These questions are shown in the following sections below.

1.5.1 Main research question

The main research question reads as follows: *What should comprise a decision support tool*[1] *for use by manufacturing enterprises*[2] *during the novel manufacturing technology adoption phase known as "The long valley of death"*[3]*? How can one achieve the above by integrating and adjusting established theoretical model*[4] *concepts of maturity and readiness indexes?*

The main research question contains four key concepts, which helped guide the project literature analysis. These concepts are summarised in Table 1-1 below:

Table 1-1: *Concepts contained within the main research question*

Main Research Question Concept	**Definition**
Concept 1	Decision support tool development
Concept 2	Manufacturing enterprises
Concept 3	Long Valley of Death
Concept 4	Theoretical Models (Maturity and Readiness)

1.5.2 Secondary research questions

The division of the main research question into four concepts creates a second tier of questions for each concept. These secondary research questions (SRQ) will help guide the project and shape the research objectives. The SRQ can be seen in Table 1-2 below:

Table 1-2: *Secondary Research questions*

Concepts contained in main research question	**Secondary research questions**
1. *Decision Support Tool*	1.1 What is the input of such a tool? 1.2 What is the output of such a tool? 1.3 What is the preferred process flow of such a tool? 1.4 Which interface can be used for such a tool?
2. *Manufacturing Enterprises*	2.1 What sizes of enterprises are relevant to the study?

	2.2 How far down the production network are criteria still relevant? 2.3 How does Smart Manufacturing fit into the application context?
3. *Long Valley of Death*	3.1 What is the long valley of death? 3.2 How can LVoD be used in a decision support tool?
4. *Theoretical Models*	4.1 Which readiness indexes are relevant to the study? 4.2 Which maturity models are relevant to the study? 4.3 Are there other theoretical models that can be useful to the study?

1.5.3 Research objectives

The overarching objective of this study is to create a decision support tool that manufacturing enterprises can use to assist decision making during the transitional phase associated with adopting novel third party manufacturing. To this end, the objectives pursued in this dissertation are summarised in Table 1-3 below. The corresponding secondary research question (SRQ) addressed by the objectives can also be seen in the table below:

Table 1-3: *Research objectives*

Objective number	**Definition**	**SRQ Addressed**
Objective 1	To conduct a comprehensive survey of the literature related to this study. In particular: a. To review the field of novel manufacturing technology adoption, maturity frameworks, readiness indexes and decision support. b. To describe the most prevalent models and frameworks used for benchmarking and analysis of technology development and adoption. c. To select and report on the models and frameworks that are most applicable to the domain of decision support for novel manufacturing technology adoption.	1.1; 3.1; 3.2; 4.1; 4.2; 4.3
Objective 2	To design and develop a functioning and interactive decision support tool by: a. Arranging the previously selected theoretical models into a logical process flow. b. Integrating the arranged models into a user-friendly IT interface. c. Incorporating additional analysis functionalities into the interface to expedite understanding of the various models' results.	1.2; 1.3; 1.4
Objective 3	To adapt and refine the existing models to better suit the application context of the decision support tool. This will be done by: a. Conducting a focussed literature analysis to refine the various dimensions of the different models.	2.1; 2.2; 2.3

	b. Conducting action research to ensure the manufacturing industry applicability of the dimensions	
Objective 4	To validate the final decision support tool by simulating a real-world scenario in a case study with an industry partner by: a. Identifying relevant and applicable participants. b. Creating a realistic simulation scenario. c. Implementing the tool along with an enterprise representative who is knowledgeable about the application context.	Main research question answered

1.6 Scope of study

The scope of the study is determined by defining the boundaries, limitations, assumptions and strengths of the study. For this project, four delimitations were set as is defined in Table 1-4 below. These delimitations were instrumental in providing a realistic and achievable scope for the proposed tool, while ensuring maximum applicability of the tool.

Table 1-4: *Delimitations of study*

Delimitation	**Description**
Delimitation 1	Although the manufacturing industry is a massive global endeavour, the hope is that this study will largely benefit enterprises within a South African context.
Delimitation 2	The delimitation of the South African context results in small and medium sized enterprises (SME's) being considered favourably for analysis.
Delimitation 3	There is a delimitation on how far down the production network influencing factors are considered. This study will only look at influencing factors from the final manufactured product up until and including the acquisition of the novel manufacturing technologies.
Delimitation 4	The final delimitation is that the study will mostly focus on high level influencing factors throughout the production network. This is to ensure a one-size-fits-all approach.

Based on these delimitations it was concluded that the proposed decision support tool must be developed for manufacturing SMEs, which require the tool to be simple enough for in-house use, but detailed enough to include elements from technology inception, through supply chain and manufacturing process all the way to the product considerations. These delimitations are represented in the Figure 1-2 below:

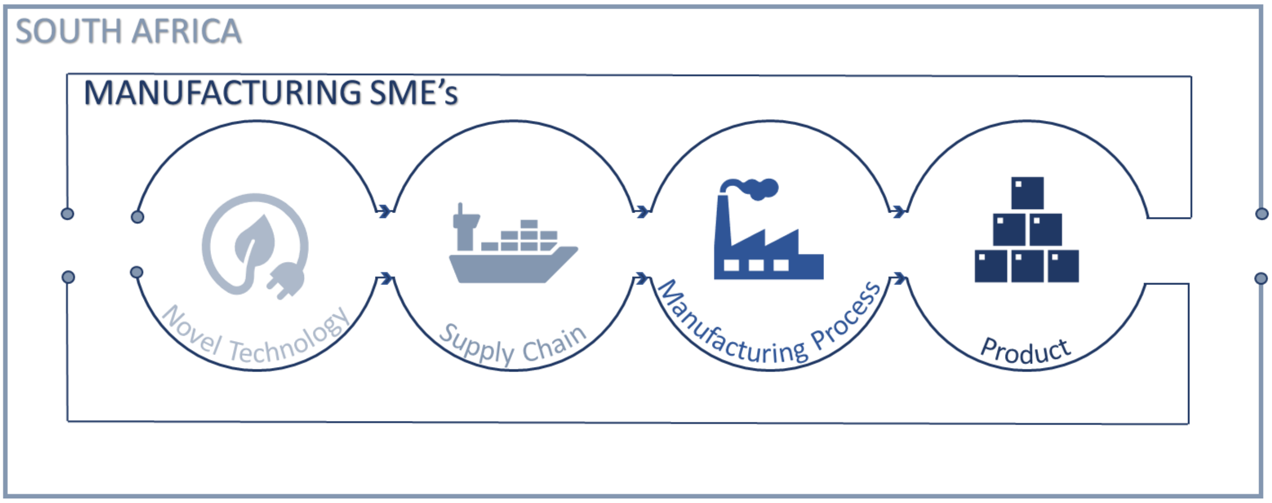


Figure 1-2: *Visual representation of study delimitations*

Next, the limitations and assumptions are defined: The usefulness of this study is limited by the size of the enterprises. Enterprises of different sizes experience different challenges, and it is therefore challenging to develop a "one size fits all" approach. Such a "one size fits all" approach favours high level analysis of dimensions and criteria. This results in a tool that can provide generally applicable decision support but will still require the expertise of trained personnel with some experience in the application field to be effective. It is, subsequently, assumed that the tool developed in this study will be used by trained personnel who are knowledgeable in the various application areas. It is also assumed that smaller enterprises will prefer a "self-help" tool, thus implying that, while trained personnel will use the tool, it must be simple enough to use as not to exhaust the enterprise's resources.

Lastly, the strength of this study relates to its holistic approach and highly applicable nature. The support tool is designed in such a way that it can be adapted to a number of different manufacturing technologies, irrespective of their application. This means the tool is easy to use and highly adaptable to ensure it will fit the specific needs of most manufacturing SMEs. This adaptability means that the tool can be used by the cemented tungsten carbide industry to support commercialization efforts of cemented carbide AM, once these technologies have undergone sufficient development. Finally, the logic flow of this tool could potentially be used as a guideline for the development of similar tool in other industries. Consulting firms could benefit hugely from the research by using it as a benchmarking tool for clients along with developing a roadmap through the benchmarking process.

1.7 Ethical implementations

When conducting interviews with individuals or company representatives, sensitive information should be respected and documented as to not share beyond the allowable jurisdiction. The researcher, subsequently applied for and received ethical clearance for conducting interviews with participants about topics relating to this project. The ethical clearance project ID is: 21566. The protocols summarised in Table 1-5 must be considered when working with confidential information:

Table 1-5: *Interview data management protocols*

Management Step	Protocol
De-identification	This process involves breaking the link between the data collection file and the interviewee's personal details. The file on which the interview questions will be completed will be assigned a generic file name i.e. "Theoretical Model Questions: Subject X". The interview will also be conducted digitally thus removing any form of personal attachment from the document.
Encryption	This is the process of assigning passwords to the various de-identified interview documents. Only the head researcher will have access to these passwords. These passwords will be set to a predetermined password creation convention only known by the head researcher.
De-centralisation	This is the process of storing the interview data on a decentralised location. This can be done using a cloud storage service such as google drive, which has a proven track record for cloud-based storage and security. A backup of the data will, however, be kept on an external hard drive locked away and only accessible by the head researcher.
Destruction of data	Once the project has been concluded it is the responsibility of the head researcher to delete the data stored on both the cloud and hard drive.

The development of more efficient manufacturing techniques could put traditional manufacturers, too small to adapt to the new technologies, out of business. This could result in a loss of jobs. The cemented tungsten carbide industry, however, is mostly dominated by relatively well-established manufacturing corporations. Lastly, the research conducted in this project could aid in further industrialisation efforts worldwide. This could have an adverse effect of the environment.

1.8 Summary of Chapter 1

Chapter 1 introduced the reader to the concepts of technology readiness and maturity while also explaining the significance of the phenomena known as the Long Valley of Death. Next, the chapter defined a problem statement that explains some of the challenges manufacturing enterprises face when looking to adopt novel manufacturing technologies and how decision support is needed during this adoption phase. Chapter 1 then integrated the newly defined concepts and problem statement to provide a comprehensive motivation for this project. The chapter also explains the intricacies of the research gap that was identified and pursued in this project. This research gap can be summarised as:

There is uncertainty and a lack of information associated with the development and adoption process of novel manufacturing technologies. Therefore, instead of developing a model to address a single area of technology adoption, combining different models, each addressing a unique problem associated with technology adoption, into a tool could provide a far more insight into the development and adoption processes.

Once the background, problem statement and research gap were explained, Chapter 1 introduced the specific research questions that the project attempts to answer. This project answers each research question by completing specific research objectives as defined in Chapter 1. These questions and objectives guided the progression and activities of the project. Finally, Chapter 1 defined the project scope by explaining the various delimitations of the project and it also explained the various ethical implications and practices that was considered during the project's lifespan.

Chapter 2: Methods and Activities

This chapter will outline the methods and activities that were used to design, develop, and validate a decision support tool for novel manufacturing technology adoption. To ensure that these activities followed a conducive structure, an overarching research methodology called Design Science Research Methodology (DSRM) was selected to guide the design process. The DSRM contains different activities, each of which is done according to specified requirements.

2.1 Overarching Research Methodology

In the pursuit of identifying an applicable research methodology, it was necessary to understand the role of research paradigms in the scientific community. Kuhn defined a research paradigm as a set of common beliefs and agreements shared between scientists about how problems should be understood and addressed (Kuhn, 1962). Additionally, the concept of a scientific research paradigm was defined by Gliner, Morgan and Leech as the approach or thinking about the research, the accomplishing process, and the method of implementation (Gliner, Morgan & Leech, 2011). From these definitions it can be contrived that a research paradigm serves as an enabler and directional guideline for the research process but does not necessarily constitute a specific methodological approach. Such a methodology must be identified for use within the research paradigm once the research process commences. When considering the objective of designing a support tool for this thesis, one can conclude that the project must be rooted in a design-centric research paradigm. Such a design research paradigm is described as the “science of the artificial” since it is concerned with the development and construction of objects and phenomena called artefacts, which aim to meet specific goals (Vaishnavi & Kuechler, 2015). Once it was understood what the purpose of the design research paradigm was, it was possible to identify an applicable methodology that could provide actionable steps, methods and activities in service of the project objectives.

This project makes use of the DSRM to guide the decision making, research activities and design processes of the decision support tool’s development. The usefulness of this DSRM was observed especially within the information systems (IS) industry due to the methodologies ability to address so-called “wicked problems”, as defined in 1984 by Rittel and Webber (Hevner and Chatterjee, 2010), but has since found use in various design and development projects. DSRM’s applicability for these design and development projects can be attributed to the prevalence of “wicked problems” in such projects and DSRM’s capability of addressing these problems. In order to check weather a project fulfils the requirements that would make DSRM the methodology of choice, Hevner and Chatterjee defined five applicability criteria as summarized in Table 2-1 below (Hevner and Chatterjee, 2010). These five criteria describe the characteristics prevalent in a specific project that would justify the use of DSRM. After careful consideration, it was concluded that this project fulfils all the criteria applicable to DSRM, as summarised in Table 2-1 below, thus justifying the use of DSRM as a viable research methodology for this project.

Table 2-1: *DSRM applicability criteria (Hevner and Chatterjee, 2010)*

	Hevner and Chatterjee criteria	*Matched by this project*
Criteria 1	*Unstable requirements and constraints based on ill-defined environmental contexts*	Agree
Criteria 2	*Complex interactions among subcomponents of the problem.*	Agree
Criteria 3	*Inherent flexibility to change design processes as well as design artifacts.*	Agree
Criteria 4	*A critical dependence upon human cognitive abilities (e.g., creativity) to produce effective solutions.*	Agree
Criteria 5	*A critical dependence upon human social abilities (e.g., teamwork) to produce effective solutions.*	Agree

The use of DSRM requires the introduction of innovative artifacts, defined broadly as knowledge containing models, methods, design theories or constructs, into an environment with the purpose of improving said environment. This requirement is met with the design of an artifact in the form of a decision support tool through the combination of maturity and readiness models, which would qualify it as a level 2 DSR contribution type according to Gregor and Hevner (Gregor and Hevner, 2013). This project was, therefore, done using DSRM, which consists of three distinct stages as defined by Hevner (Hevner, 2007) and is shown in Figure 2-1 below:

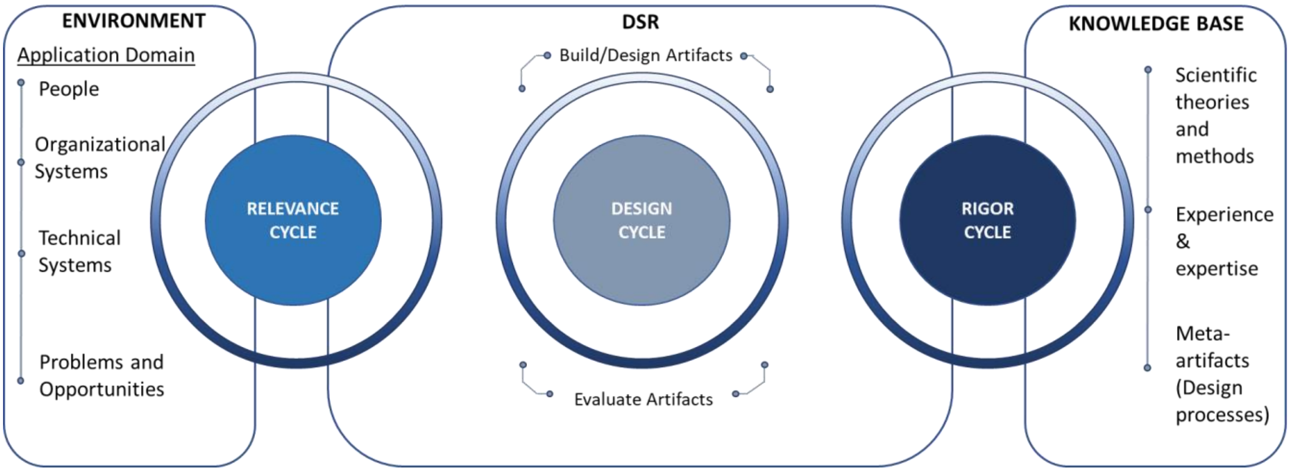


Figure 2-1: *Design science research process chart (Hevner, 2007)*

First, the relevance cycle is investigated. The focus of this cycle is the application domain. Hevner suggests that this domain consists of the interaction between people, organizational systems and technical systems in service of a common goal (Hevner, 2007). According to Hevner good DSR must attempt to identify problems and discover new opportunities within a specific application domain. The role of the relevance cycle is therefore to identify research requirements such as the problems and opportunities to be addressed. It should also define acceptance criteria for the evaluation of research results, keeping in mind that the final research results could suggest further iterative improvement of the relevance cycle (Hevner 2007). This is the first indication of the cyclic and iterative nature of DSR as the various sections are dependent on one another. The focus of this cycle is to build a high-level understanding of the literature landscape to discern between crucial, semi-crucial and irrelevant concepts.

Next, the activities of the rigor cycle are investigated. Where the relevance cycle deals with the environment, the rigor cycle deals with the knowledge base of that environment. This cycle requires the rigorous investigation of previous knowledge, models and theories in the environment. Hevner is in favour of vast exploration of multiple ideas, sources, existing artifacts and theories (Hevner, 2007). The contributions to the knowledge base will increase as the project progresses, however, this cycle is initiated through a literature review. Tracing concepts through the literature base is a crucial part of building a keen understanding of the literature. It allows the reader to develop a detailed view of the concept's application, use and requirements so it can be adapted and integrated seamlessly into a new context.

Lastly, the requirements of the design cycle are investigated. This cycle is dependent on the inputs from both the relevance and rigor cycles. The bulk of the project lies within the design cycle, and its iterative nature results in the constant creation, evaluation, and adaptation of artifacts. The management of this cycle is critical as it is reliant on multiple interconnected parts. The design cycle is represented by various chapters of this thesis, but some of the activities include the combination and integration of various theoretical models into an interactive tool followed by a refinement process to add and eliminate criteria and dimensions. This cycle also includes the creation of well thought out interview questionnaires to supplement decision making capabilities during the design process. None of the above-mentioned steps can ensue, however, before a thorough investigation of the literature and knowledge gap is completed.

2.2 Research and Design Process: Steps and Activities

Through DSRM requirements, the development of a decision support tool for this dissertation has three distinct design cycles namely: Initial Tool Creation, Development and Refinement and Final Tool Validation. Each of these three design cycles has three unique design steps that fulfil the various rigor, relevance and design requirements of the DSRM. Figure 2-2 below shows an overview of the entire design process of this project, where after the specific activities of each design step is discussed.

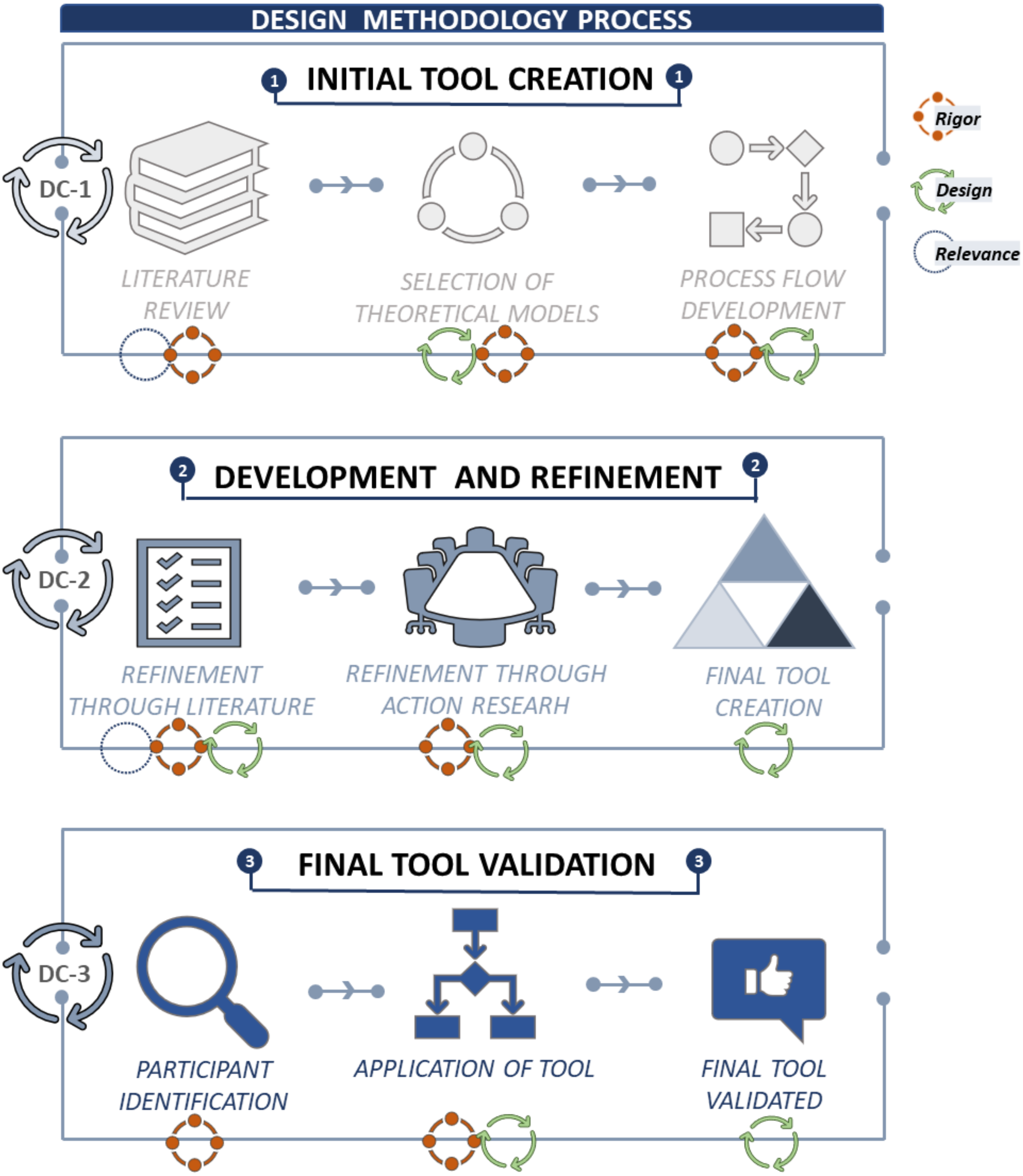


Figure 2-2: *Overall thesis design process*

As seen in Figure 2-2 above, each design cycle has three distinct design steps. Each of these design steps contains various activities that form the content of this thesis. The activities completed for each design step are summarised in Table 2-2 below:

Table 2-2: *Activities associated with each design step of this dissertation*

Design Step	**Activities**	**Chapter**
Literature review	A comprehensive literature study which involves: a. Key word identification and searches b. Identification of exclusion criteria c. Data extraction and categorization d. Key concept identification	Chapter 3
Selection of theoretical models	Selection of appropriate theoretical models for use in the decision support tool through a process of elimination which involves: a. Identification of valid alternative models b. Comparison of model objectives c. Selection of most appropriate model	Chapter 3
Process flow development	Arranging the selected models into a logical process flow by: a. Identifying the natural sequence of decision support questions b. Identifying which models best answer which decision support questions c. Organizing the models in the appropriate process flow d. Converting the paper-based models to an IT-based process flow and creating a user-friendly interface e. Incorporating additional interface features to improve process flow and result interpretation	Chapter 4
Refinement through literature	Adjusting and refining the dimensions and descriptors of the existing models to better fit the new application context by: a. Investigating the requirements of the new application domain b. Investigating literature which address specific dimensions and domains of the theoretical models c. Updating the existing dimensions and descriptors based on the newly acquired knowledge	Chapter 5
Refinement through action research	Adjusting and refining the dimensions and descriptors of the existing models to better fit the application context by: a. Identifying industry/subject matter experts b. Interviewing experts to determine possible changes that must be made to the tool c. Summarising the interview results and updating the tool accordingly	Chapter 6
Final tool creation	Updating the tool interface with all the newly acquired information.	Appendix A
Participant identification	Identifying and contacting a manufacturing SME that can partake in a case study by: a. Defining participant requirements	Chapter 7

	b. Identifying and filtering eligible participants c. Contacting participants and asking for their participation	
Application of tool	With the help of the selected manufacturing enterprise, conduct a case study by: a. Simulating the adoption of a novel, proof-of-concept AM technology into the enterprise b. Applying the decision support tool in full c. Logging the results and interpret usefulness for decision support	Chapter 7

Figure 2-2 and Table 2-2 presented in the above section can be used by the reader to orientate themselves throughout the rest of this thesis. Ultimately, the goal of these activities is to help design and develop a decision support tool interface. In essence then, all the above activities form part of the development triangle shown below in Figure 2-3. This triangle represents the tool's development process and guides the development activities. From Figure 2-3 shows that the final support tool is comprised of three development iterations, all of which is responsible for refining and improving the tool.

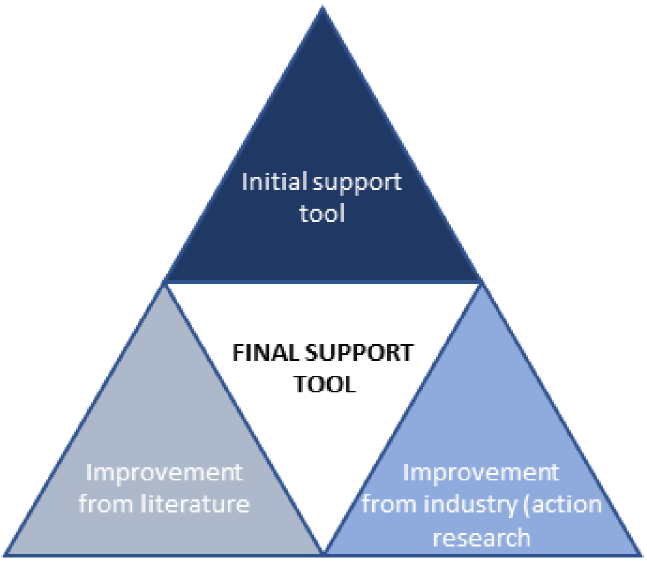


Figure 2-3: *Decision support tool development triangle*

The development triangle shown in Figure 2-3 shows the three crucial development iterations. Many of the contributions made by this project was done during the literature and action research refinement stages and the following sections discusses some of the details behind the methodology and execution of the literature refinement and action research phases of the tool's development. The initial tool creation is discussed at length in Chapter 4.

2.2.1 Literature refinement activities

Figure 2-3 shows how the position of a literature refinement stage within the tool development process. The purpose of the literature refinement stage is understood when considering the tool development process, which is initialised through the development of a first iteration tool that simply combines existing models into a process flow. While these existing models are chosen to address specific knowledge gaps for this project, they were originally developed for research projects with different objectives and application contexts to this thesis. Refinement from literature is therefore used to evaluate and modify the details of existing models to better align them with the requirements of the application context defined for this thesis. This refinement relies on relatively free-form process where the researcher manually evaluates specific details of the model and then generate applicable search terms in order to explore the relevant literature. Once the newly discovered literature domain is understood, it can be integrated into the tool. Even though this process is free form, there are some standard practices that were followed to ensure effective refinement of the dimensions. These steps are summarized below:

Step 1: ***Evaluate existing dimensions and descriptors***

The first step requires the researcher to evaluate and securitize the existing dimensions and descriptors of the models selected for use in the decision support tool. This process requires the researcher to have a strong understanding of the application context and various domain specific requirements. This understanding is developed during the initial literature review as discussed in Chapter 3. During Step 1 the researcher identifies the dimensions and descriptors which do not fully satisfy the contextual requirements.

Step 2: ***Generate applicable search terms***

Step 2 requires the researcher to generate applicable search terms which will produce literature bodies that address the deficiencies identified in Step 1. Again, these search terms will be dependent on the researchers understanding of the contextual requirements established during the literature review.

Step 3: ***Analyse and snowball***

This step requires the researcher to analyse the literature bodies found in Step 2. The researcher must decide weather the literature satisfies the contextual requirements. If not, the researcher can use snowballing techniques to trace concepts through the literature until the most applicable sources are found.

Step 4*: Update existing models*

The final step involves integrating the newly acquired knowledge and concepts into the existing model in order to update the model to a more applicable state. The final product is a literature refined model.

2.2.2 Action research activities

Section 2.2.1 discussed the importance of a literature refinement stage for aligning the models selected for use in the decision support with the contextual requirements of this research project. The tool proposed in this project, was designed with practical applicability as a main driving factor and, while literature can help align contextual requirements, it cannot sufficiently capture the intricacies of the practical domain. An additional refinement stage is therefore required wherein the various dimensions and descriptors of the models are reviewed by industry and subject matter experts where they can comment on the practical implications of specific details of the tool. This allows the researcher to aggregate and interpret the comments of the industry experts and subsequently update and refine the tool even further, thus improving practical applicability of the tool before it is tested in industry with a case study. This form of action research is defined as a scientific-technical view of problem solving, where the researcher contributes a theoretical problem statement, and the practitioner is involved to help with the intervention and improvement (Masters, 1995). The following activities were completed during the action research phase:

Activity 1: ***Identifying industry/subject matter experts***

The first activity requires the researcher to identify industry/subject matter experts whose expertise are best suited for the application context of this project. Part of the selection process involves the creation of set participant requirements that must be fulfilled by all viable candidates. These requirements can be viewed in Chapter 6.

Activity 2: ***Interviews and ratings***

The second activity relates to the interview and rating processes. Participants of the action research phase are interviewed in two stages. The first stage involves a quantitative analysis stage. The quantitative analysis requires participants to rate various aspects of the tool according to pre-defined metrics called "action research variables". These metrics can be used to evaluate the perceived relevance and applicability of specific aspects of the tool. The second stage of the interviews involves a qualitative discussion of proposed changes, additions, exclusions and improvements. This provides the participants with a chance to express their thoughts in more detail and is useful for the researcher in understanding reasoning behind the quantitative ratings.

Activity 3: ***Results summation and implementation***

The final activity requires the researcher to summarise the results of the action research. From the summaries the researcher interprets the proposed changes to the tool and decides which of the changes are relevant to the tool's application context. Finally, the changes can be integrated into the tool, thus improving the overall practical applicability of the tool.

2.3 Summary of Chapter 2

Chapter 2 explained the various research and design methodologies that were adhered to during the completion of this project. First, the chapter defined the overarching research methodology. For reasons that were explained in Chapter 2, this project used the Design Science Research Methodology (DSRM) as the guiding research methodology. All subsequent methodologies and activities that were completed in the project were in service of the DSRM requirements. Subsequently, Chapter 2 also showed the reader the design process used for this project by defining three design cycles namely the Initial Tool Creation cycle, Development and Refinement cycle and the Final Tool Validation cycle. The chapter also showed the various design steps that were completed during each design cycle, thus helping the reader to orientate themselves throughout the project. Finally, Chapter 2 provides the reader with a detailed breakdown of the various research activities that were completed during each design step of each design cycle.

Chapter 3: Literature Review

This chapter outlines the methods used to conduct a thorough review of the literature. It also presents the findings of the literature review by listing various key concepts and expanding on their importance and applicability to the project. Lastly, the review showcases the selection process and results of the appropriate theoretical models used to develop the decision support tool. Figure 3-1 below shows the position of Chapter 3 within the design process.

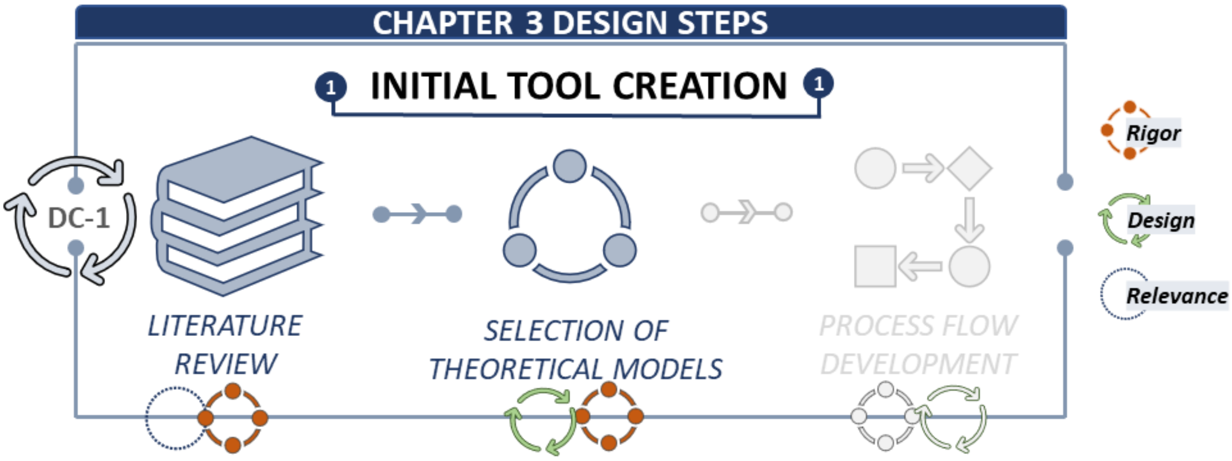


Figure 3-1: *Design steps completed in Chapter 3*

As seen in the Figure 3-1 above, Chapter 3 completes two of the three design steps of design cycle one. This is because the selection of the theoretical models for use in the decision support tool is directly related to the literature review, which results in these two design steps being presented together in one chapter.

3.1 Literature Review Methodology

Both the relevance and rigor cycles of the DSRM require iterative analysis and review of literature. However, these two cycles differ in both the nature and desired output of their respective literature review processes. The differences between the requirements of the two DSRM cycles are explained in the previous chapter, therefore this section will focus on outlining the literature review methodologies used to satisfy the requirements of each of the two DSRM cycles.

For the relevance cycle, a structured review approach is preferred, while the rigor cycle lends itself more towards a snowball or investigative methodology. The reason being that the relevance cycle deals more with higher-level contextualisation of the literature and research questions to create a clear picture of the literature landscape (Hevner, 2007). This is done through a structured process of utilising key-word searches and concept identification. The rigor cycle, on the other hand, requires a deeper dive into the knowledge base to shape the development of a new artifact (Hevner, 2007). This deep dive requires a more investigative/snowballing approach, where concepts are traced throughout various literature bodies in order to fully understand and use them for a new application.

The iterative nature of DSRM allows for two literature review processes to be conducted throughout the lifespan of the project. As the project progresses, new concepts are identified, investigated and adopted to fit the purpose of the project. Generally, the snowball process follows the systematized review as a way to improve the literature base as is showed in Figure 3-2 below.

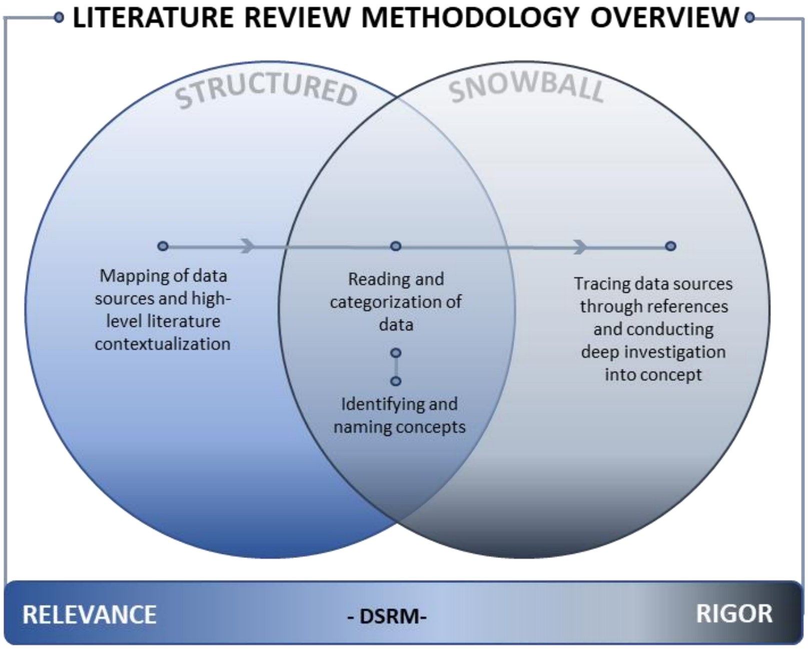


Figure 3-2: *Venn diagram of the literature review methodology within a DSRM context*

3.1.1 Structured review methodology

The purpose of the structured review is to establish a strong literature base and contextualise the literature landscape. The Karolinska Institute defines a detailed process for conducting a structured review (Karolinska Institutet, 2021). The process steps are summarised in the table below:

Table 3-1: Structured literature review steps (Karolinska Institutet, 2021)

Structured Review Steps	**Activities**
Step 1: *Formulate and delimit you research question*	a. Define a research question and clearly state the delimitations b. Break research question up into different logical parts c. Define key concepts of the research question
Step 2: *Define search terms and create search blocks*	a. Conduct test searches to identify search terms b. Define clear exclusion criteria c. Identify and read key articles d. Identify new search terms by conducting free-text searchers and reading titles/abstracts
Step 3: *Commence structured searches*	a. Use several different search databases b. Try to keep search terms uniform across databases c. Document your search queries. d. Identify key data components for structured identification of articles
Step 4: *Improve search strategy*	a. Examine search results and see where to make improvements b. Use advanced search form to improve results

Step 5: *Select appropriate review articles*	a. Read through titles and abstracts of search results to determine the article relevance b. Check the quality of the studies you include. c. Present findings using flow diagram

The structured process suggested by the Karolinska Institute and shown in Table 3-1 (Karolinska Institutet, 2021) was used as a guideline for conducting the literature searches. Throughout the search process, however, various new concepts were introduced, which in turn generated new search terms. As a result, the researcher would explore a wide variety of concepts and papers in the pursuit of understanding the entirety of the literature body and fully comprehend how the literature concepts related to one another. The search terms described in Section 3.2.1 is, therefore, only the critical terms that yielded the most promising results; however, they are not the only terms that were investigated. The final literature body is thus not the result of a strictly structured review methodology, but an extrapolation of the structured paradigm that formed a conglomerate of literature bodies. The following sections below will briefly discuss the specific processes that were followed to complete all the activities defined by the Karolinska Institute.

3.1.1.1 Multidisciplinary text searches:

The search process utilises different search engines such as Google Scholar, ResearchGate and the Stellenbosch University Library. By identifying keywords that are specific and applicable to the context of the thesis and feeding them into the search engines, a researcher can reduce the literature base to a more manageable size. It also helps create a view of the literature landscape by revealing the distribution of papers and concepts.

First, a few test searches are done using generally applicable key words. These searches help to clarify the research base and introduce applicable concepts to the researcher. Keyword searching is an effective first iteration search method, however, to improve the details of each search, the researcher can conduct free-text searches. This involves using the articles found during key-word searches and exploring their titles and abstracts for new concepts that can be included in a second round of key-word searches. It is also important to define the necessary exclusion criteria which would automatically exclude articles from use based on certain key criteria.

Additionally, discipline specific information can be found through backtracking of citations. This is known as a "snowballing" process and will be explored in the following section. Snowballing allows for the acquisition of original literature containing the same fundamental concepts from which new literature was developed. However, snowballing on its own is not sufficient as it does not encourage exploring wider fields of study or new concepts. This can cause a train of reused information where potential errors or outdated information is carried over from paper to paper. That is why it is imperative to do a proper multidisciplinary text search before starting the snowballing process.

3.1.1.2 Extensive reading and categorisation of the selected data

Part of conducting a structured review in line with the defined review steps is proper organisation and data collection processes. Although the literature must still be studied meticulously, there are qualitative data analysis software available to streamline the process. Software such as Atlas.ti can be used to organise literature as well as bookmark useful information according to specific search codes. The bookmarking process utilises inclusion and exclusion criteria to group and filter information from the literature. Furthermore, Atlas.ti allows for semi-automated extraction of data through the use of keyword, and even key-phrase, searches.

3.1.1.3 Identifying and naming concepts

Once the literature is organised and the data properly bookmarked, the final part of the structured review can commence. This process involves the identification and naming of the key concepts found in the relevant literature. This process is completed in levels, where the first level requires the identification of the main concepts contained within the research question. From there secondary and tertiary concepts are identified and listed, until a concept tree develops.

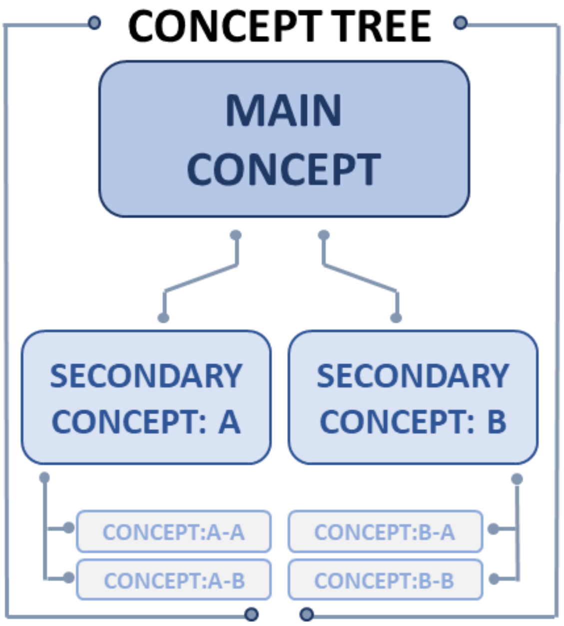


Figure 3-3: *Systematized review concept tree example*

3.1.2 Snowball methodology

The snowball methodology forms part of the rigor cycle of the DSRM, where concepts are traced through literature citations in order to establish a keen understanding of the concept's origin and possible applications. For this thesis, the snowball procedure mostly follows the multidisciplinary text search phase of the structured literature review. It is imperative to establish a strong literature base through a wide range of keyword searches before initiating the snowballing process. The reason being, that snowballing can result in tracing a narrow field of concepts without any significant influx of new information. This can lead to "tunnel-vision" where the same concepts are repeatedly researched, while crucial additional information can be overlooked and left out.

The advantage of snowballing is that concepts can be investigated from their origin to their current application. This allows the researcher to understand the concept within a wide range of application contexts and ultimately apply the concept to a new context with a higher degree of accuracy. The snowballing methodology can be broken up into "forward" and "backward" snowballing (Wohlin, 2014).

a. Forward snowballing requires the researcher to identify a specific reference and then identify any subsequent research papers that utilise that reference.

b. Backwards snowballing requires the researcher to identify a specific research paper and then trace certain references that the paper uses back to their source.

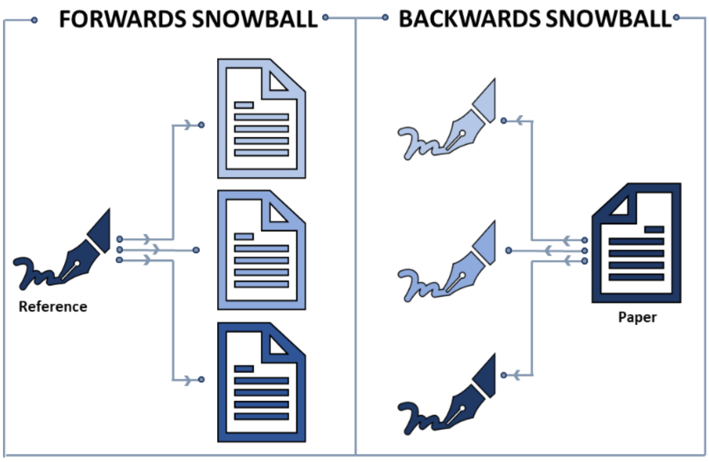


Figure 3-4: *Snowballing process*

3.2 Search Strategy Results

The following section outlines the results of the search strategies that were employed. First, it outlines the specific key-word searches that were completed along with the corresponding key concepts. Next, the exclusion criteria are discussed. These exclusion criteria are used to filter out any ineffectual papers. Lastly, the data extraction processes and results are detailed.

3.2.1 Key word searches

The key words in Table 3-2 below were used to identify relevant articles and map the literature landscape. Search engines such as Google Scholar, Research, Scopus, Elsevier's Scopus and Stellenbosch University Library were used to conduct the key word searches. The key-word searches in the table below are broken up into their corresponding key concepts.

Table 3-2: *Key word search terms used during the literature review*

Concept	**Key search words**
Maturity Models	a. 'Manufacturing' 'Maturity Model' b. 'SME' 'Manufacturing' 'Maturity Model' c. 'Advanced Manufacturing' 'Maturity Model' d. 'Novel' 'Technology' 'Maturity' e. 'Industry 4.0' 'Maturity Models'
Technological Readiness	a. 'Technology' 'Readiness' b. 'Novel' 'Technology' 'Readiness' c. 'Advanced' 'Technology' 'Readiness' d. 'Manufacturing' 'Technology' 'Readiness' e. 'Novel Technology' 'Adoption' 'Readiness'
Industry 4.0	a. 'Industry 4.0' 'Manufacturing' b. 'Industry 4.0' 'Implementation' c. Industry 4.0' 'Manufacturing' 'Roadmap'
Smart Manufacturing	a. 'Advantages' of 'Smart' 'Manufacturing' b. 'Smart Manufacturing' 'Methodologies' c. 'Smart Manufacturing' 'Requirements' d. 'Smart Manufacturing' 'Cost'

	e. 'Smart Manufacturing' in 'Industry 4.0'
Innovation Adoption	a. 'Smart Manufacturing' 'Innovations' b. 'Smart Manufacturing' 'Innovation' 'Adoption' c. 'Smart Manufacturing' 'Wireless Sensor Networks' d. 'Smart Manufacturing' 'Data' 'Storage' e. 'Cost' of 'Smart Manufacturing' 'Innovation Adoption'

3.2.2 Exclusion criteria

The next step is the creation of exclusion criteria. These are factors that, regardless of the paper's eligibility, excludes it from use. The following exclusion criteria were identified:

a. Language barrier

b. Inaccessibility due to paywall

c. Repetition of same-case study

d. Outdated or outside the context

Papers with high citation rates or recent publication dates were considered favourably. For literature dealing with the concepts of Industry 4.0, Smart Manufacturing and Innovation Adoption, papers published after 2015 were preferred. These are concepts that experience rapid growth and subsequent change in literature, therefore, papers published after 2018 were considered most relevant. However, it must be noted that earlier papers, especially those with a high citation rate, provided useful background information about fundamentals and origins of concepts.

3.2.3 Categories and data components for improved data extraction

Document analysis can be sped up by identifying predetermined metrics. These metrics can be used to determine the validity, use and application of a paper, quickly and efficiently. The following metrics in Table 3-3 were used in this study.

Table 3-3: *Data selection categories and components*

Categories	**Components**
1. *Paper characteristics*	a. Title of document b. Author's name c. Publication date d. Document type e. Number of citations f. Context of paper g. Area of application
2. *Theoretical elements*	a. Type of theoretical model b. Methodology of theoretical model creation c. Implementation steps of theoretical model d. Validation techniques
3. *Empirical elements*	a. Data collection methods b. Scope of empirical analysis c. Validation techniques

	d. Experimental methodology
4. *Observations*	a. Conclusion of author b. Oversights by author c. Assumptions and restrictions

By identifying each of the mentioned data components within a paper, it was possible to estimate the applicability and relevance of said paper. The "Theoretical components" largely applied to the theoretical frameworks and models prevalent within the maturity model and technological readiness literature, while the "Empirical components" were mostly observed within the Smart- and Advanced manufacturing literature. Generally, the "Observation components" were useful in providing a quick overview and synopsis of the document, thus guiding further investigation.

3.2.4 Final literature inclusion results

By now the process of identifying literature sources and extracting the relevant items have been explained. This section summarises the results of the literature search as seen in Figure 3-5 below:

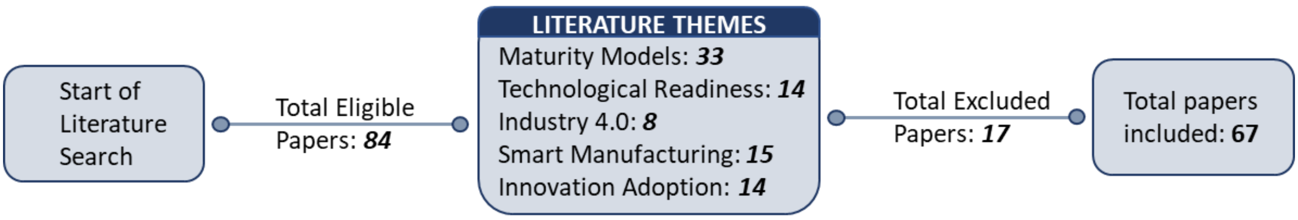


Figure 3-5: *Literature search paper count results*

Figure 3-5 shows that the combination of a structured and snowballing literature search yielded 84 eligible papers. Of these 84 papers, the majority comprised of papers on the various types of maturity models and their development procedures. There was an even distribution between literature sources on SM, TRL and Innovation adoption. These literature pieces covered a large area of expertise, which included development processes, requirements, standards and considerations for each concept. The industry 4.0 papers were in the minority but were critical to develop a holistic understanding of the project context. After the document analysis, data extraction procedures and exclusion criteria were implemented a total of 67 papers were selected for use in this project. From these 67 papers, various key concepts and development strategies were identified and used. These key concepts are defined in the following section.

3.3 Concept Identification

This section details the results of the concept identification phase. The critical concepts that were identified are summarised below. This summary can be used as a reference to develop a quick overview of the literature body, however, detailed discussions of each of the concepts listed below can be viewed in the sections following the summary. The detail discussion sections explain the origin of the concepts and the reasoning behind their inclusion in this project. Ultimately, these critical concepts shaped the structure and development of the proposed decision support tool.

Concept 1: ***Technological & Manufacturing Readiness***

Readiness assessment is seen as the process that ensues before maturing can start. Technological readiness would therefore be of relevance during concept development phases and acts in a way to capture the starting point (Schumacher *et al.*, 2016). Parasuraman proposed a 36-item readiness index, which can be used to develop industry specific models (Parasuraman & Colby, 2015). The origin of Technological Readiness Levels (TRL) can be traced back to a white paper first released by NASA in 1995 (Mankins, 1995). In the following years it was adopted and adjusted multiple times for various applications. One such an adoption was the creation of the Manufacturing Readiness Levels (MRL) by the US Department of Defence, which recognised the link between technological readiness and the ability to manufacture said technology (OSD and MRL Working Group, 2012). This would then lead to the creation of Manufacturing Capability Readiness Levels (MCRL), with the addition of the "Capability" term being crucial for the inclusion of a wide array of influencing factors (Williamson and Beasley, 2011). A paper by Peters which estimates readiness levels for new manufacturing technologies proved to be the most useful for this thesis (Peters, 2015).

Concept 2: *Maturity Models*

Maturity is a measure of the as-it-is state in relation to some specific goal to-be. A maturity model is used to quantify an enterprise's position in relation to that goal. Proença and Borbinha (Proença & Borbinha, 2016) developed a broad-based maturity development step guide. These steps are laid out simplistically and can form the basis of a more specified development process. Proença and Borbinha's work is based on a 2009 paper by Becker (Becker *et al.*, 2009), which was originally developed for IT systems, but which has subsequently been used by various researchers for industry 4.0 maturity development.

Concept 3: *Industry 4.0 & SM Maturity Model*

These maturity models attempt to quantify and guide companies in their transition towards industry 4.0 processes (Schumacher *et al.*, 2016) and, in the case of manufacturing enterprises, the transition towards Smart Manufacturing. For most manufacturing enterprises, industry 4.0 and Smart Manufacturing is interlinked, with Smart Manufacturing accounting for a large portion or sub-section of Industry 4.0 (i-Scoop, 2020). The paper by Schumacher has been used in various subsequent studies, for example a 2018 paper by Leineweber on Industry 4.0 migration models (Leineweber *et al.*, 2018) and a 2015 paper by Mittal on a similar subject (Mittal *et al.*, 2015). Schumacher's paper was heavily influenced by the 2015 IMPULS study of industry 4.0 readiness (Lichtblau *et al.*, 2015). Another large-scale study that was found important to consider is the 2017 ACHATEC: Industry 4.0 Maturity Index (Schuh *et al.*, 2017).

Concept 4: *Long Valley of Death*

The concept of a valley of death is critical to the development of this project. This concept refers to the theoretical gap between proof-of-concept technologies and the actual commercial application thereof (Ellwood, Williams and Egan, 2020). This gap is associated with high market failure rates and financial risk as the adoption of these unproven technologies could result in unknown failures and issues. Yet, pursuing the exploitation of novel manufacturing technologies is necessary, as it could provide a competitive edge to enterprises (Belz, A. *et al., 2019)*. The long valley of death is a concept suggested by Ward, who believes the theoretical gap stretches across a further distance of the technology development lifespan than previously believed (Ward et al., 2017). This is the concept that will be used for the development of a decision support tool.

Concept 5: *Smart Manufacturing Innovation*

The term Smart Manufacturing is not a single "thing", but rather encapsulates a set of different innovations (Kusiak, 2019). Most of these innovations are of a "digital" nature with several factors that influence the success of adoption (Ghobakhloo, 2020). These factors can impact managerial decision making and long-term strategy implementation (Shamim et al., 2016). It is, therefore, crucial to understand the various innovations that drive Smart Manufacturing and the pros and cons surrounding their implementation.

Concept 6: ***Small/Medium Sized Enterprise***

This project considers SMEs as the main beneficiaries of the proposed tool. The paper published by Mittal (Mittal *et al.*, 2018) highlighted how SMEs are at a disadvantage when attempting to use current industry 4.0 maturity models. Their paper criticized current industry 4.0 maturity models for focussing on multi-national enterprise application (MNE), thus, neglecting factors that largely impact maturity in small- and medium-sized enterprises. The concept of SMEs should, therefore, be explored further. Mittal also did an excellent job of summarising the various assessment models available in the literature along with the related focus and gaps of these models (Mittal *et al.*, 2018).

Concept 7: ***Technological Acceptance***

Technological acceptance is influenced by technological readiness (Erdogmus & Esen, 2011). Readiness therefore is not the sole indicator or determinant of successful technology implementation, as the technology must still gain general acceptance among individuals or industries. Fred Davis developed a technological acceptance model in 1985, aiming to quantify perceptions, motivations, and causally related variables regarding technology acceptance (Davis, 1985). The possible effects of technological acceptance on innovation adoption and, ultimately, manufacturing maturity is considered throughout this project.

3.3.1 Technological readiness

Technological readiness is seen as a measurement of how far, in terms of development, a technology is from ensured successful commercialization (Heslop, Mcgregor and Griffith, 2001). There is, however, considerable confusion surrounding this term. The terms *Maturity* and *Readiness* are sometimes used interchangeably, such as in the original paper on TRL (Mankins, 1995). As the research field developed a larger divide between the two concepts of maturity and readiness was observed, however, there is still some uncertainty surrounding the exact difference. Tetlay and John believe maturity to be part of readiness, which requires a system to first be mature before being ready (Tetlay and John, 2009). However, some of the more current literature suggests that readiness assessment is seen as the process that ensues before maturing can start. Technological readiness would therefore be of relevance during concept development phases and acts in a way to capture the starting point (Schumacher *et al.*, 2016).

Ward summarises it by suggesting that, while there is some clear overlap between the terms, their application will be context specific and validation of the technology must be done according to the requirements defined at the beginning of the process (Ward et al., 2017). Ward believes that readiness terminology is, however, best suited for scenarios where insertion of novel technologies take place while maturity-based assessment is best for analysis of the journey to generic capability within a specific field. Therefore, since this thesis deals with novel insertion of technologies for which new processes are developed, it is implied that a certain level of technological readiness must be reached before maturation processes can begin, thus cementing technology readiness assessment as the first course of action which initiates a longer chain of events. Figure 3-6 represents this chain of events.

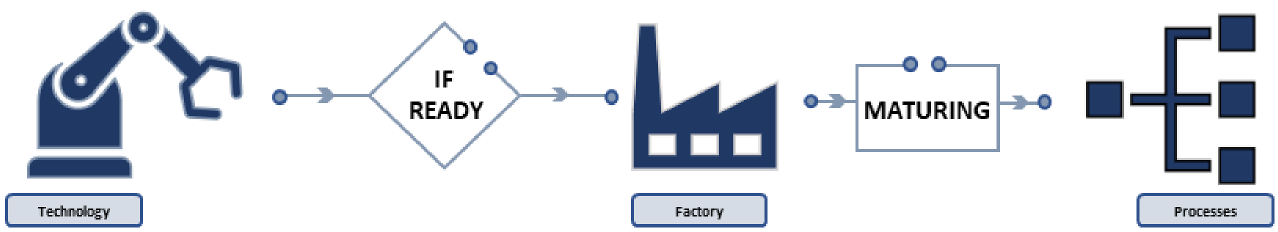


Figure 3-6: *Chronological order of readiness and maturity assessments*

As mentioned before, technological readiness is a relative measurement with "successful commercialization" being the goal. Heslop, however, highlights the fact that the metrics for "success" can differ from sector to sector. The public sector for instance pursues technological development for its pure scientific value and have more long-term innovation goals, while the private sector has explicit criteria for commercial success (Heslop, Mcgregor and Griffith, 2001). This is the first clear example of a divide or "gap" between academic and commercial goals. Using a generic Technology Readiness Level assessment matrix would therefore not fully satisfy the criteria for success of a manufacturing SME. Further investigation revealed the following secondary concepts:

3.3.1.1 Manufacturing Vs Technology readiness levels

The original paper on Technology Readiness Levels, published by NASA in 1995, provides a concise and easy-to-use tool for determining the relative level of development of a new technology. The tool defines nine levels of readiness with a focus on operational success as the benchmark against which to measure the levels (Mankins, 1995). While these levels are useful for standardising the analysis of a technology's level of development, it only measures operational capability with little consideration given to the capacity for manufacturing said technology. To address this issue the US Department of Defence (DoD) developed the Manufacturing Readiness Level (MRL) Deskbook *(*OSD and MRL Working Group, 2012*)*. The Deskbook outlines ten levels of manufacturing readiness, where each level is a function of manufacturing capability. Ward notes the addition of a MRL 10 in the Deskbook, which attempts to reflect the need for continuous improvement through the demonstration of lean production practices (Ward et al., 2017).

Manufacturing readiness levels were of specific interest to the automotive industry with key role-players such as Rolls Royce and the UK Automotive Council driving further development of structured MRL frameworks. The Automotive Councils report outlined the difference between Technological and Manufacturing Readiness as the capability of a technology to [1]deliver its function (TRL) and [2]be produced (MRL) (Williamson and Beasley, 2011). Their model directly correlates the TRL with the MRL by showing the manufacturing requirements at each level of technological readiness. In terms of content, however, the model does not deviate far from the original TRL and MRL metrics described by NASA and the DoD. The co-dependence of TRL and MRL is illustrated in Figure 3-7 below:

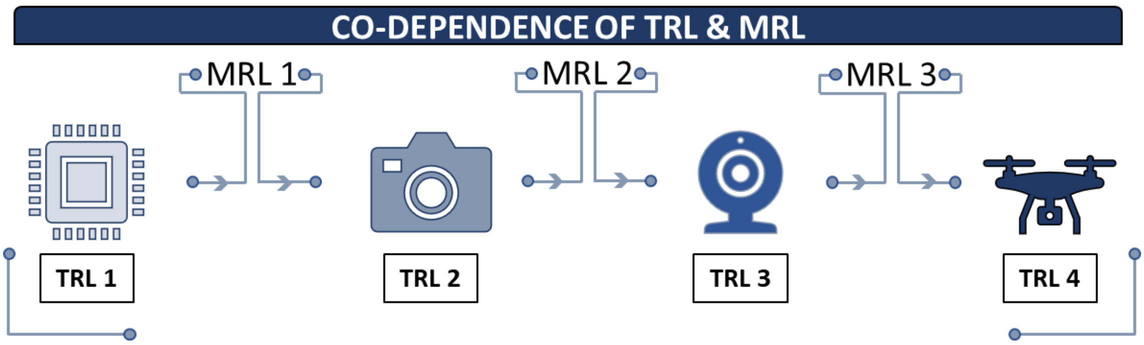


Figure 3-7: *Example of the co-dependence between TRL and MRL*

Rolls Royce on the other hand was the first to introduce the concept of "Capabilities" into the existing MRL model, to create a new Manufacturing Capability Readiness Level (MCRL) model (Ward, Halliday and Foden, 2012). What makes this paper so useful for the context of this thesis, is the fact that it tries to create an approach specifically for "Manufacturing Technology" development. Thus far, technological readiness and manufacturing readiness was seen as co-dependant but separate, now the two terms have merged as a single entity. Rolls Royce recognised the benefit of radical manufacturing capability implementation and realised that the effectiveness of the technology itself is but one factor in a network of factors that determine successful implementation (Ward, Halliday and Foden, 2012). By adding the "Capability" dimension, the MCRL approach recognises that effective delivery of manufacturing innovation depends on a multitude of factors such as operational, commercial, and organisational (Ward et al., 2017). More specifically, it tries to address the issues of performance under changing conditions in manufacturing processes (Peters, 2015).

3.3.1.2 Manufacturing technology readiness

The first venture towards Manufacturing Technology Readiness (MTR) as a single concept was done by Rolls Royce, and to a lesser extent, the DoD (see previous section). The concept was then developed fully by Peters in his paper entitled "A Readiness Level Model for New Manufacturing Technologies" (Peters, 2015). Understanding the concepts outlined in this paper is the key to initiating the decision support tool design process. Peters criticized most of the existing literature at that time, for focussing solely on "product technologies" and not considering restrictions of manufacturing and process technology. The purpose of his study was to develop a general model for estimating manufacturing technology readiness (Peters, 2015).

Peters' work was, like many other readiness assessments, founded in the fundamental literature developed by Rolls Royce and the US DoD. Through a combination of keyword searching, reading and forwards snowballing processes, it was determined that Peters' paper was by far the most applicable to the context of this thesis.

His paper clears much of the confusion associated with technology and manufacturing readiness vocabulary by taking a quantitative approach to the traditionally qualitative issue. Through his work, there is now a way to measure the duration (in months) until readiness of a manufacturing technology is at a desirable level for implementation. This is extremely useful for the early stages of the decision support tool as it serves as a basic first step for a comprehensive assessment of premature technologies (Peters, 2015).

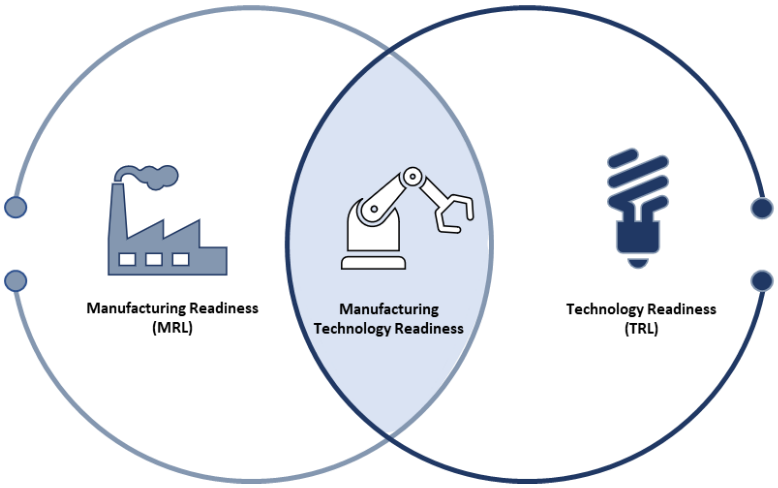


Figure 3-8: *Types of readiness levels*

3.3.1.3 Technology readiness and risk assessment

A final concept that falls under technological readiness, is the link between readiness and risk assessment. Knowledge about TRL and MRL can be used to execute a risk analysis about future R&D efforts. A rigorous Backwards Snowballing process (as discussed in Chapter 2) revealed a paper by Mankins, the same author from the NASA paper on TRL, as a reputable source for such a risk assessment model (Mankins, 2009). In his paper, Mankins emphasises the importance of understanding the risks involved in pursuing R&D effort of a new technology. He also provides a method of quantifying said R&D effort, a tool that is extremely useful for this thesis's context.

3.3.2 Maturity models

The concepts of maturity and maturity models have traditionally been a prominent feature in the IT and software engineering domains but have proven to be useful for a wide range of management applications throughout different industries (de Bruin, De Freeze and Rosemann, 2005). The term "maturity" has been defined in different ways. De Bruin simply states it is the "capability, competency, level of sophistication" of a selected domain (de Bruin, De Freeze and Rosemann, 2005). Becker defines it from an IT perspective as a measure of the as-is situation of a specific aspect of a company (Becker et al., 2009). Lastly, Tetlay and John define maturity from a system perspective (system maturity) as the verification within an iterative process of a systems' development lifecycle (Tetlay and John, 2009). Ever since, there have been multiple definitions of maturity, however, most of them deal with the evaluation and ranking of the state-of-being of a process or dimension relative to a final desired state, where the desired state is more advanced in terms of capability than lower states-of-being (Proença & Borbinha, 2016). These states represent an evolutionary process of development, and maturation is a function of formality, distribution, commitment, legitimation, and understandability (Kohlegger, Maier and Thalmann, 2009)

While defining maturity is important, the more pressing question is: *What can you do with the concept of maturity?* By evaluating the current maturity of a process or dimension and ranking it in-between a range of possible states, an evaluative and comparative framework is created that can help enterprises identify the requirements of increasing capabilities and thus derive an informed approach for future actions (de Bruin, De Freeze and Rosemann, 2005). These frameworks are known as maturity models and is a key aspect in the development of the decision support tool proposed in this project. These models are useful for decision support tools as they define a series of sequential events that provide an anticipated logical path from an initial state to a final state (Proença & Borbinha, 2016). There are, however, a vast number of different maturity models, each addressing a specific application domain. It is therefore imperative that the correct type of maturity model is identified that best fit the context of this thesis as shown in Figure 3-9 below:

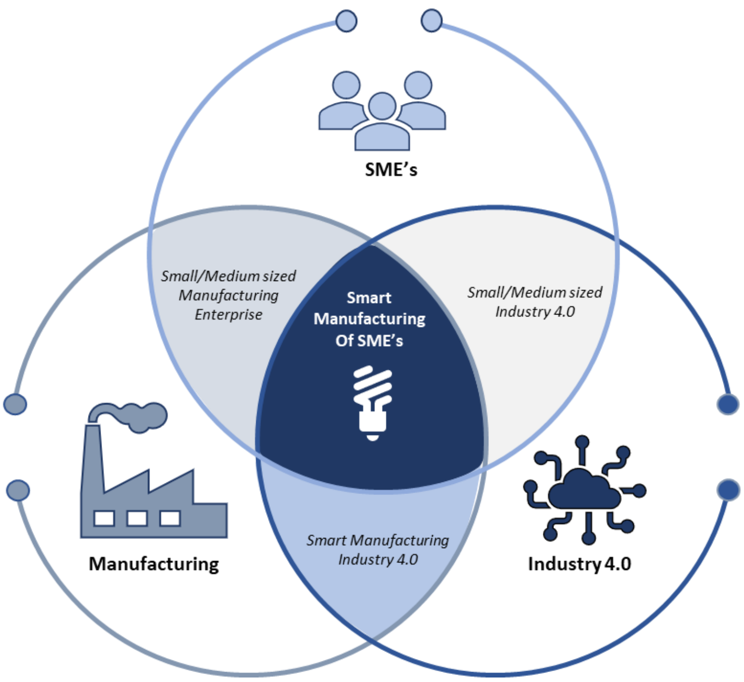


Figure 3-9: *Venn diagram of context specific application domains for maturity model selection*

3.3.2.1 Industry 4.0 maturity model

This thesis places a strong focus on advanced and novel manufacturing technology adoptions, innovations which is closely related with industry 4.0 (Deloitte, 2018) (Corò and Vope, 2020). It, therefore, stands to reason that an analysis of Industry 4.0 Maturity Models is necessary to develop a holistic understanding of the literature.

The Industrie 4.0 Maturity Index published by acatech and endorsed by various German research institutions, is an excellent starting point for analysing Industry 4.0 maturity model requirements and inputs (Schuh *et al., 2017)*. While the acatech study is extremely thorough and detailed, it is criticized by Leineweber for focussing on the entirety of an enterprise and its operations and, subsequently, is extremely high in complexity. This forces enterprises to hire external consultants which leads to high cost (Leineweber et al., 2018). Leineweber's suggests that this problem can be avoided if a maturity model, and its subsequent dimensions, are limited to a specific field, business division or area of an enterprise. This solution is adapted and implemented to a certain extent for the decision support tool developed in this thesis, by dividing an enterprise's operations into manageable compartments. (Leineweber et al., 2018).

While the acatech study provides an excellent example of an industry 4.0 maturity model, it is not the only one available. It is, therefore, helpful to consult Schumacher's paper, which provides a rigorous overview of existing models, such as the IMPULS Industie 4.0 Readiness paper (Lichtblau, 2015). Additionally, Mittal's paper does a critical review of existing industry 4.0 manufacturing maturity models (Schumacher, Erol and Sihn, 2016) (Mittal et al., 2018). Both Schumacher and Mittal place a focus not only on industry 4.0, but specifically industry 4.0 manufacturing. The added layer of "manufacturing" brings the model even closer to the context of this thesis and further investigation showed that it is imperative to include it in future searches. Figure 3-10 below shows the search hierarchy for context specific maturity models:

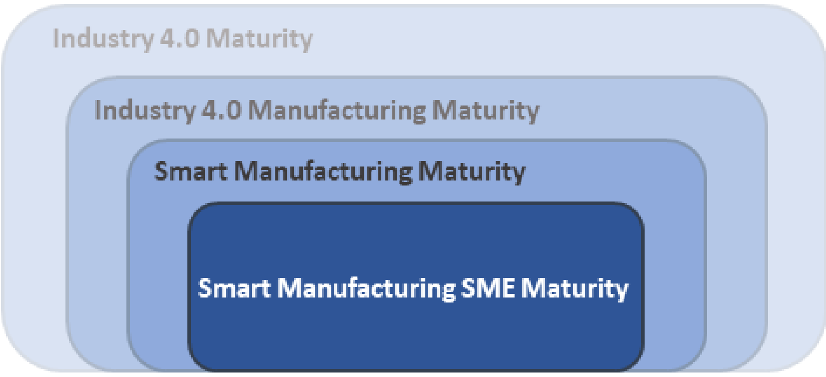


Figure 3-10: *Search hierarchy for context specific maturity models*

3.3.2.2 Smart manufacturing maturity models

The previous section established the importance of including "manufacturing" as a search term within industry 4.0 maturity models. This section will explain how manufacturing and industry 4.0 is linked through the common term "smart manufacturing (SM)". It will also explore the available maturity models which fit in the context of SM.

Industry 4.0 is defined as "a new level of organization and control over the entire value chain of the life cycle of products and it is geared towards increasingly individualized customer requirements" (Vaidya, Ambad and Bhosle, 2018). A part of that value chain is manufacturing; however, traditional manufacturing methods do not allow for the level of control demanded by industry 4.0's definition. Adoption of various disruptive technologies such as cloud-computing, IoT, big data analytics and AI into the manufacturing process, enables fusion between the virtual and physical world (Zheng et al., 2018), thus satisfying the control requirements of industry 4.0. This fusion is known today, as Smart Manufacturing (SM) and is one of the enablers of industry 4.0.

The literature body contains various examples of SM maturity models. A paper by Mitsubishi Electric Corporation provides an in-depth maturity assessment case study with a focus on sustainable SM implementation (Shi, X. et al., 2019). The paper introduces a process-driven model that utilise Key Performance Indicators (KPI). The model also attempts to utilise a data-driven methodology to standardise the process. Weber also published a paper on a SM maturity model, but with a focus on Data-Driven Manufacturing (Weber et al., 2017). The paper argues that the strategic goals of industry 4.0 and subsequently SM, is heavily influenced by data collection, storage, and analysis processes. Like most models in its class, it follows a multi-dimensional approach and places a strong emphasis on self-assessment capability of the model. The requirement of self-assessment is a recurring one, especially with models that try and cater for the needs of SMEs. Lastly, Mittal and Wuest published a series of papers on SM maturity models and provides an in-depth review of the literature body. These papers will be discussed in the following section (Mittal et al., 2018).

A curious link between the above-mentioned models, is that they all place an emphasis on SMEs as their chief target. This could be attributed to the struggle of SMEs to adopt SM paradigms as they lack the financial and organisational resources of MNEs (Mittal et al., 2018). This struggle is confirmed again by a case study done on Taiwan enterprises (Lin, Wang and Sheng, 2019). Therefore, the final search term that must be included in the search for the most context applicable maturity model is “SMEs”.

3.3.2.3 Smart manufacturing maturity models for SME’s

The previous section discusses different existing SM maturity models, each of them establishing a link to SMEs. Additionally, Ganzarain and Errasti developed a three-stage maturity model for SMEs, but it is geared towards the broader goal of industry 4.0 and not solely SM (Ganzarain and Errasti, 2016). While their model is too broad for the context of this project, it does outline some of the challenges of industry 4.0 adoption for SMEs in maturity terms. A more applicable model, however, would be the Digital Manufacturing Toolbox developed by Kaartinen (Kaartinen, Pieska and Vahasoyrinki, 2016). The paper excels at outlining the requirements of digital manufacturing processes and, while it is not a maturity model, it provides useful insights into the dimensions that must be considered when developing a SM maturity model for SMEs.

While these previous two papers provide valuable background information, the real issue of a SM maturity model for SMEs is best approached by Mittal and Wuest (Mittal et al., 2018). Their initial paper provides an excellent review of existing models in the application domain along with outlining the maturity requirements specific to SMEs. Next, their paper entitled “Toward a SM Maturity Model for SM^{3}E” provides an extensive analysis of the organizational dimensions and maturity levels in existing literature. Through their review, they developed their SM^{3}E maturity model, a SM maturity model specific to SME use, and justify the model’s organizational dimensions and maturity level rankings (Mittal, Romero and Wuest, 2018). They would also author a paper on a Smart Manufacturing Toolkit for SMEs, a concept discussed in their SM^{3}E tool (Mittal, Romero and Wuest, 2018). Lastly, they would publish a paper on a smart manufacturing adoption framework for SMEs (Mittal et al., 2019). The literature body of Mittal, Romero and Wuest is quite extensive within the realm of maturity of SMEs and SM. Their combined papers provide an excellent overview of the literature along with useful toolkits and frameworks.

The section on industry 4.0 maturity models discussed the problems surrounding current industry 4.0 models, in that they were far too complex and costly to use (Leineweber et al., 2018). Leineweber suggested the solution of limiting a maturity model to a specific field, business division or area of an enterprise to reduce complexity. Through a continuous and rigorous search process this solution was implemented by focussing on specific Smart Manufacturing maturity dimensions for SMEs, and the SM^{3}E model developed by Mittal was selected as the most applicable and useful for the application domain.

3.3.3 Long Valley of Death

The "Valley of Death" (VoD) is a well-researched and established concept in the field of technology adoption, and it deals with the challenges associated with market commercialization of early-stage innovation implementation (Ellwood, Williams and Egan, 2020). It must be elucidated, however, that there is a difference between the concepts of the "Valley of Death" and the "Long Valley of Death" (LVoD), with the latter being an extension of the former. This section will therefore first provide an overview of the "Valley of death" and then detail the concepts contained in the "Long Valley of Death" (LVoD). Figure 3-11 below serves as an example of the Valley of Death.

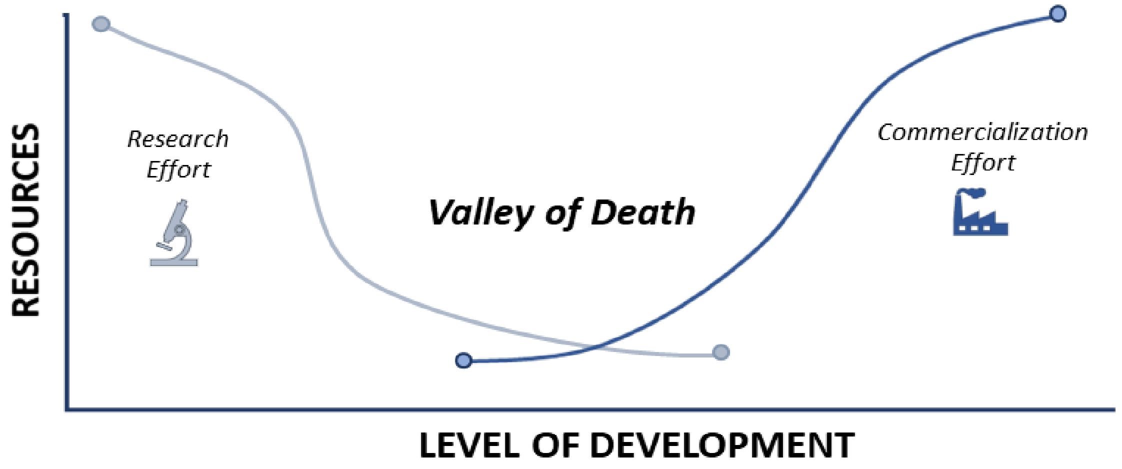


Figure 3-11: *The Valley of Death example*

3.3.3.1 The valley of death

The valley of death is observed in any industry where enterprises seek to exploit novel research and it is associated with high levels of market-failure and unsuccessful project execution (Ward et al., 2017). In many cases, however, it deals with the issues surrounding development, adoption, and exploitation of new technologies (Belz, A. *et al., 2019)*. Subsequently, a narrow link between TRL and the VoD has developed over the years, thus encouraging the investigation of VoD for this study (Belz, A. et al., 2019). There exists, however, multiple iterations of the VoD problem throughout the literature, some of which falls under different nomenclature i.e., university technology transfer and university-industry engagement (Ellwood, Williams and Egan, 2020). Regardless, there is a clear need to address the issues relating to VoD before investing in further resources into a project (Ellwood, Williams and Egan, 2020).

Some earlier literature viewed the VoD problem as an economical one, with funds (specifically governmental support) being too focussed on early-stage development, thus resulting in inefficient distribution of finances throughout the development cycle (Ford, Koutsky and Spiwak, 2007). This economic view suggests that overinvestment in research leads to inflated theoretical output which does not correlate with commercial needs and resources, thus creating a fiscal valley of death (Ford, Koutsky and Spiwak, 2007). The literature has since matured to recognise that the solution for VoD is not as simple as effective economical distribution of funds, since high levels of uncertainty in research, technologies and markets lead to, uncomfortable risk for investors (Ellwood, Williams and Egan, 2020). Investment uncertainty is especially severe for manufacturing-orientated technologies as prototyping costs increase rapidly without a significant reduction in adoption risk (Belz, A. et al., 2019). Subsequently, a more refined VoD approach is required so enterprises can understand the influencing risk-factors of new technology development, thereby making investment opportunities more secure.

Where in the past, technological change was seen as a linear process from invention to innovation and diffusion, the more recent understanding of the problem has shifted towards an evolutionary, non-linear approach (Hudson and Khazragui, 2013). This new view emphasises the importance of organizational, financial, and commercial aspects of innovation and recognizes the need for their inclusion in the research requirements (Hudson and Khazragui, 2013). This issue, that was believed to be a consequence of fund distribution, has developed into a multi-dimensional and interactive problem which has extended the original VoD to what is now described as the Long Valley of Death (Ward et al., 2017).

3.3.3.2 The Long Valley of Death

The LVoD was first described in a paper by Ward et al., where they discuss the shortcomings of VoD in the manufacturing domain and attempt to rectify these deficiencies by developing three dimensions of maturity to bridge the LVoD (Ward et al., 2017). Their critique of the VoD states that it was traditionally bridged only by demonstrating a manufacturing technology at full scale, in factory representative environments in terms of equipment, process control and operation. They argued that this original solution did address the key gap of full-scale pre-production capability demonstration, but that it is insufficient in driving exploitation of the full potential of new-age manufacturing technologies (Ward et al., 2017). To achieve full-scale exploitation in the modern era, the paper suggests supplementing the traditional "demonstration" dimension with two additional dimensions. The first dimension being the position of the target product application in its product life cycle, an idea supported by Markham (Markham et al., 2010), and the second dimension being the readiness of the supply chain to receive the technology.

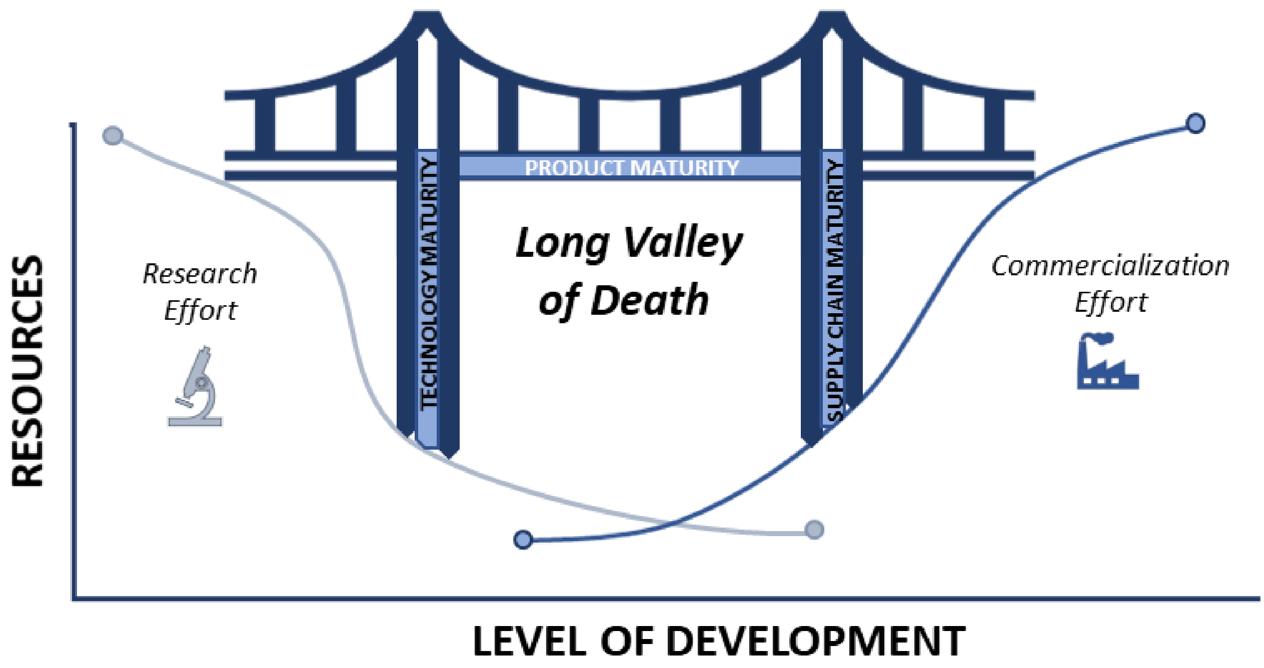


Figure 3-12: *The Long Valley of Death and the maturity dimensions needed to bridge it*

3.4 Selection and Discussion of Theoretical Models

By conducting a thorough literature review, a clear understanding of the literature landscape and accompanying key concepts was developed. Subsequently, the most applicable theoretical frameworks and models was chosen to develop the support tool. It is important to remember that the purpose of the support tool is to facilitate decision making during acquisition of novel manufacturing technologies. It does so, by identifying frameworks that best answer the most pressing questions proposed by enterprises during acquisition. The acquisition process can thus be broken down into the four questions below, noting that the questions are presented in chronological order from the inception of the project to its final implementation.

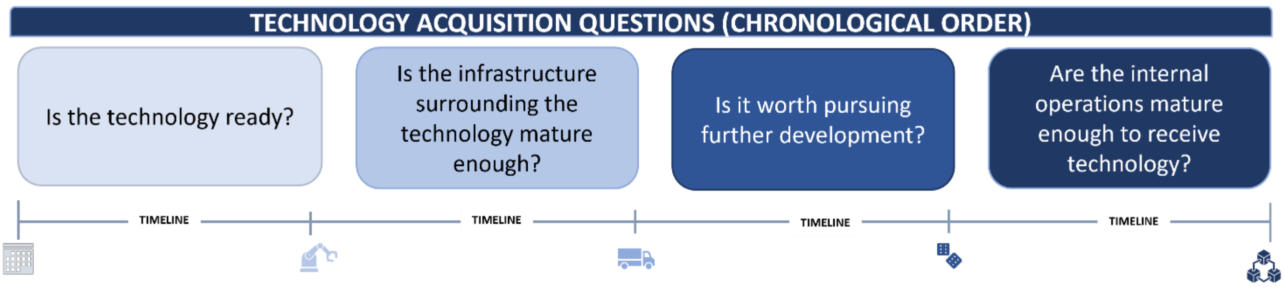


Figure 3-13: *Chronological order of technology acquisition questions that must be answered with applicable theoretical models*

These questions were selected based on the researchers understanding of the research gap and literature body developed during the literature review. Based on the questions proposed above and the knowledge of the literature landscape, the following theoretical models and frameworks were selected for the creation of the decision support tool. The remainder of this section will provide a detailed discussion of each model by explaining why it was chosen and how it adds value to a decision support tool.

Table 3-4: *Theoretical models selected for the development of a decision support tool*

Model Name	**Acquisition Question**	**Source**
A Readiness Level Model for New Manufacturing Technologies (MTRL)	Is the technology ready?	(Peters, 2015)
Long Valley of Death: Foundation for Innovation (LVoD)	Is the infrastructure surrounding the technology mature enough?	(Ward et al., 2017)
Technology Readiness and Risk Assessment: A New Approach (TRRA)	Is it worth pursuing further development?	(Mankins, 2009)
SM^{3}E Manufacturing Maturity Model	Are the internal operations mature enough to receive the technology?	(Mittal, Romero and Wuest, 2018) (Mittal, Romero and Wuest, 2018) (Mittal et al., 2018) (Mittal et al., 2019)

As mentioned above, four models were selected for the purpose of this study through a process of elimination that is explained in the following sections. This elimination process compared various models applicable at each stage of the acquisition questions by identifying specific objectives that the models must fulfil. These objectives were identified on a case-by-case basis as each phase of the acquisition questions generated unique problems to be addressed. The objectives for each elimination procedure were determined according to the following process:

Step 1: ***Investigate acquisition question problems***

The first step of identifying appropriate objectives for the elimination procedure is to analyse the acquisition question that the models under investigation are trying to answer. The analysis should ultimately show the most important problems associated with the acquisition questions.

Step 2: ***Set objectives to answer the problems identified in step 1***

Select appropriate objectives that address the various problems that were identified for each acquisition question. These objectives should answer the main acquisition question along with any secondary questions that branch from the main question.

Step 3: ***Search models for any additional functionalities which can be added as objectives***

The final step is to analyse all the models that are being compared and identify unique functionalities that each model provides. If these functionalities are relevant to the acquisition question that the model tries to answer, the functionality is translated into an elimination process objective. The remaining models are then compared to see if they contain these additional functionalities.

The following sections explore the details of the elimination procedure followed for each of the selected models by showing the various objectives that were identified for each round of elimination along with the models that fulfilled the requirements of the objectives. The sections also explain the details and inner workings of each of the four selected models.

3.4.4 A Readiness Level Model for New Manufacturing Technologies (MTRL)

The first question posed during the acquisition of novel technology is: *How long before the technology is ready for use?* The concept of readiness is discussed in section 2.4 and is split into TRL, as first proposed by NASA (Mankins, 1995) and MRL as first proposed by the US DoD (OSD and MRL Working Group, 2012). Further refinement was done by Rolls Royce with the addition of the MCRL model (Ward, Halliday and Foden, 2012). Lastly, Peters proposed a readiness model which incorporates elements of the previously mentioned models but applied specifically to a manufacturing technology domain (MTRL) (Peters, 2015). The theoretical model which best answers the proposed question within a context of manufacturing technology adoption can be chosen through a process of elimination as presented in the table below:

Table 3-5: *Elimination process for choosing an applicable readiness model*

Objectives	**Models**			
	TRL (NASA)	*MRL (DoD)*	*MCRL (RR)*	*MTRL (Peters)*
Addresses readiness of technology development	✓	-	✓	✓
Addresses readiness of manufacturing processes for the technology	-	✓	✓	✓
Addresses influencing factors on readiness outside of direct development processes	-	-	✓	✓
Provides a quantitative result	-	-	-	✓

The Manufacturing Technology Readiness Level (MTRL) model developed by Peters is the most applicable for the application domain of this thesis. His addition of a mathematically determined quantitative output for the estimated time to readiness (in months) of a manufacturing technology makes it extremely useful for practical application. Furthermore, Peters' model contains most of the information developed by the other three studies. The readiness levels for a new manufacturing technology are defined by Peters as shown in Table 3-6 below:

Table 3-6: *Manufacturing Technology Readiness Levels (Peters, 2015)*

MTRL	**Descriptor**
Level 1	Manufacturing principle described.
Level 2	Concept of machinery equipment to run the process in series production described; General EBIT (earnings before interest and taxes) potential estimated; interaction with material analysed.
Level 3	Manufacturing principle tested (e.g. in laboratory); Impact on product design described.
Level 4	Technology capability proven; material proven
Level 5	Concept of plant and production line designed (incl. capacity planning); suppliers identified; EBIT potential further validated.
Level 6	Series capability proven.
Level 7	Suppliers and materials certified.
Level 8	Low-rate production demonstrated (pilot run).
Level 9	Start of (series) production.
Level 10	Overall equipment effectiveness at comprehensive level (e.g. C85 % as benchmark).

The qualitative descriptors of the MTRL model provides a strong guideline for an initial estimation of readiness by enterprises. They can be used to gauge the level of readiness before committing further to a project along with identifying a desired level of readiness where an enterprise would be willing to adopt the technology. Once committed, the second phase of Peters' model can be used to estimate the time it will take a technology to reach the desired level of readiness. The table below summarises the three possible distribution types used to calculate the time it takes to pass a single readiness level. A new distribution is chosen for each movement between readiness levels and the results are cumulated to find the total estimated time it will take to move through all the levels. The symbols used in the formulas are:

a. t_i = Required time to pass readiness level i

b. μ = forecasted duration to pass readiness level

c. m = a deterministic minimal duration to pass readiness level

For example: *To move between MTRL 6 and MTRL 7 the most applicable distribution type must be chosen. Thereafter, the forecasted or predicted time μ to move between the levels is chosen and is based on industry knowledge. If the exponential distribution is selected for use, an additional minimal predicted time m must be selected.*

Table 3-7: *Probability distribution types to calculate the estimated time of movement between MTRLs (Peters, 2015)*

Probability Distribution Type	**Use Case**	**Formula**
Dirac	A deterministic duration μ is forecasted e.g., for MTRL 7 of certifying suppliers in the case of incremental development.	$f_i(t_i) = \begin{cases} 1 & if\ \ t_i = \mu \\ 0 & otherwise \end{cases}$
Lognormal	A mean value μ for the duration is suggested and it is assumed that an early success is more likely than a late one e.g., for MTRL 8 of demonstrating low-rate production of an incremental development.	$f_i(t_i) = \begin{cases} \frac{1}{\sqrt{2 \cdot \pi \cdot \ln(2)} \cdot t_i} \cdot e^{-\frac{(\ln(\frac{t_i}{\mu}\sqrt{2}))^2}{\ln(4)}} & if\ t_i > 0 \\ 0 & otherwise \end{cases}$

Exponential	A deterministic minimal duration m and a mean value of the duration μ are suggested, but no more behaviour can be assumed e.g., only poor information is available about the technology in case of a disruptive technology.	$f_i(t_i) = \begin{cases} \frac{1}{\mu - m} \cdot e^{-\frac{1}{\mu - m} \cdot (t_i - m)} & t_i \geq m \\ 0 & otherwise \end{cases}$

The distributions provided above can be utilised in a Monte-Carlo simulation to estimate the total time it will take to move from the current readiness level to the desired level (Peters, 2015). Enterprises now have a forecasting tool that can help with project planning and timeline estimation. The model presented by Peters, therefore, fully satisfies the first question of technology acquisition.

3.4.5 Long Valley of Death: Foundation for Innovation (LVoD)

The second question posed during the acquisition of novel technology is: *Is the infrastructure surrounding the technology mature enough?* This question is vital to the success of any technology adoption, and it is imperative that it is addressed early in the acquisition process. The genesis of this question is first discussed in section 2.4.3 since it is closely related with the issue of LVoD. The LVoD model explains how there are other dimensions, in addition to technology demonstration/readiness, that heavily influence the success of novel technology adoption. The LVoD model proposed by Ward et al., best addresses these "external" influencing factors (Ward et al., 2017) and was chosen through a process of elimination as presented in the table below:

Table 3-8: *Elimination process for choosing an applicable model to assess maturity of external infrastructure elements*

Objectives	**Models**		
	MCRL (RR)	*Crossing the VoD* (Ellwood, Williams and Egan, 2020).	*LVoD (Ward)*
Addresses the problems associated with VoD	-	✓	✓
Provides possible solutions to VoD problems		✓	✓
Considers actors outside of direct technology development	✓	✓	✓
Addresses gaps specific to manufacturing technology domain	✓	-	✓
Provides a context specific tool with which the gaps can be analysed, and current capability can be assessed against	-	-	✓

The model developed by Ward et al., is the most applicable for the application context of this thesis and will thus be used as the second model in the development of decision support tool. Ward identified three specific domains of maturity that must be assessed before attempting to adopt a new manufacturing technology. These three domains are "Technology Elements", "Supply Chain Elements" and "Product Elements" (Ward et al., 2017). These maturity dimensions can help provide an excellent overview of the external factors that influence the implementation success of a new technology.

3.4.5.1 Technology maturity elements

The technology dimension investigates the factors that influence the operation of a new technology. Utilising a new technology is not as simple as placing it on the factory floor and starting it up. There are multiple role players that contribute to the successful operation of the technology and an enterprise must ensure all the role players are in place before acquiring new technologies.

	TECHNOLOGY: DIMENSION ELEMENTS				
MATURITY LEVEL	***Sustainability***	***People/Skills***	***Equipment***	***Demonstration***	***Process Control***
Lvl 0: *No Capability*	No understanding of what is needed to ensure on-going availability of the capability	No experience of the process	No definition of equipment needs	No experience of the capability	No understanding of process control
Lvl 1: *Understanding of Process Requirements*	Requirements for maintaining and advancing the capability in line with strategy defined (including skills, people / continuity, equipment maintenance, replacement equipment, etc)	Required skills / expertise identified	Definition of specification in place	Defined set of demonstration requirements / acceptance criteria	Process variables defined
Lvl 2: *Basic Capability Available*	Continuity plan for maintaining and advancing the capability in line with strategy defined (including skills, people / continuity, equipment maintenance, replacement equipment, funding source etc)	Lead Staff trained and have operational experience, training plan in place	Access to potentially suitable equipment	Process demonstrated on available equipment	Control strategy defined
Lvl 3: *Demonstrated Capability Available*	Demonstration of the effectiveness of the plan for maintaining and advancing the capability in line with strategy defined	All staff operating the capability have demonstrated proof of competency	Suitable equipment available and demonstrated on similar application	Process used on at least one customer project, to the customer's satisfaction	Control strategy applied and tested
Lvl 4: *Advanced Capability Available*	Continual assessment and realignment of the plan for maintaining and advancing the capability in line with strategy defined	Expert team available to operated the capability	Equipment available, fully commissioned, and proven track record within the scope of use	Process used on sufficient customer projects within a defined scope of use that there is full confidence in use of the process to the customer's satisfaction	Process control strategies proven

Figure 3-14: *Original Technology maturity dimension for crossing the LVoD (Ward et al., 2017)*

3.4.5.2 Supply Chain maturity elements

The adoption and operation of any manufacturing technology requires a constant influx of materials and resources which must be supplied with consistency to ensure success. The supply chain dimension therefore investigates the various aspects which influence the efficacy and success of the supply chain and ultimately the technology's operations.

	SUPPLY CHAIN: DIMENSION ELEMENTS					
MATURITY LEVEL	***Raw Material***	***Equipment***	***Tooling and Consumables***	***Sustainability of Resources***	***Willingness***	***Standards, Quality and Systems***
Lvl 0: *No Capability*	No viable source for even small qualities of material OR no understanding of production implications	No viable source of equipment OR no understanding of requirements	No understanding of what is needed to ensure on-going supply	No understanding of what is required to ensure on-going supply	Supplier attitudes to the technology proposition are unknown or hostile	No clarity on requirements
Lvl 1: *Understanding of Process Requirements*	Raw material supply chain available to support small scale process development AND understanding of production implications	Equipment supply chain available to support small scale process development AND understanding of production implications	Requirements for maintaining and advancing the supply chain are defined and understood	Key resources which are defined and understood can be acquired with an on-going supply.	Suppliers have been approached and enough are known to support the technology proposition to confirm feasibility	Areas where standards, specifications and systems are needed are defined and agreed
Lvl 2: *Basic Capability Available*	Material supply chain available to support large scale process development and small volume initial production	Equipment supply chain available to support large scale process development and small volume initial production	Minimum standards defined and implemented to ensure sustainable supply	Supply chain design model addresses issues of resource scarcity, non-sustainable logistics and through life support	Suppliers (material, equipment, and consumables) are supporting the technology to a level which enables production	Areas where standards, specifications and systems are needed are defined and agreed
Lvl 3: *Demonstrated Capability Available*	Material supply chain in place which can support some of the market potential	Equipment supply chain in place which can support some of the market potential	Demonstration of the effectiveness of the minimum standards	Demonstrated supply chain design model which addresses issues of resource scarcity, non-sustainable logistics and through life	Suppliers (material, equipment and consumables) are supporting the technology in production	Standards, specifications and systems are demonstrated as effective
Lvl 4: *Advanced Capability Available*	Material supply chain in place to support full market potential	Equipment supply chain in place to support full market potential	Continual assessment and re-alignment of the minimum standards	Continual assessment and re-alignment of improvements in resource sustainability	Suppliers (material, equipment and consumables) are supporting the technology in production, and proactively planning for the future	Standards, specifications and systems are sufficient to drive world class performance

Figure 3-15: *Original Supply Chain maturity dimension for crossing the LVoD (Ward et al., 2017)*

3.4.5.3 Product maturity elements

The product dimension is a vital addition to the maturity model. It is possible for a technology to be fully functioning and ready for adoption, but it is not clear how the technology can be used to create a marketable product. In some cases, there might even be a viable product but there is no market interest. Enterprises must therefore first consider the reasoning behind adopting a new technology and justify the financial investment through proper market research and profit gain projections.

	PRODUCT: DIMENSION ELEMENTS					
MATURITY LEVEL	***Market Intelligence***	***Product Concept***	***Financial Viability***	***Customer Pull***	***Intellectual Property***	***Legislative Requirements***
Lvl 0: *No Capability*	No awareness of the potential market for the technology	Technology is scientifically interesting without obvious commercial outlets	No assessment of development cost or potential revenue from the technology	No commercial entities aware of or supportive of the technology	No awareness of background intellectual property; no consideration of potential foreground IP	No consideration given to legislation relating to the technology
Lvl 1: *Understanding of Process Requirements*	Market potential of the technology is understood and supports ongoing investigation	Product applications are defined and under development	Cost and benefit drivers related to the technology are understood and support further investigation	Potential customers are aware of the technology and offering low level support	Background IP is understood with mitigation plan for any issues; areas for foreground IP are identified	Legal obstacles which need to be navigated are known with plans to address
Lvl 2: *Basic Capability Available*	Defined market is being pursued for the technology	First-off products have been developed for commercial use with the technology	Business case for the technology has been developed and supported investment	Early adopters of the technology are in place and active	Background IP issues addressed; foreground IP protected	Legal requirements are understood but implementation is still in progress
Lvl 3: *Demonstrated Capability Available*	Technology is supported by an active market with clear growth potential	Products based on the technology are successful in the marketplace, with clear growth potential	Application costs for routine use of the technology are understood	Technology is widely considered to be essential with a high level of demand to implement	IP management issues addressed; potential for product / service differentiation	The technology has been implemented in a legally compliant manner on lead applications
Lvl 4: *Advanced Capability Available*	Market growth is only restricted by the pace of technology development	Second or third generation products based on the technology are available in the marketplace	Application costs for implementation on next generation products can be readily obtained	Technology is a basic requirement or prerequisite for all relevant businesses	Product or process IP provides product or service differentiation	Legal framework for use of technology is well understood and implemented

Figure 3-16: *Original Product maturity dimension for crossing the LVoD (Ward et al., 2017)*

3.4.6 Technology Readiness and Risk Assessment: A New Approach (TRRA)

The third question posed during the acquisition of novel technology is: *Is it worth pursuing further development?* Since the acquisition question are posed in a chronological order, the answer to the third question can be influenced by the knowledge acquired from the first two questions. The need for understanding further development effort and risk is predicated on the idea that, depending on technology readiness and external infrastructure maturity, there are some R&D efforts that a third party must invest in to ensure successful development. Enterprises, therefore, need a tool that can determine the probability that the third party will develop the technology successfully, based on the current knowledge of the technologies' readiness and infrastructure. Even though, there are comprehensive risk mitigation packages available, only a few is useful for self-assessment of SMEs. The two most notable papers are the Technology Readiness Assessment (TRA) model developed by NASA (Hirshorn and Jefferies, 2016) and the Technology Readiness and Risk Assessment developed by Mankins (Mankins, 2009). Both these papers provide a risk assessment process, however, the NASA paper is a more broad-based assessment framework with a focus on readiness, while the paper by Mankins provides a detailed description of risk calculation specifically for technology R&D efforts.

Table 3-9: *Elimination process to determine the most applicable model for estimation of further development risk*

Objectives	**Models**	
	TRA (NASA)	*TRRA (Mankins)*
Incorporates TRL into model	✓	✓
Addresses the need for risk analysis and mitigation	✓	✓
Provides a measurement scale of development risk	✓	✓
Considers the need for a technology (TNV) as a risk reduction factor	-	✓
Provides a detailed tool which calculates level of risk on the measurement scale	-	✓

The paper by NASA is comprehensive and touches on various topics with regards to TRL making it viable for consideration (Hirshorn and Jefferies, 2016). However, the broad nature of the TRA model makes it slightly harder to use and provides a less specific answer to the proposed acquisition question. On the other hand, the TRRA model developed by Mankins also provides a nice overview of the influencing factors of TRL and R&D, with the inclusion of a mathematically driven risk estimation tool. Additionally, the TRRA model also incorporates a technology need value (TNV) as a risk reduction factor, which is helpful. Therefore, the TRRA model fully satisfies the proposed acquisition question.

3.4.6.1 TRRA tool inputs

The TRRA model relies on the following inputs to function:

MTRL: The first input for the risk matrix is both the current and desired manufacturing technology readiness levels, as defined in section 2.5.1.

R&D Degree of difficulty: The second input is the degree of difficulty of R&D effort as shown in Figure 3-17. This input describes the degree of difficulty associated with achieving R&D objectives for a new technology and is based on the probability of success of these projects. An R&D3 level must be selected based on intricate knowledge of a new technologies R&D requirements.

Technology Need Value: The TNV is an estimate of how critical a technology is to the success of an enterprises upgrade program or strategy as seen in Table 3-10. A high TNV will have a net reduction in the overall perceived risk as the need/benefit of the technology outweighs the possible negatives. A TNV must be selected based on detailed knowledge of the technology and the surrounding market, to ensure an educated estimate is made.

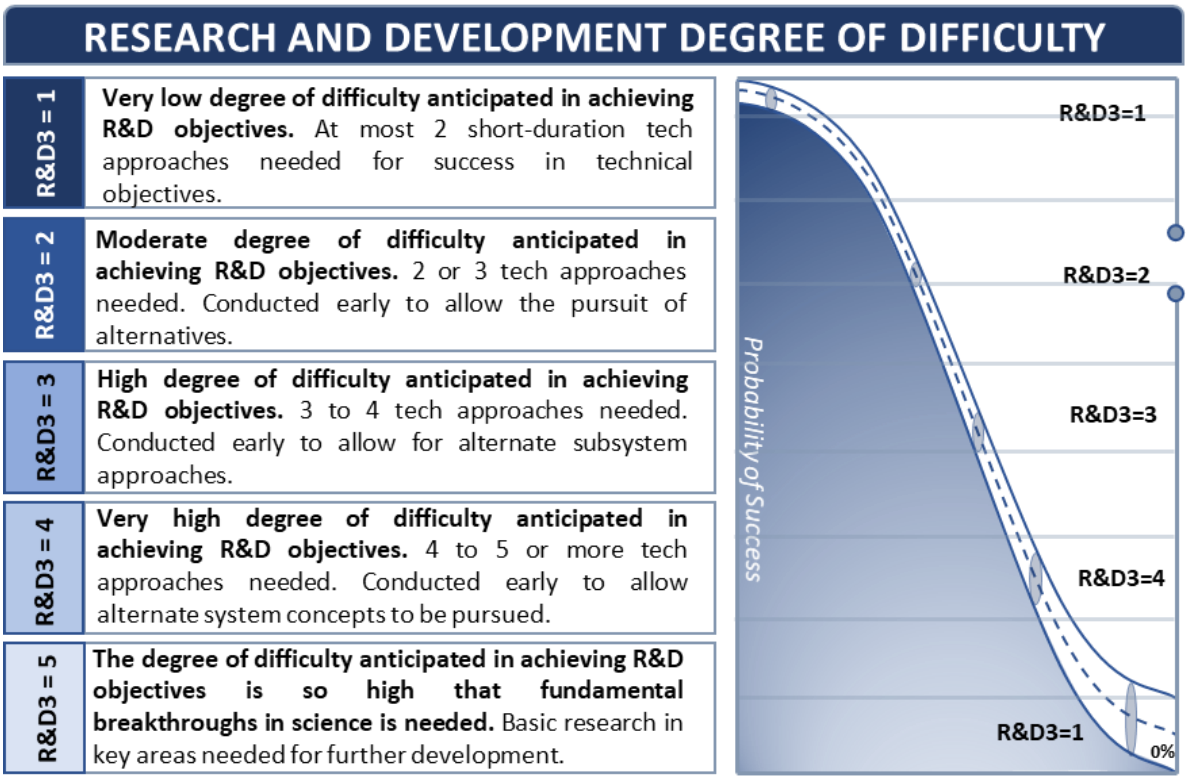


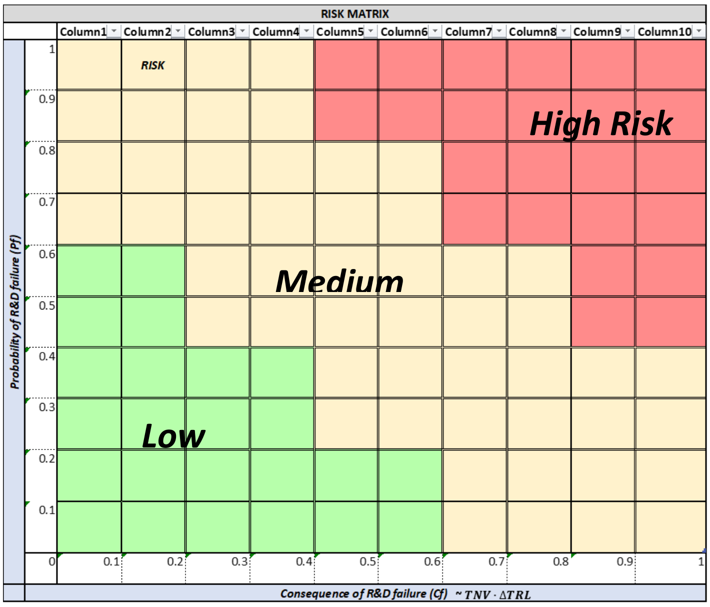
Figure 3-17: *R&D degree of difficulty scale (Mankins, 2009)*

Table 3-10: *Technology need value scale (Mankins, 2009)*

Technology Need Value	**Weighting Factor**	**Description**
TNV-1	40%	The technology is **not critical at this time** to the success of the program – the advances to be achieved are useful for some cost improvements; However, the information to be provided is not needed for management decisions until the far- term.
TNV-2	60%	The technology effort is **useful** to the success of the program - the advances to be achieved would meaningfully improve cost and/or performance; However, the information to be provided is not needed for management decisions until the mid-to far- term.
TNV-3	80%	The technology effort is **important** to the success of the program – the advances to be achieved are important for the performance and/or cost objectives and the information to be provided is needed for management decisions in the near- to mid- term.
TNV-4	100%	The technology effort is **very important** to the success of the program; the advances to be achieved are enabling cost goals and/or important for performance objectives and the information to be provide would be highly valuable for near-term management decisions
TNV-5	120%	The technology effort is **critically important** to the success of the program at present – the performance advances to be achieved are enabling and the information to be provided is essential for near-term management decisions.

3.4.6.2 Risk matrix output

The risk matrix uses the inputs discussed in the previous section to calculate and output the following matrix:



Probability of Failure (P_f)		
LEVEL		LIKELIHOOD
P_f	R&D3	
0.0 – 0.2	1	Remote
0.2 – 0.4	2	Unlikely
0.4 – 0.6	3	Likely
0.6 – 0.8	4	Highly likely
0.8 – 1.0	5	Near certain

Consequence of Failure (C_f)		
LEVEL		Impact
C_f	Rating	
0.0 – 0.2	A	Minimal
0.2 – 0.4	B	Some
0.4 – 0.6	C	Moderate
0.6 – 0.8	D	Major
0.8 – 1.0	E	Unacceptable

Figure 3-18: *Risk matrix output (Mankins, 2009)*

The above tool can be used quickly to estimate the risk of pursuing a project. In the context of the decision support tool, the word "risk" can be seen as the probability that a third party will successfully complete the R&D effort. Any project that is classified as "High Risk" must be reconsidered by re-evaluating the details of the input requirements to see if there are any additional risk reduction or increasing factors. This tool relies heavily on qualitative knowledge to produce a quantitative output, it is therefore, important to have a firm grasp of the technology, project landscape and previously known risks before utilising this tool.

3.4.7 SM^{3}E Manufacturing Maturity Model

The fourth and final question posed during the acquisition of novel technology is: *Are the internal operations of the enterprise mature enough to receive and integrate the newly adopted technology?* The advent of SM presents challenges in the organization of unprecedented integration of systems across the manufacturing hierarchy (Shi et al., 2019). SM specific maturity models can provide a holistic view of the interconnected process steps in system implementation (Shi et al., 2019), which can help alleviate some of the uncertainty surrounding the effects of technology implementation. Furthermore, if there are operational dimensions that are clearly lagging, enterprises can choose to first invest in operational improvement before introducing a new technology. Overall, a SM maturity model can be a useful tool that provides a common understanding of how components in a manufacturing enterprise relate to each other, thereby, improving decision making for implementation projects (Weber et al., 2017). There are different SM maturity models available in the literature. The following table will outline the process of elimination that was followed to select the most applicable model.

Table 3-11: *Elimination process for choosing an applicable model to assess maturity of internal operations and activities in the context of smart manufacturing*

Objectives	**Models**			
	SMKL (Shi et al)	*TARGET (Kaartinen et al)*	*M2DDM (weber et al)*	*SM³E (Mittal et al)*
Deals with maturity factors commonly observed in SM	✓	✓	✓	✓
Utilises data driven methodologies for maturity estimation	✓	-	✓	✓
Considers multiple enterprise departments when measuring maturity	✓	✓	-	✓
Considers the effect of cross-departmental interactions on maturity progression	✓	-	-	✓
Considers and utilises the adoption of specific SM innovations as a measure of SM maturity	-	✓	✓	✓
Measures the maturity of multiple operational dimensions within each enterprise department	-	-	-	✓

The maturity model proposed by Mittal provides a comprehensive overview and analysis of SM maturity criteria. What sets the SM³E model apart from similar SM maturity models, is the fact that it deals not only with cross-departmental interactions, but also with a sub-set of dimensions within each department. The SM³E model utilises various "toolboxes" which represent the different operational departments of an enterprise. Each of these toolboxes have a sub-set of the same five organisational dimensions, with one of the toolboxes having an additional sixth dimension as summarised in the table below:

Table 3-12: *SM³E toolboxes and their corresponding organisational department*

Toolbox/Department	**Organisational dimensions**
Manufacturing (M)	Finance, People, Process, Product
Data & Analytics (D&A)	Finance, People, Process, Product, Strategy
Cloud & Storage (C&S)	Finance, People, Process, Product
Design & Simulation (D&S)	Finance, People, Process, Product
Sensors & Connectivity (S&C)	Finance, People, Process, Product
Robotics & Automation (R&A)	Finance, People, Process, Product
Business Management (BM)	Finance, People, Process, Product

The interplay between the above-mentioned toolboxes creates a unique network of cross-dependant maturity levels. In layman's terms, this means that the maturity of some toolboxes cannot be advanced before some other toolbox is at a desired maturity level. This provides the user with a holistic view of the activities that must be completed in order to advance overall maturity. The interdependencies of the toolboxes are shown in Figure 3-19 below. The following, however, is an example contrived from Figure 3-19 below to expedite understanding of the system.

Example: *In order to upgrade the organisational dimensions of the Manufacturing (M) toolbox from level 2 to level 3, it is required that the corresponding organisational dimensions of the Design & Simulation (D&S) toolbox is at least at a maturity level 1.*

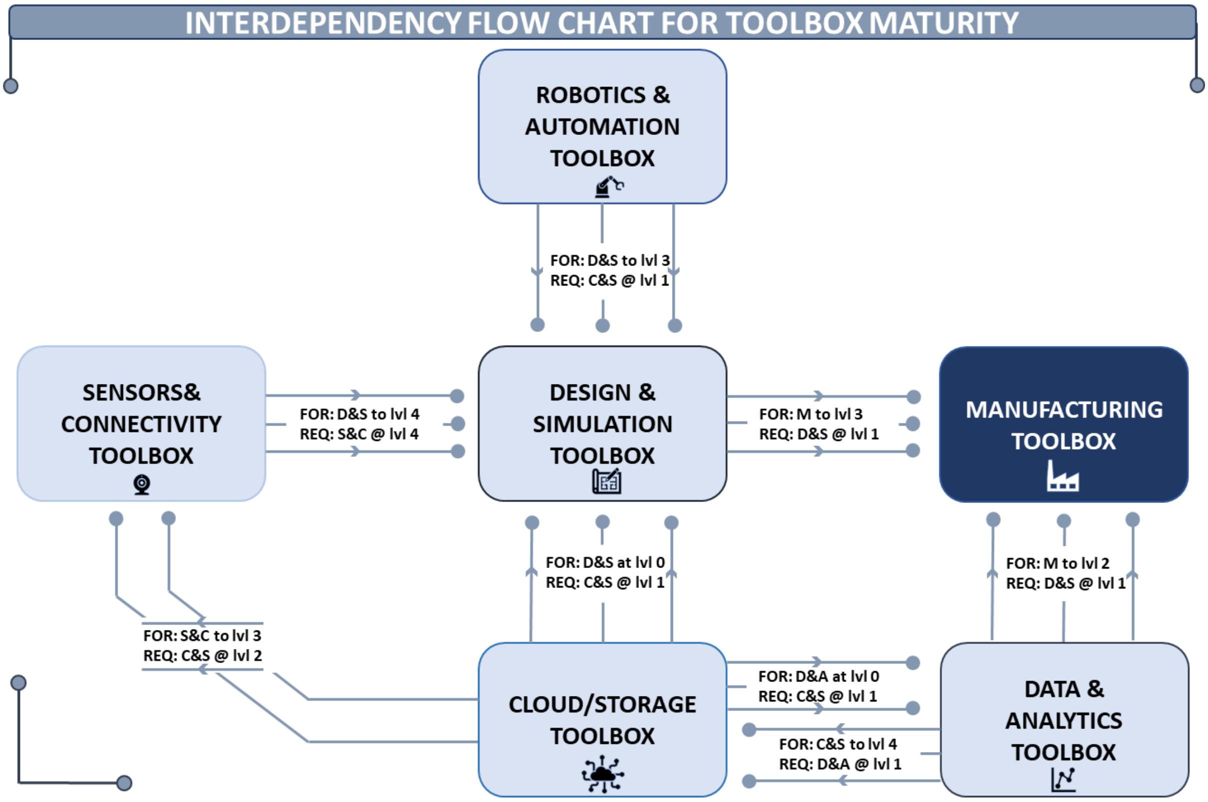


Figure 3-19: *Unrefined interdependency of toolbox model (Mittal, Romero and Wuest, 2018)*

Figure 3-19 is, however, missing the Business Management Toolbox (BMT) as this toolbox is not a data-driven toolbox and is semi-independent from the other, more technically driven, toolboxes. While the BMT has no direct inter-dependency in the tool, the business and organizational decisions of an enterprise have a massive impact on the future development and implementation of projects and innovations (van de Vrande et al., 2009). However, business, and organizational strategies and decisions require a more broad-based approach with fewer finite and quantifiable outputs, thus making it difficult to link with corresponding levels of maturity of the technical toolboxes. It, therefore, stand to reason that the BMT cannot be included in the interdependency flowchart, but rather serves as a separate toolbox that must be upgraded parallel to the technical toolboxes. The BMT is, however, still a crucial part of decision support. The paper by Mittal unfortunately does not address the intricacies of a BMT effectively. However, this project is part of a research group where extensive analysis and development of a business model tool has been done. Subsequently, the reader can investigate the paper by Van Heerden entitled: *The Development of a Business Model Innovation Framework from a Value Network Perspective Applied to the Cemented Tungsten Carbide Additive Manufacturing Sector in South Africa* (Van Heerden, Grobbelaar and Sacks, 2022).

The next step in understanding this model is to investigate the details of each toolbox. The model developed by Mittal utilises data-driven techniques to analyse maturity levels (Mittal et al., 2019). This requires enterprises to output and/or utilise various datatypes generated through different value adding capabilities at each level of maturity in each organisational dimension. These capabilities are generally acquired by adopting and implementing certain SM innovations (Mittal, Romero and Wuest, 2018). The result of this method is that the maturity of the organisational dimensions will rely on the same operational capability and data outputs at the respective maturity levels. This standardises the maturity ranking and allows for ease of analysis across toolboxes; however, this method does run the risk of generalisation between organisational dimensions. The data types and SM capability requirements for each maturity level in each toolbox must, therefore, be selected carefully to ensure that it reflects a level of maturity consistent with and applicable to all the organisational dimensions. Figure 3-20 outlines the details of the SM^{3}E toolbox (Mittal, Romero and Wuest, 2018).

Figure 3-20: *Maturity descriptors of toolboxes (Mittal, Romero and Wuest, 2018)*

3.5 Summary of Chapter 3

Chapter 3 provided the reader with a thorough overview and explanation of the literature landscape that formed the foundation of this project. The chapter started by explaining how both a structured and snowball literature review process was followed to the rigor and relevance requirements of the DSRM. The various activities and methods that were completed during the literature review is also defined in Chapter 3, thus providing the reader with a detailed understanding of the review process and allowing them to repeat the review process themselves.

Once the review process is understood, Chapter 3 delved into the details of the literature body, first by defining and summarising key concepts and then by explaining the intricacies of the concepts. This section of Chapter 3 presents a logical progression of the literature concepts and how they relate to one another and the project as a whole. Understanding the concepts presented in the literature review is critical to the final section of Chapter 3. The final section explains which theoretical models were selected for use in the proposed decision support tool of this project. More importantly, however, the final section of Chapter 3 shows the reader exactly how the various eligible models that were identified during the literature review were compared and eliminated. Finally, the reader could use Chapter 3 to investigate and understand of the basic details of each theoretical model selected for use in the tool.

Chapter 4: Process Flow and Tool Interface Development

This chapter presents the development details of the decision support tool's process flow and IT-based user interface. First, the chapter explains how the selected theoretical models were arranged to create a logical flow of questions and information. Next, the chapter discusses the various IT-driven functionalities provided by the digital user interface. These discussions include screenshots of the digital tool as well as references to the appendices, in an attempt to guide the readers understanding of the tool's uses. Figure 4-1 below shows the position of Chapter 4 within the design process.

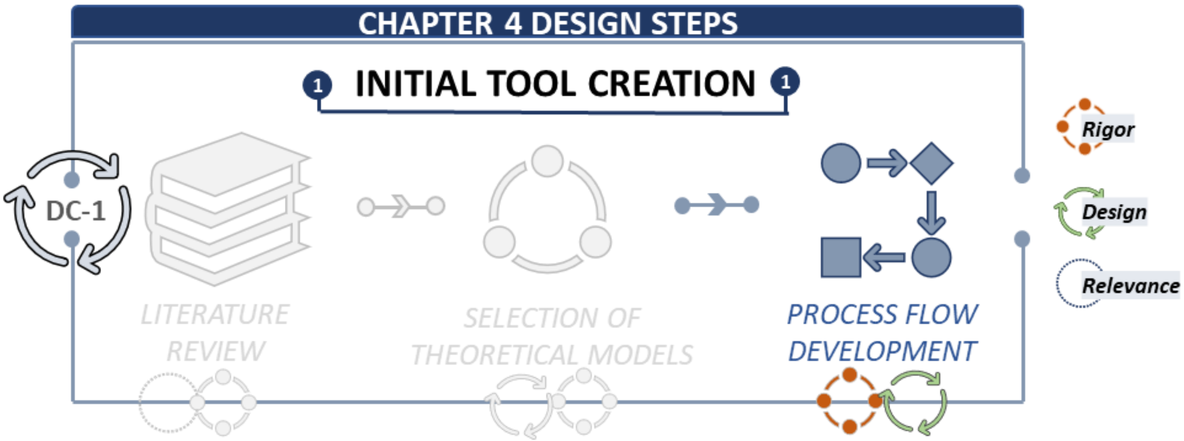


Figure 4-1: *Design steps completed in Chapter 4*

4.1 Process Flow Development

After selecting various theoretical models, they were organised into a process flow structure which facilitates an intuitive and logical sequence of events when using the tool. Ultimately, the theoretical models link together in a linear chain and help guide the user's decision making throughout the acquisition process. The process flow development is supported by the chronological acquisition questions proposed in Chapter 3. Since the theoretical models were selected to answer the various proposed acquisition questions, it stands to reason that the models must follow the same process flow as the chronological acquisition questions. The figure below shows the chronological order of the acquisition questions.

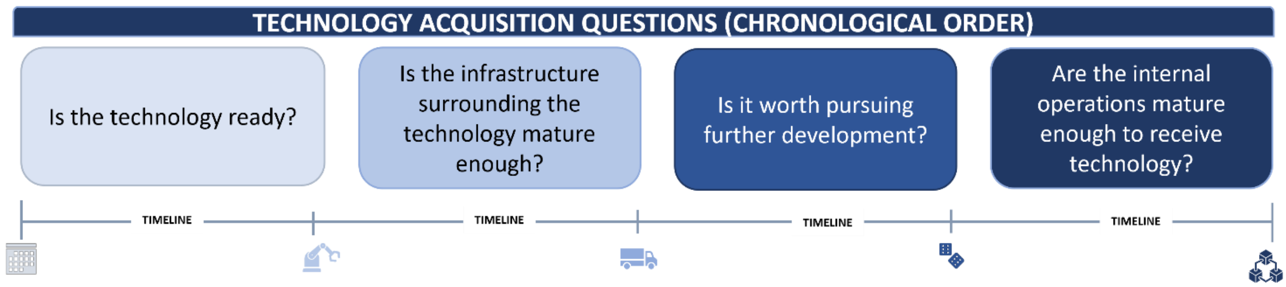


Figure 4-2: *Chronological order of technology acquisition questions*

The selection of appropriate theoretical models which successfully answer the questions proposed in Figure 4-2 above is discussed in-depth in Chapter 3. By answering the chronological acquisition questions, the following process flow was created through the implementation of the theoretical models:

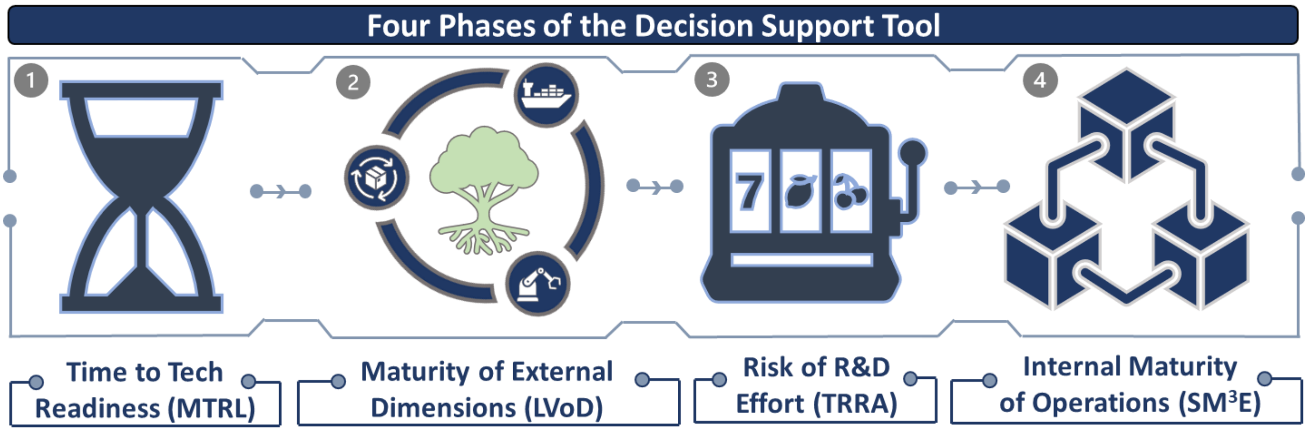


Figure 4-3: *Proposed process flow of the theoretical models in the digital decision support tool*

Figure 4-3 above, shows that the decision support tool is comprised of four phases. The first phase deals with calculating the time until the novel technology is at an acceptable readiness level for adoption. The tool will then move on to the second phase, which analyse various external maturity dimensions, such as supply chain and product considerations. These two phases represent factors which are somewhat out of the enterprise's control but have a massive influence of the future success of the project. It therefore makes sense to first consider these two phases, before starting on any internal operational work.

The third phase of the tool is a R&D risk analysis model. The inputs of this phase deals with the user's estimates of future R&D difficulty and need. These inputs will be influenced, to a certain degree, by the outputs of phase one and phase two. While there are no variables that directly carry over from one phase to the other, the qualitative nature of the phases results in decisions being influenced by the knowledge and understanding of the previous phases.

The fourth phase of the tool is the most intricate and deals with the maturity of the enterprise's internal operations. This phase analyses the various operations of a manufacturing enterprise and rate their maturity with relation to a SM paradigm. These dimensions represent that which can be influenced directly by management to ensure seamless and successful integration of the newly acquired technology.

These phases, needed to be integrated into an IT-interface. For this particular project, Microsoft Excel was selected as the interface of choice. This is due to its widespread use and ease of access for most enterprises. Furthermore, excels built-in Visual Basic programming language is powerful enough to produce the desired results. Figure 4-4 below shows the "Final Results" page of the developed interface. This page summarises and visually represents the results of the four phases of the decision support tool. This *Overview of Data* page, in essence, represent the process flow of the tool. For each phase on the *Overview of Data* page, there is a corresponding *Operational* page. The operational pages are where the user interacts with the tool by providing the relevant inputs for each phase. The rest of this chapter methodically explains the functionalities of each phase of the digital tool by showing the details of both the *Overview of Data* and the *Operational* pages. Figure 4-4 to Figure 4-6 below shows the entire *Overview of Data* page of the tool from Phase 1 to Phase 4. This is to help orientate the reader by positioning each phase in their mind. The development of each phase is discussed in detail throughout the rest of the chapter.

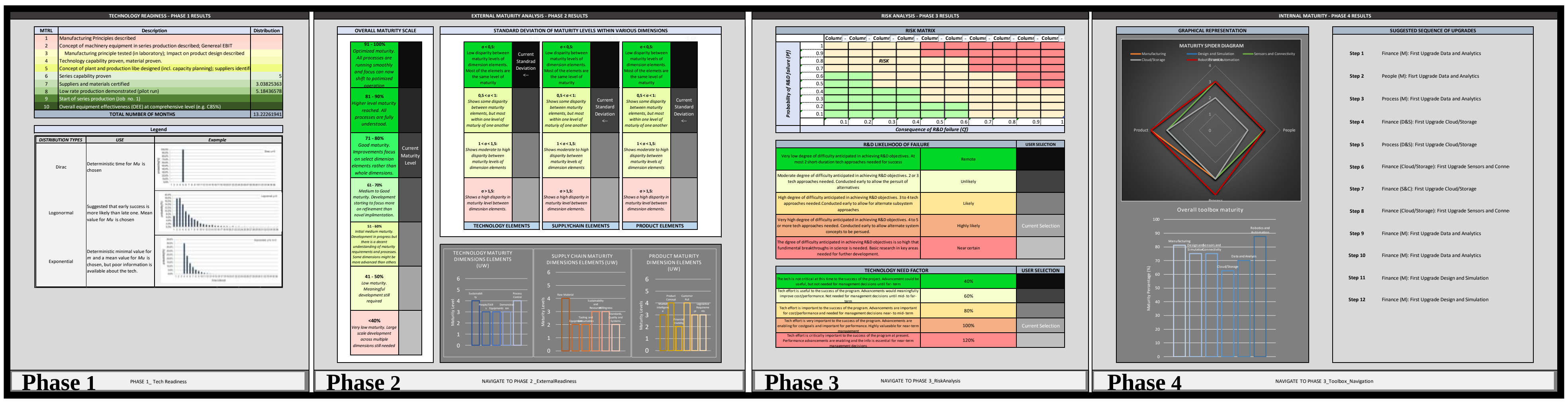


Figure 4-4: *Decision support tool interface - Overview of Data page*

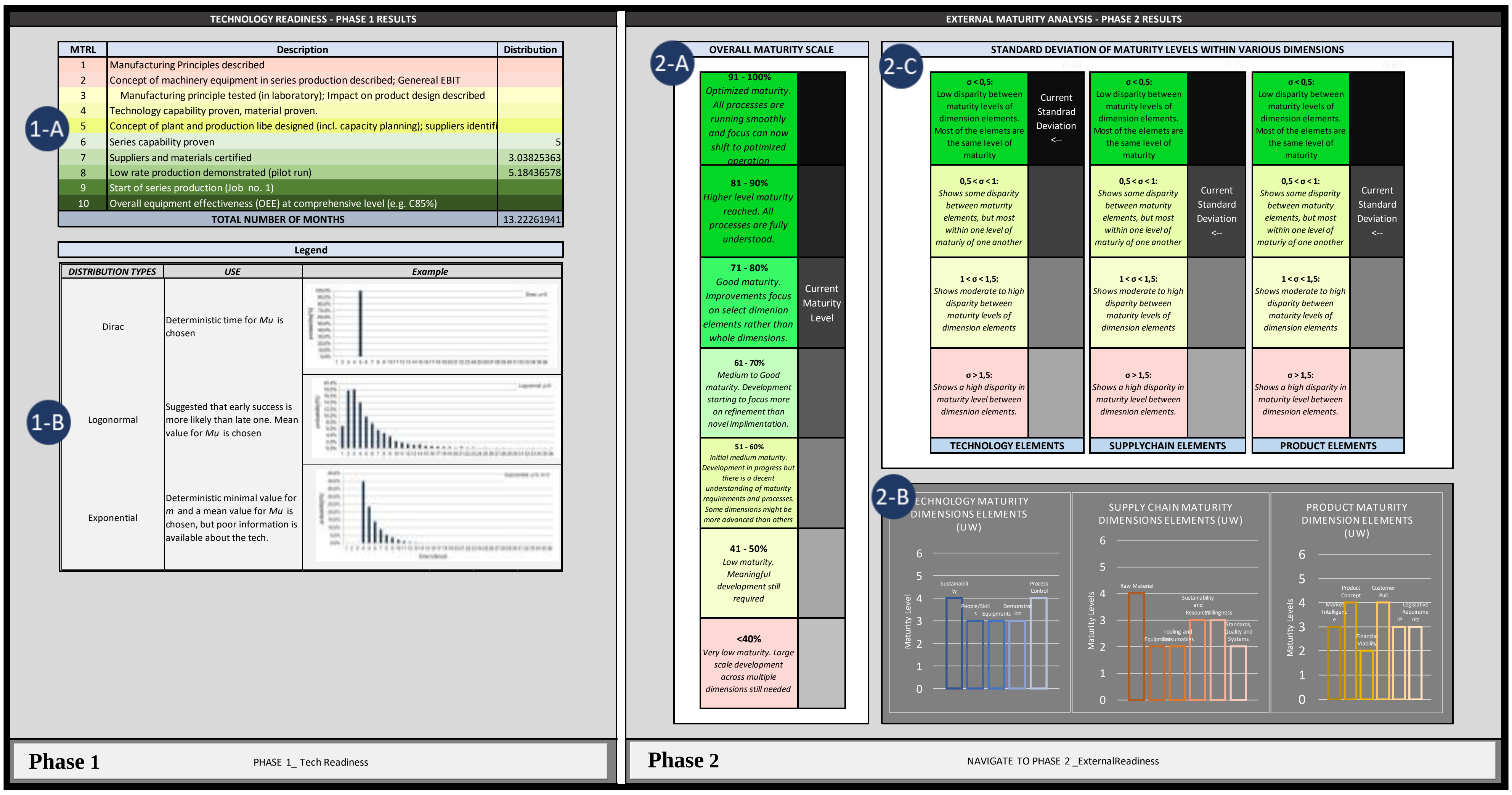


Figure 4-5: *Enlarged image of the Overview of Data page - Phases 1 and 2*

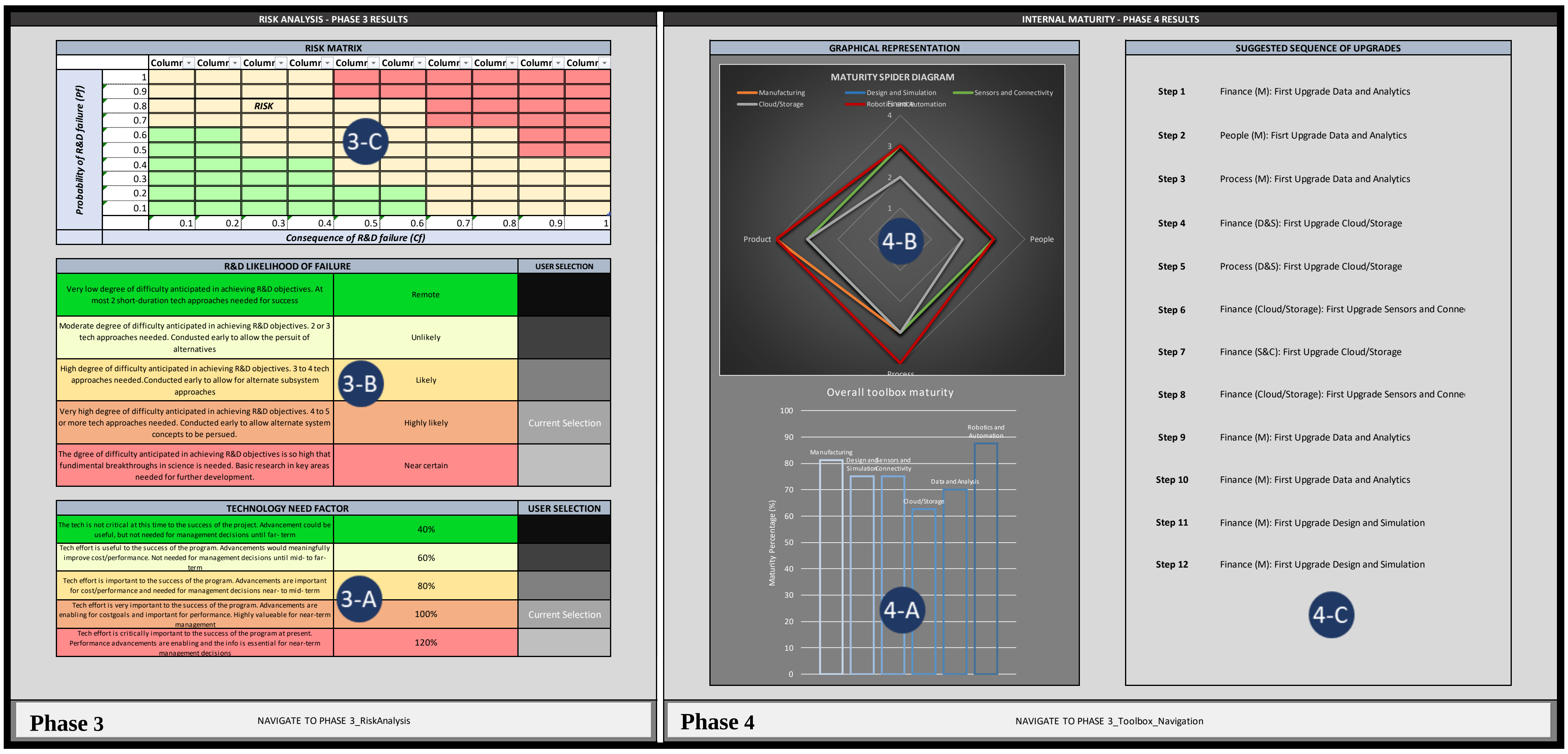


Figure 4-6: *Enlarged image of the Overview of Data page - Phases 3 and 4*

4.2 Phase 1: MTRL Tool Interface

The first phase of the decision support tool uses the 10 levels of manufacturing technology readiness along with probability distribution convolution and Monte Carlo simulations, to estimate the time it will take for a manufacturing technology to move from the current level of readiness to the desired level. It is important to realise that, even though Phase 1 incorporates some quantitative analysis features, it still relies heavily on the qualitative knowledge of the user in terms of current technology progression. This is because the user will have to select the appropriate probability distributions for each level of readiness based on their knowledge of the technology and its possible future development timeline. Since some of the probability operations can be intricate and hard to execute correctly, it was decided to utilise Palisade's @Risk excel plug-in for the Monte Carlo simulation. This plug-in allows the user to select appropriate probability distributions for each level of readiness and then run a simulation with relative ease. The @Risk input operations are, however, difficult to automate and as a result this phase will require the most direct user intervention. Phase 1 is also the only phase where the tool operations are done directly on the overview page, rather than on a separate operational page. These operations will be explained in the following section.

TECHNOLOGY READINESS - PHASE 1 RESULTS

1-A

MTRL	Description	Distribution
1	Manufacturing Principles described	
2	Concept of machinery equipment in series production described; Genereal EBIT	
3	Manufacturing principle tested (in laboratory); Impact on product design described	
4	Technology capability proven, material proven.	
5	Concept of plant and production libe designed (incl. capacity planning); suppliers identifi	
6	Series capability proven	5
7	Suppliers and materials certified	3.03825363
8	Low rate production demonstrated (pilot run)	5.18436578
9	Start of series production (Job no. 1)	
10	Overall equipment effectiveness (OEE) at comprehensive level (e.g. C85%)	
	TOTAL NUMBER OF MONTHS	13.22261941

1-B

Legend

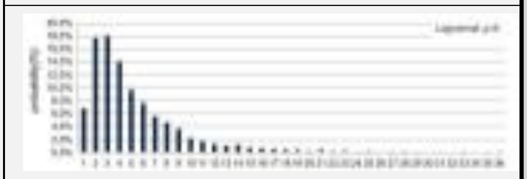
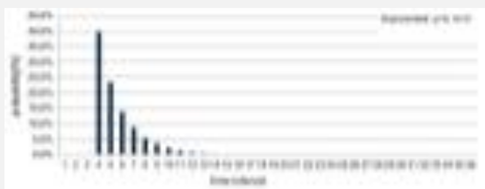
DISTRIBUTION TYPES	*USE*	*Example*
Dirac	Deterministic time for *Mu* is chosen	
Logonormal	Suggested that early success is more likely than late one. Mean value for *Mu* is chosen	
Exponential	Deterministic minimal value for *m* and a mean value for *Mu* is chosen, but poor information is available about the tech.	

Figure 4-7: *Phase 1 MTRL estimate – Digital tool overview and operational page*

4.2.1 Selection of probability distributions

The estimation of the total time it takes to move from the current TRL to the desired TRL, is done by estimating the development time to move between each individual readiness level and then calculating the sum of the various development increments. Since each development increment has multiple variables which will influence the development time, it is nearly impossible to select a precise number of months per increment. A more accurate method is therefore to select a probability distribution for each of these development increments. This distribution will represent the various possible timelines of a development increment around a mean number of months. The MTRL paper by Peters suggests that a user selects a lognormal distribution for development increments where an early success is more likely than a late one; and a exponential distribution for when there is only poor information available about the technology development (Peters, 2015). The table below summarises the process of selecting appropriate probability distributions for each TRL.

Table 4-1: *MTRL tool user steps*

MTRL Tool User Steps	**Description**
Step 1	Investigate the ten levels of the MTRL table shown in "A" of Figure 4-8 From this table, decide the current MTRL of the technology under investigation, along with the desired MTRL where the technology becomes eligible for adoption.
Step 2	Start with the current MTRL and investigate the information available on how long the development will take to promote the technology to the next MTRL.
Step 3	In the "Distribution" column of Figure 4-8 select the cell which corresponds to the MTRL under investigation. Click on the @Risk tab in excel and then click "Define Distribution". From the list of distributions, select either "Lognormal" or "Exponential" distributions. If "Dirac" distribution is desired, then do not define a distribution, but rather input the Mu value directly into the cell. The appropriate application scenarios for each of these three distribution types can be seen in "1-B" of Figure 4-7
Step 4	Once the appropriate distribution has been selected, set the desired mean and standard deviation values for the distributions. These values will be based off of the user's knowledge of possible development times.
Step 5	Repeat the process for each subsequent MTRL up to, and including, the desired MTRL.
Step 6	In the @Risk tab, click "Simulate" and wait for the results.

Screenshots of these user steps can be viewed in Appendix A.2, Alternatively, there are various detailed support lectures available on the internet for @Risk (https://www.youtube.com/watch?v=XLVgGHt1srQ.

4.2.2 Monte Carlo simulation interpretation

The interpretation and results of the Monte Carlo simulation is best explained using an example. The same example used in the MTRL as Peters (2015) will be used and the inputs of the proposed digital tool can be seen in Figure 4-8 below:

MTRL	Description	Distribution
1	Manufacturing Principles described	
2	Concept of machinery equipment in series production described; Genereal EBIT	
3	Manufacturing principle tested (in laboratory); Impact on product design described	
4	Technology capability proven, material proven.	
5	Concept of plant and production libe designed (incl. capacity planning); suppliers identifi	
6	Series capability proven	5
7	Suppliers and materials certified	6.007438988
8	Low rate production demonstrated (pilot run)	13.33259963
9	Start of series production (Job no. 1)	
10	Overall equipment effectiveness (OEE) at comprehensive level (e.g. C85%)	
TOTAL NUMBER OF MONTHS		24.34003862

Figure 4-8: *MTRL Monte Carlo example inputs*

The example is executed as follows: Figure 4-8 shows the analysis of a technology which is currently at the start of MTRL 6, and which can be adopted once it fully satisfies the MTRL 8 requirements. The user knows it will take five months exactly to prove series capabilities and therefore selects a Dirac distribution with µ at 5. Next, the user must estimate the time it will take to complete the requirements of MTRL 7. The user estimates it should also take around five months, however, they realise that earlier completion is more likely and, therefore, selects a Lognormal distribution with µ at 5. Lastly, the user must estimate how long it will take the technology to fulfil the requirements of MTRL 8. While they believe it will also take another five months, there is very little information available. The best course of action for the user is, therefore, to select an exponential distribution with µ at 5. Unfortunately, @Risk does not allow the user to select a minimum number of months (*m)* as suggested by Peters (2015), however, since the final result is a probability estimate, it is not too much of a concern. Finally, the graph of Monte Carlo simulation with 10 000 iterations is outputted as shown in Figure 4-9:

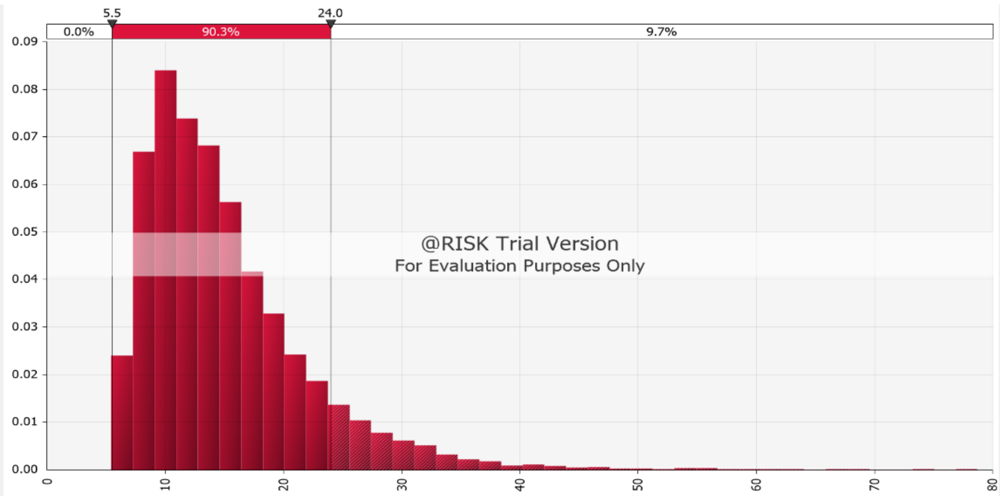


Figure 4-9: *Example output of phase 1 MTRL Monte Carlo simulation*

The graph shows that 90% of the data lies between 5.5 and 24 months. This allows an enterprise to adopt the assumption that, with reasonable confidence the process of developing a technology from MTRL 6 to MTRL 8 will be completed within 24 months.

4.3 Phase 2: LVoD Tool Interface

The LVoD model measures the maturity elements of the Supply Chain, Product and Technology. The inputs to the tool are provided by the user based on their knowledge of the application domain and the qualitative descriptors provided by the model. First, the overview page where the results of the model application are summarised is explored followed by the details of the application page where the model is used.

4.3.1 Phase 2 LVoD - Tool overview page

The overview page for the external maturity analysis outputs three key elements as shown in Figure 4-10. First, it shows the user the weighted average overall maturity percentage range as represented in section 2-A. While this range is an indicator of maturity, it should not be interpreted on its own. Another important metric is, therefore, the standard deviation metric as shown by the 2-C. This metric indicates the deviation between the sub-dimension within a dimension element. The reason being that it is possible to achieve a high overall maturity while some sub-dimension elements are still at extremely low maturity levels. It would, therefore, be unwise to assume the maturity metric is purely positive. Finally, 2-B shows the output of the bar graphs of the dimension elements' sub-dimension maturities. This provides the user with a visual representation of lagging and leading elements

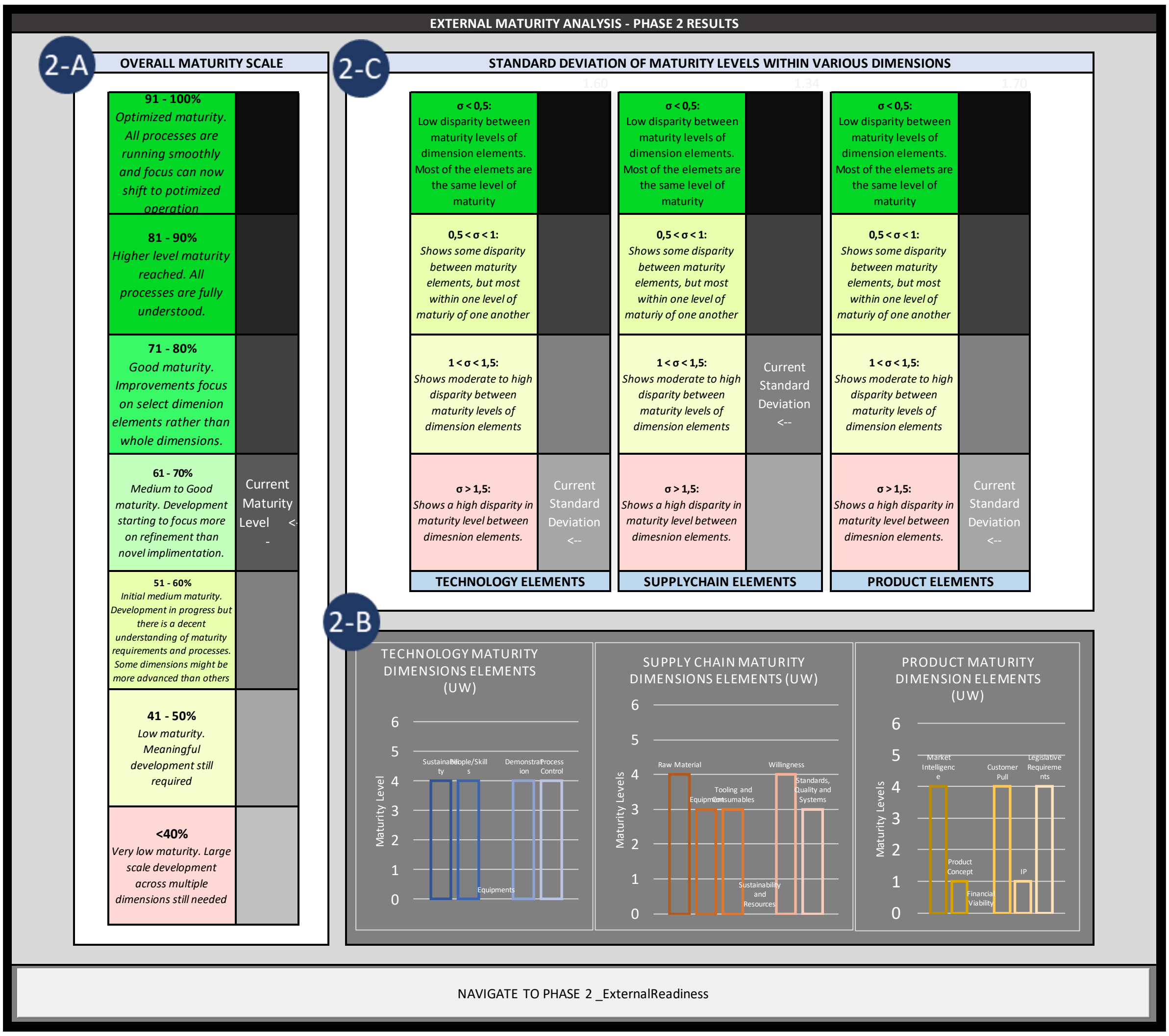


Figure 4-10: *Phase 2 LVoD – Digital Tool Overview Page*

4.3.2 Phase 2 LVoD - Tool operational page

Figure 4-11 below serves simply as a reference image with a full-sized version being available in Appendix A.3 The reference image is subdivided into three sections to demonstrate the functionalities of the tool. Section 2.1 represents the inputs provided by the user and sections 2.2 and 2.3 show the output of the tool.

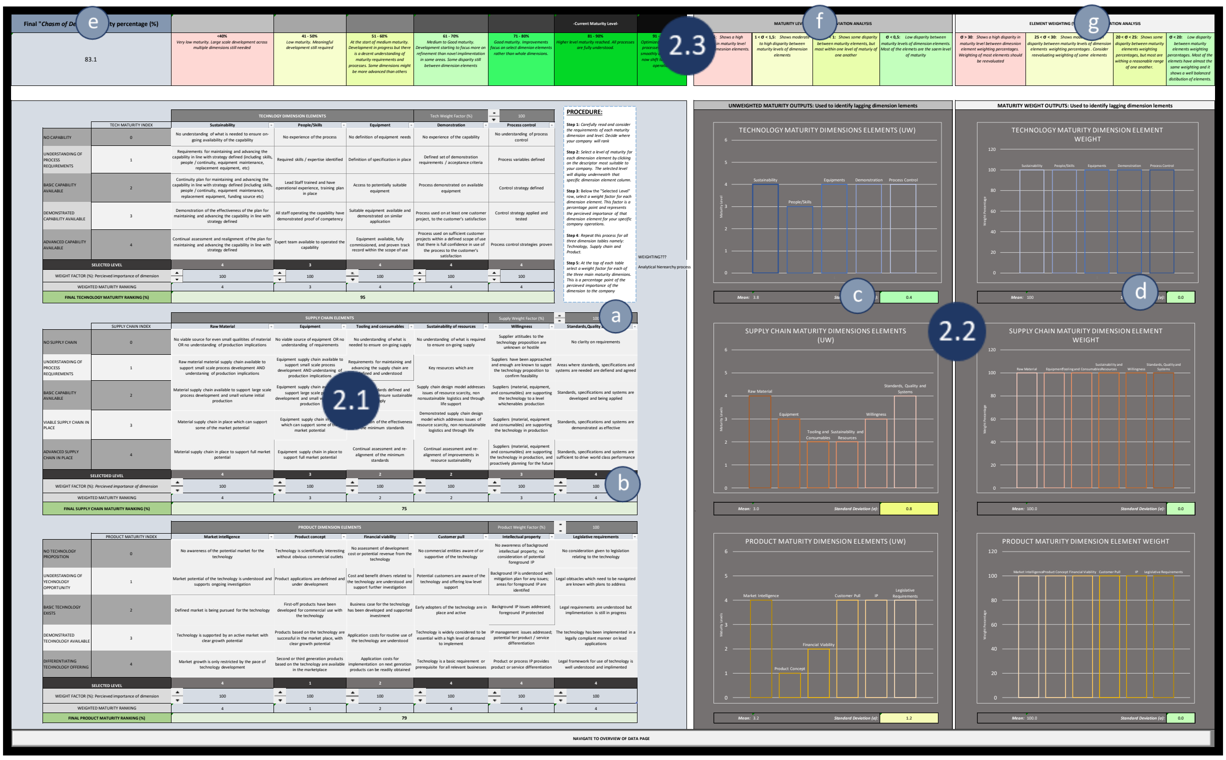


Figure 4-11: Phase 2 *LVoD - Digital tool operational page*

4.3.2.1 LVoD tool qualitative inputs

The tool inputs are derived from the maturity descriptors as shown in the literature review. The tool uses clickable buttons, where the user can simply click on the descriptor that they believe to be most relevant, and the tool will automatically select and save the corresponding maturity level for that dimension element. Enlarged versions of Figure 4-12 below can be viewed in Appendix A.3.

		TECHNOLOGY DIMENSION ELEMENTS			Tech Weight Factor (%)	100
	TECH MATURITY INDEX	Sustainability	People/Skills	Equipment	Demonstration	Process control
NO CAPABILITY	0	No understanding of what is needed to ensure on-going availability of the capability	No experience of the process	No definition of equipment needs	No experience of the capability	No understanding of process control
UNDERSTANDING OF PROCESS REQUIREMENTS	1	Requirements for maintaining and advancing the capability in line with strategy defined (including skills, people / continuity, equipment maintenance, replacement equipment, etc)	Required skills / expertise identified	Definition of specification in place	Defined set of demonstration requirements / acceptance criteria	Process variables defined
BASIC CAPABILITY AVAILABLE	2	Continuity plan for maintaining and advancing the capability in line with strategy defined (including skills, people / continuity, equipment maintenance, replacement equipment, funding source etc)	Lead Staff trained and have operational experience, training plan in place	Access to potentially suitable equipment	Process demonstrated on available equipment	Control strategy defined
DEMONSTRATED CAPABILITY AVAILABLE	3	Demonstration of the effectiveness of the plan for maintaining and advancing the capability in line with strategy defined	All staff operating the capability have demonstrated proof of competency	Suitable equipment available and demonstrated on similar application	Process used on at least one customer project, to the customer's satisfaction	Control strategy applied and tested
ADVANCED CAPABILITY AVAILABLE	4	Continual assessment and realignment of the plan for maintaining and advancing the capability in line with strategy defined	Expert team available to operated the capability	Equipment available, fully commissioned, and proven track record within the scope of use	Process used on sufficient customer projects within a defined scope of use that there is full confidence in use of the process to the customer's satisfaction	Process control strategies proven
SELECTED LEVEL		4	3	4	4	4
WEIGHT FACTOR (%): Percieved importance of dimension		100	100	100	100	100
WEIGHTED MATURITY RANKING		4	3	4	4	4
FINAL TECHNOLOGY MATURITY RANKING (%)		95				

Figure 4-12: *Phase 2 LVoD - user inputs*

The tool also has two additional user input capabilities as shown by *a* and *b* in Figure 4-12 above. These inputs allow the user to adjust the perceived weighting factor of the dimension elements.

4.3.2.2 LVoD tool weighting factor input

In Figure 4-13 below, section *a* represents the weighting of the main dimension element. Next, section *b* represents the weighting of the sub-dimension element. By changing the weighting, the user can adjust the perceived importance of the dimension and subsequently reduce the dimension's overall influence on the maturity rating. An example of why such a weighting procedure is useful can be derived from the *Demonstration* sub-dimension. For an enterprise interested in becoming an early adopter of a technology in order to exploit the possible future advantages of the technology, it does not make sense to wait until the technology has reached full demonstration maturity. In fact, such an enterprise would hope to adopt and exploit a technology before competitors have reached demonstrative capabilities. To prevent the low maturity rating of an early adoption technology from lowering the overall project maturity and thus shutting the project down, users can simply lower the weight that the *Demonstration* dimension carries.

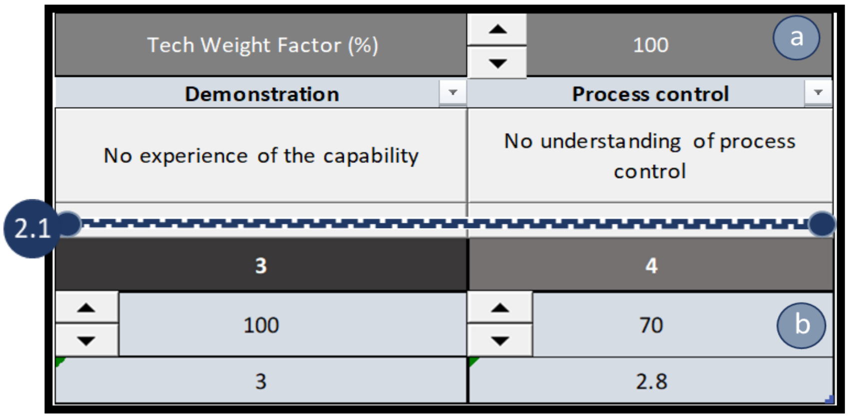


Figure 4-13: *Phase 2 LVoD - Weighting factor input*

There are, however, specific protocols that are proposed to be followed when weighing dimensions to prevent unnecessary and biased reduction of dimension weights. The protocols are summarised in Table 4-2 below:

Table 4-2: *Dimension weighting protocol*

Protocol	**Description**
1	The weighting must be done by an individual with intricate knowledge of the technology, the project, and the industry of the application domain.
2	The recommended weight of all dimensions is 100.
3	The weighting works on a relative scale. This means that the user must first identify the dimension(s) that is most important to the success of the project, and therefore 100. If they wish to then change the weighting of the remaining dimensions, it must be changed to represent its importance relative to the most important dimensions.
4	It is recommended that no weighting is set below 60.

4.3.2.3 LVoD tool bar graph outputs

The first output of the LVoD stage consists of bar graphs and standard deviation calculations. In Figure 4-14 below, the bar graph at section *c* shows the maturity rating of each sub-dimension along with a colour-coded cell for the standard deviation between the sub-dimensions. The colour of the standard deviation cell corresponds with the qualitative descriptor range in section 2.3-f of Figure 4-17. The bar graph at section *d* shows the weighting factor of each sub-dimension along with the standard deviation of the sub-dimension weightings. Again, the colour of the standard deviation cell corresponds with a qualitative description range in 2.3-g of Figure 4-18 The importance of adding standard deviation to the analysis will be discussed in the following sections. Enlarged versions of Figure 4-14 can be viewed in Appendix A.3

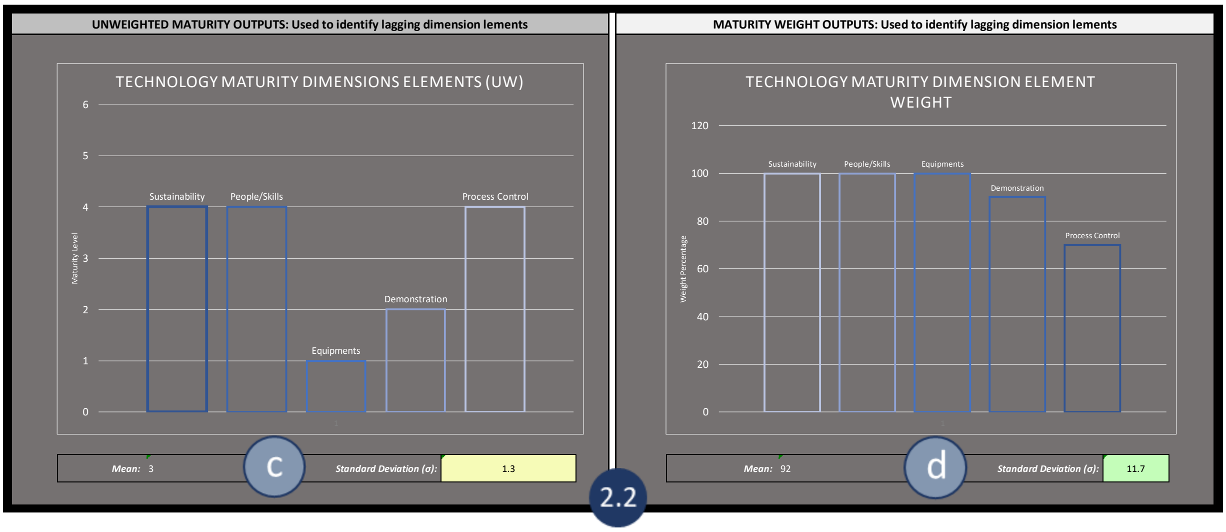


Figure 4-14: *LVoD Maturity Bar Graphs*

4.3.2.4 LVoD tool maturity output

For the output, the tool calculates the weighted average maturity and then presents the value along with the selected maturity range. Each maturity percentage range has an accompanying qualitative descriptor. Figure 4-15 below, shows the maturity ranges for a low to medium maturity. These descriptors were evaluated by simulating multiple different maturity level combinations and then extrapolating a qualitative descriptor from the results. This process is explained in section 4.3.3.

Final "*Chasm of Death*" maturity percentage (%)		**-Current Maturity Level-**	
e 44.8	**<40%** *Very low maturity. Large scale development across multiple dimensions still needed*	**41 - 50%** *Low maturity. Meaningful development still required*	**51 - 60%** *At the start of medium maturity. Development in progress but there is a decent understanding of maturity requirements and processes. Some dimensions might be more advanced than others* 2.3

Figure 4-15: *LVoD external maturity output (Low to Medium Maturity)*

Figure 4-16 below, shows the maturity ranges for a medium to optimized maturity. These are the maturity ranges that an enterprise should wish to achieve when investigating adoption viability.

e

61 - 70% *Medium to Good maturity. Development starting to focus more on refinement than novel implimentation in some areas. Some disparity still between dimension elements*	**71 - 80%** *Good maturity. Improvements focus on select dimenion elements rather than whole dimensions.*	**81 - 90%** *Higher level maturity reached. All processes are fully understood.*	**91 - 100%** *Optimized maturity. All processes are running smoothly and focus can now shift to optimized operation*

2.3

Figure 4-16: *LVoD external maturity output (Medium to Optimized)*

4.3.2.5 LVoD tool standard deviation output

The inclusion of a standard deviation element is a key factor in providing a holistic maturity analysis. The purpose of the standard deviation element is to show how large the disparity between the sub-dimension's maturity within a dimension element is. For example: It is possible to achieve an element maturity of 78%, which is considered a good maturity level, while having a standard deviation larger than 1.5, which shows a high disparity between the sub-dimensions. What this implies is that, even though you can achieve a seemingly impressive average maturity rating, there are sub-dimension elements which are lagging far behind the rest. These elements will have to be addressed and improved before assuming a position of "good maturity". Figure 4-17 below, shows the qualitative outputs for measuring the standard deviation results. The colours of the output ranges correspond with the colour of the standard deviation cell as shown in 2.2-c of the tool in Figure 4-14.

f

MATURITY LEVELS STANDARD DEVIATION ANALYSIS			
σ > 1,5: *Shows a high disparity in maturity level between dimesnion elements.*	**1 < σ < 1,5:** *Shows moderate to high disparity between maturity levels of dimension elements*	**0,5 < σ < 1:** *Shows some disparity between maturity elements, but most within one level of maturiy of one another*	**σ < 0,5:** *Low disparity between maturity levels of dimension elements. Most of the elemets are the saem level of maturity*

2.3

Figure 4-17: *LVoD external maturity standard deviation output*

The second standard deviation output of Figure 4-18 shows the qualitative standard deviation ranges between the weighting factors of the sub-dimensions. The reason for including this analysis, is to discourage users from implementing weighting factors with a large disparity between them. Ideally the weighting of the sub-dimensions should be as close to 100 as possible. This output will flag a user who has implemented a weighting scheme with too large a disparity between the elements.

g

ELEMENT WEIGHTING (%) STANDARD DEVIATION ANALYSIS			
σ > 30: *Shows a high disparity in maturity level between dimesnion element weighting percentages. Weighting of most elements should be reevaluated*	**25 < σ < 30:** *Shows moderate to high disparity between maturity levels of dimension elements weighting percentages . Consider reevaluating weighting of some elements*	**20 < σ < 25:** *Shows some disparity between maturity elements weighting percentages, but most are withing a reasonable range of one another.*	**σ < 20:** *Low disparity between maturity elements weighting percentages. Most of the elemets have almost the same weighting and it shows a well balanced distibution of elements.*

2.3

Figure 4-18: *LVoD external maturity weighting factor standard deviation output*

4.3.3 Maturity output range development

The maturity and standard deviation output ranges depicted by 2.3 of Figure 4-11 in the previous section, could not be acquired from literature, but instead had to be developed using a scenario-based approach. This approach required the researcher to simulate multiple different scenarios by providing various unique combinations of input variables. By aggregating and comparing the various results, the researcher can develop an output scale that is representative of a perceived qualitative maturity or standard deviation perception. Table 4-3 below, summarises the steps that were followed during the scenario creation along with an example input/output.

Table 4-3: *Maturity output descriptors development steps*

Scenario-Based Development Steps	**Description**
Step 1: *Baseline*	The first step is to select a percentage range to investigate i.e., 41-50%. Next, a baseline percentage, inside or close to the chosen percentage range, is selected by selecting the exact same maturity input for all the elements i.e., all maturity inputs are a 2 which corresponds to 50% overall maturity. This will then represent a baseline maturity percentage and standard deviation. This baseline is the theoretical maturity output of an enterprise that upgrades all their sub-dimensions synchronously. It is, therefore, easier to create a first iteration maturity description for such a scenario. The descriptor is then tested and updated in the following steps.
Step 2: *Refine*	The second step is to select various random inputs above and below the baseline maturity. The results are logged until the upper or lower limit of the percentage range under investigation is reached i.e., 41% or 50%.
Step 3: *Interpret*	The third step is to interpret the results. The interpretation is influenced by the researcher's knowledge of the literature and application area. Key areas that the researcher considered was the disparity between sub-dimension elements, type of improvements required and number of sub-dimensions under baseline level.
Step 4: *Extremes*	Once the first iteration output scale is developed, it is tested by trying to achieve a certain percentage range using the most extreme input values possible i.e., 0 for one sub-dimension and 4 for another. If the output descriptor still provides an accurate representation of the scenario, it is deemed appropriate for use.

The steps described in the table above were used for both maturity and standard deviation descriptor development. However, developing the standard deviation descriptors were easier since the bar graph that the tool outputs could be used as a visual aid to assist the researchers understanding of the disparity between sub-dimension elements.

4.4 Phase 3: TRRA Tool Interface

The TRRA model is used to estimate the likelihood that a third party will complete the necessary R&D efforts successfully. While the TRRA is not a purely quantitative tool and relies heavily on the user's knowledge of the technology and R&D landscape, it effectively approximates the expected risk - or possibility of failure – of a R&D project.

4.4.1 Phase 3: TRRA -Tool overview page

The TRRA section of the tool's overview page consists of three parts as shown in Figure 4-19. Part 3-A shows the user's selection of the Technology Need Factor. Part 3-B shows the user's selection of the R&D effort or likelihood of R&D failure. Finally, section 3-C displays the risk on the risk matrix.

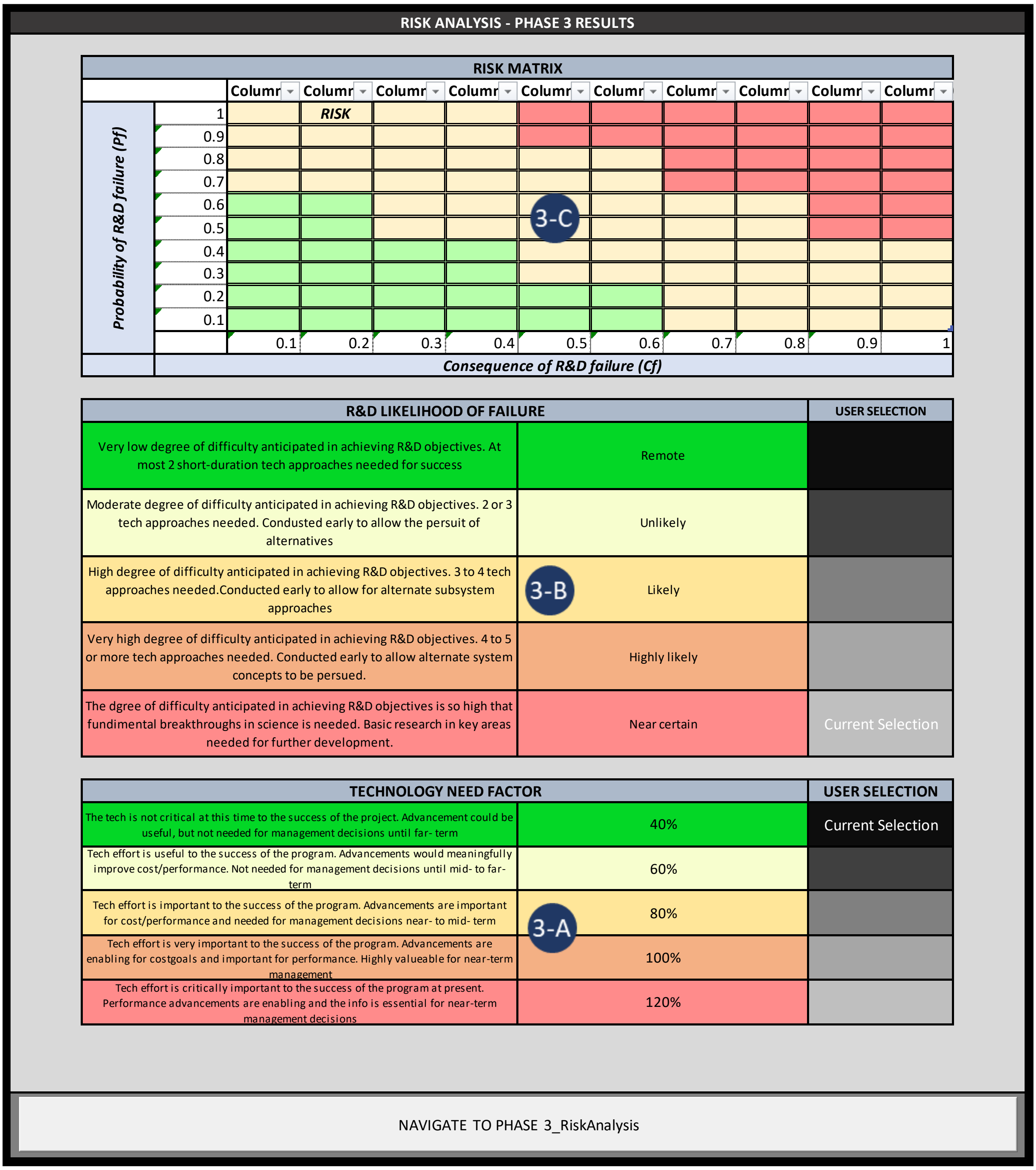


Figure 4-19: *Phase 3 TRRA - Digital tool overview page*

4.4.2 Phase 3: TRRA - Tool operational page

Figure 4-20 below, serves only as a reference image with an enlarged version being available in Appendix A.4 The reference image is subdivided into three sections to demonstrate the functionalities of the tool. In Figure 4-20 below, section 3.1 shows the qualitative information that must be used by the user to inform their input decisions. The information contained in section 3.1 can be seen in the literature review and will therefore not be discussed further in this chapter. Next, section 3.2 shows the interface where the user can select the appropriate input for the tool. Lastly, section 3.3 shows the risk matrix output of the tool.

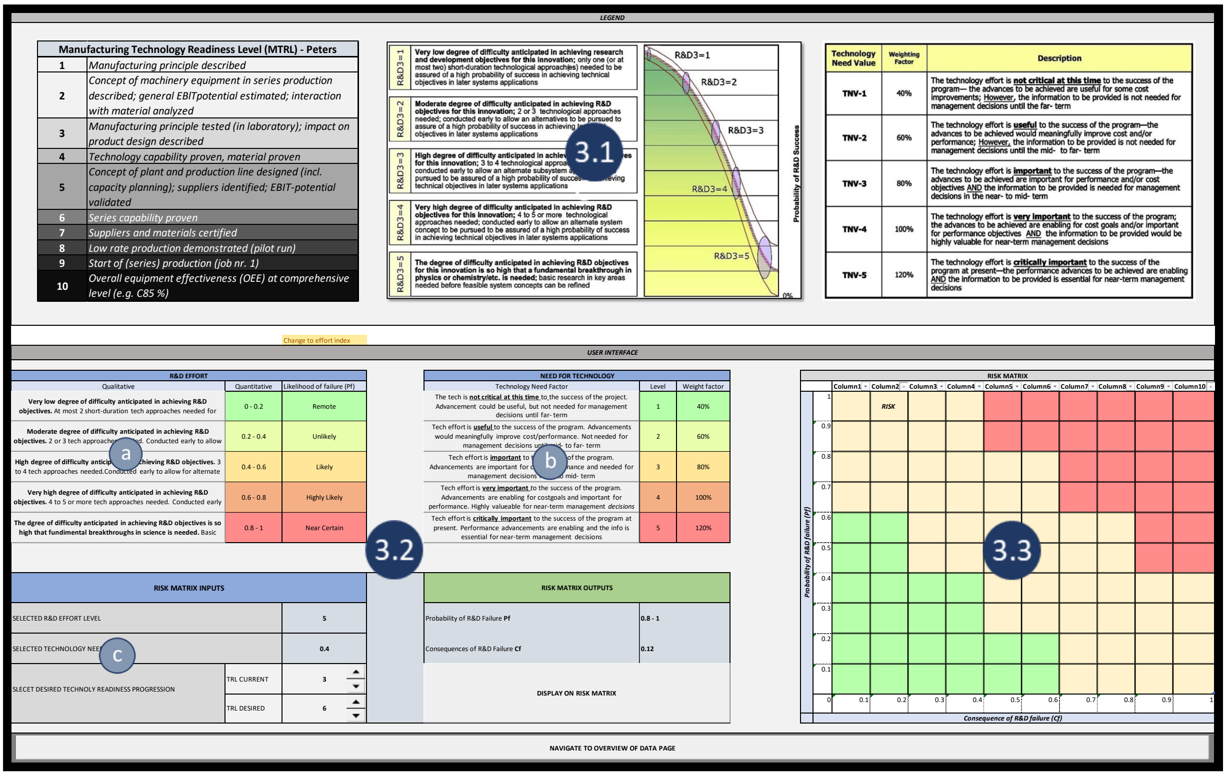


Figure 4-20: *Phase 3 TRRA – Digital tool operational page*

4.4.2.1 TRRA tool input interface

The TRRA input interface works similar to the LVoD external maturity interface, where there are interactive qualitative descriptors that the user can click. The user can read through all the descriptors and then, based on their knowledge of the technology, industry and R&D requirements, select the most appropriate descriptor by clicking on the descriptor button. The TRRA tool has some quantitative features where the user must select the current technology readiness level and the desired level, as seen in 3.2-c of Figure 4-21. The larger the gap between the readiness levels, the less likely the R&D effort is to succeed. Once all the inputs have been selected, the tool will display the risk on the risk matrix. The full tool input interface can be viewed in the following figure.

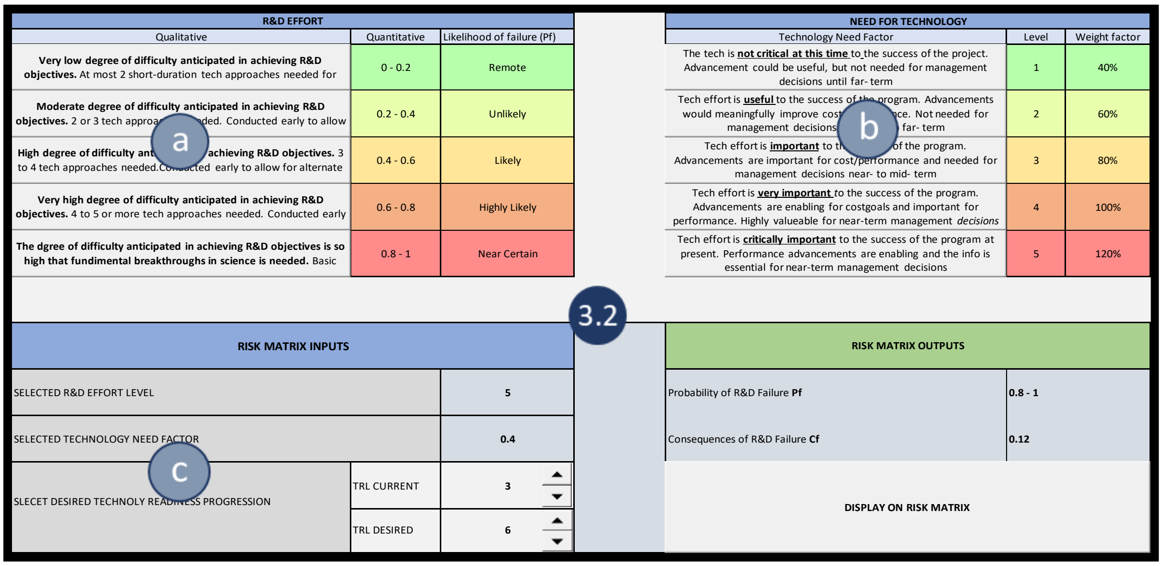


Figure 4-21: *Phase 3 TRRA – Digital tool input interface*

4.4.2.2 TRRA tool matrix output

The risk matrix displays the estimated chance that the R&D project will be completed successfully by a third party. The Y-axis shows the "probability of R&D failure", and the X-axis shows the "Consequence of R&D failure". The matrix is divided into three sections denoted by the green, yellow, and red areas on the figure below. The green shows low risk, yellow is a medium risk and then red represents a high risk, which suggests that the R&D effort will most likely not be completed successfully by the third party.

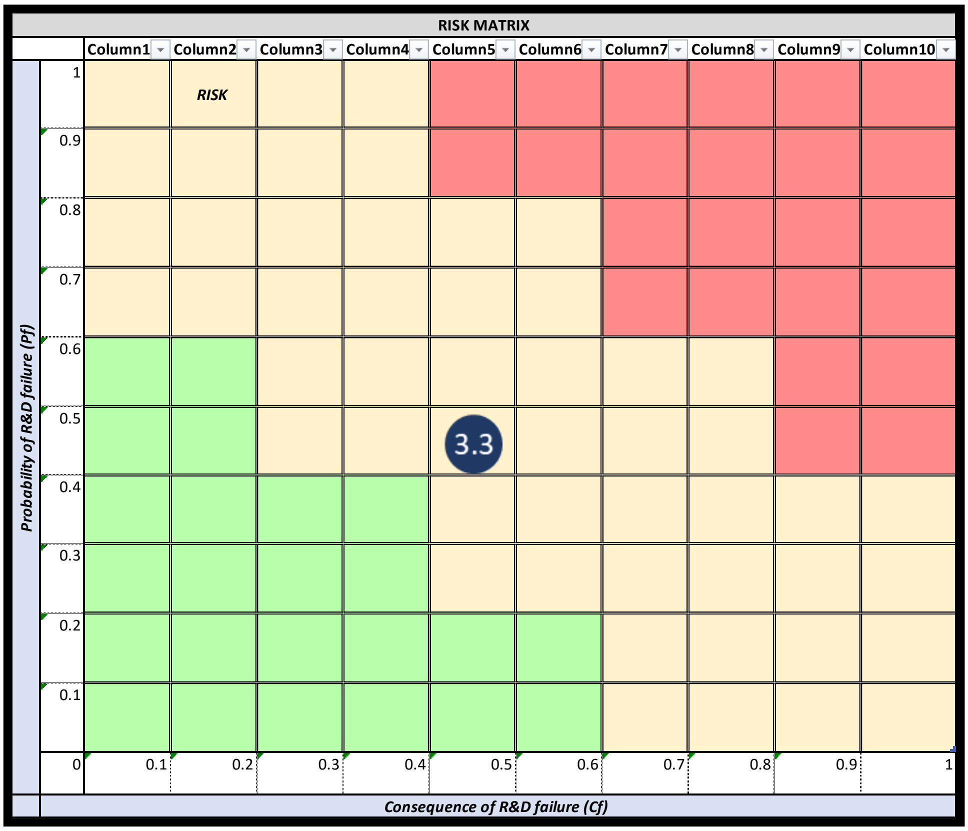


Figure 4-22: *Phase 3 TRRA - Digital tool risk matrix output*

4.5 Phase 4: SM^{3}E Tool Interface

The SM^{3}E model is used to determine the maturity of various operations within an enterprise. The toolbox was originally designed within the scope and context of SM operations. Even though the analysis takes place within the SM paradigm, many of the maturity levels are considered to be basic requirements for any manufacturing enterprise that wish to operate at an acceptable capability level. The SM^{3}E model consists of 7 "toolboxes" or operational departments that have interdependent maturity levels. These interdependencies presented some challenges when visually representing the toolboxes in a user interface. The following interface was found to be most efficient for the purposes of this thesis.

4.5.1 Phase 4: SM^{3}E - Tool overview page

Figure 4-23 below, serves only as a reference image with a full-sized version available in Appendix A.5 The reference image is divided into three sections. Section 4-A is a bar graph of the average maturity of all the toolboxes. Section 4-B is a spider graph showing the maturity distribution between the organisational dimensions of all the toolboxes. Finally, section 4-C shows the suggested steps that had to be followed in order to upgrade the various toolboxes' maturity. The interdependent nature of the tool requires the uses to follow specific steps when attempting to upgrade the maturity of certain dimensions.

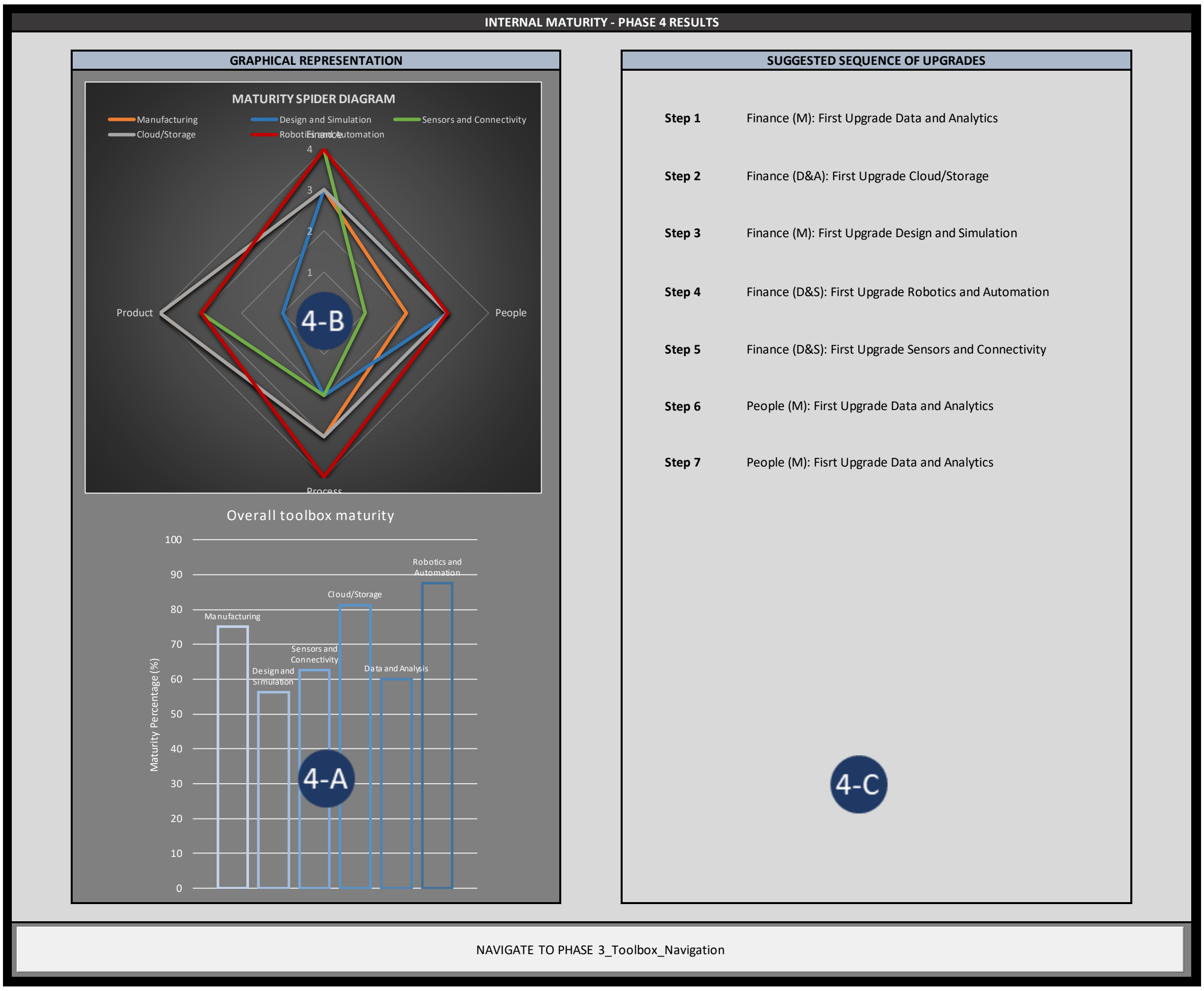


Figure 4-23: *Phase 4 SM^{3}E - Digital tool overview page*

4.5.2 Phase 4: SM³E - Toolbox navigation and results page

Figure 4-23 below, serves as a reference image for the SM³E internal operational maturity tool navigation and results page. An enlarged version of Figure 4-23 is available in Appendix A.5. This page is an intermediate aggregation page that is used before sending data to the *Overview of Data* page. This *Navigation and Results* page is used to navigate between the various toolboxes by clicking on the desired toolbox in section 4-BB. Section 4-AA of the page shows the suggested steps that the user had to follow to reach a specific maturity and acts as a first iteration roadmap. How these steps are generated will be discussed in section 6.4.3.2. The page also aggregates the results of the maturity analysis in sections 4-CC and 4-DD. Some of the results are then sent to the Phase 4 of the *Overview of Data* page that is discussed in the previous section. Section 4-CC shows a bar graph of the average maturity of each toolbox. Section 4-DD shows a spider graph of each toolbox to illustrate the disparity between the organisational dimensions of each toolbox.

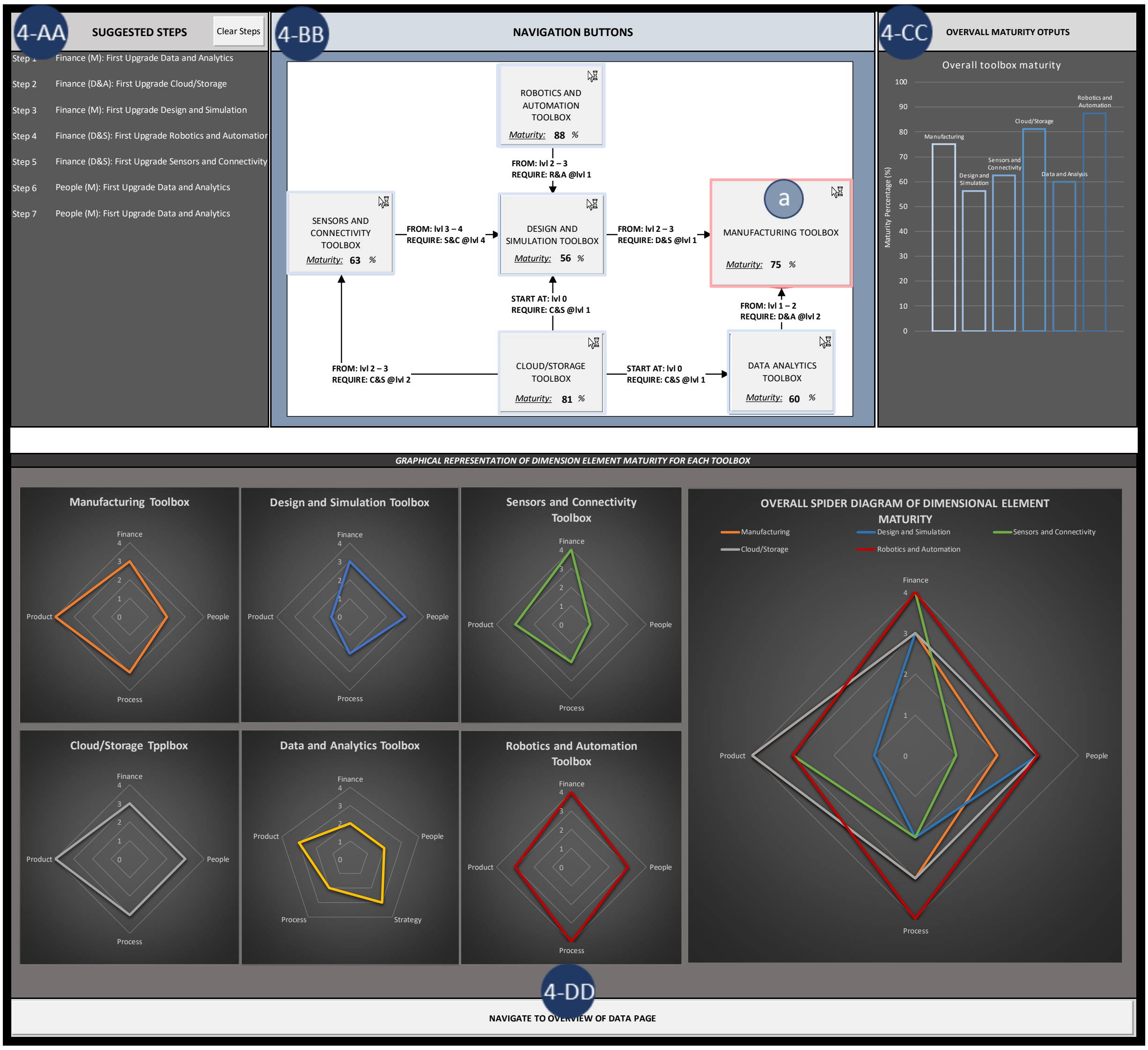


Figure 4-24: *Phase 4 SM³E – Digital tool navigation and results page*

4.5.3 Phase 4 Toolbox application page example: Manufacturing

Since the toolboxes all share the same structure and process flow, and in trying to keep the thesis body as concise as possible, only the details of the Manufacturing toolbox application page is discussed in the thesis body. These details can be extrapolated to understand the details of the other toolboxes. The details of the other toolboxes can be viewed in Appendix A.5.2 The user can navigate to the Manufacturing toolbox by clicking on the "Manufacturing Toolbox" button shown in 4-BB-a in Figure 4-24 above. The tool will then navigate them to the page seen in Figure 4-25 below:

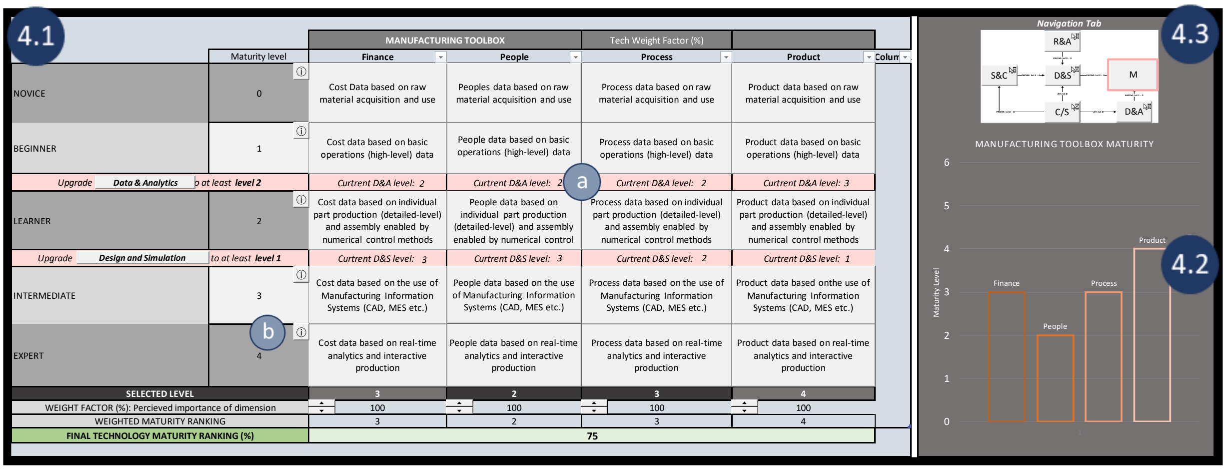
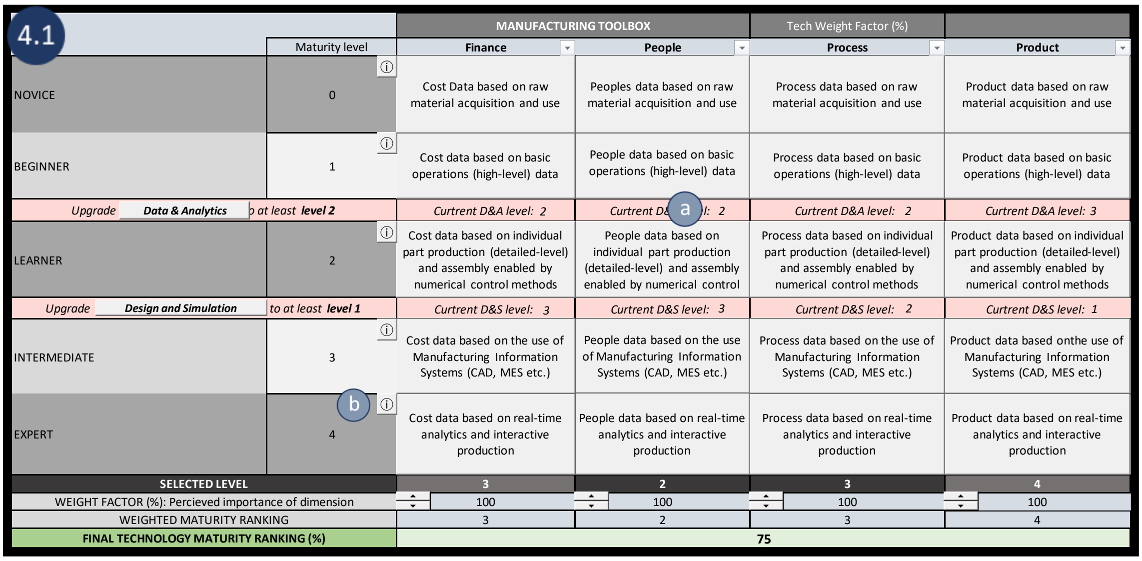


Figure 4-25: *SM³E manufacturing toolbox – Digital tool operational page*

Figure 4-25 above, serves as a reference image for the application page of the manufacturing toolbox within the decision support tool. Section 4.1 is where the user interacts with the tool as they select the applicable maturity levels based on the qualitative descriptors. A detailed discussion of section 4.1's functions is done in the chapter sub-sections below. Section 4.2 of Figure 4-25 provides a visual output of the maturity selections in the form of a bar graph. Lastly, section 4.3 of Figure 4-25 is a navigation tab where the current toolbox selection is highlighted with a red outline. The user can navigate to any of the toolboxes by clicking on the desired toolbox in the navigation tab.

4.5.3.3 Manufacturing toolbox application page interface



4.1		MANUFACTURING TOOLBOX		Tech Weight Factor (%)	
	Maturity level	Finance	People	Process	Product
NOVICE	0	Cost Data based on raw material acquisition and use	Peoples data based on raw material acquisition and use	Process data based on raw material acquisition and use	Product data based on raw material acquisition and use
BEGINNER	1	Cost data based on basic operations (high-level) data	People data based on basic operations (high-level) data	Process data based on basic operations (high-level) data	Product data based on basic operations (high-level) data
Upgrade Data & Analytics	p at least level 2	Current D&A level: 2	Current D& a l: 2	Current D&A level: 2	Current D&A level: 3
LEARNER	2	Cost data based on individual part production (detailed-level) and assembly enabled by numerical control methods	People data based on individual part production (detailed-level) and assembly enabled by numerical control	Process data based on individual part production (detailed-level) and assembly enabled by numerical control methods	Product data based on individual part production (detailed-level) and assembly enabled by numerical control methods
Upgrade Design and Simulation	to at least level 1	Current D&S level: 3	Current D&S level: 3	Current D&S level: 2	Current D&S level: 1
INTERMEDIATE	3	Cost data based on the use of Manufacturing Information Systems (CAD, MES etc.)	People data based on the use of Manufacturing Information Systems (CAD, MES etc.)	Process data based on the use of Manufacturing Information Systems (CAD, MES etc.)	Product data based onthe use of Manufacturing Information Systems (CAD, MES etc.)
EXPERT	b 4	Cost data based on real-time analytics and interactive production	People data based on real-time analytics and interactive production	Process data based on real-time analytics and interactive production	Product data based on real-time analytics and interactive production
SELECTED LEVEL		3	2	3	4
WEIGHT FACTOR (%): Percieved importance of dimension		100	100	100	100
WEIGHTED MATURITY RANKING		3	2	3	4
FINAL TECHNOLOGY MATURITY RANKING (%)		75			

Figure 4-26: *Manufacturing toolbox user interface*

The toolbox's interface can be viewed in Figure 4-26 above. The user can interact with the tool by clicking the descriptor most applicable to their enterprise. The detail of each descriptor is discussed extensively in Chapter 5. The tool also has the standard weighting functionalities described in section 6.2.2.2. Additionally, the tool has two functionalities denoted by *a* and *b* of Figure 4-26, where *a* represents a validation function coded into the tool, as is discussed in the following section, and *b* represents a "more information" function. By clicking on the information button in section *b*, the user is presented with detailed information about the qualitative descriptor of the specific maturity level. These details are derived from the discussions found in Chapter 5.

4.5.3.4 Toolbox validation function

The validation function incorporates the toolbox interdependencies (shown by the interdependency chart in Chapter 3 and refined in Chapter 5) directly into the logic if the VBA code. This prevents the user from selecting maturity levels if the associated dependent maturity level is not high enough. An example can be taken from the Figure 4-27 below: The maturity of the Manufacturing toolbox is dependent on the maturity of the Data and Analytics toolbox. For the user to upgrade the "People" organisational dimension of the Manufacturing toolbox to a level 2 maturity, the "People" dimension of the Data & Analytics toolbox needs to be at a minimum maturity of level 2. However, the figure shows that the current Data & Analytics toolbox maturity of the "People" dimension is 0. When the user tries to select level 2 for the "People" dimension in the Manufacturing toolbox, an error message as shown in the figure below will appear. This rule applies globally to all other organizational dimensions.

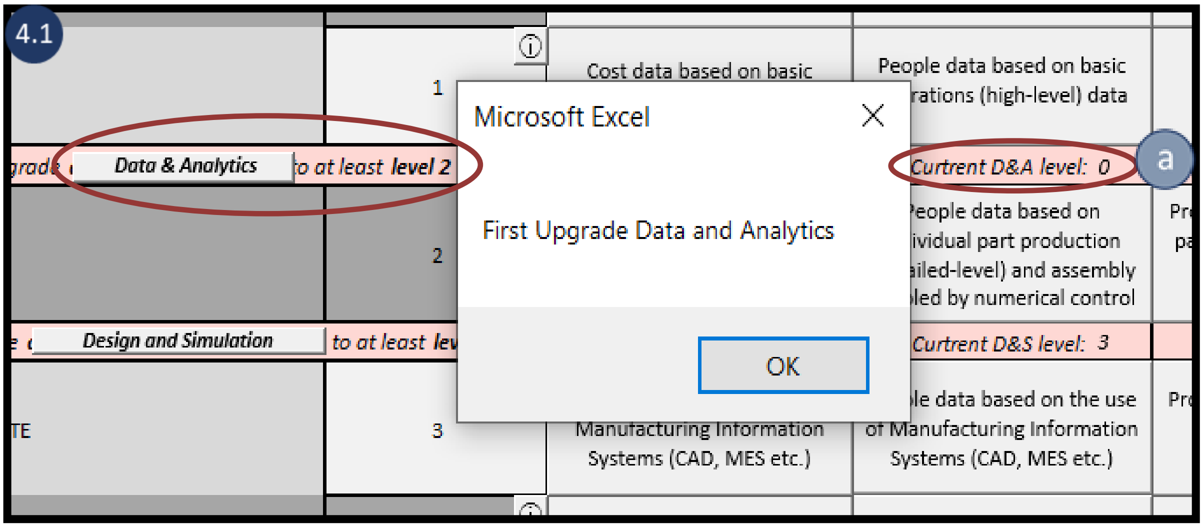


Figure 4-27: *SM³E toolbox validation function*

Once the user selects an inappropriate maturity level and the validation message is displayed, the tool logs the required step that the user must first complete. These steps are logged in section 4-AA of the "*SM³E internal operational maturity tool navigation and results page*" under "*Suggested Steps*" as seen in Figure 4-24 and they act as a first iteration road map for the user to understand what the requirements were to achieve a specific maturity.

4.6 Summary of Chapter 4

In Chapter 4 the reader is introduced for the first time to the process flow of the proposed decision support tool. The chapter starts by defining four chronological questions that will be asked during the acquisition of novel manufacturing technology. It then explains how the proposed decision support tool follows the same chronological order as the acquisition questions. This created a process flow in which the four theoretical models selected in Chapter 3 are matched with the acquisition question that they address.

Once the process flow of the selected theoretical models was explained, Chapter 4 introduced the reader to the first iteration of the proposed decision support tool's user interface. The user interface was responsible for translating the contents of the selected theoretical models to a functional and practical digital realm. During the interface creation, serious consideration was given to the representation of the input and output data to ensure optimal decision support can be provided. Subsequently, Chapter 4 explores the various functions of the tool's user interface and navigates the reader through the relevant details. By first understanding how the proposed tool operates, it is easier for the reader to grasp the contents of the refinement chapters following Chapter 4.

Chapter 5: Refinement Through Literature Analysis

This chapter forms part of the second design cycle of the design methodology which deals with improvement and refinement. This design cycle continues after the process flow of the selected theoretical models within the support tool is established and the first iteration of the digital tool is developed. The purpose of this chapter is to refine, through careful consideration of literature, the inputs and outputs of the various models selected for the support tool as seen in Figure 5-1. Since all the models are derived from published work, it is not within the scope of this thesis to re-evaluate and validate the entire body of work. It is, however, important to remember that the application context and scope of the original models can differ slightly from the newly developed support tool's context. An additional literature refinement stage is therefore justified, wherein the existing models are scrutinized and improved to fit the new context. This chapter also discusses the development of a maturity level selection process that was identified and developed during the literature refinement stage. This selection process is an addition to the existing tool.

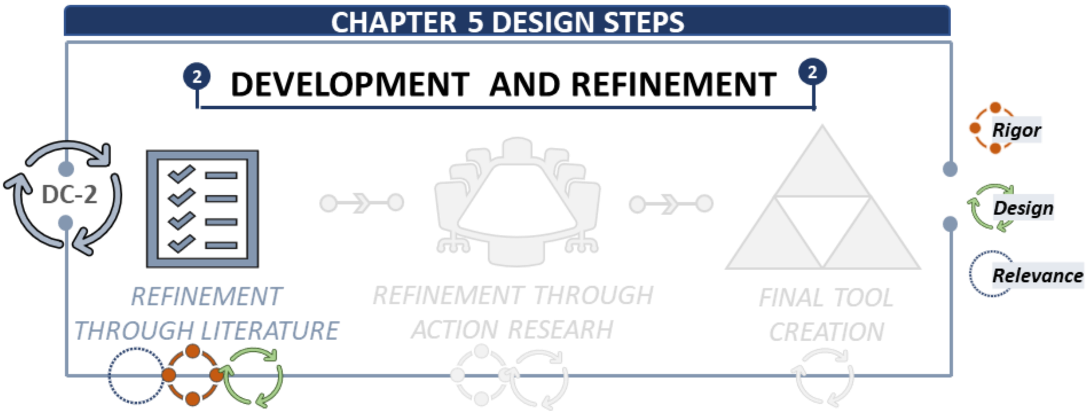


Figure 5-1: *Design steps completed in Chapter 5*

The proposed decision support tool consists of four phases. In this chapter, however, only Phase 2 and Phase 4 is validated and refined. Phase 1 and Phase 3 is directly applicable to the context of this thesis; therefore, further refinement was not considered necessary. Phase 2 and Phase 4 represent the LVoD and SM^{3}E maturity analysis models, which corresponds to the maturity of external dimensions and internal operations respectively. These two models were carefully selected to help bridge the research gap and they contain various dimension elements, qualitative descriptors and data driven input requirements. It is important to understand that each model was originally created for a stand-alone purpose that addresses specific research gaps which differ from the gap identified for this thesis, thus justifying the need for further refinement. The combination of these models into a coherent support tool is what creates unique research value.

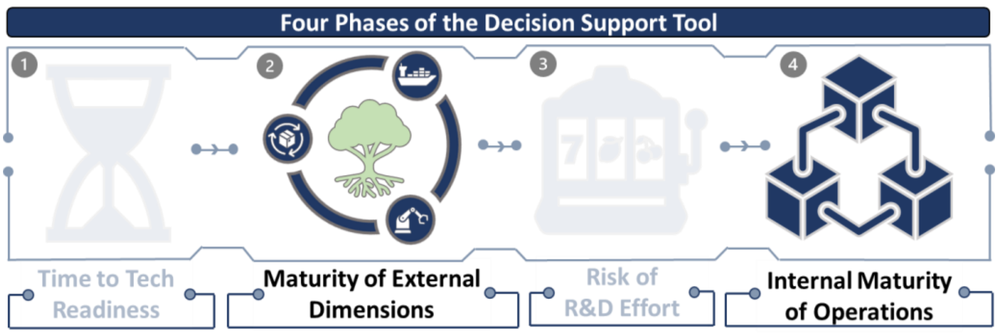


Figure 5-2: *The two phases of the tool that require refinement from literature.*

5.1 Phase 2: LVoD Literature Refinement

The purpose of the external maturity analysis is to assess the different influencing factors that operate outside of the enterprises control. The chosen model identified three main dimension elements each comprised of various sub-dimensions (Ward et al., 2017). The purpose of this section is to firstly, explain the relevance of the selected maturity dimensions and secondly, elaborate on the sub-dimension descriptors to improve the understanding of the application context and logic behind the maturity dimensions.

For the external maturity model, refinement and validation largely happened during the action research section of this thesis. The reasoning for this is twofold: Firstly, it is extremely difficult to validate purely qualitative descriptors exclusively from literature as these descriptors are generally extremely broad and could be justified for any number of obscure scenarios. The relevance of the descriptors, however, can still be assessed by building an understanding of the application context (as will be done in this chapter) but the validation and refinement of the descriptors must be backed by the opinion of industry experts who understand the intricacies of the problem.

Secondly, Rolls Royce developed the Manufacturing Capability Readiness Levels (MCRL) (Ward, Halliday and Foden, 2012) (Ward and Winton, 2007) which has been cited numerous times and is considered to be a leading authority in the realm of manufacturing readiness (Peters, 2015). The same authors of the MCRL would go on to develop the model for the “Long valley of death” model used in this thesis (Ward et al., 2017). Their work is thus considered to be relevant and would only constitute refinement through action research to improve the applicability within the context of this thesis. Furthermore, during the literature analysis and subsequent research gap identification of this paper, Ward’s paper on the “Long Valley of Death” was considered the only paper to address the chosen research gap. The figure below shows the three main maturity dimension elements with their associated sub-dimension elements.

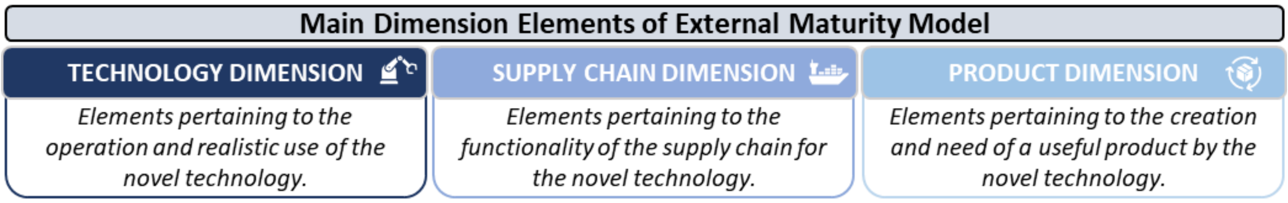


Figure 5-3: *Main dimension elements of the external maturity model.*

The LVoD model operates like a traditional maturity model with purely qualitative descriptors. Utilising data-driven descriptors for an external maturity model is a difficult task due to large variety and variability of external processes and data production. This lack of control over data-creation during external operations therefore encourages the use of qualitative methods during external analysis. To ensure the qualitative descriptors are implemented and understood correctly, the model should be applied by a knowledgeable employee who understands not only the enterprise but also the industry and surrounding landscape. Since qualitative descriptors are much broader than data-driven descriptors it is imperative that the descriptors are detailed and clear. The following sections will attempt to explain each qualitative descriptor to improve the user’s understanding of the maturity dimension and the reasoning they should follow when selecting a descriptor.

5.2 Phase 4: SM³E Literature Refinement

The maturity of internal operations, within the context of SM, is measured using the toolbox system, where the interdependencies between different "departments" of a manufacturing SME are accounted for. The original model relies on a three-axis system, seen in Figure 5-4 below, where each toolbox uses the same four main-dimensions, called organisational dimensions. Each organisational dimension has the same input requirement for data types or actions at a given maturity level. These input requirements do, however, differ between toolboxes. This "data-driven" approach attempts to mitigate the possibly vague nature of purely qualitative maturity descriptors and is believed to provide a more quantifiable and thus accurate analysis of maturity (Mittal *et al.*, 2019). Although this idea has merit, it is not entirely without error. As a data driven model tries to universalise the measurement of maturity, effectively creating a one-size-fits-all approach, it runs the risk of losing the nuance associated with enterprise operations, thus resulting in a shallow and ultimately vague maturity analysis. The following section discusses the process and results of improving the data driven approach to better fit the application of this thesis.

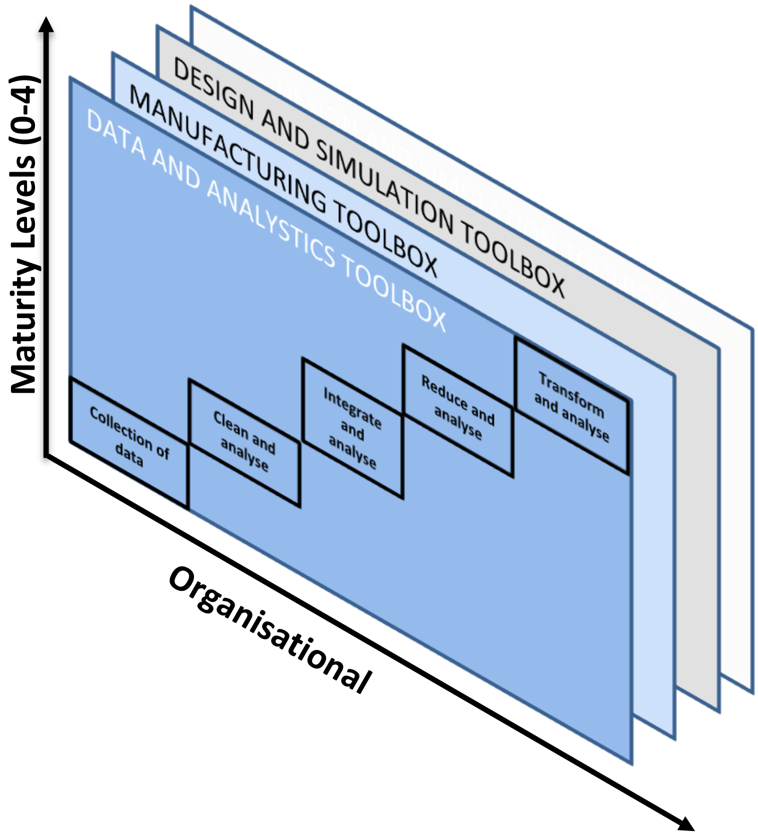


Figure 5-4: *Example of a three-axis data-driven toolbox system (For visual representation only).*

One should also note that the data types generated at each level of maturity coincides with a specific SM innovation that must be adopted. These innovations can be as simple as CAD software and as intricate as full-scale digital twins. The type of data that these innovations output is used as the measure of maturity. While adoption of SM innovations can help improve an enterprise's operations, it is also expensive. It is, therefore, important that enterprises carefully consider their options when it comes to adopting innovations in order to improve maturity. An explanation of these considerations is given in the final sections of this chapter.

5.2.1 Validation of data-driven methodologies

In the previous section the merit of data driven dimensions is discussed briefly, however, the question of whether data-driven dimensions are beneficial to internal maturity analysis, must still be answered. A paper published in 2019 seems to support the notion of data -driven methodologies (Kuo and Kusiak, 2019). Their research suggests that the manufacturing industry is one of the domains that has seen the most dominant shift from analytical models to data-driven models in recent years. This shift is believed to be related to the large increase in available process data that accompanies smart manufacturing technologies and innovations. New manufacturing technologies and data management go hand in hand to help form the pillars of modern smart manufacturing processes, thus creating a need for data-driven methodologies (Kusiak, 2018). This notion is also supported by a detailed collaborative acatech study entitled "*Industry 4.0 Maturity Index*" (Schuh et al., 2017). The study cites digitalisation of manufacturing enterprises as one of the main transformation goals of industry 4.0 development. To achieve the goal of digitalisation the study suggests that enterprises focus on computerisation and then connectivity upgrades, once again supporting data-driven methodologies as a viable means of measurement. These studies validate the need for data-driven methodologies, but what are the actual advantages associated with data collection, storage and analysis? A comprehensive research report by the CTT Technical Research Centre of Finland, lists the following five uses of data driven operations (Kortelainen et al., 2019):

a. To conduct R&D and testing in the pre-production phase

b. To manage part manufacturing, internal logistics and final assembly

c. For overarching control and coordination of production

d. For efficient supply chain management

e. For after-sale and product life cycle services

5.2.2 Refinement of toolbox interdependency chart

As mentioned in Chapter 3, the toolboxes operate within an interconnected system, where the maturity level of one toolbox is dependent on the maturity of another. These interdependencies create a network of toolboxes which can only be upgraded in specific sequences. While the original SM^{3}E paper did mention these interdependencies, it failed to provide a concise visual chart (Mittal, Romero and Wuest, 2018). After some investigation it was found that the existing set of interdependencies were inadequate and that some restructuring had to be done. After careful consideration of each toolbox's maturity progression, it's position in the system and the required SM innovation adoptions, a revised interdependency chart was created. The validity of the chart was also tested by doing multiple fictional simulations to ensure no one toolbox can be upgraded fully without upgrading some other toolbox's dimensions. Figure 5-5 below is a visual representation of the interdependencies. To expedite the understanding of the figure, an example can be used:

Example: *To upgrade the maturity of any of the organisational dimensions within the manufacturing toolbox from level 1 to level 2, an enterprise must first upgrade the maturity of the corresponding organisational dimensions within the data and analytics toolbox to the required level 2.*

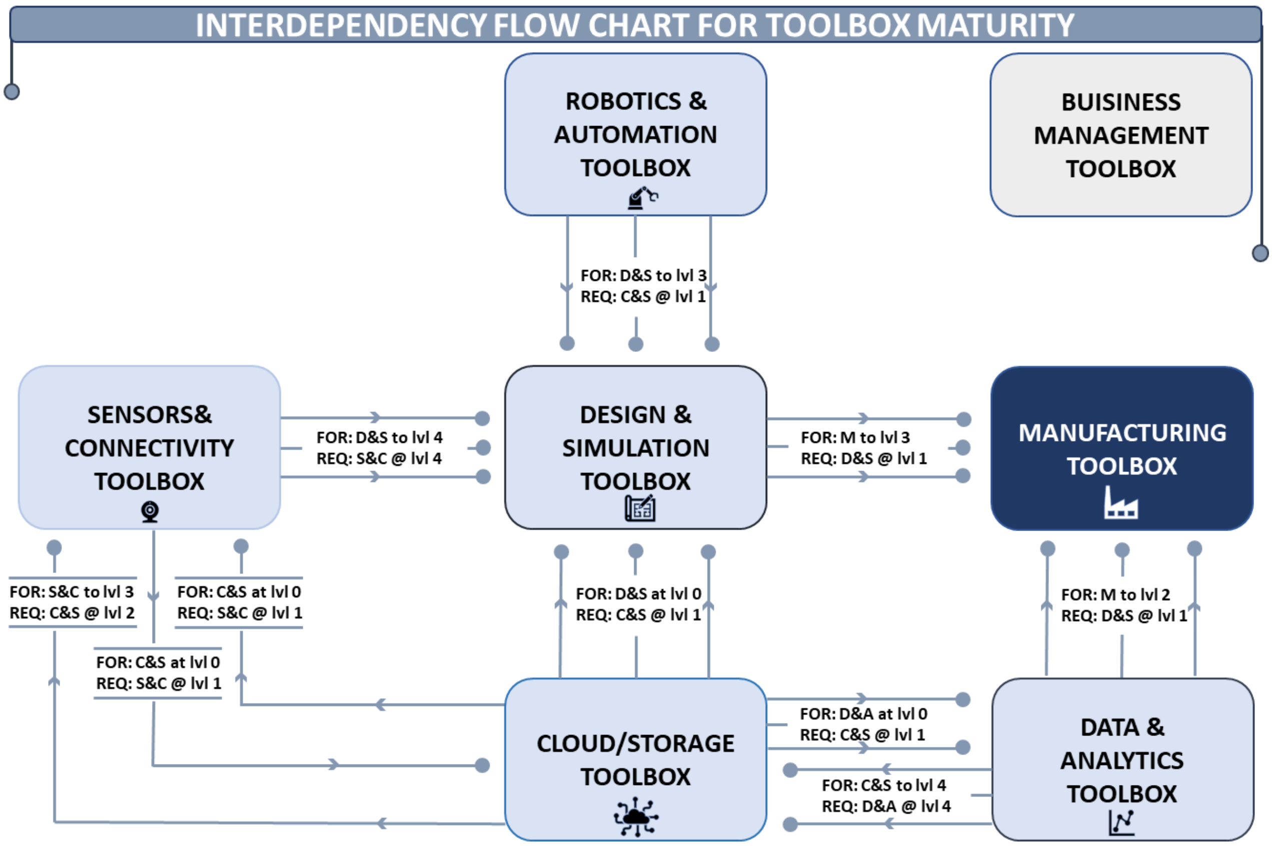


Figure 5-5: *Refined Process flow and interdependency of toolbox model*

5.2.3 Manufacturing toolbox refinement

The manufacturing toolbox investigates the type of data generated from manufacturing activities at each level of SM maturity. Some enterprises could have multiple manufacturing methods operating at different capacities. In these cases, enterprises must consider their highest functioning capability, the data output of that capability and the translation of the capability to another manufacturing method.

Table 5-1: *Unrefined and unvalidated manufacturing toolbox (Mittal, Romero and Wuest, 2018)*

UNVALIDATED AN UNREFINED				
	MANUFACTURING TOOLBOX: DIMENSION ELEMENTS			
MATURITY LEVEL	*Finance*	*People*	*Process*	*Product*
Lvl 0: *Novice*	Raw Material data			
Lvl 1: *Beginner*	Energy consumption data			
Lvl 2: *Learner*	Parts and assembly of products data			
Lvl 3: *Intermediate*	CAD design of products data			
Lvl 4: *Expert*	Sustainable production data			

Manufacturing Level 0: ***Raw Material data***

It is suggested that relying on data based purely on the acquisition and use of raw materials is considered the lowest form of maturity (Mittal, Romero and Wuest, 2018). There is no support of an IT infrastructure behind processes and as a result only rudimentary information i.e., raw material consumption, of the manufacturing process is known. This definition of level 0 maturity is supported by a Data-driven manufacturing maturity model developed by Christian Weber (Weber et al., 2017). The unrefined model suggests that level 0 maturity represent exclusive use of hand tools, however, this notion must be challenged for the application context of the refined model. The modern manufacturing concepts of industry 4.0 and smart manufacturing does not necessarily discern between tool types, but rather emphasizes the integration of the tool use into a digital infrastructure (Lichtblau et al., 2015). It is therefore quite possible for an enterprise to operate at a level 0 maturity by utilising power-tools without any form of IT integration or effective data capturing protocols. Naturally, however, hand-tools will be far more difficult to incorporate into an IT infrastructure, thus making their use a decent benchmark for level 0 operation. The refined model's data input will thus accept the inclusion of excessive hand-tool use but ignore the exclusion of power-tools at level 0.

Manufacturing Level 1: ***Energy consumption data***

The use of energy consumption data in the unrefined model is predicated on the idea of hand-tool vs power-tool use between level 0 and level 1 (Mittal, Romero and Wuest, 2018). Even though this notion is challenged for the refined model (see level 0 refinement), the use of energy consumption data is still very much relevant for a level 1 maturity, and here is why: Level 1 signifies a beginner level and thus the start of IT integration and sensory technology. According to Weber, machines are now integrated and managed by a central instance and data is collected to measure key performance indicators at a rather basic level (Weber et al., 2017). From this definition, the shift towards power-tools, machinery and automation is clear and the capturing of energy consumption will provide some insight into operations. The Impuls report on Industry 4.0 Readiness defines level 1 in a similar manner by mentioning the incorporation of IT system support, however, it does not recognise data collection as a level 1 trait (Lichtblau et al., 2015). Now, according to the unrefined SM^{3}E model, level 1 is defined as a beginner level which signifies a recent awareness and basic notion of SM concepts, with "awareness" being the key word (Mittal, Romero and Wuest, 2018). Awareness of the role data collection plays does not imply effective data collection methods are in place, yet it cannot be assumed that no attempt at incorporating some first-attempt data collection methods will be made. Therefore, for the refined model, level 1 will acknowledge not only the role of a centralised IT support infrastructure, but also the manual collection of rudimentary high-level data.

From the new understanding of level 1 that requires the manual collection of rudimentary high-level data mostly relating to the operation of machines and power-tools, the required input data type can be chosen. While energy consumption is an applicable data type it only signifies one aspect of machine operations and is therefore too narrow for the application context of the refined model. A more applicable umbrella term is chosen: ***Basic operations (high-level) data***, as this term incorporates different aspects of basic data collection such as energy consumption, operation times, production quantity and downtime data to name a few.

Manufacturing Level 2: ***Parts and assembly of products data***

This description of the data type input for the unrefined model is quite vague and constitutes some clarification. According to Mittal, level 2 sees the introduction of numerical control machines (automated control machines such as CNC) which allows for larger volume production, thus supporting the idea of parts and assembly of parts data use (Mittal, Romero and Wuest, 2018). It is, however, unclear what a practical example of such a data type would look like. First, the definition of a learner level must be revisited. According to Mittal learner stands for an SME that has started to experiment with SM technologies and paradigms (Mittal, Romero and Wuest, 2018).

The Impuls report deviates from the unrefined SM^3E model since it has six maturity levels as opposed to the five levels of the SM^3E model (Lichtblau et al., 2015). From the available information, it may be assumed the definitions of the Impuls level 2 and level 3 can be integrated in order to equate it to the learner level of the unrefined model. This report would then define an equivalent learner level as an enterprise that has started to move away from a centralised IT support structure toward an integrated IT system with some link through various interfaces. At a learner level there will be a mixture between automated and manual data collection with the possibility of upgrading current functionality for future requirements.

Lastly, the M2DDM proposed by Weber, would require a learner Enterprise to integrate Cross-Life-Cycle data and start focus on Service Orientation Architecture (SOA) implementation (Weber et al., 2017). SOA is required to support data exchanges between components within a well-defined interface in order to improve automation. Once again, a focus is placed on moving towards automation and data sharing.

From these three studies a learner level seems to require some type of initial upgrade to automation, interface linkage and data capturing in order to improve traditional processes, however, the question of which data-driven dimension best encapsulates this must still be answered. One can start by looking at what type of data will be produced during this phase and knowing that level 2 will see the first application of numerical control machines, these machines provide a strong basis for the investigation. The main improvement these machines provide is the capability of control and analysis on a product or part level. For example, a CNC machine enables precise control over part production time, production standard and production quantity while also allowing for more detailed-level data collection than the high-level inputs of level 1. This control over parts is described by the original descriptor of “parts and assembly of products data”. The original unrefined descriptor is therefore accurate, if slightly vague. A clearer rephrasing would be: ***Data based on individual part production (detail-level) and assembly enabled by numerical control methods***.

Manufacturing Level 3: ***CAD design of products data***

By level three an enterprise will have established IT integration processes and a functioning service orientation architecture (SOA). The unrefined SM^3E model describes this as the level at which manufacturing information systems are utilised for production. These systems are packages and platforms that allow enterprises to track the progress of finished goods from raw materials to final product. These packages can be real time (such as MES) or predictive such as CAD. According to Impuls the equipment infrastructure satisfies most SM requirements or at the very least is upgradable to fit the required functions (Lichtblau et al., 2015). Weber on the other hand suggests that this level is characterized by the use of digital twins in an enterprise. This is the concept of creating a digital replica of physical states in order to create a digital model of the enterprise. According to Weber this is a way of decentralising self-control of assets which can then be monitored by humans on a central platform (Weber et al., 2017). Although the full version of Weber’s concept is still under development and could be considered too advanced for a level 3 enterprise, there are instances of lower-level digital twins that will be applicable at an intermediate level. The use of CAD models, for instance, allows for the replication of physical objects in a digital environment from where various forms of analysis can be done.

The golden thread through all three studies is that a level 3 enterprise will have a well-established IT infrastructure along with a functioning SM equipment infrastructure that at the very least can be upgraded to the desired level. Furthermore, all the studies mention the use of some form of manufacturing information system i.e., CAD, MES or Digital Twins, clearly supporting the idea of input data types originating from these systems. To ensure the data-driven descriptor is clear it will be changed to**:** ***Data based on the use of Manufacturing Information Systems (CAD, MES etc.).***

Manufacturing Level 4: ***Sustainable production data***

The final maturity level of the SM^{3}E model is defined as a stage where enterprises deploy SM technologies in a strategic way (Mittal, Romero and Wuest, 2018). The unrefined model suggests that at this level enterprises should concern themselves with the sustainability of its production resources.

Weber suggests a slightly different definition by focussing on the role of advanced analytics and the relaying of context-sensitive information to workers in run-time rather than design-time (Weber et al., 2017). An emphasis is placed on self-learning of the system and an optimized symbiosis between machine and worker. In effect, weber implies that the final level is the optimization and full exploitation of the capabilities implemented in level 3.

Finally, the Impuls report defines the final maturity level as a state where all equipment infrastructure satisfies future capabilities, and all data is collected and used efficiently, effectively echoing Weber.

The data type "sustainable production data" does not properly encapsulate the requirements of the final level. Once again one must investigate the major change observed between level 3 and level 4 and analyse the new data types that will be generated. These data types will best define and separate level 4 from level 3. The addition of real-time analytics and, more specifically, self-learning and subsequent live adjustment from real-time analytics is unique to level 4. While level 3 enterprises are able to track real time production processes with packages such as MES, it is purely observational and not interactive. Level 4 is therefore defined by the real-time interaction between data collection and analytics and subsequent communication between machine and worker. The level 4 data-driven descriptor can thus be changed to: ***Data based on Real-Time analytics and interactive production***.

5.2.4 Design and Simulation toolbox refinement

The design and simulation toolbox investigates the types of data generated during the design process of the enterprise.

Table 5-2: *Unrefined and unvalidated Design and Simulation toolbox (Mittal, Romero and Wuest, 2018)*

UNVALIDATED AN UNREFINED				
	DESIGN AND SIMULATION: DIMENSION ELEMENTS			
MATURITY LEVEL	*Finance*	*People*	*Process*	*Product*
Lvl 0: *Novice*	Data based on Paper-Based Design			
Lvl 1: *Beginner*	Data based on the design (model)			
Lvl 2: *Learner*	Data based on simulations			
Lvl 3: *Intermediate*	Data based on prototyping			
Lvl 4: *Expert*	Data based on customer design interface			

Design & Simulation Level 0: ***Data based on Paper-Based Design***

The current data type for unrefined SM^3E model provides and accurate description for the level 0 state. Both the Impuls study and the M2DDM proposed by Weber suggest that there is no support from an IT infrastructure thus resulting in a reliance on paper-based designs (Weber et al., 2017) (Lichtblau et al., 2015). This type of design is extremely outdated and rudimentary and should be updated quickly.

Design & Simulation Level 1: ***Data based on the design (model)***

To understand this data type, one must again investigate the interdependency chart of Figure 5-5. In order to improve the manufacturing toolbox from level 2 to level 3, it is required that the design and simulation (D&S) toolbox is upgraded to level 1. This means that the data input type provided by level 1 D&S capability must align with the data requirements of a level 3 manufacturing capability which is defined as: *Data based on the use of Manufacturing Information Systems (CAD, MES etc.).* Extrapolating this suggests that the current level 1 D&S data descriptor is indeed correct as design data should be based on modelling to fulfil the manufacturing toolbox's level 3 requirements. The descriptor can, however, be made more coherent by redefining it to: ***Data based on digital designs and models (CAx, CAD)***.

Design & Simulation Level 2: ***Data based on simulations***

In theory, the manufacturing toolbox can improve to level 4 without further development of the D&S toolbox. However, the SM paradigm is one of optimization and improvement. The goal should be to utilise technology to such an extent that it can predict and negate future obstacles. The logical development for the D&S toolbox is therefore to improve upon the predictive capabilities by utilising the CAD models (level 1) and incorporating simulations into the design process. Another staple of smart product design is the ability to create an accurate first iteration design (Zawadzki and Żywicki, 2016). Simulations allow manufacturers to test and predict the probability of a design outcome and can vastly improve the time spent on design iterations.

Design & Simulation Level 3: ***Data based on prototyping***

The next product design goal of an enterprise applying a SM paradigm, should be to incorporate rapid prototyping into their design process (Zawadzki and Żywicki, 2016). Although digital simulations are extremely useful in the design process, they only provide a designer with an approximation of a probable outcome. The only way to truly determine the success of a design is by manufacturing a prototype and testing it in a real-world application. Traditional manufacturing of prototypes can take too long and be too costly to add value to the design process, however, with the advent of rapid prototyping technologies, such as 3D printing, is changing the design landscape. One major addition to the prototyping process could be that of hybrid-prototyping, where virtual reality processes are used to run tests on a digital prototype in a real-world simulation (Zawadzki and Żywicki, 2016). It should be noted that, for an enterprise to incorporate prototyping into their D&S toolbox, they will be required to have a functioning Robotics and Automation (R&A) toolbox. The level 3 data-driven descriptor is thus partly validated; however, it should be adjusted to: ***Data based on rapid or hybrid prototyping***.

Design & Simulation Level 4*: Data based on customer design interface*

Zawadzki and Żywicki describe the previously explained improvements to the design process as "time-compression" improvements where each addition to the design process is made in such a way as to save more time on the overall process (Zawadzki and Żywicki, 2016). So far, the focus of the improvements has been on the enterprise's side of the design, once they have received all the design requirements. The traditional interface between customer and designer is an area with some design pitfalls and that, if left untouched, can lead to miscommunication, redesigning and time wasting.

Creating an interface that connects the customer directly to the design process could decrease back-and-forth communication and drastically speed up the design process. Such an interface could incorporate modern machine learning and computer vision techniques and would truly be a sign of an advanced design process. For such an interface to work it will be required that an enterprise has a highly advanced Sensors and Connectivity (S&C) toolbox.

5.2.5 Sensors and Connectivity toolbox refinement

The Sensors and Connectivity toolbox investigates the processes through which data is collected and transmitted.

Table 5-3: *Unrefined and unvalidated Sensors and Connectivity toolbox (Mittal, Romero and Wuest, 2018)*

UNVALIDATED AN UNREFINED				
	SENSORS AND CONNECTIVITY: DIMENSION ELEMENTS			
MATURITY LEVEL	*Finance*	*People*	*Process*	*Product*
Lvl 0: *Novice*	Manually collect data			
Lvl 1: *Beginner*	Sensors collect data			
Lvl 2: *Learner*	Signals collect data			
Lvl 3: *Intermediate*	Digitally stored cost data			
Lvl 4: *Expert*	Data based on customer design interface			

Sensors & Connectivity Level 0: *Manual data collection*

Manual collection of data is the correct determinant for a level 0 enterprise. This collection method is extremely inefficient and does not fit within the SM paradigm (Lichtblau et al., 2015). While, traditionally, it might have been more difficult to incorporate automated data collection into the manufacturing processes, the modern manufacturing age allows for much easier adoption of digital tools and should thus be pursued as soon as possible.

Sensors & Connectivity Level 1: *Sensors collect data*

The very first level of SM data collection involves the use of local sensors to collect data from machines. These sensors collect and store data of specific machines but does not relay that data anywhere else (Yin, Wang and Jha, 2018), thus the addition of the word ‘local’ to the data descriptor is important. Although the incorporation of sensory technology is a step in the right direction, it is still considered the very beginning of the industry 4.0 and IoT journey. The data descriptor will therefore change to: ***Local collection of data via offline sensors***.

Sensors & Connectivity Level 2: *Signals collect data*

The original purpose of this descriptor was to explain how, at level 2, sensors are able to convert the data into readable signals. After some literature analysis of high-functioning sensory systems (Yin, Wang and Jha, 2018) (Chan et al., 2020) it can be concluded that this is not a satisfactory definition of a level 2 sensory maturity. From the literature, sensor communication and networks are more indicative of maturity improvement than the signal conversion. It can thus be concluded that a learner enterprise would distinguish itself from a beginner enterprise by not only utilising sensory capability but also start with establishing a wireless communication network between sensors. However, it should be noted that the Sensors and Connectivity toolbox (at level 2) should be able to operate without a well-established Cloud and Storage toolbox (see interdependency chart in Figure 5-5). Communication between sensors and servers will therefore be difficult to implement at level 2, however, transfer of data to a single storage point should still be possible. The data descriptor for level 2 will therefore change to: ***Sensory data transferable to a single storage point and interface*.**

Sensors & Connectivity Level 3: ***Digitally stored data***

The descriptor changes for level 3 and level 4 are based heavily on the research done by Chan and Yin. These papers introduce the idea of sensor networks and hierarchical routing protocols. Wireless sensor networks (WSN) are considered a key role player within the SM and IoT paradigm (Chan et al., 2020). An intermediate enterprise will therefore have a secure and reliable network of sensors that can communicate and relay information effectively. This will of course require a decent level of cloud and storage maturity to ensure the data traffic can be managed. In light of this new information, the original data descriptor can be changed: ***Data collected and transferred via a Wireless Sensor Network (WSN).***

Sensors & Connectivity Level 4: ***Data based on customer design interface***

Once a reliable WSN infrastructure is in place, the focus of an expert-level enterprise will shift toward optimization. Machine learning algorithms are used to optimise data analysis and transfer to create a self-organising network (Yin, Wang and Jha, 2018) (Chan et al., 2020). The main focus should be on improving not only effectivity, but efficiency. The main measure of efficiency in a WSN is energy usage, thus, implying higher efficiency at lower energy usages. While machine learning can help with efficiency, the only true way of reducing energy usage is by optimizing the network hierarchy and structure. Yin proposes that the highest energy consumption is associated with data transfer between communication levels. If data inference (analysis) can be conducted at the bottom sensory level, rather than at a server/cloud level, the amount of data transferred between the levels can be reduced, thereby optimizing the energy usage and efficiency (Yin, Wang and Jha, 2018). The new data descriptor should thus read: ***Data collection through an optimised WSN that utilises hierarchical sensor-level inference (smart sensors) and machine learning algorithms.***

5.2.6 Cloud and Storage toolbox refinement

The Cloud and Storage toolbox investigates the methods of data storage utilised by an enterprise.

Table 5-4: *Unrefined and unvalidated Cloud and Storage toolbox (Mittal, Romero and Wuest, 2018)*

UNVALIDATED AN UNREFINED				
	CLOUD AND STORAGE: DIMENSION ELEMENTS			
MATURITY LEVEL	*Finance*	*People*	*Process*	*Product*
Lvl 0: *Novice*	Store data using spreadsheets			
Lvl 1: *Beginner*	Store data using hard drives			
Lvl 2: *Learner*	Store data using shared hard drives			
Lvl 3: *Intermediate*	Store data using cloud			
Lvl 4: *Expert*	Store data using fog			

Cloud & Storage Level 0: *Store data using spreadsheets*

The original descriptor is based on the idea that data is still entered manually from paper-based logbooks and spreadsheets are populated by hand (Mittal, Romero and Wuest, 2018). Considering the massive number of storage options that are available at affordable prices in the modern IT age, manual entry of data, even if utilising IT supported spreadsheets, is not sufficient. The original descriptor, however, focusses on the wrong aspect of the novice level characteristic. The focus should be shifted towards the manual entry aspect of the data storage. A better descriptor would thus read: ***Storage of data through manual population of data fields from paper-based logbooks or spreadsheets.***

Cloud & Storage Level 1: *Store data using hard drives*

A beginner level is signified by the writing of data directly to physical hard drives. There are, however, no communication between the hard drives as they are purely for safekeeping of data dumps. A distinct aspect of a beginner level is that, although IT systems and hardware are being incorporated, there is no use of a database management system (i.e., SQL) and thus no efficient way to run data queries. The original descriptor should thus be changed to*:* ***Store data using hard drives without the use of a database management system (DBMS).***

Cloud & Storage Level 2: *Store data using shared hard drives*

At a learner level an enterprise will utilise shared hard drives such as an intranet (Mittal, Romero and Wuest, 2018). More advanced learner enterprises will share data to a dedicated server where it will be stored on hard drives in a data centre. Although this is an acceptable method of data storage, it is still a learner level in terms of SM. The reason being that dedicated server storage space was designed for structured data storage and not the massive amounts of unstructured data associated with big data collection and thus is not optimal for a truly smart manufacturing enterprise (Tao et al., 2018). At this level a DBMS will be used. Lastly, a learner enterprise can be identified by the type of data recovery management they employ. If data recovery protocols only utilise physical backups, they are considered to be at a level 2 maturity, at least in the recovery aspect of data storage. A new descriptor can be written as: ***Store structured data using shared hard drives (intranet, server host etc.) and only utilise physical backups for data recovery.***

Cloud & Storage Level 3: ***Store data using cloud storage***

From level 3 an enterprise starts to move into the realm of big data, with vast amounts of unstructured data being generated and stored. Cloud computing and subsequently cloud storage helps enterprises to handle the immense data load by providing a secure and powerful decentralised storage network. At level 3, however, enterprises mainly use block storage which places a focus on structured data as their main information source (Tao et al., 2018). Recovery management at this level is both remote and physical with a continuous backup policy in place (Saqlain et al., 2019), where, if the system goes offline, data is rerouted in a loop until it can be stored remotely again. In light of the new information, the original data descriptor can be changed to: ***Store data using cloud computing with a focus on structured data as the main source of information along with both physical and remote data recovery capability***.

Cloud & Storage Level 4: ***Store data using fog***

At an expert level, enterprises focus on the optimization of their data usage to ensure they utilise every possible aspect of data. While cloud computing and storage is still the main feature of this level, the introduction of object-based data storage allow enterprises to utilise semi-structured and unstructured data (Poojary, 2019) (Tao et al., 2018). Object-based storage is a flat storage structure as opposed to the traditional tree or hierarchy structures, which allows for storage of massive amounts of data. Furthermore, expert level enterprises will utilise the power of edge-device computing to continuously filter and store upstream data as to ensure only useful data is utilised (Saqlain et al., 2019), thus creating a smart distributed storage network. Finally, a level 4 enterprise will incorporate event management in their data storage, where novel 'event' data is differentiated from 'regular' data by machine learning algorithms and subsequently promoted directly to the application layer of the data for further processing. The original descriptor is updated to: ***Store structured, semi-structured and unstructured data by utilising the cloud, object-based storage and edge-device computing along with machine learning algorithms for event management.***

5.2.7 Data and Analytics toolbox refinement

This toolbox does not represent the type of data used in the enterprise, as this will be determined by the various maturity levels of the other toolboxes. Instead, the D&A toolbox investigates the processing methods used once data has been gathered. Cloud and Storage toolbox is closely related to the development of the Data and Analytics toolbox. The two toolboxes should be upgraded simultaneously.

Table 5-5: *Unrefined and unvalidated Data and Analytics toolbox (Mittal, Romero and Wuest, 2018)*

UNVALIDATED AN UNREFINED				
	DATA AND ANALYTICS: DIMENSION ELEMENTS			
MATURITY LEVEL	*Finance*	*People*	*Process*	*Product*
Lvl 0: *Novice*	Collect and analyze data			
Lvl 1: *Beginner*	Clean and analyze data			
Lvl 2: *Learner*	Integrate and analyze data			
Lvl 3: *Intermediate*	Reduce and analyze data			
Lvl 4: *Expert*	Transform and analyze			

Data & Analytics Level 0: ***Collect and analyse data***

Note that data analytics cannot start before a cloud and storage maturity of at least level 1 is achieved. A novice enterprise will engage in basic collection and analysis of purely structured data (Tao et al., 2018). Very little to no refinement of the data is done post-collection. A more descriptive input-data type would be: ***Collection and analysis of raw data with no form of post-collection processing.***

Data & Analytics Level 1: ***Clean and analyse data***

Level 1 sees the introduction of resource management. This improves discovery and visibility of physical data-creating resources by sorting and structuring the database fragment locations (Saqlain et al., 2019). By now the enterprise should make use of a database management system (DBMS) to assist with the management process. This process consists of resource identification, resource registration and intelligent brokering (Saqlain et al., 2019). A more descriptive input-data type would be: ***Management and mapping of physical data-creating resources through sorting and structuring protocols of raw data.***

Data & Analytics Level 2: ***Integrate and analyse data***

At this level it is vital that pre-processing and filtering of data is executed efficiently (Saqlain et al., 2019). This process involves removing duplicate, redundant or misleading data entries (Tao et al., 2018). By now an enterprise should have a well-established database management system (DBMS) in place to run the necessary queries. These processes along with the resource management from level 1 now forms a stable middleware layer. This middleware layer is the link between the connected devices and allows for the integration of the data to create heterogeneous computing (Saqlain et al., 2019). A more descriptive input-data type would be: ***Cleaning and integrating of data through the establishment of a strong middleware data-analysis layer.***

Data & Analytics Level 3: ***Reduce and analyse data***

Level 3 requires the aggregation of data (Tao et al., 2018). This is simply the process of summarizing the pre-processed data as to only provide the crucial and significant data. This reduces storage cost and improves analysis performance (Saqlain et al., 2019). A more descriptive input-data type would be: ***Reduction of data through data aggregation processes.***

Data & Analytics Level 4: ***Transform and analyse data***

The final level is indeed data transformations. Specifically, the conversion of data from file or block structures to object orientated structures. This allows enterprises to not only store massive amounts of data, but also provides easier access and analysis of semi-structured and unstructured data. A more descriptive input-data type would be: ***Transform data to an object-orientated structure.***

5.2.8 Robotics and Automation toolbox refinement

The Robotics and Automation toolbox investigates the level of automation by measuring the type of data that the automation infrastructure outputs.

Table 5-6: *Unrefined and unvalidated Robotics and Automation toolbox (Mittal, Romero and Wuest, 2018)*

UNVALIDATED AN UNREFINED				
	ROBOTICS AND AUTOMATION: DIMENSION ELEMENTS			
MATURITY LEVEL	*Finance*	*People*	*Process*	*Product*
Lvl 0: *Novice*	Data based on manually operated machines			
Lvl 1: *Beginner*	Data based on non-programmable machines			
Lvl 2: *Learner*	Data based on programmable machines			
Lvl 3: *Intermediate*	Data based on collaborative robots (mimic human)			
Lvl 4: *Expert*	Data based on collaborative robot (based on AI)			

Robotics & Automation Level 0: ***Data based on manually operated machines***

Based on the knowledge gained from the refinement of the various other toolboxes, it can be concluded that the current descriptor for the novice level of R&A is indeed correct. Manual operation is a consistent identifier of novice smart manufacturing enterprise who have not yet adopted the SM paradigm.

Robotics & Automation Level 1: ***Data based on non-programmable machines***

Non-programmable machines are machines with very basic parameter control such as speed and direction (Mittal, Romero and Wuest, 2018). This is the logical next step up from manually operated machines, but only satisfy the beginner level requirements due to their limited adaptability.

Acquisition of these machines does, however, signify a first attempt at improving smart manufacturing and is thus at the beginning of the journey.

Robotics & Automation Level 2: ***Data based on programmable machines***

Programmable machines are extremely useful as they provide versatility and optimisation to the manufacturing process. This is the first proper step towards full automation and signifies an enterprise fully committed to improving within the SM paradigm.

Robotics & Automation Level 3: ***Data based on collaborative robotics (mimic human movement)***

Collaborative robots refer to a network of interconnected automated machines that reform specific tasks. This achieves a high level of automation and optimization. At an intermediate level, such an automated collaborative network is achieved through machine to machine (M2M) communication within a local network communication cluster (Yan et al., 2017). The advantage of such a cluster computing system is its high availability and manageability, however it is not associated with an expert level enterprise due to constraints surrounding storage resources, information learning capacity and programmability issues (Shankar and Sharma, 2017) (Yan et al., 2017). The data descriptor should thus be changed to: ***Data based on collaborative robotic networks via cluster computing*****.**

Robotics & Automation Level 4: ***Data based on collaborative robotics (Based on AI)***

Finally, at an expert level an enterprise will further optimise the collaborative capabilities established at level 3. The literature suggests that the best way to do this is by utilising cloud rather than cluster computing (Yan et al., 2017). This also makes it easier to incorporate multiple edge-devices with lower storage capacity into the collaborative network, thus vastly improving performance. The goal is to utilise machine learning techniques along with the cloud computing capabilities to create a fully virtual digital twin of all the operations, thus allowing for real-time, network-wide, simulation and adjustments to be made (Weber et al., 2017). The new data descriptor should thus read: ***Data based on collaborative robotic networks via cloud computing and AI driven digital twins.***

5.2.9 Results of literature refined and validated toolboxes

Here follows the literature refined and validated data-input types associated with each level of maturity of the various toolboxes.

LITERATURE VALIDATED AND REFINED

	MANUFACTURING TOOLBOX: DIMENSION ELEMENTS			
MATURITY LEVEL	***Finance***	***People***	***Process***	***Product***
Lvl 0: *Novice*	Data based on raw material acquisition and use			
Lvl 1: *Beginner*	Data based on basic operations (high-level			
Lvl 2: *Learner*	Data based individual part production (detail-level) and assembly enabled by numerical control methods			
Lvl 3: *Intermediate*	Data based on the use of Manufacturing Information Systems (CAD, MES, etc)			
Lvl 4: *Expert*	Data based on Real-Time analytics and interactive production			

	SENSORS AND CONNECTIVITY: DIMENSION ELEMENTS			
MATURITY LEVEL	***Finance***	***People***	***Process***	***Product***
Lvl 0: *Novice*	Manual collection of data			
Lvl 1: *Beginner*	Local collection of data via offline sensors			
Lvl 2: *Learner*	Sensory data transferable to a single storage point and interface			
Lvl 3: *Intermediate*	Data collected and transferred via a Wireless Sensor Network (WSN)			
Lvl 4: *Expert*	Data collection through an optimized WSN that utilizes hierarchical sensor-level inference (smart sensors) and machine learning algorithms			

	DATA AND ANALYTICS: DIMENSION ELEMENTS			
MATURITY LEVEL	***Finance***	***People***	***Process***	***Product***
Lvl 0: *Novice*	Collection and analysis of raw data with no form of post-collection processing			
Lvl 1: *Beginner*	Management and mapping of physical data-generating resources through sorting and structuring protocols of raw data			
Lvl 2: *Learner*	Cleaning and integrating of data through the establishment of a strong middleware data-analysis layer			
Lvl 3: *Intermediate*	Reduction of data through data aggregation processes			
Lvl 4: *Expert*	Transform data to an object-orientated structure			

Figure 5-6: *Results of literature validated and refined SM3E toolboxes*

LITERATURE VALIDATED AND REFINED

<table>
<tr><th></th><th colspan="4">DESIGN AND SIMULATION: DIMENSION ELEMENTS</th></tr>
<tr><th>MATURITY LEVEL</th><th>Finance</th><th>People</th><th>Process</th><th>Product</th></tr>
<tr><td>Lvl 0: Novice</td><td colspan="4">Data based on paper-based designs</td></tr>
<tr><td>Lvl 1: Beginner</td><td colspan="4">Data based on digital design and models (Cax, CAD</td></tr>
<tr><td>Lvl 2: Learner</td><td colspan="4">Data based on simulation</td></tr>
<tr><td>Lvl 3: Intermediate</td><td colspan="4">Data based on rapid or hybrid prototyping</td></tr>
<tr><td>Lvl 4: Expert</td><td colspan="4">Data based on customer design interface</td></tr>
</table>

<table>
<tr><th></th><th colspan="4">CLOUD AND STORAGE: DIMENSION ELEMENTS</th></tr>
<tr><th>MATURITY LEVEL</th><th>Finance</th><th>People</th><th>Process</th><th>Product</th></tr>
<tr><td>Lvl 0: Novice</td><td colspan="4">Storage of data through manual population of data fields from paper-based logbooks or spreadsheets</td></tr>
<tr><td>Lvl 1: Beginner</td><td colspan="4">Store data using hard drives without the use of a database management system (DBMS)</td></tr>
<tr><td>Lvl 2: Learner</td><td colspan="4">Store structured data using shared hard drives (intranet, server host etc.) and only utilize physical backups for data recovery</td></tr>
<tr><td>Lvl 3: Intermediate</td><td colspan="4">Store data using cloud computing with a focus on structured data as the main source of information along with both physical and remote data recovery capabilities</td></tr>
<tr><td>Lvl 4: Expert</td><td colspan="4">Store structured, semi-structured and unstructured data by utilizing the cloud, object-based storage and edge-device computing along with machine learning algorithms for event management</td></tr>
</table>

<table>
<tr><th></th><th colspan="4">ROBOTICS AND AUTOMATION: DIMENSION ELEMENTS</th></tr>
<tr><th>MATURITY LEVEL</th><th>Finance</th><th>People</th><th>Process</th><th>Product</th></tr>
<tr><td>Lvl 0: Novice</td><td colspan="4">Data based on manually operated machines</td></tr>
<tr><td>Lvl 1: Beginner</td><td colspan="4">Data based on non-programmable machines</td></tr>
<tr><td>Lvl 2: Learner</td><td colspan="4">Data based on programmable machines</td></tr>
<tr><td>Lvl 3: Intermediate</td><td colspan="4">Data based on collaborative robotic networks via cluster computing</td></tr>
<tr><td>Lvl 4: Expert</td><td colspan="4">Data based on collaborative robotic networks via cloud computing and AI driven digital twins</td></tr>
</table>

Figure 5-7: *Results of literature validated and refined SM3E toolboxes*

5.3 Critical Considerations for Maturity Improvement Through SM Innovation Adoption

As has been discussed in detail by now, the final phase of the proposed decision support tool utilises an existing SME[3] maturity toolbox model (Mittal, Romero and Wuest, 2018). This model divides the various operations of a manufacturing SME, such as Design and Simulation or Data and Analytics to name a few, into their own individual toolboxes. The maturity of these operations is analysed within their toolbox by comparing the current state of the operation to the proposed desired state of operation associated with industry 4.0 smart manufacturing paradigms. Each toolbox requires the adoption of a certain set of digital SM innovations to achieve higher levels of maturity within the SM paradigm. For example, to achieve an expert level maturity in the Sensors and Connectivity toolbox, an enterprise must acquire expensive smart-sensors and machine learning algorithms. During the literature refinement phase the following was discovered: While these innovations, if integrated correctly, can improve the overall efficiency of operations, they are potentially extremely costly to acquire. This is one of the issues relating to technology acceptance (Davis, 1985), and the more "novel" the innovation is, the worse the problem of technology acceptance becomes (Erdogmus & Esen, 2011**)** (Shi et al., 2019)

It is believed that early adopters of industry 4.0 and SM digital paradigms are especially at risk of generating a negative return on investment (Corò and Vope, 2020). The main reason for this anomaly relates to the steep learning curve and complexity of SM adoption and the fact that a standardised adoption procedure is still under development. Another influencing factor is the need of more skilled, and thus more costly, labour to support a more complex system (Corò and Vope, 2020). The question then becomes weather or not the gain in efficiency justifies the required financial investment?

Most multi-national enterprises have the resources to be future focussed and drive developments within the industry, however, the proposed model considers the needs of SMEs whose limited resources and shorter-term considerations does not allow for risky long-term investments. The shift towards a SM paradigm is, however, crucial for long-term financial gain and productivity improvement (Corò and Volpe, 2020). This can be achieved through accelerated corporate decision making and adaptability of processes due to the flexibility introduced through industry 4.0 and SM (Schuh et al., 2017). To avoid being left behind, manufacturing SMEs must start investigating and slowly implementing digital and innovation capabilities to shift towards a SM paradigm. These SMEs will have to use the proposed support tool to investigate the various innovation capabilities required for achieving different maturity levels within a SM paradigm. Through careful consideration of the cost-benefit, SMEs must select the most realistic innovations to invest in, in order to achieve a maturity level that proves beneficial to the SMEs current SM strategy. It is important to understand that achieving the highest level of maturity across all facets of the SM paradigm, is not necessarily a realistic goal for most manufacturing SMEs and could lead to detrimental financial loss. Therefore, the final part of the literature refinement phase, as presented in the following section, is the creation of a process for selecting a desired and realistic maturity level. This selection procedure accompanies the final decision support tool.

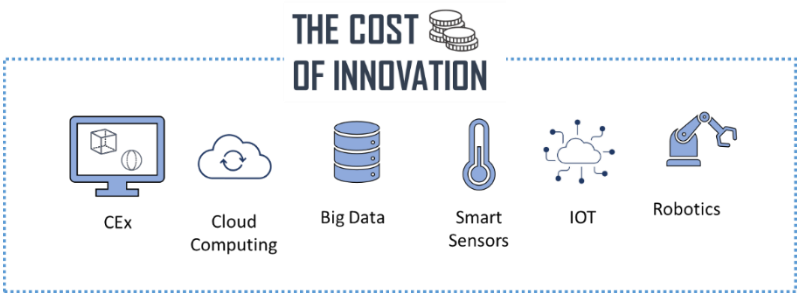


Figure 5-8: *Examples of SM innovations that can be adopted.*

5.3.1 Infrastructure costs and considerations

Improving the operations of an enterprise requires effective execution of a delicate combination of policies, processes and best practices. An underlying physical infrastructure is required to enable such operations and will generally contribute massively to the overall cost of improvement. It is widely accepted within industry 4.0 paradigms that Cyber-Physical Systems (CPS) and the Internet of Things are the two critical enabling innovations (Davies, Coole and Smith, 2017). Enterprises that strive towards SM will therefore be required to implement these two critical innovations by acquiring and installing the necessary infrastructure. This section will elaborate on each of these innovations and outline the basic infrastructure requirements.

5.3.1.1 Cyber-physical systems

A CPS consists of a collection of embedded devices that are in constant communication with one-another. These embedded devices are mechatronic systems or objects comprised of various components such as software, hardware and sensors, as seen in Figure 5-9 (Davies, Coole and Smith, 2017). Embedded devices are becoming increasingly complex as they integrate multiple technologies and disciplines into a centralised architecture, ultimately providing powerful automated systems (Penas et al., 2017). It is important to understand, however, that a single embedded device is not considered a CPS, but rather that the collection of these devices and their ability to communicate, co-operate and organise themselves is what gives value to the concept (Penas et al., 2017). Enterprises must therefore first invest in the acquisition of multiple embedded devices, whilst installing them with an overarching strategy to ensure future integration of the infrastructure into a CPS. This is a costly endeavour and will ultimately beg the question of: If embedded devices provide such powerful automation systems, why should an enterprise invest in a CPS infrastructure? In truth, each enterprise will have to analyse their unique situation and determine whether the gain in efficiency is worth the investment. **Theoretically, however, the introduction of a CPS should result in the following (Penas et al., 2017):**

a. Improvement in the production line capability.

b. Improved quality control.

c. Faster response to market changes and increased flexibility.

d. Reduction of manufacturing costs through standardisation of their manufacturing system.

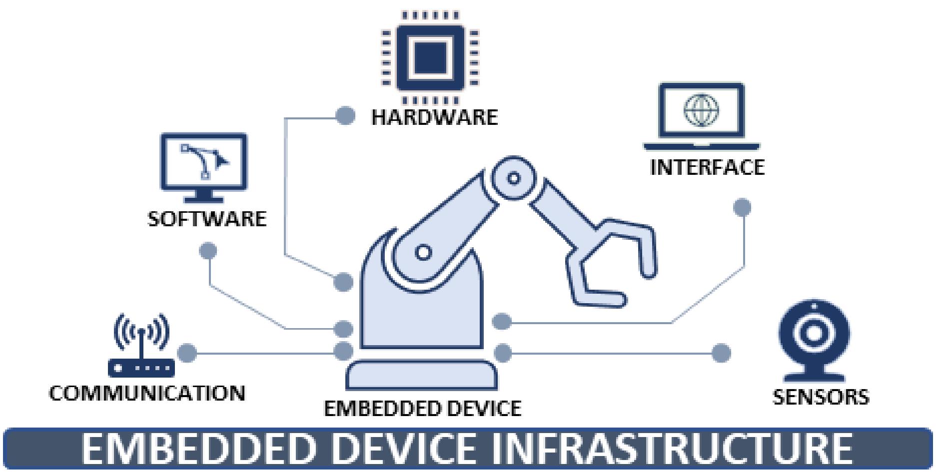


Figure 5-9: *Example of infrastructure requirements of an embedded device in a CPS*

If an enterprise decides to invest in building a CPS, they will require the following infrastructure summarised in Table 5-7 and presented in Figure 5-10.

Table 5-7: *CPS infrastructure requirements (Ahmed, Kim and Kim, 2013)*

Infrastructure Requirement	**Description**
Actuators	Actuators refer to any physical device which interacts with the physical world. For a manufacturing enterprise it could refer to their equipment such as CNC machines, conveyers, lathes etc. It should be relatively easy to estimate the cost of actuator acquisition as there will be a finite number of physical assets to consider.
Sensing module	A sensing module is required to translate the actuators physical experiences to a digital domain. These sensors allow for real time observation, analysis and ultimately intervention of the actuator process. Sensing modules can be in various network types depending on the requirement. Estimating the full cost of sensor module acquisition can be hard. Ideally an enterprise would want to collect every possible type of data through sensors. This would, however, be extremely inefficient and costly. It is therefore imperative that enterprises acquire and implement sensor modules strategically. The total cost of creating a sensory network will thus be dependent on the specific strategy chosen by the enterprise and should be researched thoroughly (Al-Turjman, 2019).
Data management module	The DMM enables the various activities conducted after data capturing. These activities usually relate to sorting and cleaning the data before it is analysed. An enterprise should have various database management systems, packages and protocols in place that can perform these tasks efficiently and effectively (Saqlain et al., 2019) (Tao et al., 2018). These management systems must be tailored to the needs of each enterprise; therefore, consultation costs must be accounted for along with the acquisition cost of the software.
Advanced internet and storage	By now it is understood that a CPS consists of multiple embedded devices that are in constant communication. Advanced internet is required to establish such a communication network along with a robust storage system to host the constant stream of data. While it is possible to run smaller CPNs with traditional server hosting and networking, once big data comes into play, cloud computing and storage is required (Poojary, 2019) (Tao et al., 2018). Installation of advanced internet infrastructure can be costly; however, it is a crucial requirement for any enterprise looking to advance their processes. Cloud storage is becoming more and more accessible as it is decentralised and can operate on a monthly subscription basis and the packages are easily upgradeable.
Service aware module (SAM)	The SAM acts as the brain of the CPN. It receives the sensed and cleaned data and then preforms decision-making, task analysis and task scheduling. The SAM then sends the data to the relevant services. Investing in a robust SAM is imperative to effective implementation since the sensed data is almost useless without proper decision-making.
Application module	The application module deploys the services requested by the SAM. During this stage data is also stored on a secure database for quality of service (QoS) support.

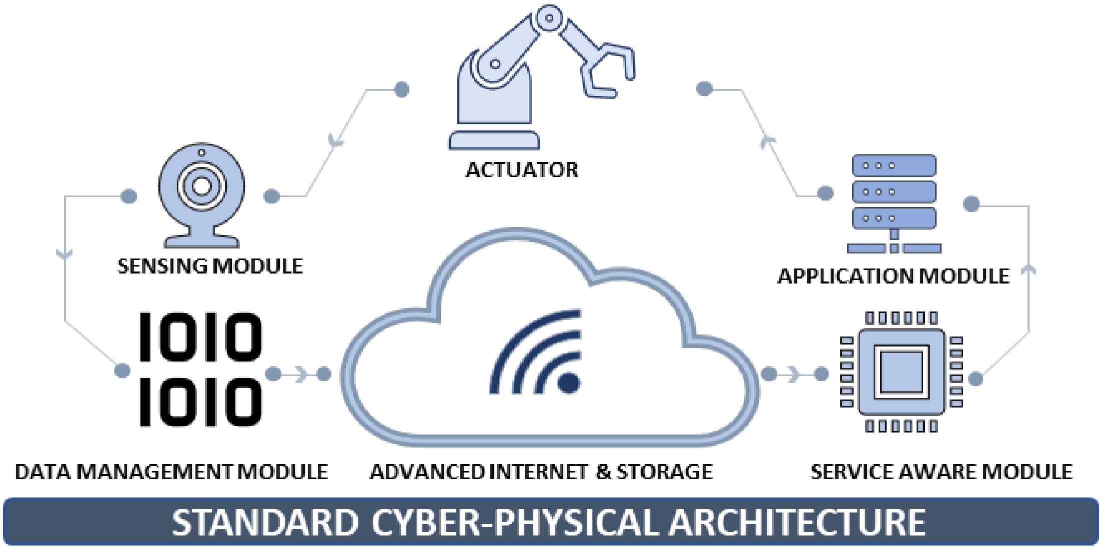


Figure 5-10: *Example of standard cyber-physical architecture*

5.3.1.2 Internet of things

IoT is listed as the second critical enabling innovation for I4.0 and Smart Manufacturing and, while it is listed as separate from CPNs, it is in actuality a special case of CPN (Davies, Coole and Smith, 2017). The difference is subtle but can be explained as such: IoT deals with connecting "things" such as objects and machines to the internet from where they can be connected to one another and share data, while a CPS attempts to integrate computing and networking into a physical process with a continuously updating output. CPS is more closely related to manufacturing processes where control through action is required while IoT is more generally applicable to everyday use objects where communication is central (Rahman & Chen, 2019). By adding a control and execution modules to an IoT system, one can arrive at a CPS, which shows how closely related the systems are. At the end of the day both concepts refer to the integration of the physical and virtual world via a communication network and the concepts will start to merge as the technologies are refined (Barton, Maturana and Tilbury, 2018). IoT concepts can, however, move away from the factory floor and into the civilian space, thereby improving not only physical processes, but operational and strategic ones as well.

Before discussing the advantages of IoT one must investigate a major issue associated with IoT integration in a CPS. This is the issue of untrustworthy and unreliable data (Rahman & Chen, 2019). Unreliable data can trigger false alarms within the system which could cost an enterprise valuable time and resources; therefore, every necessary precaution must be taken to ensure secure and reliable data transfer. Development of new data collection framework such as the In-Network Generalized Trustworthy Data Collection (IGTDC) framework, could help to overcome the reliability issues (Rahman & Chen, 2019), however, research is still being done on the subject. Enterprises adopting IoT must therefore do so whilst realising that continuous future improvements and updates to the system will be necessary.

Table 5-8 below summarises the various advantages of adopting IoT in an enterprise's operations, followed by Figure 5-11 which provides an example of an IoT ecosystem.

Table 5-8: *Advantages of IoT adoption (i-Scoop, no date)*

IoT Advantage	**Description**
Manufacturing Operations	The main advantage of IoT adoption in manufacturing is the improvement it can bring to manufacturing operations through integration of IT and physical processes. This creates a cyber-physical network as described in the previous section. Adoption of this innovation is believed to improve productivity, efficiency and effectivity across a wide spectrum of operational processes.
Asset management and maintenance	IoT can be seen as a way to integrate physical assets into a virtual space where they can be visualised as part of a larger network. This allows enterprises to precisely track each asset and monitor its location in, and effect on, the network. Furthermore, it enables non-stop tracking of performance indicators along with potential damage or breakdowns. Since this network can digitally represent the as-is physical state of the asset, it improves predictive maintenance capabilities which could be extremely beneficial to the longevity of the operations. Lastly, where IoT as part of a CPN mostly improves operations on the manufacturing floor, the asset management capabilities of IoT can extend far outside the factory. Staff monitoring, business operations, strategy performance, security and shipment tracking are but a few examples. Ultimately, the potential of instant, full digital control over all enterprise operations is extremely vast.
Field service	Service provision can be improved dramatically through the adoption of IoT. By combining instant communication with the improved flexibility of digital/virtual networks, allows more efficient integration of service-related queries. IoT can reduce red-tape between product-, business- and process-related operations and optimise the interaction between the different departments of an enterprise. Ultimately, IoT can create a digital ecosystem that interacts efficiently and effectively, thus improving service delivery capabilities.

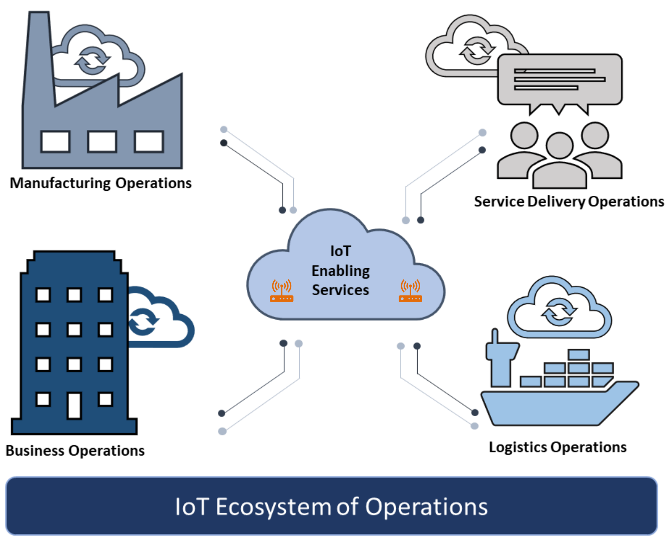


Figure 5-11: *Example of an IoT enabled ecosystem where each department has internally integrated IoT processes which communicate with the external IoT network.*

Now that the advantages of IoT is understood, the costs of installing a functioning IoT infrastructure must be considered as shown in Table 5-9 below:

Table 5-9: *Cost of IoT adoption (Barton, Maturana, Tilbury, 2018)*

IoT Costs	**Description**
Hardware tools	For IoT hardware infrastructure there are two kinds of considerations: IoT-to-legacy and IoT-aware infrastructure. IoT-to-legacy refers to infrastructure that has been retrofitted with IoT devices while IoT-aware infrastructure has been designed from scratch with IoT capabilities in-mind. At the time of writing this thesis, the IoT-to-legacy option is cheaper than the IoT-aware one and is a good starting point for enterprises looking to join the IoT paradigm. While retrofitted IoT devices are regularly available and relatively inexpensive compared to the cost of acquiring new IoT-aware devices, there can be hidden costs that should be accounted for. Since legacy infrastructures were not originally designed for IoT applications, each legacy device presents a unique set of variables and problems that must be accounted for when retrofitting IoT technologies. IoT devices can therefore not be fitted according to a standardised architecture, thus driving up consultation and labour costs during installation. (Paul, 2018)
Software tools and system development	The purpose of software implementation must be to provide processes data in a fast and scalable manner (Barton, Maturana, Tilbury, 2018). Enterprises will have the option of a centralised- vs. distributed data processing system, each of which has pros and cons. Ultimately, the SM paradigm will require IoT systems to utilise edge computing processes and cloud-based analytics to optimise the output (Cognizant, 2019). A manufacturing enterprise will have multiple use cases for IoT, each of which will present a unique challenge to solve and optimise. Enterprises will therefore have to budget for a system designer who will design and help implement a software solution. It is vital that enterprises implement IoT devices with a clear strategy and overarching architecture. Unstructured implementation of IoT can create confusing and redundant data generation, which can have a serious impact on the return on investment (Barton, Maturana, Tilbury, 2018).
Data processing capability	Effective data processing requires multiple levels of processing power. Low-level control processing can happen at the machine level while higher-level processing must happen elsewhere. The highest energy consumption is associated with data-transfer and not data-storage, therefore, an ideal system will utilise smart sensors to do data processing at machine level (Yin, Wang and Jha, 2018). The introduction of edge-device computing can also help regulate the flow of data to ensure only useful data is transferred, however, as with all the IoT innovations the cost trade off must be considered (Saqlain et al., 2019). Lastly, most enterprises will move towards cloud-based processing and storge, most of which can be accessed via a subscription basis, the cost of which must be considered and re-evaluated regularly.

Figure 5-12 below serves as a visual representation of the various hardware and software considerations and how they are integrated to create an IoT control architecture.

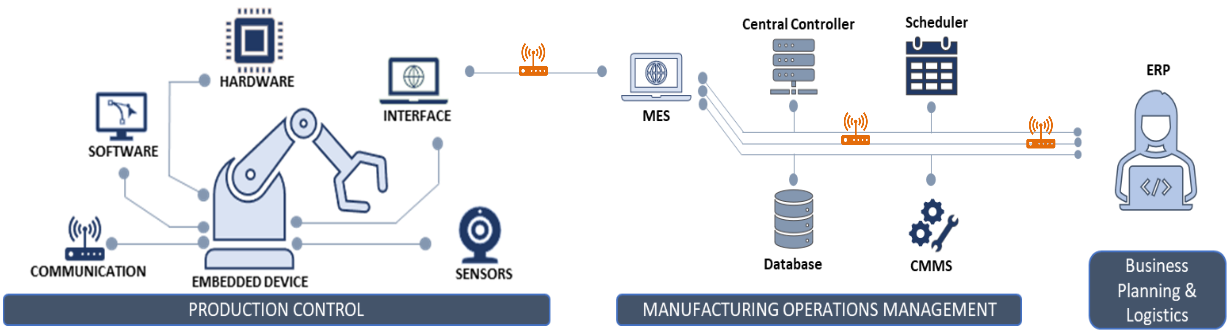


Figure 5-12: *Example of IoT control architecture with hardware and software considerations*

5.3.2 Management, operations and maintenance costs and considerations

Full integration of industry 4.0 technologies can change the traditional management and operational structures. Additionally, maintenance processes must be employed differently. If enterprises adopt industry 4.0 and SM paradigms without adjusting their traditional operational structures, subsequent clashes and misunderstandings could lead to downtime and a loss in efficiency, which would undermine the sustainability of the new project (Ghobakhloo, 2020). This section will briefly outline the various challenges and subsequent changes associated with industry 4.0 adoption that could lead to increased costs.

5.3.2.1 Management and operational challenges

A comprehensive review of Industry 4.0 published by Deloitte outlines a lack of clarity surrounding roles, rules and relationships as the main managerial hinderance associated with industry 4.0 innovation adoption (Deloitte, 2018). This lack of clarity undermines taking responsibility within the enterprise which can lead to incomplete or inaccurate work. The review explains that increased automation can create a role confusion between humans and computers, virtual bonds can weaken connectedness between workers and a shift in pace can lead to rapid rule changes which makes it more difficult to consider the potential results of decisions (Deloitte, 2018). The review then suggests introducing digital leadership that provides consistent and clear expectations from the top down. Next enterprises should think of ways to bring employees together to intentionally collaborate and lastly management should show reciprocity as a way to encourage employees to take responsibility. While these suggestions are applicable, they lack clear practical steps that management should take. Some practical steps are, however suggested by Shamim, each of which will cost money to implement successfully (Shamim et al., 2016):

a. **Investigate advantage of new organizational structures:** *The traditional hierarchical structure could be replaced by a matrix structure, team-based structure, flat hierarchy structure or decentralised structure.*

b. **Leadership style:** *An enterprises leadership style can have a massive impact on operations. It is worth investing in exploring, understanding and implementing the style best suited to your enterprise and application domain.*

c. **Human resources practices:** *It is suggested that HR practices are the primary driver of organisational change. Assessing practices such as training, staffing, compensation, performance appraisal and job design could be vital to the success of industry 4.0 innovations implementation.*

d. **Focus on short-term innovation, but long-term capabilities:** Lastly, it is suggested that enterprises should understand that the technological landscape is constantly changing, and today's innovations can become commonplace extremely quickly. It is thus beneficial to have short development periods and innovation adoption as part of a routine which fulfil a longer-term capability improvement goal. Clearly, constant innovation can be costly, and enterprises must choose wisely which innovations are worth investing in.

5.3.2.2 Maintenance considerations

One of the major advantages of industry 4.0 SM innovations such as CPN and IoT is improved asset maintenance monitoring and scheduling (i-Scoop, no date). However, the network that allows for this amazing predictive capability, must itself be maintained. As mentioned before, a system designer will design an IoT structure for each use case (Barton, Maturana, Tilbury, 2018). The cost of maintaining these structures will depend purely on the system, however, the more complex the system, the more expensive the maintenance will be. Enterprises must ensure they have the necessary expertise to maintain such a network, which then leads into the next section of this chapter.

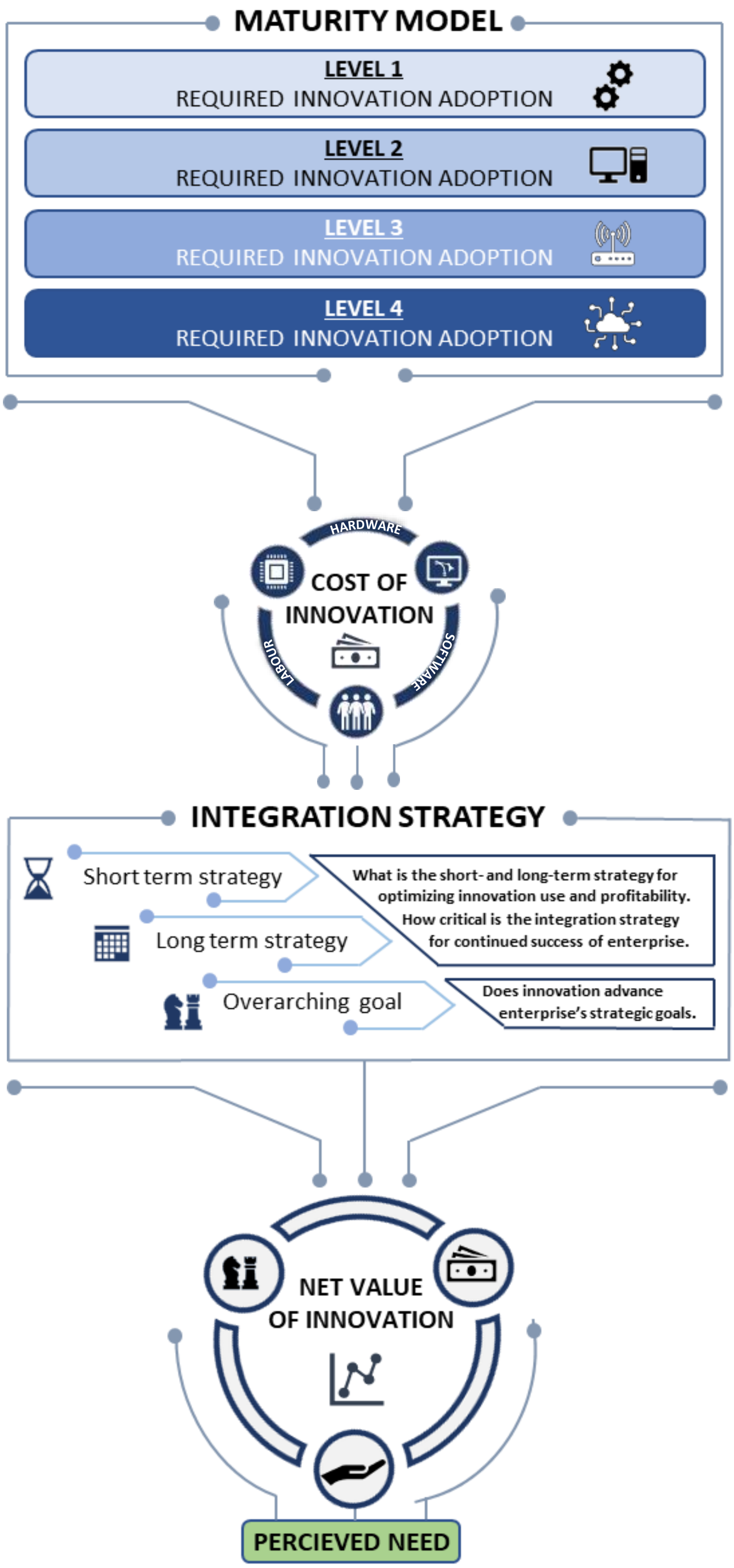
5.3.3 Human capital costs and considerations

As mentioned in the introduction of this chapter, one of the main factors that reduces ROI and ROE of innovation adoption in manufacturing SMEs is that of human capital (Corò and Volpe, 2020). The study by Corò and Vope found that early adopters of digital innovations also had to employ more highly skilled workers. A higher skilled workforce will of course cost enterprises more therefore reducing the profit gained through innovation adoption. The study concluded, however, that even though the value added by a more skilled workforce results in lower profitability in the short term, the future reinvestment of the value added by such a workforce will have a net positive effect in the long run ROI (Corò and Volpe, 2020). This hypothesis highlights the importance of anticipating a series of risk investments when adopting innovations such that the value created by the investment is reinvested rather than distributed to shareholders. The usefulness of employing skilled labour is supported by Corò and Volpe's study as most the firms they interviewed indicated a shift towards hiring skilled labour and outsourcing low-skilled tasks regardless of the firm's innovation adoption status Corò and Volpe, 2020. This leads to the conclusion that the long-term value of skilled labour, if managed and reinvested correctly, is self-evident.

The re-investment of value created by skilled labour is a key feature of industry 4.0 human capital considerations and enterprise management will have to select strategically sound skills to introduce into their workforce. It is suggested that innovation, problem solving, and dynamic/flexibility are some of the most important personality traits in the industry 4.0 paradigm. Enterprises wishing to reinvest the value of their workers to drive SM implementation will have to invest in a workforce with a high IT competency and a decent understanding of practical engineering and programming skills (Ahmad, Seman and Shamsuddin, 2019)

5.3.4 Selection process of a realistic SM maturity level aspiration

The following Figure 5-13 outlines the process that an enterprise must follow before aspiring to reach a higher SM maturity level. It is, however, crucial that enterprises identify and achieve the baseline maturity level that is associated with innovations that are critical for sustaining baseline operations.



❶ The first step is to analyze the innovation requirements for moving up the SM maturity hierarchy. In the proposed decision support tool, there are multiple toolboxes that represent various operations within a SM enterprise. To improve the maturity of these operations there are very specific innovations that must be adopted at each maturity level. It is crucial to identify the maturity level associated with innovations that are considered as critical for baseline operations. This will represent the minimum required maturity.

❷ After selecting a maturity level aspiration and accompanying innovation requirement, an enterprise must do a cost analysis of the innovation adoption. The cost analysis will be broken down into hardware costs, software costs and human capital or labor costs. The previous section of this chapter discusses various cost considerations and will serve as a helpful guide for navigating the costs associated with SM innovation adoption. This step is crucial as it will have a noticeable impact on adoption viability.

❸ How, and if, an innovation fits into the company strategy are crucial considerations for any enterprise looking to advance their operational sustainably. Enterprises must have a clear short-term strategy for effectively integrating the innovation into current operations. They must also have a long-term strategy for increasing profitability and use. Lasty, an enterprise must understand how the innovation fits into the overarching enterprise goal and vision. They must ask weather the innovation is crucial to the advancement of enterprise sustainability.

❹ The final step is to weigh the cost of the innovation against the strategic significance and expected gain. E.g. EVA and MVA analysis methods can be used for. This will provide an enterprise with the net value of an innovation and help them decide if it is worth investing in the innovation in order to achieve a higher level of internal operational maturity. As mentioned in step one, it is vital that enterprises adopt innovations that are crucial for future operational capability and sustainability. The maturity level that corresponds to the crucial innovation is the **baseline maturity.**

Figure 5-13: *Process for selecting a realistic internal operation maturity level to aspire towards*

5.4 Summary of chapter 5

Chapter 5 represents the first refinement step of the decision support tool, and the significance of the chapter is explained extensively in the previous section of the chapter. However, the purpose of Chapter 5 can be summarised as: The literature refinement process allowed the researcher to refine, adapt and improve the existing theoretical models that were selected for use in the proposed decision support tool, by investigating the applicability of the models' details with regards to the application context of this project. The literature refinement step satisfies the relevance, rigor and design cycle requirements of the DSRM.

The chapter found that only Phase 2 and Phase 4 of the proposed tool had to be refined through literature analysis, however, the purely qualitative nature of Phase 2 (LVoD) proved to be difficult to refine through literature as qualitative work can generally be supported by a variety of opinions with no objective basis from which to judge the validity. Phase 4 of the tool, however, utilised data-driven descriptors to estimate maturity, which is much easier to validate from literature. Subsequently, most of the chapter focussed on refining the details of Phase 4 through literature analysis. Multiple changes were made based on the newly acquired literature and these changes are presented throughout the chapter.

Finally, Chapter 5 introduced the reader to the concept of innovation adoption risk vs reward. Throughout the literature refinement stage, the researcher found some stringent innovation adoption requirements with regards to SM maturity improvement. Upon further investigation, the researcher found that many SM innovations could improve maturity but is extremely costly. It, therefore, became relevant to investigate and explain the costs involved in improving the maturity of an enterprise's operations and, subsequently, provide the reader with an easy-to-use tool to estimate the possible risk and reward of adoption new innovations in the pursuit of improved maturity.

Chapter 6: Refinement Through Action Research

This chapter forms part of the second design cycle and deals specifically with the action research refinement process as shown in Figure 6-1. The purpose of the action research phase is to refine the tool by conducting interviews with industry/subject matter experts. The experts can provide insights about the details of the tool in terms of relevance, difficulty of implementation and overall applicability. The action research phase is a critical step in the DSR process followed in this thesis to tailor the tool to fit the application context of the thesis. While literature analysis provides a strong basis on which to build the tool, it lacks the rigor provided by expert interviews, thereby justifying the inclusion of an action research step.

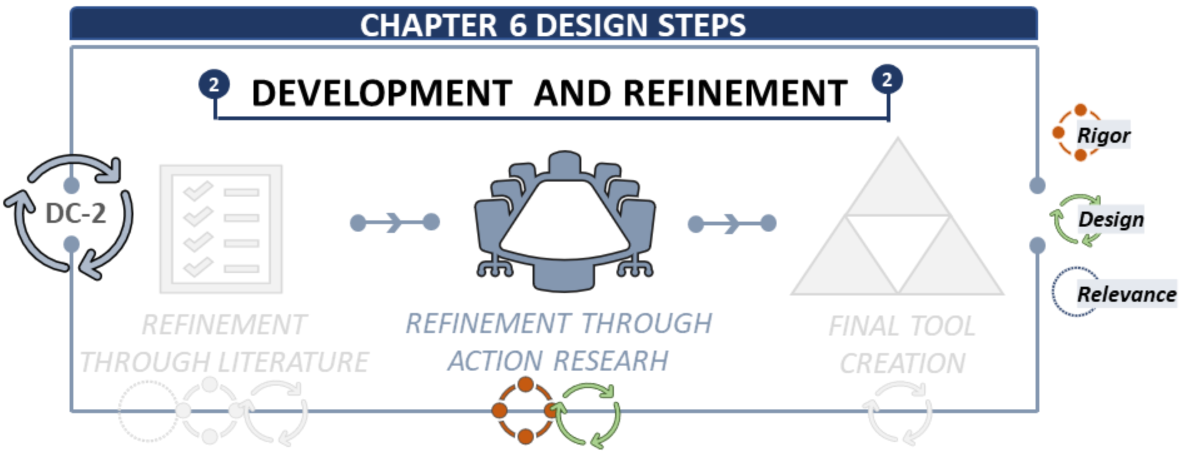


Figure 6-1: *Design steps completed in Chapter 6*

In these interviews the experts were guided through the initial support tool and asked to rate various dimensions and elements of the tool according to predetermined criteria. Following the ratings, a qualitative discussion was held with each interviewee.

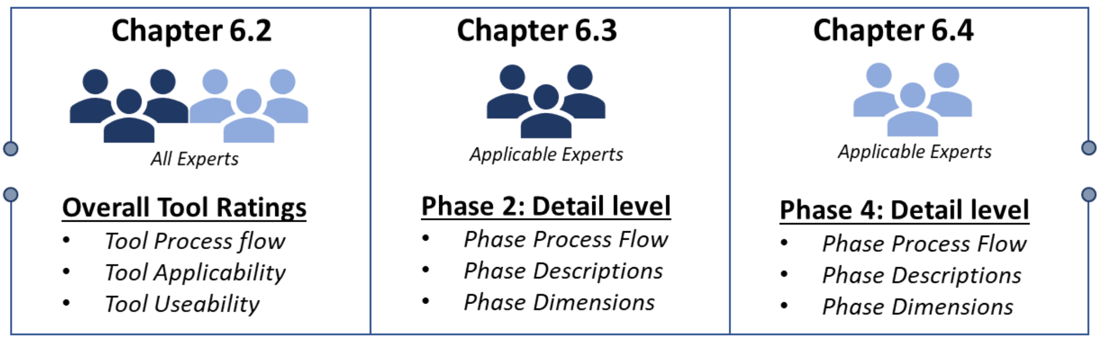


Figure 6-2: *Action research activities and presentation of results*

First, the overall tool relevance, need and difficulty of implementation results is discussed. Next, the detailed results of the action research phase are presented for two of the four phases of the decision support tool. Not all the interviewees were asked to do a detailed review of all four phases, as experts were interviewed based on their area of expertise to ensure only valuable inputs are recorded. Lastly, the results for the MTRL (Phase 1) and TRRA (Phase 2) is only presented in section 6.1, the overall rating result section, as the quantitative nature of these phases did not require much detailed level action research analysis. The LVoD (Phase 2) and SM^{3}E (Phase 4) phases is, however, explored further in separate sub-sections as both these phases have intricate qualitative details that were analysed by experts.

6.1 Action Research Inputs, Variables and Outputs

This section outlines the process requirements that were followed in the interviews and data collection procedures. The interviews were split into a quantitative and qualitative stage. The quantitative stage focussed on rating the various aspects of the decision support tool's dimensions and functions according to predefined rating metrics, such as relevance and difficulty of implementation. These quantitative ratings allow for detailed visual representation of data and is a useful analysis tool. The ratings can, however, be somewhat restrictive in terms of feedback since they only function within discrete rating ranges. To counteract this problem, the interviewees were engaged through a qualitative feedback session where they could freely discuss their thoughts and ideas on the tool.

6.1.1 Quantitative interview inputs

The final interview questions can be viewed in Appendix B. The questions were developed according to the fowling outlines: The question should be stated in a way that allows for a quantitatively rated answer with a focus on both relevance and difficulty of implementation of the theoretical model dimensions, criteria and overall application. A set of questions is created to analyse the relevance of the dimensions for each individual theoretical model contained in the support tool. A different set of questions is developed to analyse the usefulness and relevance of the overarching process flow of the tool. Lastly, a set of questions surrounding the difficulty of implementation is developed. The difficulty of implementation relates to how difficult it is to understand and implement certain aspects of the tool.

The seven experts that were interviewed are summarised in the table below. For the purpose of visual representation, the titles of the industry/subject matter experts were abbreviated as shown in the following table. These abbreviations were used on all subsequent graphs and charts. Table 6-1 below also shows which of the eligibility criteria, as determined in the following section 6.1.1.1, the various experts fulfil. A more detailed breakdown of the interviewee's expertise can be seen in Appendix B.1.

Table 6-1: *Abbreviation legend for industry/subject matter expert title*

Subject matter/Industry Expert	**Abbreviation**	**Eligibility Criteria**
Additive Manufacturing PhD	AdM_PHD	(b) (d)
Additive Manufacturing (Cemented Carbide) Specialist/PhD	AdM_S	(d)
Asset Management and Manufacturing Expert	AM&M	(a) (c)
Business Intelligence Engineer	BIE	(a) (c)
Carbide Manufacturing and Distribution Expert	CM&D	(b) (c)
Management Consulting and Manufacturing Expert	MC&M	(a) (b) (d)
Digital Transformation in Manufacturing Expert	DTM	(a) (c) (d)

The seven experts that were selected cover a large area of expertise which allows for the analysis of every aspect of the decision support tool. While most of the experts are knowledgeable in a wide variety of subjects relating to manufacturing technologies and the decision support tool, some have their speciality rooted in fields specific to select areas of the tool. Therefore, not all the experts were expected to analyse and rate each phase of the tool on a detailed level but were rather asked to focus their detail feedback on their area of expertise, while providing higher-level feedback for the other phases.

6.1.1.1 Selection of experts

The expert identification process must be designed in a way that allows for a wide variety of opinions and expertise in order to develop a holistic view of the tool's application domain. Experts should be identified in the following areas of expertise and the corresponding eligibility criteria is summarised in Table 6-2:

a. Theoretical modelling with a focus on maturity and readiness

b. Manufacturing enterprises and enterprise requirements

c. SM innovation adoption and integration

d. Advanced manufacturing adoption

Table 6-2: *Eligibility criteria for expert identification*

	Interviewee Area of Expertise			
	(a)	(b)	(c)	(d)
Eligibility Criteria	The interviewees should understand the general process of developing theoretical models.	The interviewees should have knowledge of the manufacturing industry in South Africa.	The interviewees should have a detailed understanding of SM paradigms and associated SM innovations.	At least one interviewee should have extensive knowledge of advanced manufacturing adoption in manufacturing enterprises.
	At least one of the interviewees should have extensive knowledge specific to maturity and readiness models.	At least one of the interviewees should have practical experience within a manufacturing SME.	At least one interviewee should have extensive industry knowledge of practical SM integration.	Interviewees should have knowledge of the obstacles surrounding novel manufacturing technology adoption.
	The interviewees should have knowledge of the practical application of maturity and readiness models.	-	-	-

6.1.1.2 Action research variables

In an attempt to quantify the interviewees' qualitative opinions of the various aspects of the tool, certain characteristics of the tool had to be rated according to a 0 to 4 scale. These characteristics are called "action research variables" throughout this thesis. Table 6-3 below shows the variables that were identified for use during the action research phase. The rating legend for each of the variables is also discussed in this section.

Table 6-3: *Action research variables*

Variable	**Description**
Relevance (R)	This variable investigates the how relevant a specific dimension, description or phase is in terms of decision support within the application context of this thesis. In layman's terms the relevance variable describes the usefulness of incorporating and understanding an element into the proposed decision support tool.
Difficulty of Implementation (DoI)	This variable investigates the perceived effort required to understand and correctly implement an element of the tool. The rating of this variable is generally determined by the required level of expertise to accurately interpreted and use an element.
Need for tool (N)	This variable is used to estimate the perceived need for the decision support tool developed in this thesis.
Need addressed by tool (NAT)	This variable investigates how well the proposed tool addresses the need associated with the research gap.
Overall tool rating (O)	This is a percentage value which rates the experts' overall impression of the tool in terms of the theoretical value it contributes to bridging the research gap.

The "Relevance (R)" of the dimensions was rated from 0 to 4 based on the following descriptions for the levels shown in Table 6-4 below:

Table 6-4: *Relevance (R) rating legend*

Quantitative Relevance (R) Rating	**Corresponding Qualitative Description**
0	No relevance to the application context.
1	Relevant only for highly limited and specific use cases.
2	Relevant for some use cases but limited in overall applicability.
3	Good relevance to application context. Useful for performing quality analysis.
4	Excellent relevance to application context and basic requirement to perform a trusted and quality analysis.

The "difficulty of implementation (DoI)" of the tool process, or specific dimensions contained in the tool, was rated from 0 to 4 based on the descriptions for the levels shown in Table 6-5 below:

Table 6-5: *Difficulty of implementation (DoI) rating legend*

Quantitative DoI Rating	**Corresponding Qualitative Description**
0	Extremely easy to implement even for a person with no knowledge of application context
1	Easy to implement for most. Requires some very basic technical knowledge but can be implemented via contextual understanding and logic only.
2	Can be implemented by someone with basic technical knowledge along with and understanding of the application domain.
3	Difficult to implement. User must have decent technical understanding of both the technology and the industry requirements. Industry experience will most likely be required.
4	Extremely difficult to implement. User must have specialised knowledge of the technology and industry with a good grasp of the application context and industry needs.

The "Need (N)" variable was rated according to the following descriptions shown in Table 6-6:

Table 6-6: *Need (N) for tool rating legend*

Quantitative Need (N) Rating	**Corresponding Qualitative Description**
0	No need for such a tool
1	Need is scientifically interesting, but there is very little applicable need.
2	There is a some need for such a tool.
3	There is a strong need for such a tool.
4	It is critical for the industry that such a tool is developed.

Next, the degree to which the proposed decision support tool addresses the need discussed in the research gap, was measured using the following descriptions in Table 6-7:

Table 6-7: *Addressed need (NAT) rating legend*

Quantitative Need Addressed (NAT) Rating	**Corresponding Qualitative Description**
0	Tool fails to address the needs expressed
1	Tool is scientifically interesting but has very little industry applicability.
2	The tool addresses the basic need but can be refined in all areas to fit industry needs.
3	The tool successfully addresses most of the need but can be refined in some areas to fit practical industry needs.

4	The tool addresses the need successfully with little to no refinement required.

6.1.2 Qualitative interview inputs

The qualitative section of the interview is less structured than the quantitative section. This is by design as it is necessary to provide the interviewees with a free-form discussion opportunity in order to express their opinions properly. That being said, it is important to maintain some structure in the interview process and to ensure that the interviews fulfil all ethical clearance requirements, the following interview guidelines shown in Table 6-8 were set up:

Table 6-8: *Qualitative interview guideline*

Interview Guidelines	**Description**
Guideline 1	Participant may be asked to clarify statements made during the qualitative comment section of the questionnaire. Participants may refuse to further clarify any statements.
Guideline 2	Participants may be asked to divulge their opinion on the use and application of the tool. This opinion will not be linked to them directly and they may refuse to give their opinion.
Guideline 3	Participants may be asked to discuss the areas of the tool they believe should change. This allows them a more detailed expansion of their thoughts on specific issues. Participant may refuse to share their thoughts.
Guideline 4	Participant may be asked to clarify the reasoning behind their quantitative ratings of the questionnaire. Participant may refuse to clarify.
Guideline 5	The interviewer must avoid guiding the interviewee to a desired answer. The interviewer is allowed to clarify certain dimensions or statements but must not pose leading questions.

While keeping in accordance with the above guidelines, interviewees were asked to clarify their ratings or provide an opinion in the following scenarios shown in Table 6-9:

Table 6-9: *Qualitative discussion scenarios*

Scenario	**Description**
Scenario 1:	Interviewee is not satisfied with a dimensions relevance or need. Interviewee must then clarify why and how it can be improved.
Scenario 2:	Interviewee is not satisfied with a description. Interviewee must clarify why and try and improve the description.

Scenario 3:	Interviewee is satisfied with the dimensions and descriptions but would like to add something. An open-ended discussion will be held.

6.2 Overall Decision Support Tool Rating Results

This section shows the rating results for the decision support tool as a whole. It investigates the perceived need for such a tool, how well the tool addresses this need along with the difficulty of implementation and applicability scores provided by various experts. It will also summarise some qualitative comments surrounding the tool's use

6.2.1 Overall tool Need (N) vs Addressed Need (NAT)

This section discusses the interviewees' response to their perceived need for a decision support tool such as the one created for this thesis, for addressing the proposed research gap in the manufacturing industry, vs the degree to which the tool successfully addresses the perceived need. The responses of the interviewees are summarized in the spider graph in Figure 6-3 below and shows the rating given by the interviewees based on the rating criteria defined in the previous section.

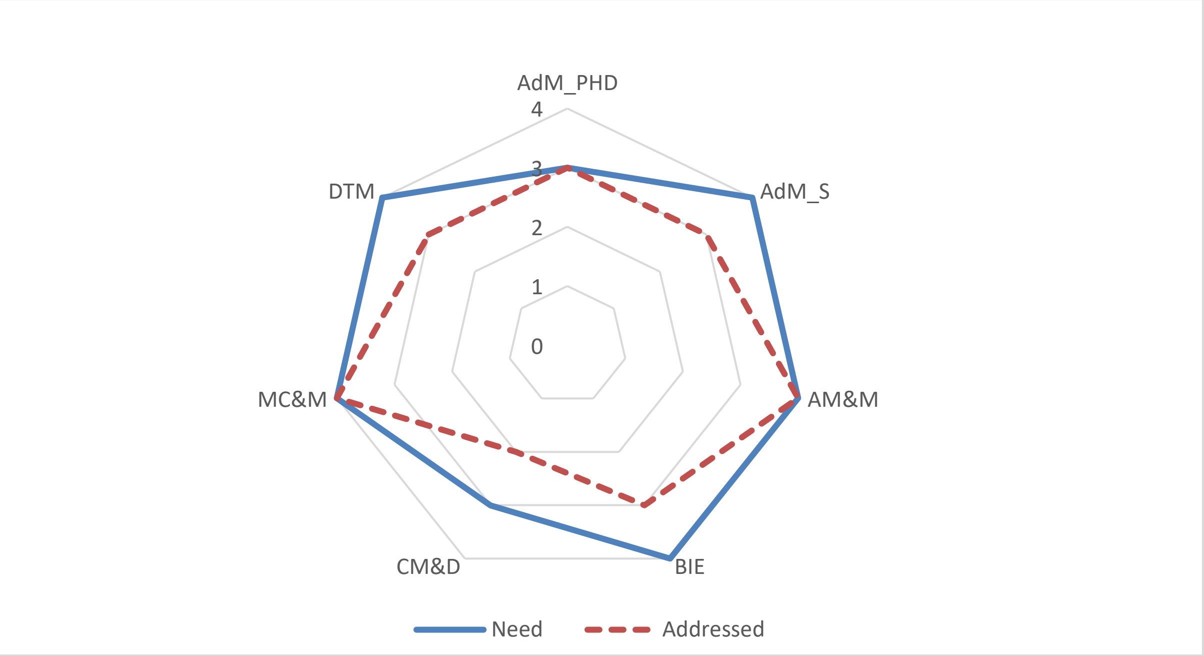


Figure 6-3: *Overall tool Need (N) vs Need Addressed (NAT) Spider Graph*

Figure 6-3 above shows that the interviewees believed the need for developing a tool such as this one to address the proposed research gap is between 'Strong" and "Critical". The general consensus is that the tool addressed the need successfully, however, some experts were of the opinions that, while the tool is still applicable, some refinement was required.

The box plot in Figure 6-4 below shows that there is an overlap between the *Need* and *NAT*, which would suggest that the tool successfully addressed the need for a tool, however, it seems that the *NAT* is skewed towards the lower end compared to the *Need*, which could suggest that some slight adjustments must be made to the tool to ensure that the tool fully addresses the need. The box plot also shows that the *NAT* rating with a value of 2 is considered to be an outlier within the dataset, which is to say it falls outside 1.5 times the inter quartile range (IQR), meaning that it's importance is reduced for the analysis of the result.

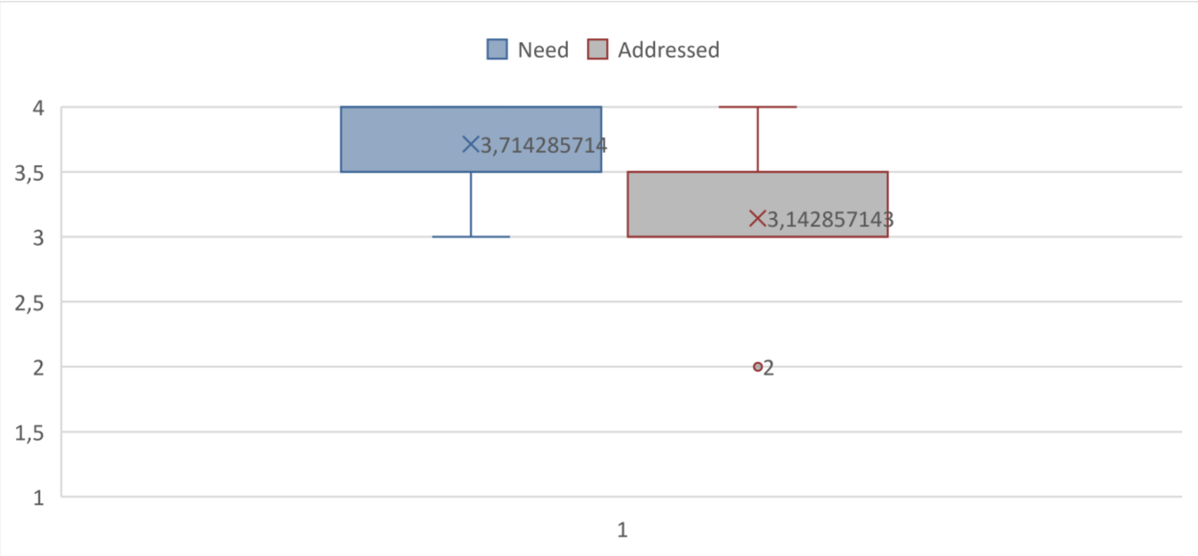


Figure 6-4: *Overall tool Need (N) vs Need Addressed (NAT) Box Plot*

6.2.2 Overall phase Relevance (R) vs Difficulty of Implementation (DoI)

The next metric that was used to determine the overall applicability of the tool, was the comparison between the *Relevance (R)* of each phase of the tool, to how difficult it is to implement/use (*DoI*) that phase. If a phase is extremely difficult to implement while having little relevance to the application context, as would be represented by the upper left quadrant of a 2x2 matrix such as the one in the graph of Figure 6-5 below, then that phase must be excluded from the support tool. The graph of Figure 6-5 below summarises the responses of the interviewees, where each data point represents the average of their ratings for that phase.

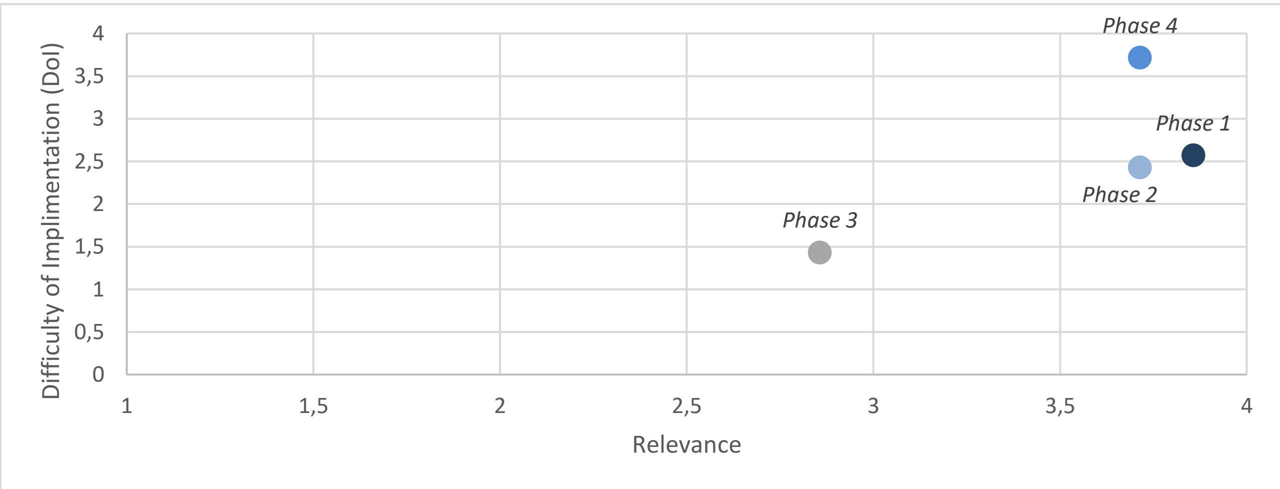


Figure 6-5: *Average Relevance (R) vs Difficulty of Implementation (DoI) per Phase*

From Figure 6-5 above, Phase 1 and Phase 2 is at the preferred position in the matrix, where they have a high *Relevance* rating with a comparatively lower *DoI* rating. This ensures the continued inclusion of these phases in the support tool. Phase 4 has the same *Relevance* and *DoI* score, with both considered to be high. The high relevance score supports the continued inclusion of the phase; however, some investigation was done into making the phase easier to implement. Lastly, Phase 3 has a lower *Relevance* score compared to the other phases. The *Relevance* score is, however, still in the upper quadrant of the matrix and the comparatively low *DoI* score implies that the phase is eligible for continued use in the support tool.

Since the experts' ratings are dependent on discrete ranges with a qualitative correlation, it is insufficient to investigate only the average score per phase as these averages are not necessarily representative of the qualitative range the interviewee was trying to select. By drawing a box plot of the *Relevance* and *DoI* for each of the four phases, it is possible to create a clearer overview and understanding of the distribution of responses per phase. The reason for this is that the box plot shows the highest rating, lowest rating, IQR and mean rating for *Relevance* and *DoI* of each phase. This creates a visual representation of the data distribution and skewed elements. The box plot is shown in Figure 6-6 below.

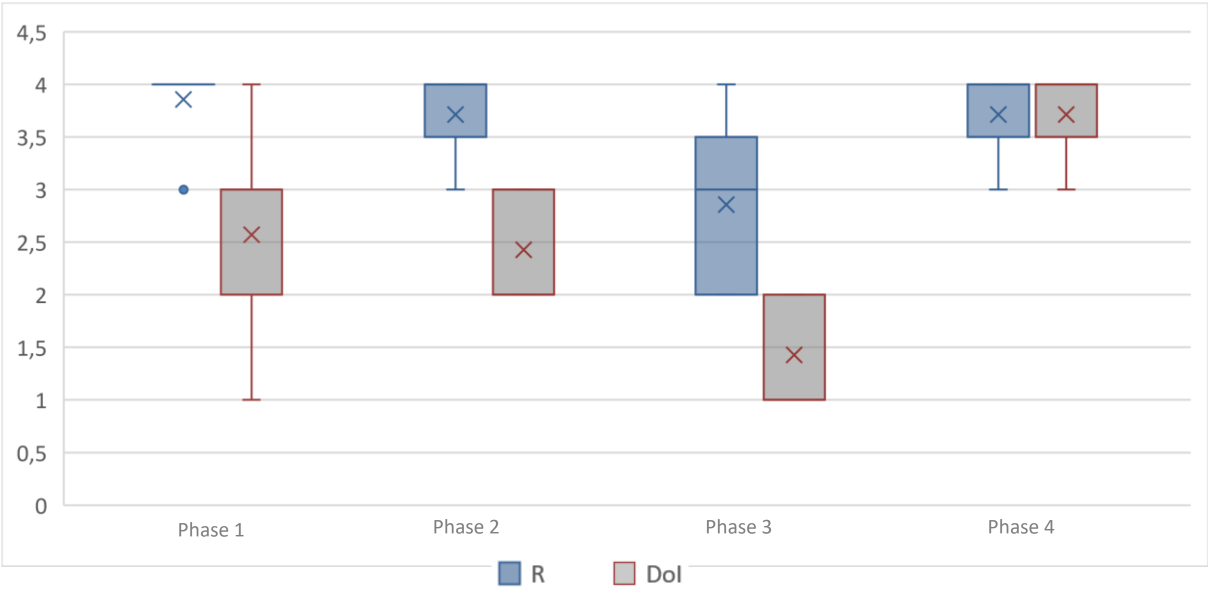


Figure 6-6: *Box plot of Relevance vs DoI per Phase of Tool*

The box plot in Figure 6-6 above can be used to compare the responses across the tool's phases. Most noticeably the plot shows that the *DoI* of Phase 1 and the *Relevance* of Phase 3 have comparative large variability in responses. The *DoI* ratings of Phase 1 varies between values of a low 1 and a high 4. This could be attributed to how the expert interpreted the implementation method and knowledge requirements to use Phase 1. The low *DoI* rating of Phase 1 is predicated on the belief that it will be easy to acquire the necessary information in order to select the correct inputs, while the high *DoI* rating value of 4 assumes that expert knowledge will be needed to implement the phase successfully. Considering that Phase 1 represents the estimated time to readiness section of the tool, the variability in responses is reflective of the notion that this phase is highly dependent on the technology type and application context to complete an analysis. The responses of the interviewees will therefore differ depending on their background, expertise and understanding of the application context.

Next the response range for *Relevance* of Phase 3 can be addressed. The ratings for this phase ranged from a value of 2 to a value of 4. From the data it seems that the interviewees with a background in consulting and business intelligence seemed to rate *Relevance* of Phase 3, the risk analysis phase, quite high. Conversely, the interviewees with a practical industry application background seemed to rate the *Relevance* of Phase 3 lower. Through qualitative investigation, the practically orientated experts revealed that they believed Phase 3 to be important for decision making, however, in its current form, some dimensions lacked the intricate details that are required for in-depth practical analysis. The consulting and business orientated interviewees on the other hand, believed the phase to be extremely important for decision making even though it lacked some detail. They believed Phase 3 had a strong relevance for baselining of consulting clients and can help guide decision making by highlighting key risk considerations.

6.2.3 Overall tool score

The overall tool score is a percentage score that provide the interviewees with an opportunity to give a more open-ended score of their overall impression of the research and practical value of the tool. The idea is that the percentage score allows the interviewee to break free from the restricting discrete 0 to 4 rating system to help them express their impression of the tool more accurately. To guide their understanding of the following percentage points were used as a benchmark. The legend in table 6-10 below does not specify specific qualitative ranges but merely serves as a way for the interviewee to evaluate their rating.

Table 6-10: *Overall tool score percentage benchmarks*

Percentage	**Associated qualitative description**
<45%	The tool fails at its purpose and the research contribution is negligible.
50%	Research contribution and tool application is somewhat relevant but not significant. Multiple additions and iterations need to be done in order to achieve a realistic and meaningful tool.
75%	Significant research contribution is made, and tool delivers its base purpose while introducing useful additional functionalities. Some practical application is immediately available, but some refinement is required before tool is fully industry ready.

Keeping the benchmark descriptions in mind, the interviewees was given the chance to score the tool. The result of their score in summarised in the bar graph of Figure 6-7 below, with the average of their scores being 76.7%.

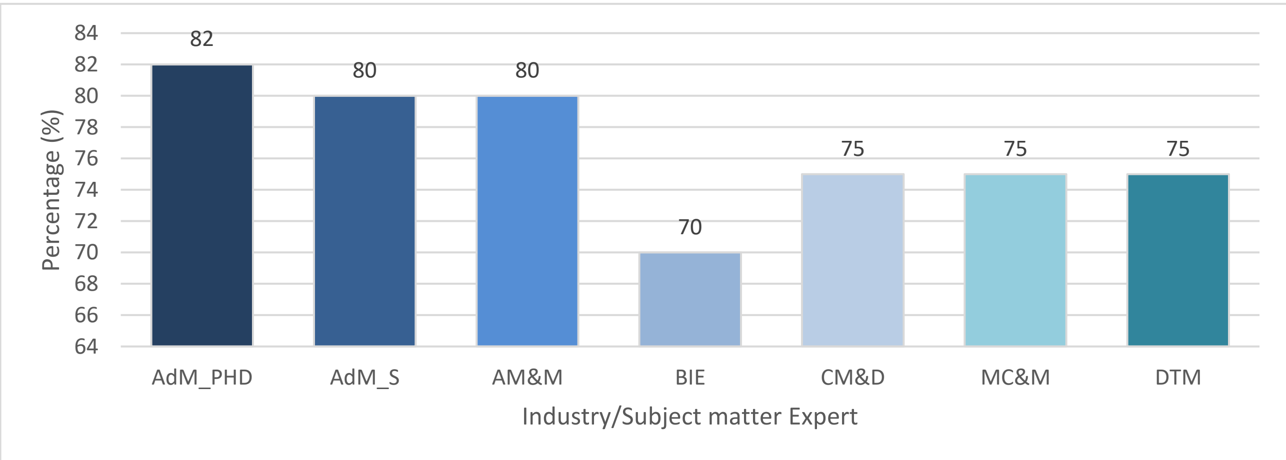


Figure 6-7: *Overall tool score results*

6.2.4 Summary of overall decision support tool rating results

Based on the overall responses, it can be concluded that the tool successfully identified and addressed the need created by the research gap. This sentiment is reflected by the *Need* and *NAT* of the tool, with all the interviewees scoring both these variables between 3 and 4. The spider graph and box plots of *Need* vs *NAT* does, however, show that *NAT* tends to lag slightly behind *Need*. This implies that the tool could undergo some refinement to fully match the required need, however, from the description of a 3 score, these refinements are only required in certain areas, and not the entire tool.

The inclusion of the four theoretical models selected in Chapter 3, and the subsequent inclusion of the four phases of the support tool, is justified by the *Relevance* vs *DoI* ratings. All the phases excluding phase 3 scored a *Relevance* of 3 or higher. While the responses of the third phase's *Relevance* had the most variation, its average relevance score of 2.8 is still high enough to justify its inclusion. This argument is enforced by the fact that the third phase had the lowest *DoI* score, therefore, making it a quick and easy-to-use phase with decent *Relevance*. The high *DoI* score of Phase 4 does warrant some investigation and improvement of the phase application process, however, given Phase 4's high *Relevance* score, it is crucial to include it in the tool. It should also be considered that, while the tool was designed to be a self-assessment instrument, it tries to incorporate detailed elements of technology acquisition and operational analysis. It can therefore be expected that the implementation of the tool will have some complexity and require prior industry knowledge.

Finally, the overall tool score is an average of 76.7%. This corresponds with the belief from the industry/subject matter exerts that the tool makes a significant research contribution and delivers on its base purpose while introducing additional functionalities.

6.3 Phase 2: Detail Level Tool Rating Results

The previous section showed that, while the tool scored high in *Relevance* and *NAT*, it did not score a perfect 4. This implies that the tool still requires some refinement before reaching full practical implementation capability. In an attempt to identify the elements that need refinement, a detailed level assessment and rating of the tool dimensions and sub-elements was done with the industry/subject matter experts. As explained in the previous section, only Phase 2 and Phase 4 were analysed on a detailed level and only the interviewees with expertise in the specific application domain of these two phases were asked to provide feedback on a detailed level. For Phase 2, the following experts, shown in Table 6-11, were asked to provide responses:

Table 6-11: *Phase 2 Subject matter/Industry Experts Interviewed*

Phase 2: Subject matter/Industry Expert	**Abbreviation**
Additive Manufacturing PhD	AdM_PHD
Additive Manufacturing (cemented carbide) Specialist/PhD	AdM_S
Asset Management and Manufacturing Expert	AM&M
Carbide Manufacturing and Distribution Expert	CM&D
Management Consulting and Manufacturing Expert	MC&M
Digital Transformation in Manufacturing Expert	DTM

The interviewees were asked to first rate the *Relevance* of the sub-dimensions for each of the three main dimensions of the Phase 2 tool. Thereafter, they were asked to investigate the descriptors and rate the overall *Relevance* of each sub-dimension's descriptors. This process is shown in Figure 6-8. After the rating the interviewees were asked to expand on their thoughts about the dimensions and possible additions to the phase.

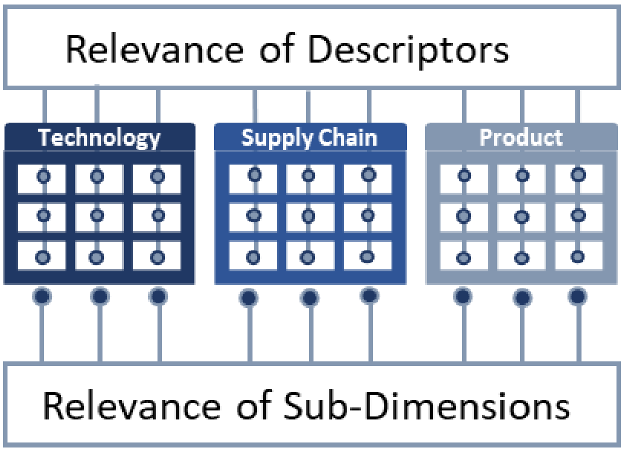


Figure 6-8: *Analysis process for Phase 2 detail level relevance*

6.3.1 Technology dimension rating results

The *Technology* main dimension of Phase 2 consists of five sub-dimensions. The interviewees were asked to rate the *Relevance* of these five dimensions along with the *Relevance* of the descriptors. They were also asked comment on any change or additions that must be made. The rating results is summarised in the figures below.

6.3.1.1 Technology sub-dimension relevance rating

Figure 6-9 below shows a box plot of the relevance ratings per sub-dimension element of the *Technology* main dimension:

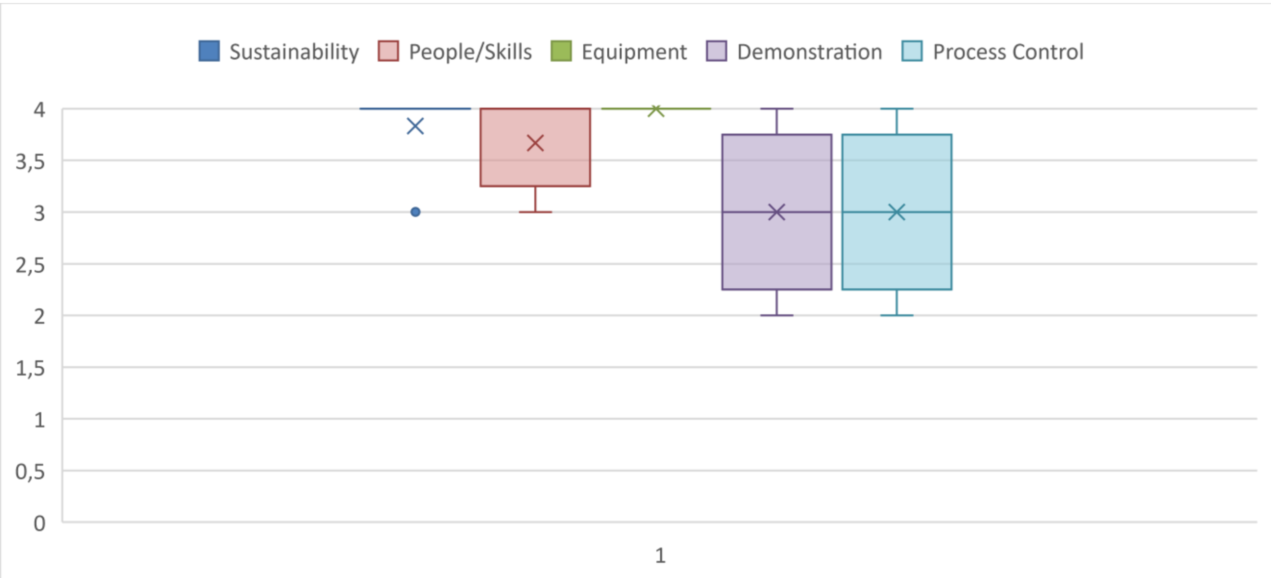


Figure 6-9: *Technology sub-dimension Relevance (R) rating results*

From Figure 6-9 above, it can be concluded that the *Demonstration* and *Process Control* had the most variability in responses along with the lowest overall *Relevance* rating. To understand why *Demonstration* and *Process Control* were rated lower, the qualitative responses are summarised in Table 6-12 below:

Table 6-12: *Technology sub-dimension qualitative comments summary*

Expert	Demonstration Comments	Process Control Comments
AdM_PHD	N/A	Process control should be continuous improvement.
AdM_S	N/A	Process control depends on use case.
AM&M	Demonstration depends on early adoption.	N/A
CM&D	Demonstration depends on early adoption. Not as critical as the other dimensions	Process control is a very broad term. It could be implicit in Demonstration.
MC&M and DTM	Demonstration is important; however, it can be done in terms of simulation.	Process control is important for confidence in adoption and is critical for OEE.

For *Demonstration*, the interviewees seemed to justify a lower *Relevance* rating, by suggesting that the purpose of early adoption is to exploit a technology before full demonstration capability is reached in the industry. While using a technology with a low demonstration maturity is risky, it could be beneficial to adopt the technology before full demonstration capability is reached. While the relevance of demonstration for early adopters were lower, the interviewees agreed that the *Demonstration* sub-dimension should at least be considered before adoption to ensure it fits within the enterprise's adoption risk profile. An interesting comment that should be considered is that not all demonstration requirements are physical, and that some demonstration can be done through simulation.

The comments on the *Process Control* rating were varied. While most interviewees agreed that process control is extremely important within an enterprise, some had to lower the *Relevance* rating for this sub-dimension due to the contextual ambiguity within the tool. One expert believed *Process Control* could be implicit in the *Demonstration* dimension, while another felt process control is a continuous improvement activity that cannot be rated effectively on a five-level maturity model. The key take-away from the discussions about the *Process Control* sub-dimension was to reduce ambiguity by better defining the sub-dimension in terms of activities and processes.

6.3.1.2 Technology sub-dimension descriptors relevance rating

Next the interviewees were asked to read the descriptors from level 0 maturity to level 4 maturity of each sub-dimension. They were then asked to give a single *Relevance* rating per sub-dimension for the descriptors. This rating serves as a way to quantify the clarity and logical progression of the descriptors as the user moves through the maturity levels. The results are summarised in Figure 6-10 below:

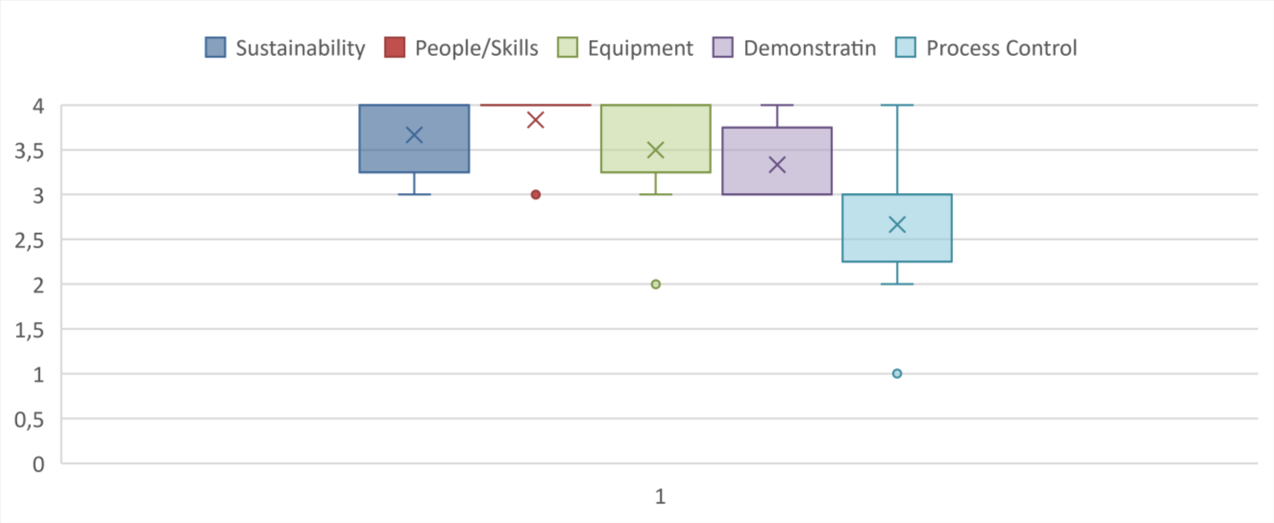


Figure 6-10: *Technology sub-dimension descriptor Relevance (R) rating results*

From Figure 6-10 above it can be concluded that the descriptors of the various sub-dimensions, excluding *Process Control*, were satisfactory, with only minor changes required. The variability in responses for the *Relevance* of the *Process Control* descriptors, corresponds with the variability discussed in the previous section. The qualitative responses of the interviewees are summarised in Table 6-13 below and can be used to identify how the descriptors of the *Process control* sub-dimension can be improved:

Table 6-13: *Technology sub-dimension qualitative comments on description relevance*

Expert	**Equipment Descriptors Comments**	**Process Control Descriptors Comments**
AdM_PHD	Consider adding an "in house" requirement for equipment lvl 4.	Include continuous improvement requirements for the descriptors.
AdM_S	N/A	Too vague. Include specific activities.
AM&M	N/A	Add details.

First, the outlier rating of the *Equipment* sub-dimension descriptor is explained by the comment in Table 6-13 above. The interviewee believed that at a level 4 maturity there should be a “in-house” requirement. This implies that the required equipment needs can be met through in-house processes which will lead to further independency.

Next, the *Process Control* descriptors were accused of being too vague or lacking actionable activities to investigate. One expert requested the inclusion of continuous improvement requirements as a metric of process control maturity.

6.3.2 Supply Chain dimension rating results

The *Supply Chain* main dimension of Phase 2 consists of six sub-dimensions. The interviewees were asked to rate the *Relevance* of these six dimensions along with the *Relevance* of the descriptors. They were also asked to comment on any changes or additions that had to be made. The rating results is summarised in the various figures below.

6.3.2.3 Supply Chain sub-dimension relevance rating

Figure 6-11 below shows a box plot of the relevance ratings per sub-dimension element of the *Supply Chain* main dimension:

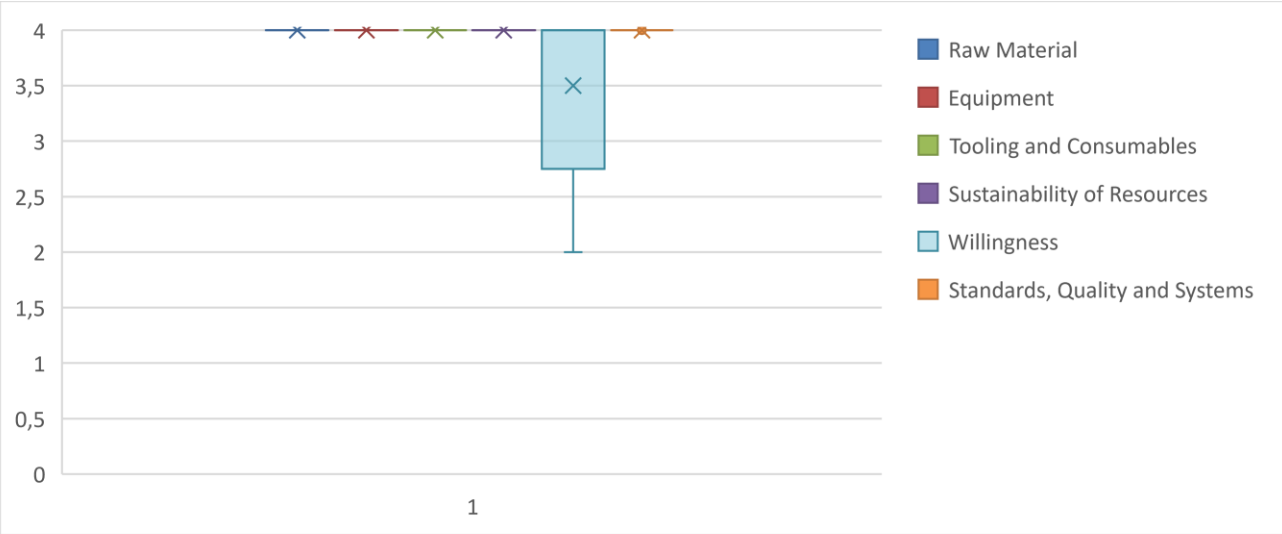


Figure 6-11: *Supply Chain sub-dimension descriptor Relevance (R) rating results*

From Figure 6-11 above it is clear that analysing specific supply chain elements is extremely relevant. The only sub-dimension which had a variable response was *Willingness*. The lower rating is a result of the expert believing that willingness of suppliers is implicit in the other *Supply Chain* sub-dimensions and that a high level of maturity in the other sub-dimensions would automatically mean a high level of supplier willingness. This theory was, however, dispelled by the additive manufacturing experts, who mentioned that in an international market, such as the case with AM, suppliers who have full operational capability can choose not to supply to a country if the market in that country is too small. This would then be an example of a supply chain being mature, but willingness to supply being low.

6.3.2.4 Supply Chain sub-dimension descriptor relevance rating

Next the interviewees were asked to read the descriptors from level 0 maturity to level 4 maturity of each sub-dimension. They were then asked to give a single *Relevance* rating per sub-dimension for the descriptors. The results are summarised in the Figure 6-12 below:

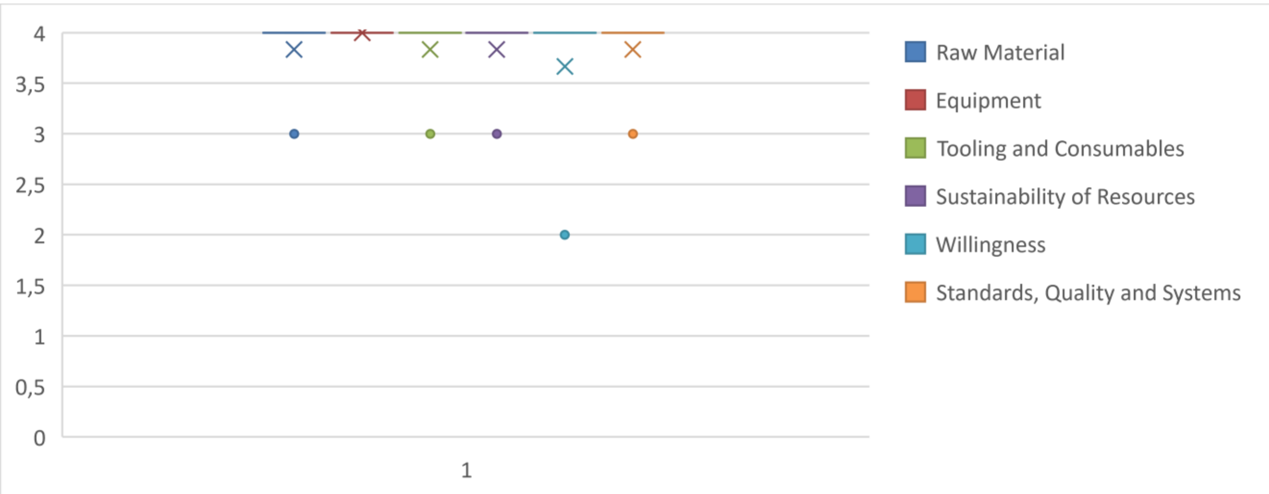


Figure 6-12: *Supply Chaim sub-dimension descriptor Relevance (R) rating results*

Figure 6-12 shows that the descriptors for the *Supply Chain* sub-dimensions are satisfactory. There are outliers for each dimension, however, the effect of the outliers is negated by the majority result and the fact that most of the outlier points are still at a high rating of 3. The outlier of the *Willingness* dimension can again be explained by the scenario described in the previous section 6.3.2.3.

6.3.3 Product dimension rating results

The *Product* main dimension of Phase 2 consists of six sub-dimensions. The interviewees were asked to rate the *Relevance* of these six dimensions along with the *Relevance* of the descriptors. They were also asked comment on any change or additions that must be made. The rating results is summarised in the various figures below.

6.3.3.1 Product sub-dimension relevance rating

Figure 6-13 below shows a box plot of the *Relevance* ratings per sub-dimension element of the *Product* main dimension.

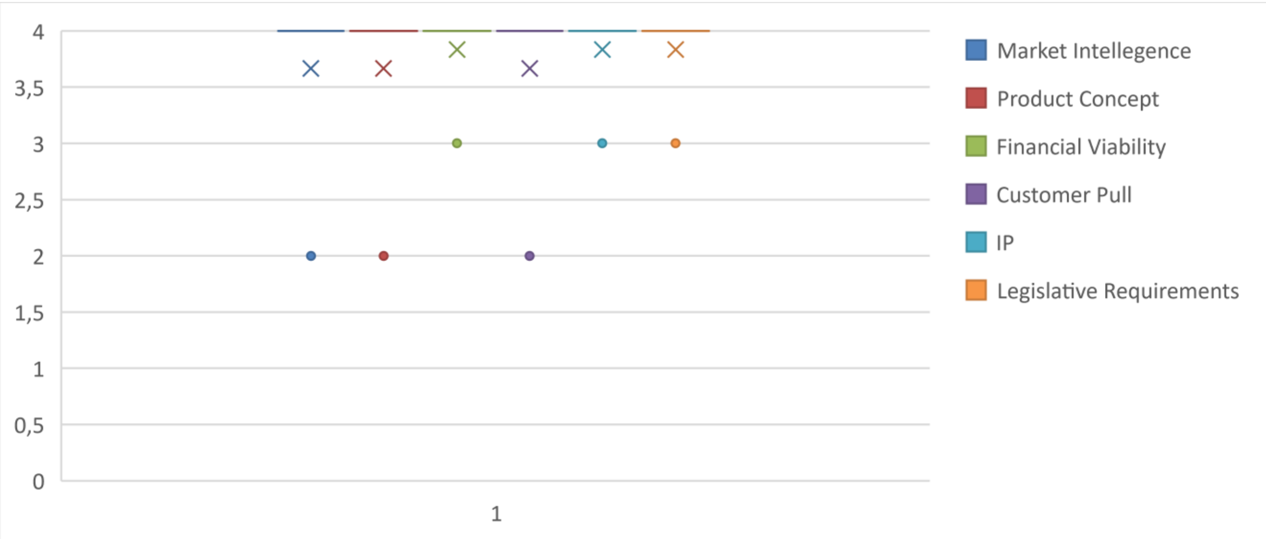


Figure 6-13: *Product sub-dimension descriptor Relevance (R) rating results*

Figure 6-13 above shows that all the sub-dimensions are extremely relevant. There are, however, outliers for each sub-dimension. The reasoning of the experts who rated the outliers is summarised in Table 6-14 below:

Table 6-14: *Product sub-dimension relevance qualitative comments*

Expert	**Product Concept Comments**	**Customer Pull Comments**	**Market Intelligence Comments**
AdM_PHD	N/A	Sub-dimension needs more context. Customer Pull is a very specific type of actor.	N/A
AM&M	With new tech there is a learning curve and to be an early adopter you don't need to fully understand product concept.	N/A	If you create a new market with novel tech then it is not so critical. Go's hand-in-hand with financial viability.

While the above comments were outliers, the application context fell directly within the area of expertise of these two interviewees. It is, therefore, worth considering their comments and including it as an additional description. These comments add an extra level of detail to the descriptors which ultimately makes the support tool a more rounded instrument.

6.3.3.2 Product sub-dimension descriptor relevance rating

Next the interviewees were asked to read the descriptors from level 0 maturity to level 4 maturity of each sub-dimension. They were then asked to give a single *Relevance* rating per sub-dimension for the descriptors. The results are summarised in Figure 6-14 below:

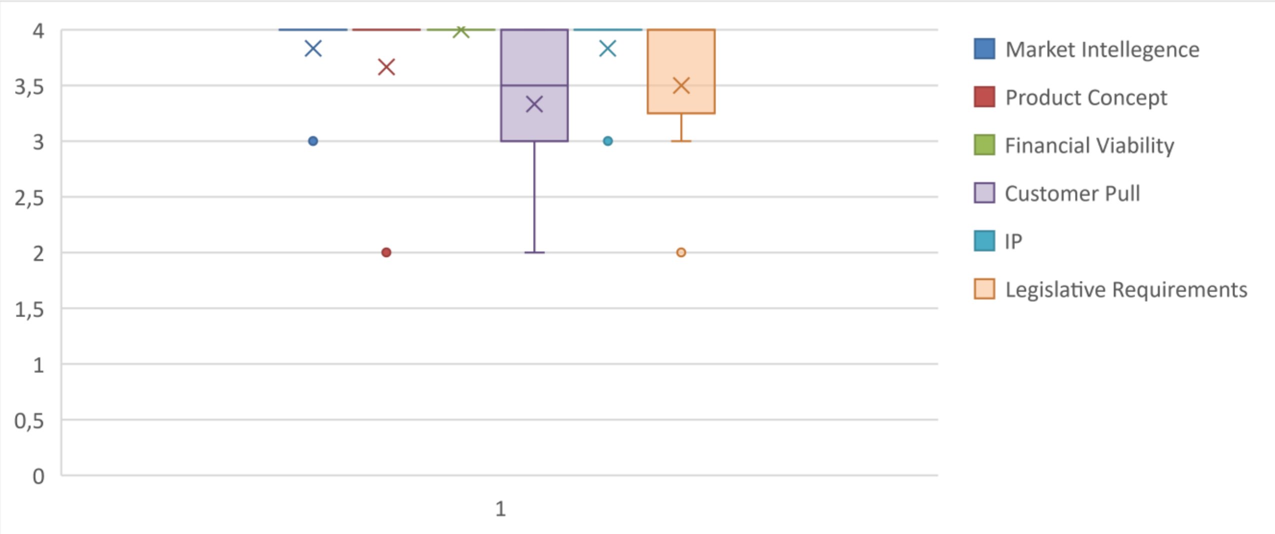


Figure 6-14: *Product sub-dimension descriptor Relevance (R) rating results*

Figure 6-14 above shows that the sub-dimension descriptors of the *Product* main dimension was relevant and successfully conveyed the necessary information regarding the maturity levels. Some variability is, however, observed in the *Relevance* of the *Customer Pull* and *Legislative Requirements* sub-dimension descriptors. This variability is explained by the qualitative comments summarised in Table 6-15 below:

Table 6-15: *Technology sub-dimension qualitative comments on description relevance*

Expert	**Customer Pull Descriptor Comments**	**Legislative Requirements Descriptor Comments**
AdM_PHD	Sub-dimension needs more context. Customer Pull is a very specific type of actor.	N/A
AM&M	Provide more context for what "Customer Pull" specifically means.	Description progression very broad and generic. Can include more specific activities.
CM&D	The word "essential" is too strong. Make it less of a strict requirement.	Revise progression of descriptors.

6.3.4 Summary of Phase 2 detail level rating results

After considering the various responses for the *Technology*, *Supply Chain* and *Product* dimensions it can be concluded that the existing LVoD maturity model used in Phase 2 of the decision support tool satisfies the contextual requirements of the proposed decision support tool. The overall responses for *Relevance (R)* were high for most sub-dimensions and their corresponding descriptors. That being said, while the *Relevance* responses for the sub-dimensions for *Product* and *Supply Chain* were very high, the *Technology* sub-dimension had more variability. However, even when considering the variability, the average of each of the responses for the *Technology* dimension was at least a 3, which would still make it eligible for inclusion with the expectation of some minor changes and additions. Most of the additions and improvements proposed by the interviewees were mentioned in the previous sections and could be integrated easily by adding details to existing descriptors. However, Table 6-16 below will summarise the few major changes that were made after the interviews, that extended beyond the scope of simply adding more detail. The final tool can be viewed in Appendix A.

Table 6-16: *Changes made to Phase 2 of the tool after the action research phase*

Dimension	**Changes made to existing model based on action research**
Technology	a. The *Demonstration* sub dimension was adjusted to allow simulations as a viable form of demonstration. Users will also be encouraged to use the weighting function to weight Demonstration lower if they wish to be an early adopter. b. The *Process Control* sub-dimensions was overhauled to include specific activities and continuous improvement requirements.
Product	a. The *Customer Pull* dimension was revised to include more specific details around what "Customer Pull" means in the context of the model.

6.4 Phase 4: Detail Level Tool Rating Results

Phase 4 of the decision support tool uses the SM^{3}E model to determine internal operational maturity in the context of Smart Manufacturing paradigms. This is an intricate model with multiple interdependent elements. The SM^{3}E model was originally designed as a general-purpose manufacturing maturity model for SMEs. Refinement of the dimensions and descriptors was required to ensure the model will fit the new application context of the proposed decision support tool. The first refinement cycle was done in Chapter 5 by investigating literature sources to improve the model's applicability. While literature sources are useful, the newly refined model still had to be validated for practical use by interviewing industry/subject matter experts. These interviews therefore serve as the second and final refinement of the SM^{3}E model, whereafter the model is suited to the application context of the proposed decision support tool. The action research refinement results of the SM^{3}E model can be divided into three distinct stages as shown in Figure 6-15 below:

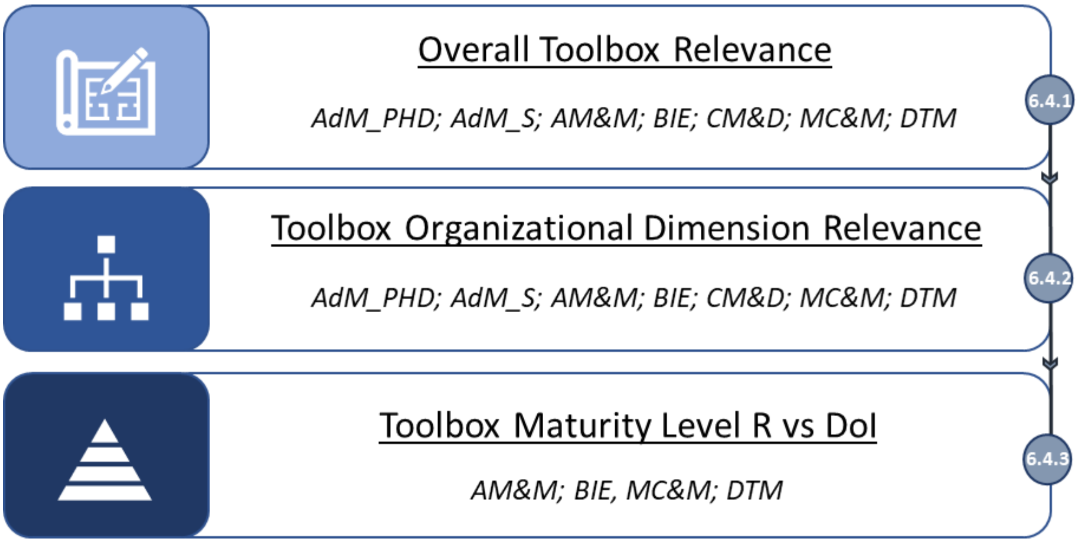


Figure 6-15: *Action research refinement stages of the SM^{3}E model*

Figure 6-15 above shows how the action research stages for SM^{3}E model of Phase 4 was arranged. First, all the interviewees were asked to verify the *Relevance* of the various toolboxes used in the SM^{3}E model. They were also free to suggest any additional toolboxes that could be added. Next, all the interviewees were asked to rate the *Relevance* of the six organisational dimensions. They were also asked to comment on the applicability of the dimensions and suggest any additional dimensions. Lastly, a select number of the interviewees were asked to analyse the detailed description of each maturity level of each toolbox. The selected interviewees are experts in SM, innovation adoption and operational activities of a manufacturing enterprise. For visual representation the toolbox names were abbreviated as shown in Table 6-17 below:

Table 6-17: *Toolbox name abbreviations*

Toolbox name	**Abbreviation**
Manufacturing toolbox	M
Data and Analytics toolbox	D&A
Cloud and Storage toolbox	C&S
Design and Simulation toolbox	D&S
Robotics and Automation toolbox	R&A
Sensors and Connectivity toolbox	S&C

6.4.1 Overall toolbox relevance ratings

Fist, the interviewees were asked to rate the *Relevance* of each toolbox within the SM^{3}E toolbox ecosystem. The results of the ratings are summarised in Figure 6-16 below:

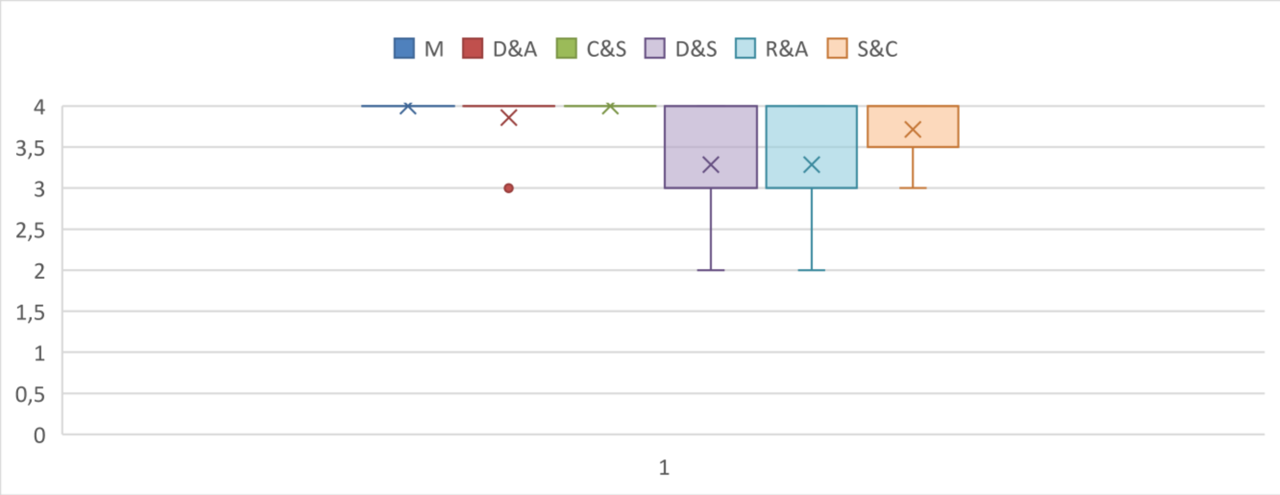


Figure 6-16: *Toolbox Relevance (R) ratings*

Figure 6-16 above shows that the overall *Relevance* ratings was very high, with the highest variability in responses observed in the *Design & Simulation* and *Robotics & Automation* toolboxes. To understand why these toolboxes were rated slightly lower in *Relevance*, the qualitative comments of the interviewees are summarised in Table 6-18 below:

Table 6-18: *Toolbox relevance qualitative comments summary*

Expert	**Design and Simulation Comments**	**Robotics and Automation Comments**
AdM_PHD	Some pure manufacturing enterprises receive designs from clients and therefore do not require high level simulations and design.	N/A
AdM_S	Depends on the type of manufacturing enterprise.	Robotics depends on type of manufacturing enterprise.
BIE	N/A	Robotics are important, but dependent on manufacturer and in terms of SM maybe not as important as the other dimensions.
MC&M and DTM	Design and Simulation could form part of strategy as well. Depends on enterprise	While most enterprises will incorporate automation, robotics does depend somewhat on the type of manufacturer.

For *Design and Simulation*, the main concern seemed to be that the necessary designs are provided by the clients for enterprises who focus solely on manufacturing, and subsequently they do not require intensive design capability. This argument can, however, be countered by realising that the proposed tool focusses on adoption of novel technologies. To integrate these technologies into production and start creating new products, enterprises will need to be involved in the design and simulation process, even if the process requires guiding the client to more efficient designs for the technology's application domain. It is, therefore, important that the *Design and Simulation* toolbox is included even if, for some enterprises, it will only serve as a road mapping or consultation tool.

For the *Robotics and Automation* toolbox the comments seemed to focus around the "robotics" aspect rather than automation. All the experts agreed that SM enterprises will integrate some automation into their processes, however, some experts argued that automating specifically through robotics is not necessarily as relevant as the other toolboxes. Again, the toolbox should still be included as it does provide valuable insight into the various options available for enterprises in the current sphere of automation.

6.4.2 Toolbox organisational dimensions Relevance ratings

Next, the interviewees were asked to rate the *Relevance* of the six organisational dimensions used in the toolbox ecosystem of the SM^{3}E model. They were also asked to suggest any changes or additions to the dimensions. Their rating results are summarised in Figure 6-17 below:

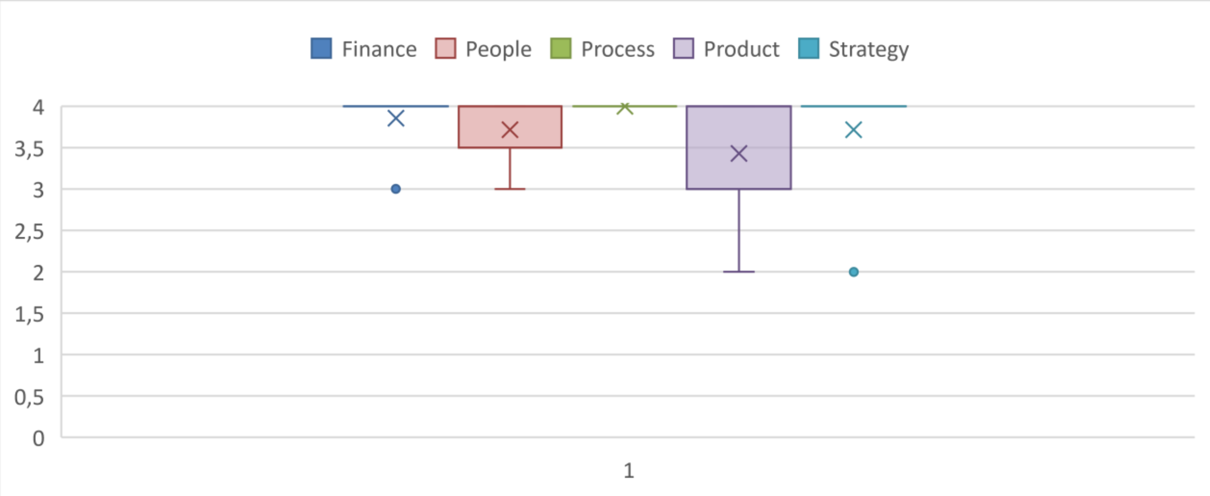


Figure 6-17: *Toolbox organisational dimensions Relevance (R) ratings*

Again, the responses were positive for the organisational dimensions. The variability in the responses for the *Product* dimensions and the outlier of the *Strategy* dimension can be explained by the comments summarised in Table 6-19 below:

Table 6-19: *Organisational Dimensions qualitative comments summary*

Expert	**Product Dimension Comments**	**Strategy Dimension Comments**
CM&D	Product is an output while all the others are enablers. Equipment could be a better dimension?	N/A
AM&M	N/A	Strategy can be short medium and long term. The current strategy is more long term focussed and it is therefore less important for real time analytics associated with SM.

The above comments can be considered for the final version of the tool, however, they are single instances of lower ratings, while the overall response still scored very high for *Relevance*. The six organisational dimensions are, therefore, acceptable for future use.

6.4.3 Toolbox maturity level Relevance vs DoI

For the detail level rating of each maturity level of each toolbox, only the experts with intensive experience in SM, digital transformation and manufacturing enterprise operations were interviewed. The reasoning is twofold: Firstly, the detail level of SM operational maturity is a highly specific area and to ensure quality responses is gathered, only the interviewees who are experienced in that domain must be asked. Secondly, the detail level analysis is extremely time consuming, which made it difficult to complete for each interviewee. As a result, only the following four experts were asked to rate the detail of the maturity levels of each toolbox: *AM&M; BIE, MC&M; DTM.*

For this round of rating the interviewees were asked to investigate the various innovations that are required for maturity progression within each toolbox. Based on the description of each level of maturity, the interviewees were asked to rate the *Relevance* of that description in relation to the maturity level, as well as the *Difficulty of Implementation* for the activities described at each level of maturity. To expedite understanding of the process, the example following the figure below can be followed:

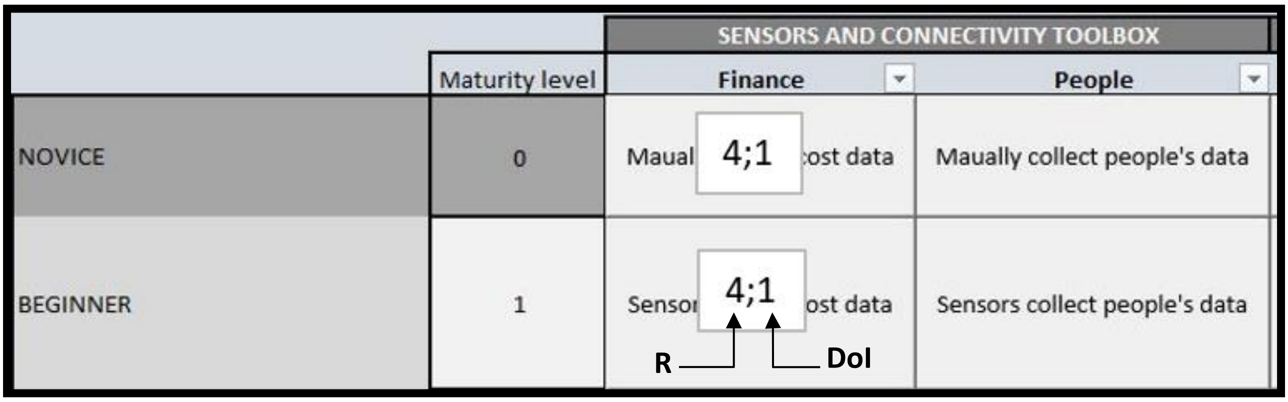


Figure 6-18: *Example of a detail level toolbox maturity level rating*

Example: *The interviewee would go to the Sensors & Connectivity toolbox and inspect the description of each maturity level. They would see that a Level 0 enterprise relies on manual data collection while a Level 1 enterprise relies on basic sensors for collection. They would then decide if these descriptions accurately reflected the S&C operations of a Level 0 and Level 1 enterprise and, subsequently, give it a R rating with 4 being extremely relevant. They would then decide how difficult, financially or practically, it would be for an enterprise to implement the activities described at each level of maturity and rate the DoI, with a 4 DoI being extremely difficult to implement.*

6.4.3.1 Manufacturing toolbox maturity levels Relevance vs DoI

Figure 6-19 below shows the *Relevance* vs *DoI* rating for each maturity level of the *Manufacturing* toolbox:

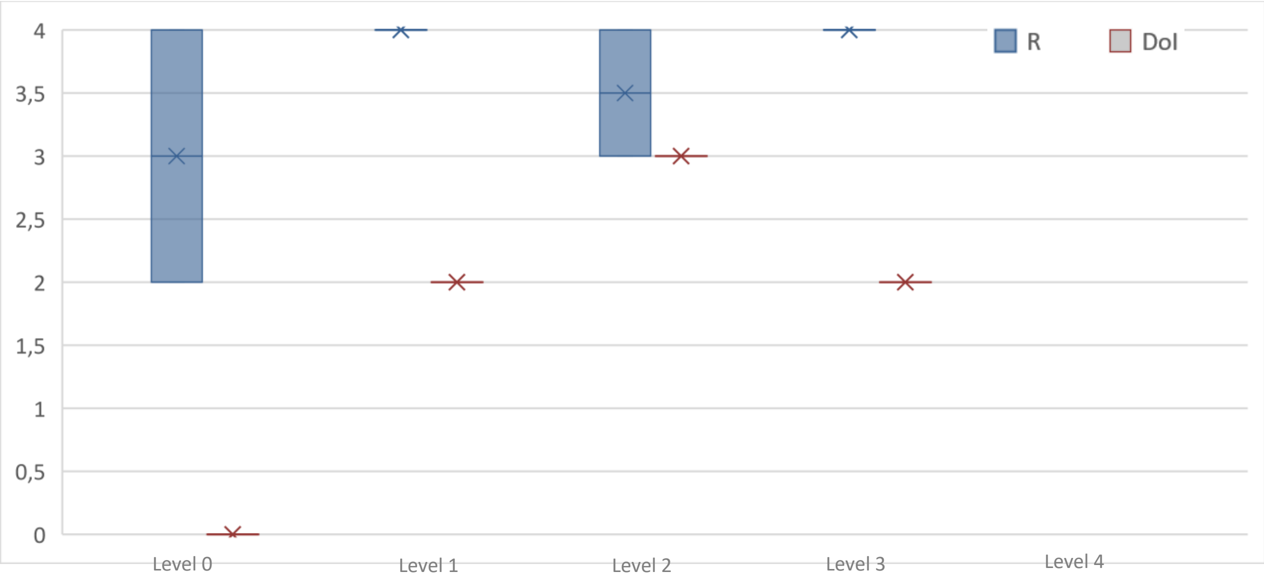


Figure 6-19: *Manufacturing toolbox maturity level R vs DoI rating results*

The results show that the interviewees were satisfied with the relevance of the various maturity levels with almost no observed variability in responses except for the level 0 and level 2 maturity. The level 2 maturity had a small variability with the *Relevance* results ranging between rating values of 3 and 4. The *Relevance* results for level 0, however, had a bigger variability in responses with the reasoning explained by the qualitative responses summarised in Table 6-20 below:

Table 6-20: *Manufacturing toolbox maturity level qualitative comments*

Expert	**Manufacturing Maturity Level 0**
MC&M	Level 0 definition is too thin. Raw materials are not the best metric.
DTM	Add direct costs as a metric of measurement.

Based on these comments, it is worth considering the addition of direct costs as a metric on which a level 0 enterprise relies. This adds extra detail to the definition which will make the model more accurate and easier to use.

6.4.3.2 Design and Simulation toolbox maturity levels Relevance vs DoI

Figure 6-20 below shows the *Relevance* vs *DoI* rating for each maturity level of the *Design and Simulation* toolbox:

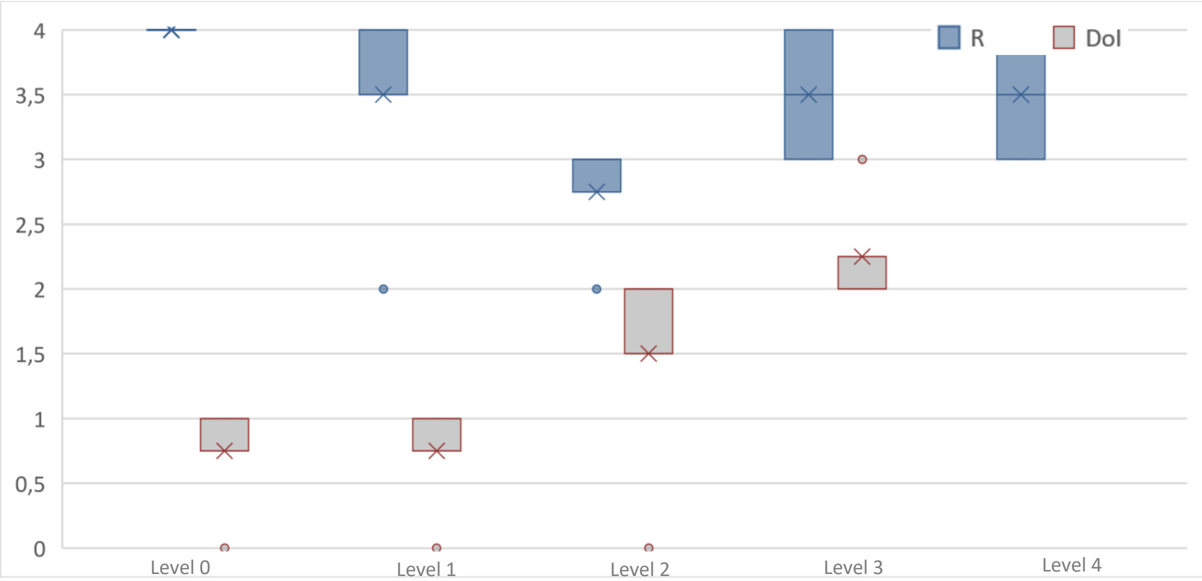


Figure 6-20: *D&S toolbox maturity level R vs DoI rating results*

The results of for the *Design and Simulation* maturity levels have some variability in responses. While the overall *Relevance* ratings are still high, special consideration should be given to the level 2 and level 4 responses, especially since level 4 is the only level where the *DoI* is higher than the *Relevance*. The qualitative responses of the interviewees are summarised in Table 6-21 below:

Table 6-21: *D&S toolbox maturity level qualitative comments*

Expert	**D&S Level 2**	**D&S Level 4**
AM&M	Simulation is not necessarily always dependent on 3D modelling and can sometimes ensue before 3D modelling (i.e., Monte Carlo and Financial simulations). Descriptors must therefore be changed to include basic simulations at level 1.	N/A
MC&M	N/A	Level 4 descriptor is not irrelevant; however, the technology does not yet exist and must still be developed. It is therefore possible to strive towards it, but it will be very difficult to reach.

The AM&M expert raised a valid point, in that it is possible to do some form of simulation/forecasting without the use of 3D modelling. It is, therefore, worth including basic forecasting simulations, independent of the 3D models, as a level 1 requirement in the Design and Simulation toolbox.

6.4.3.3 Sensors and Connectivity toolbox maturity levels Relevance vs DoI

Figure 6-21 below shows the *Relevance* vs *DoI* rating for each maturity level of *the Sensors and Connectivity* toolbox:

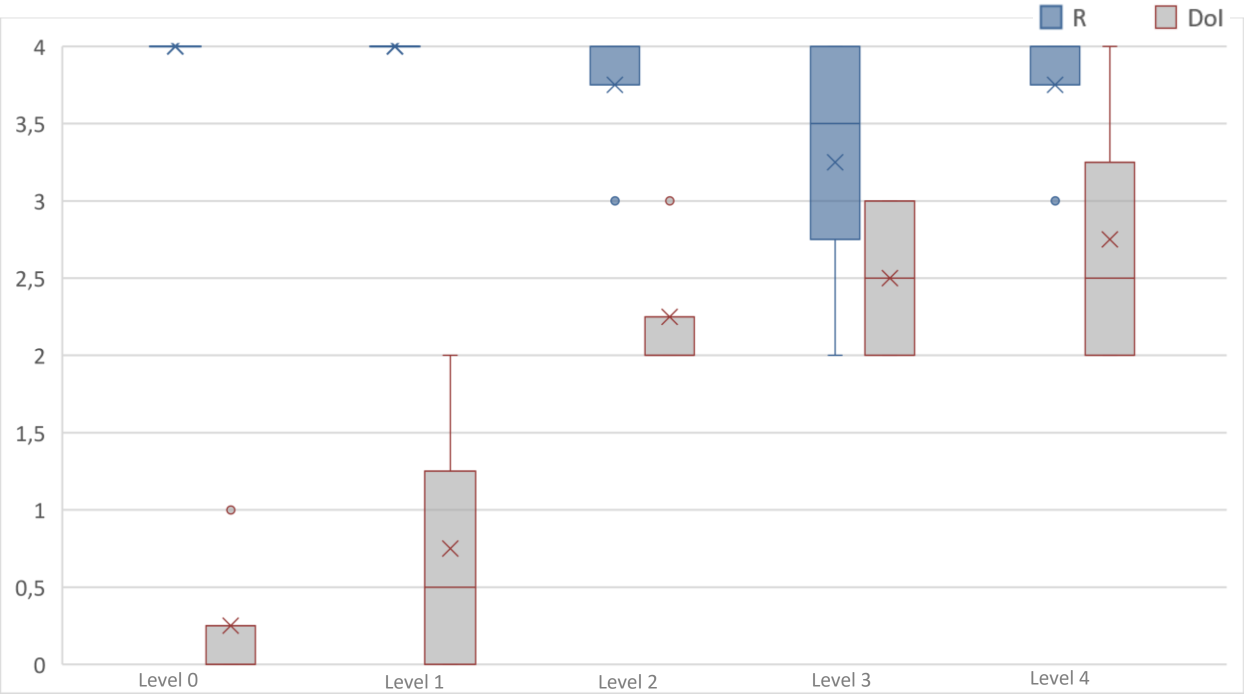


Figure 6-21: *S&C toolbox maturity level R vs DoI rating results*

The overall *Relevance* results for the *Sensors and Connectivity* maturity levels are positive with little to no variability in responses. The highest variability is observed for level 3 and the qualitative response for this level is summarised in Table 6-22 below:

Table 6-22: *S&C toolbox maturity level qualitative comments*

Expert	**S&C Maturity Level 3**
BIE	At level 3 add: aggregation of data and transfer to single cloud platform for further use.

The addition of a single cloud platform at level 3 of the *Sensors and Connectivity* toolbox, as suggested by the BIE expert, is already solved by the *Cloud and Storage* interdependency of the *Sensors and Connectivity* toolbox. This implies that an enterprises storage capability will have to be upgraded continuously as they improve their sensory capabilities. It is, therefore, not necessary to add the definition provided by the BIE to the *Sensors and Connectivity* toolbox, since it is implicit in the *Cloud and Storage* toolbox.

6.4.3.4 Data and Analytics toolbox maturity levels Relevance vs DoI

Figure 6-22 below shows the *Relevance* vs *DoI* rating for each maturity level of the *Data and Analytics* toolbox:

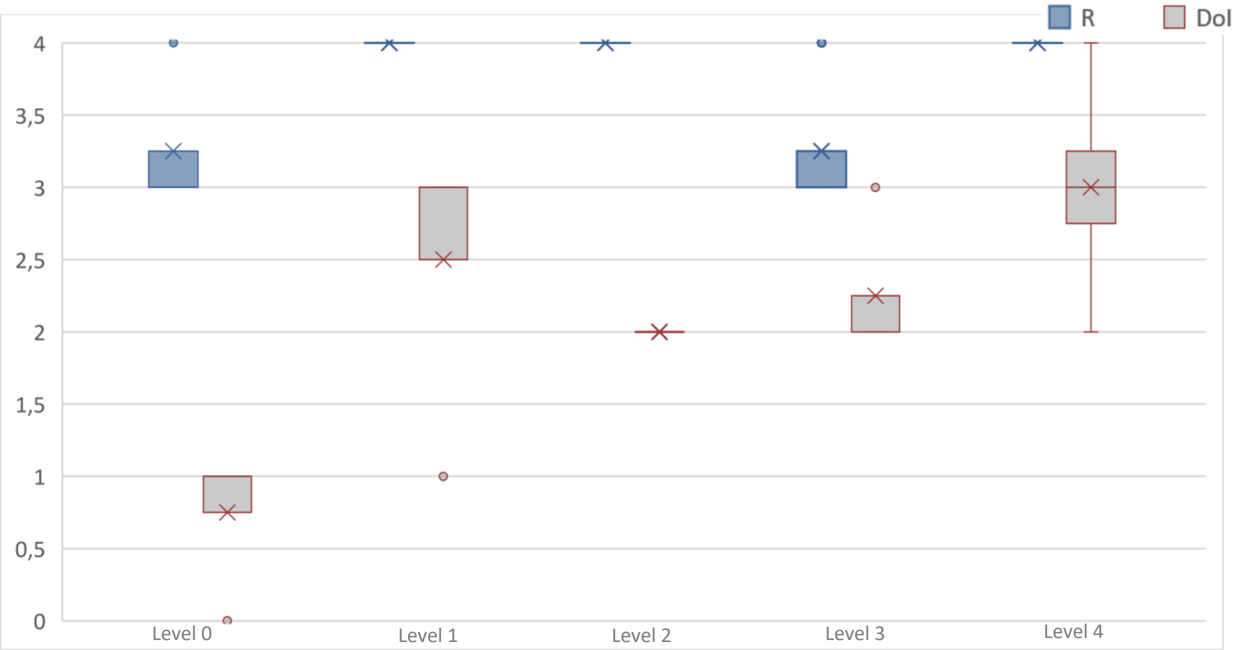


Figure 6-22 : *D&A toolbox maturity level R vs DoI rating results*

The overall *Relevance* results for the *Data and Analytics* maturity levels were positive with little to no variability in responses. While the interviewees were happy with the various maturity levels, there were some qualitative comments to consider. These comments are summarized in Table 6-23 below:

Table 6-23: *D&A toolbox maturity level qualitative comments*

Expert	**D&A maturity levels overall comments**
BIE	Incorporate more of the analytics parts i.e., decision making and stakeholder alignment activities.
MC&M	Add more data prep and analysis activities if possible.

The qualitative comments seemed to focus on the fact that the activities should include more analysis capabilities. There was a request to include specific activities that show the user what to do with the data at the various stages of data prepping. While these comments are valid, the overall score of the maturity levels were still very high and any additions would not be a necessity, but rather complimentary to the current definitions.

6.4.3.5 Cloud and Storage toolbox maturity levels Relevance vs DoI

Figure 6-23 below shows the *Relevance* vs *DoI* rating for each maturity level of the *Cloud and Storage* toolbox:

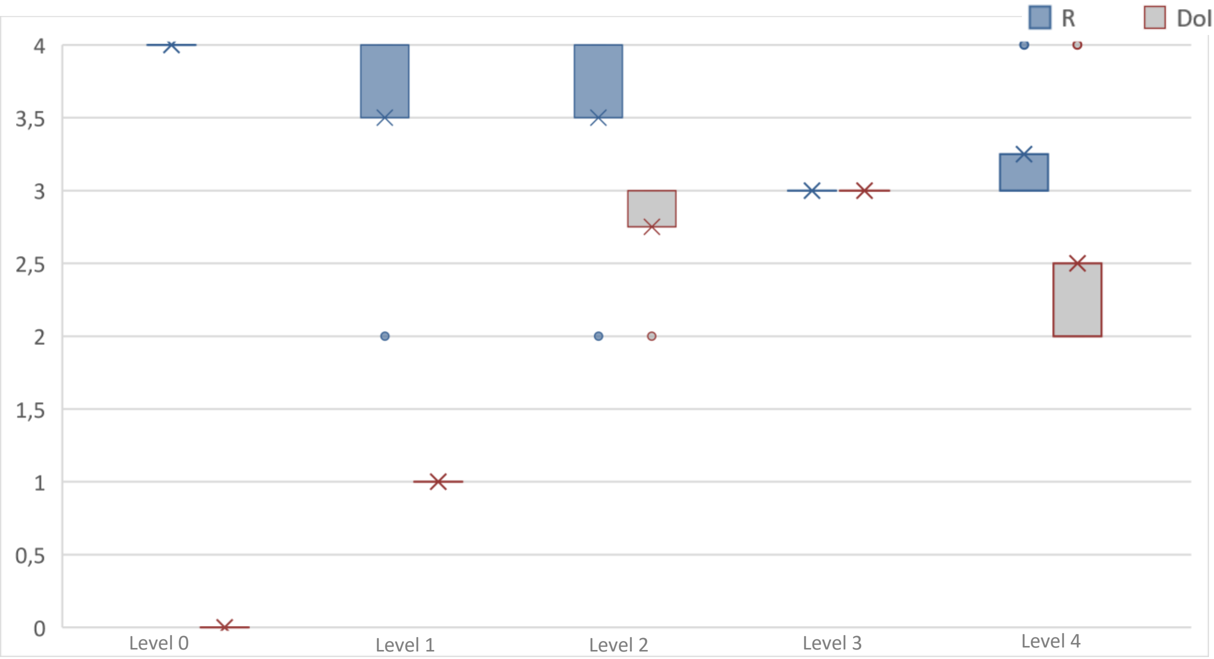


Figure 6-23: *C&S toolbox maturity level R vs DoI rating results*

The overall *Relevance* results for *Cloud and Storage* were positive with little variability in the responses. There were, however, some outlier ratings which can be explained by the qualitative comments summarised in Table 6-24 below:

Table 6-24: *C&S toolbox maturity level qualitative comments*

Expert	C&S Level 1	C&S Level 2	C&S Level 3
AM&M	Level 1 enterprises will have backups, but it will be manual and unstructured.	Cloud is no longer novel and services like Dropbox can be used from an early stage. Level 2 does not have to be only physical storage.	N/A
BIS	N/A	N/A	Start incorporating specific storage security in addition to backups.

The comments from the AM&M expert are valid and is included in the final tool. Even at a level 1 maturity, enterprises can save files on memory sticks as backup. Additionally, Dropbox and Google Drive makes free cloud storage accessible to all, even if it is unstructured and less powerful than a dedicated and structured storage scheme.

6.4.3.6 Robotics and Automation toolbox maturity levels Relevance vs DoI

Figure 6-24 below shows the *Relevance* vs *DoI* rating for each maturity level of the *Robotics and Automation* toolbox:

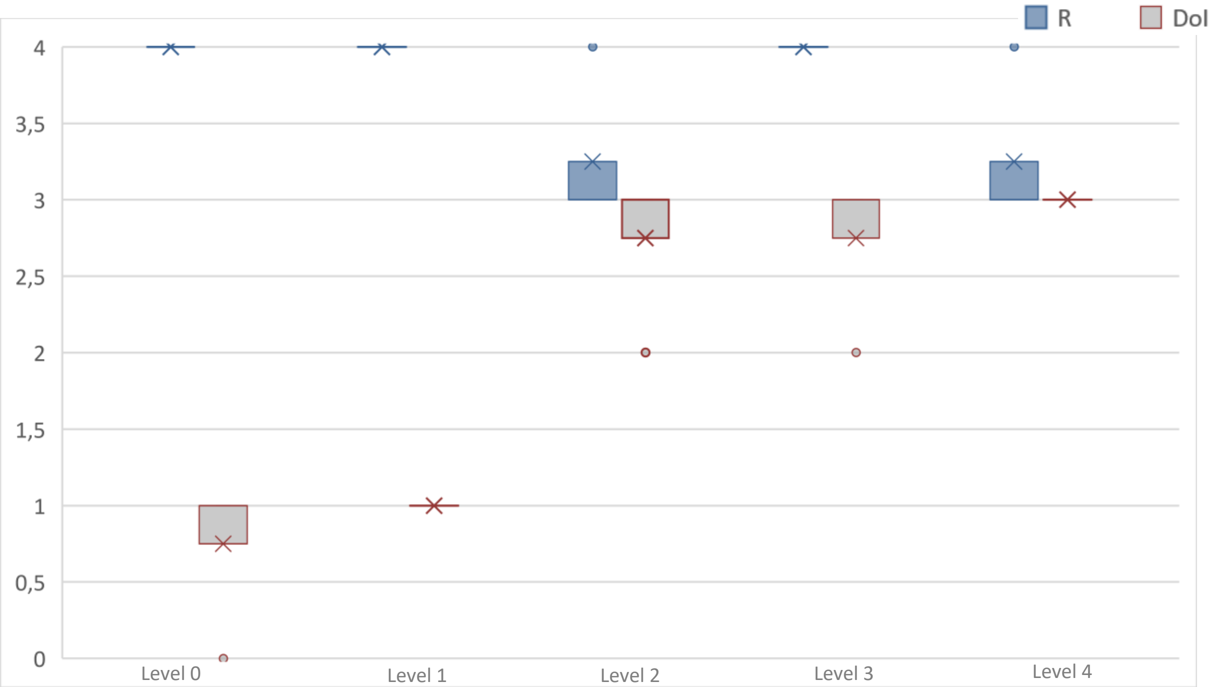


Figure 6-24: *R&A toolbox maturity level R vs DoI rating results*

The overall *Relevance* results for the *Robotics and Automation* maturity levels were positive with little to no variability in responses. Some variability is observed at level 2 and level 4, and can be explained by the qualitative comments summarised in Table 6-25 below:

Table 6-25: *R&A toolbox maturity level qualitative comments*

Expert	**R&A Level 2**	**R&A Level 4**
BIE	N/A	Include at level 4 that robots react in real time to adjust to scenarios.
MC&M	Depends on application	N/A

The qualitative comments for *Robotics and Automation* were not as constructive as the comments for the other toolboxes and will therefore not be included in the final tool. The general consensus from the discussions were that the type of manufacturing enterprise could influence the *Relevance* of some of the maturity levels, but not to such an extent that the level is completely irrelevant. The toolbox can therefore be kept as is.

6.4.4 Summary of Phase 4 detail level rating results

Overall, the experts believed the various maturity levels and descriptions of each toolbox to be adequate for use in a practical setting. The *Data and Analytics*, *Robotics and Automation and Sensors and Connectivity* toolboxes scored, on average, the highest. The *Manufacturing*, *Design and Simulation and Cloud and Storage*, while still scoring mostly higher average ratings, had more variability in their responses. The variability is, however, not drastic enough to exclude any of the maturity descriptors or levels from use, but rather indicate that some refinement is required. While the previous sections clearly describe the feedback received from the interviews for each toolbox, Table 6-26 below summarises the major changes made to the decision support tool following the feedback session. The final tool can be viewed in Appendix A.

Table 6-26: *Summary of changes made to the Phase 4 toolboxes after action research*

Toolbox	**Changes made to toolbox based on action research feedback**
Manufacturing toolbox	At Level 0, direct costs data are added to the description.
Design and Simulation toolbox	Basic simulation capability is added from level 1. Simulation is no longer solely dependent on 3D models.
Cloud and Storage toolbox	From level 1 basic unstructured backup capability is added. From level 2 basic free-to-use cloud services are added.

6.5 Summary of Chapter 6

Since there are intermittent section summaries throughput Chapter 6, this chapter summary focusses only on high level discussions of the conclusions drawn in Chapter 6. The summary starts by reiterating that there were three main stages of action research conducted. The first stage focussed on rating aspects of the tool's overall functions such as *Relevance* of the various phases and overall tool *Need*. The second stage of the action research focussed on rating the details contained in Phase 2 of the decision support tool. This allowed the researcher to refine the dimensions and descriptors of this phase. Finally, the third stage of action research focussed on rating the details contained in Phase 4 of the decision support tool. By interpreting the various ratings and qualitative comments it was possible to refine multiple aspects of the tool to create a more relevant and effective decision support tool.

In general, the ratings were positive across the board. The experts that were interviewed were happy with most of the functionalities and details of the tool. There were some cases where experts believed more detailed descriptors were required or changes had to be made. These cases were clearly logged and are explained in the various sub-sections of Chapter 6. When considering the mostly positive rating results along with the prospect of improved dimensions based on expert comments, it is possible to conclude that the action research phase fulfilled its purpose effectively and lead to an improved and more applicable decision support tool.

Chapter 7: Final Tool Validation Simulation

This chapter forms part of the third and final design cycle of this project and it deals with the final validation of the tool. The chapter outlines all the processes involved in conducting a practical simulation case study with an industry partner. The purpose of such a simulation is to apply the tool in a practical setting and determine the applicability and validity of the final tool. The simulation is not an additional refinement step as no changes are made to the tool based on the simulation results. It, therefore, serves as a qualitative approximation of an "experiment" and will give a final indication of the proposed decision support tools worth. Figure 7-1 below shows that this chapter details all three design steps of the third design cycle.

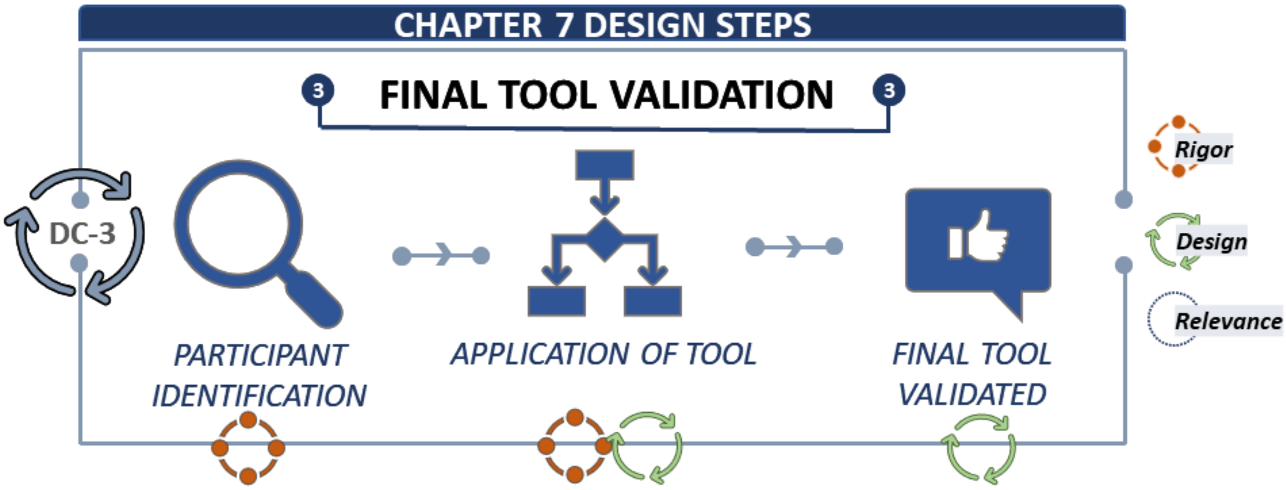


Figure 7-1: *Design steps completed in Chapter 7*

7.1 Simulation Requirements

This research project provides largely qualitative research outputs. Where quantitative research projects can rely on data gathered from practical experiments and tests to verify a hypothesis, qualitative research does not have a binary "yes or no" answer. One way to try and validate qualitative work, is through practical application of the tool in a simulated real-world scenario. The output of the practical application differs from the action research used to refine the tool in that the tool application is purely observational. This means that the results of the application are only used to measure the efficacy of the tool and not to improve or develop it further.

The enterprise participating in the tool's application was selected carefully to ensure the most effective use of the tool. It is important to note that the proposed decision support tool originated from the need within the cemented tungsten carbide industry for support during future cemented carbide AM technology commercialization efforts. However, as was explained in Chapter 1, none of the current cemented carbide AM technologies have viable commercial applications. The researcher was, therefore, unable to find a suitable participant that is investigating, or have experience with, cemented carbide AM technology adoption. The proposed decision support tool was, however, designed as a general-purpose tool for the adoption of most novel manufacturing technologies, of which cemented carbide AM is only a portion. It therefore stands to reason that the tool simulation can be applied to a manufacturing SME investigating some other novel manufacturing technology in order to prove the tool's efficacy. The tool would then be viable for use during the commercialization of cemented tungsten carbide AM, once the technology has reached a desired TRL.

7.1.1 Simulation process steps

Conducting the simulation is relatively simple due to the time spent during the *Interface Creation* step of the design process. Having a user-friendly interface allows the subject of the case study to navigate the tool effectively and efficiently. The simulation process was done according to the following steps:

Table 7-1: *Simulation steps*

Simulation Step	**Description**
Step 1: *Participant identification*	Careful consideration is given to the participant requirements during this stage to ensure the best candidate is chosen for the simulation. Not only is it important not select the correct enterprise, but also to select a knowledgeable participant who can apply the tool successfully.
Step 2: *Scenario creation*	The purpose of the simulation is to evaluate the usefulness of the decision support tool in a real-world application. To achieve this, a specific scenario is created for which the tool will then be used and tested. In this case study, a manufacturing enterprise is asked to simulate the implementation of a novel manufacturing technology into their current operations. The scenario simulated in this chapter was proposed by the selected enterprise as they are, at the time of writing this thesis, investigating the adoption and implementation of a novel technology into a new manufacturing process. This novel "proof-of-concept" technology simulation fits perfectly within the requirements of the long valley of death and is also accompanied by the adoption and development of a novel manufacturing process, which will subsequently test the decision support tool's usefulness on both a technology and process level. In the interest of confidentiality, the participating enterprise wished not to reveal any further details about the technology in question, other than it is part of the development of a new forming manufacturing process, where the *Novel Technology* investigated by the tool is the combination of a technology and process.
Step 3: *Application of tool*	First, the simulated scenario is discussed with the participant. Thereafter, the participant is asked to apply and thoroughly examine all aspects of the tool. Participants will be free to communicate any issues or questions during the simulation with the head researcher via Microsoft Teams.
Step 4: *Feedback and data collection*	After the tool is applied successfully the participant is asked to provide feedback during a qualitative discussion. The discussion provides them with the opportunity to express their views, opinions and feedback of their experience of the tool and what they found to be useful or not. The simulation results will not focus on quantitative ratings as the feedback of the simulation is multi-faceted and difficult to encapsulate using a rating legend such as the ones used in Chapter 6.

7.1.2 Simulation participant requirements and selection

Selection criteria were developed for the selection of a suitable simulation participant. These criteria are based on the knowledge of the decision support tool's application and use developed during the action research phase of this project. The following requirements must be met by the participant of the study for it to be effective:

a. Participant must be an established manufacturing enterprise

b. Participant must be a small to medium sized enterprise.

c. Participant must have some smart manufacturing capabilities already in place.

d. Support tool must be used by an expert of manufacturing technologies within the enterprise.

Participants were identified largely through networking and communication with knowledgeable figures in the manufacturing space. After some deliberation, a company, "Company A", was identified and approached for participation. After inspection of the tool, Company A stated that they have been struggling with a use-case very similar to the one described in this project and subsequently agreed to participate in the simulation. Company A fulfils all the participant requirements as shown in Table 7-2 below:

Table 7-2: *Company A description and fulfilled requirements*

Company A Description	**Participant requirements fulfilled**
Manufacturing enterprise founded in 1956. Since 2001 they focus solely on production manufacturing and their core business is to serve the automotive industry.	(a)
The enterprise has 51 – 200 employees.	(b)
The enterprise prides themselves in business sustainability which stems from a willingness to invest in the adoption of emerging technologies and continual process improvement.	(c)
The CEO, along with the enterprise's Operations Manager, implemented the proposed decision support tool. The CEO also founded a successful consulting company that specialises in software consulting solutions and decision support. They are, therefore, the ideal candidates for the tool implementation.	(d)

From the description in Table 7-2 above it is clear that Company A fulfils all the requirements for an ideal participant. The experience of the CEO in both the manufacturing and software tool decision support consulting industries, along with the specialised and intricate manufacturing knowledge of the Operations Manager, made the implementation of the decision support tool proposed in this project much easier.

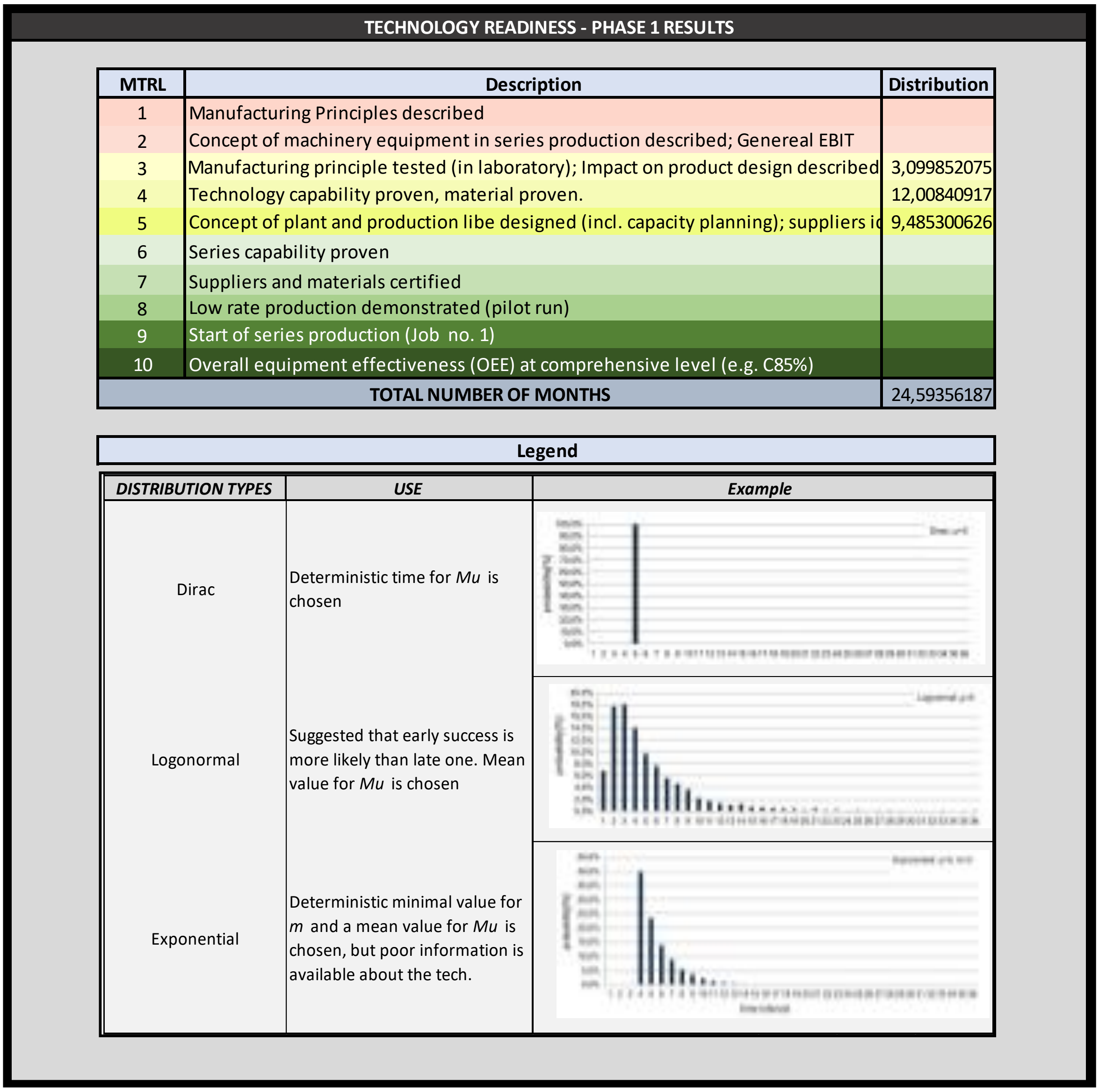
7.2 Simulation Results

The detailed screenshots of the tool inputs and outputs for each phase can be seen in Appendix A. This section discusses the results as summarised in the "*Overview of data*" page of the digital tool. The results for each of the four phases of the decision support tool is discussed in their own sections.

The final verdict about the applicability and validity of the decision support tool will be discussed in section 7.3

7.2.3 Phase 1: Simulation results

Figure 7-2 shows the tool inputs for Phase 1. For Phase 1 of the tool, the current readiness level of the new technology had to be estimated. Company A's representatives believed that the technology is currently at MTRL 3 with early success expected. A lognormal distribution with μ = 5 and σ = 5 was, therefore, assigned to MTRL 3. Next, Company A was happy to adopt the technology once it completes MTRL 5, however, there is very little information available in terms of development time for MTRL 4 and 5. Subsequently, Company A assigned an exponential distribution to MTRL 4 and 5 with β = 3.



TECHNOLOGY READINESS - PHASE 1 RESULTS

MTRL	Description	Distribution
1	Manufacturing Principles described	
2	Concept of machinery equipment in series production described; Genereal EBIT	
3	Manufacturing principle tested (in laboratory); Impact on product design described	3,099852075
4	Technology capability proven, material proven.	12,00840917
5	Concept of plant and production libe designed (incl. capacity planning); suppliers i	9,485300626
6	Series capability proven	
7	Suppliers and materials certified	
8	Low rate production demonstrated (pilot run)	
9	Start of series production (Job no. 1)	
10	Overall equipment effectiveness (OEE) at comprehensive level (e.g. C85%)	
TOTAL NUMBER OF MONTHS		24,59356187

Legend

DISTRIBUTION TYPES	*USE*	*Example*
Dirac	Deterministic time for *Mu* is chosen	
Logonormal	Suggested that early success is more likely than late one. Mean value for *Mu* is chosen	
Exponential	Deterministic minimal value for *m* and a mean value for *Mu* is chosen, but poor information is available about the tech.	

Figure 7-2: *Company A - Phase 1 simulation inputs*

Once the input values were selected, the Monte Carlo simulation was set to run 10 000 iterations. The simulation yielded the graph in Figure 7-3 below. The figure shows that there is an 89.9% chance that the technology in question will move from MTRL 3 to a completed MTRL 5 within 19 months.

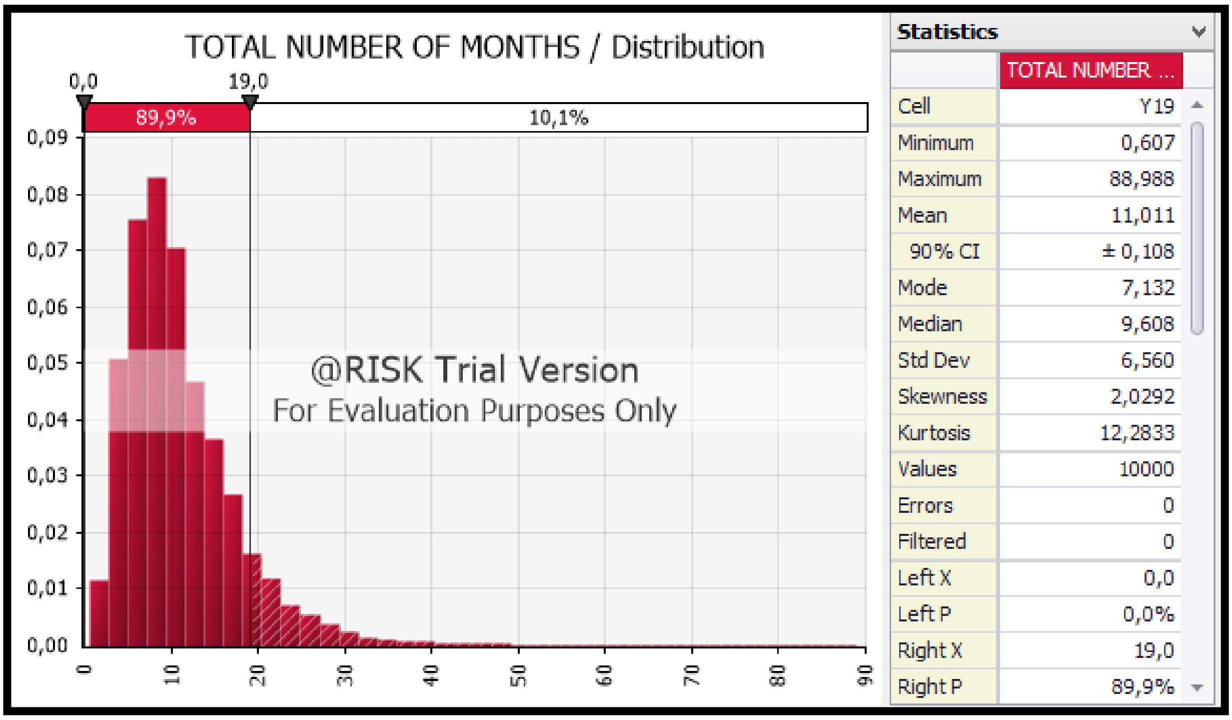


Figure 7-3: *Company A - Phase 1 simulation output*

Company A was satisfied with the estimation of 19 months as they believed this was a realistic estimation. They also felt that understanding the development timeframe of the technology will be beneficial to their adoption efforts as they could plan any upgrades or integration activities according to a more rigid timeline.

7.2.4 Phase 2: Simulation results

The second phase of the tool investigated the maturity of various external dimension elements. The overview of the simulation results can be seen in Figure 7-4 below. The figure serves only as a reference and the enlarged version can be seen in Appendix A.1 The details of the Phase 2 application page can also be viewed in Appendix A.3

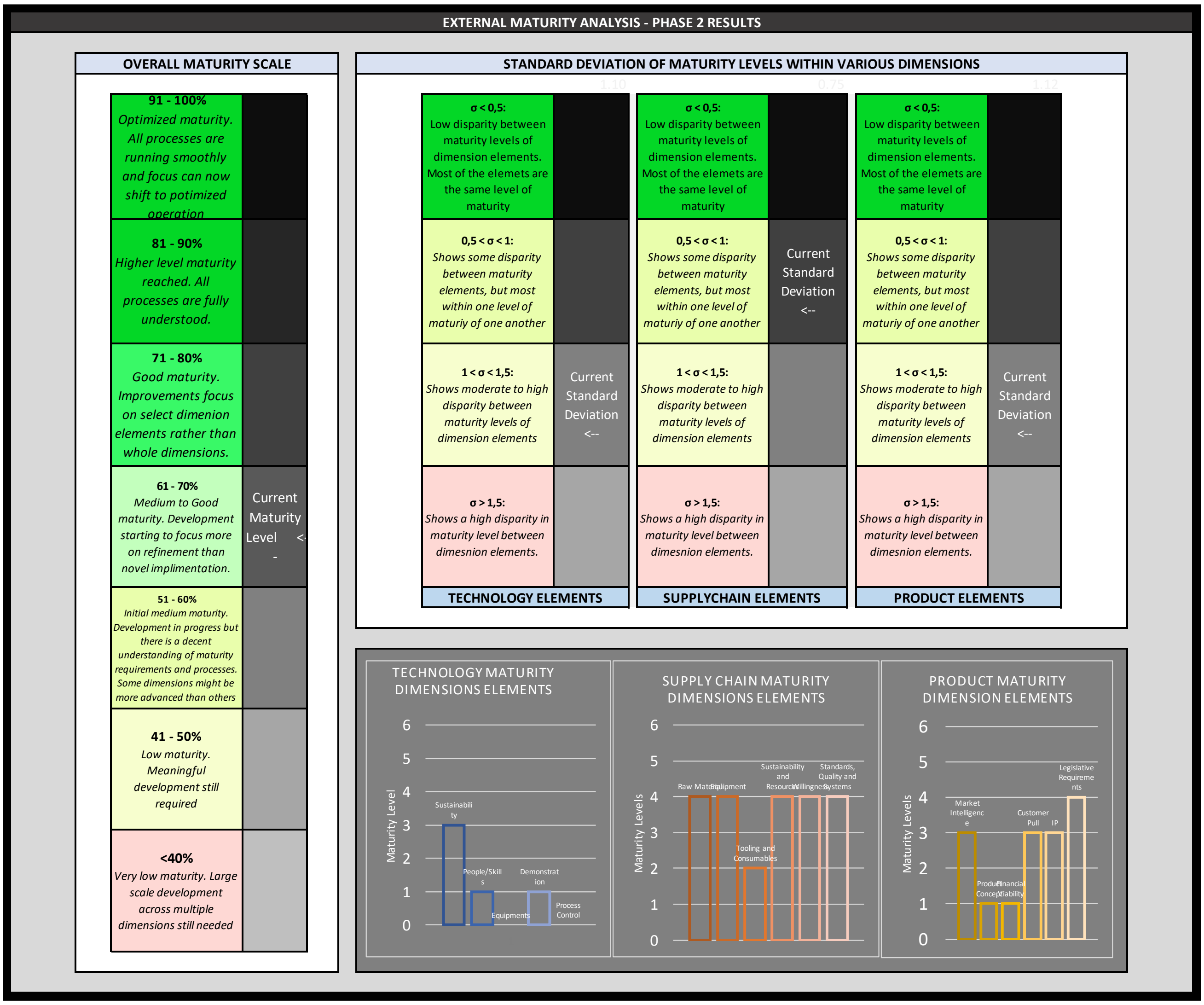


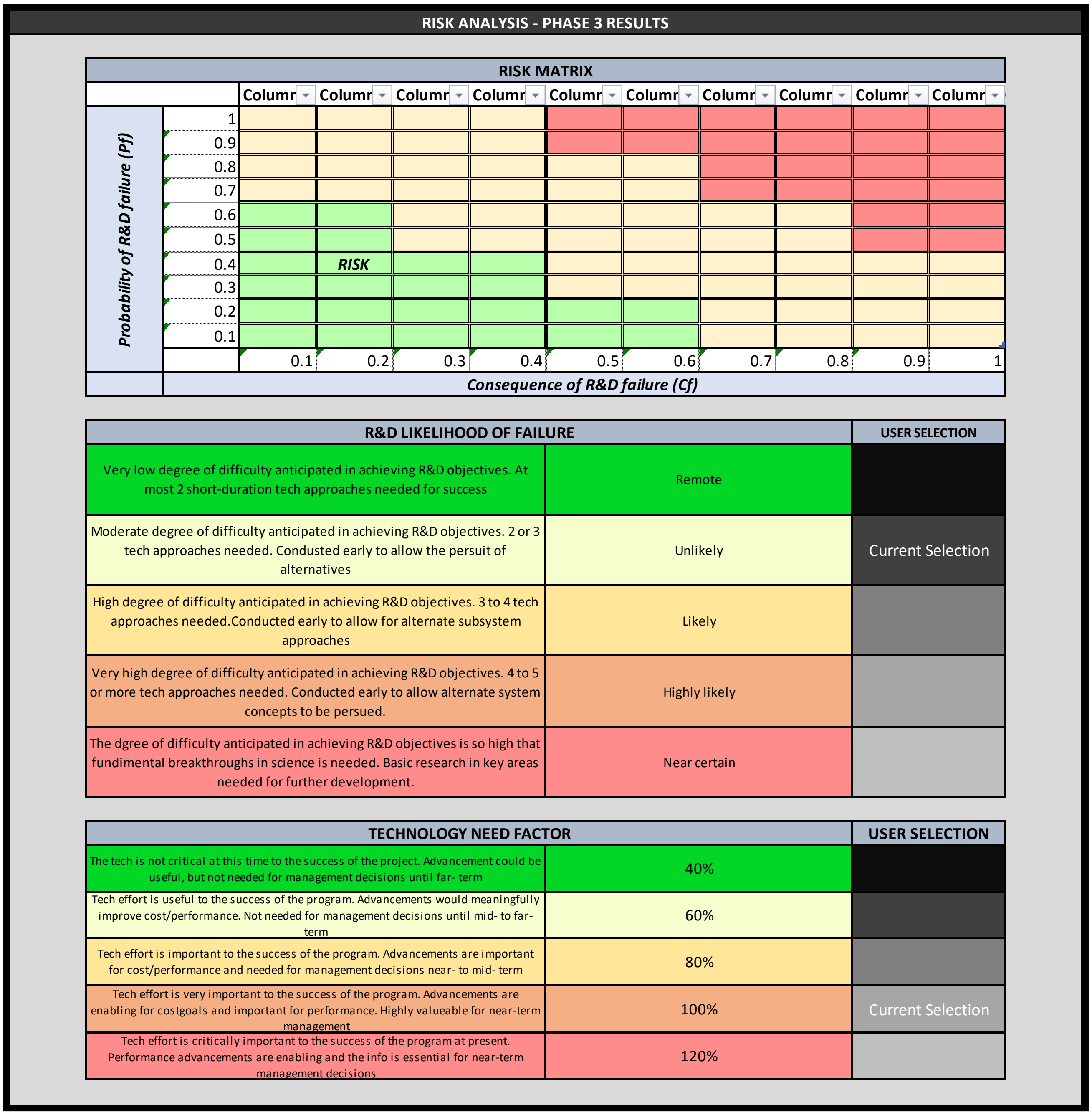
Figure 7-4: *Company A - Phase 2 (LVoD) simulation results*

Figure 7-4 above and Appendix A.1 shows that Company A's overall LVoD maturity falls within the 61 – 70% range, which is characterised by: *Medium to good maturity. Development starting to focus more on refinement than novel implementation.* Company A believed this description to be an accurate depiction of their position, however, they believed the standard deviation results to be critical in interpreting the maturity percentage range correctly.

Figure 7-4 above and Appendix A.1 shows that the *Technology* and *Product* dimensions had a moderate to high disparity between the maturity levels of the sub-dimension elements. This implies that some sub-dimension elements had much higher maturity ratings than others, which is indicative of inconsistent development strategies. Company A must, therefore, be aware that some dimension elements are lagging far behind others and will first need to be improved. Figure 7-4 above also shows that the *Technology* dimension will have to undergo the most development. Company A was happy with this estimation as they are aware of specific technological obstacles that need to be addressed.

7.2.5 Phase 3: Simulation results

The third phase of the tool investigated the likelihood that a 3rd party will successfully complete the required R&D effort. Figure 7-5 below serves as a reference and the enlarged version along with the details of the application page can be seen in Appendix A.4



RISK ANALYSIS - PHASE 3 RESULTS

RISK MATRIX

Probability of R&D failure (Pf)	Columr	Columr	Columr	Columr	Columr	Columr	Columr	Columr	Columr	Columr
1										
0.9										
0.8										
0.7										
0.6										
0.5										
0.4		RISK								
0.3										
0.2										
0.1										
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1

Consequence of R&D failure (Cf)

R&D LIKELIHOOD OF FAILURE		USER SELECTION
Very low degree of difficulty anticipated in achieving R&D objectives. At most 2 short-duration tech approaches needed for success	Remote	
Moderate degree of difficulty anticipated in achieving R&D objectives. 2 or 3 tech approaches needed. Condusted early to allow the persuit of alternatives	Unlikely	Current Selection
High degree of difficulty anticipated in achieving R&D objectives. 3 to 4 tech approaches needed.Conducted early to allow for alternate subsystem approaches	Likely	
Very high degree of difficulty anticipated in achieving R&D objectives. 4 to 5 or more tech approaches needed. Conducted early to allow alternate system concepts to be persued.	Highly likely	
The dgree of difficulty anticipated in achieving R&D objectives is so high that fundimental breakthroughs in science is needed. Basic research in key areas needed for further development.	Near certain	

TECHNOLOGY NEED FACTOR		USER SELECTION
The tech is not critical at this time to the success of the project. Advancement could be useful, but not needed for management decisions until far- term	40%	
Tech effort is useful to the success of the program. Advancements would meaningfully improve cost/performance. Not needed for management decisions until mid- to far-term	60%	
Tech effort is important to the success of the program. Advancements are important for cost/performance and needed for management decisions near- to mid- term	80%	
Tech effort is very important to the success of the program. Advancements are enabling for costgoals and important for performance. Highly valueable for near-term management	100%	Current Selection
Tech effort is critically important to the success of the program at present. Performance advancements are enabling and the info is essential for near-term management decisions	120%	

Figure 7-5: *Company A - Phase 3 (TRRA) simulation results*

Figure 7-5 above shows the selections and output of Phase 3 of the tool. Company A believed the technology in question will require a moderate degree of difficulty to complete the required R&D activities. Company A, however, believes that the technology effort is very important to the success of the program and that advancements in development is an enabling factor for cost and performance. Based on these inputs, along with the TRL inputs from Phase 1, the tool suggests that this project is a low-risk project. Company A was happy with this estimation and believed it accurately reflected their position.

7.2.6 Phase 4: Simulation results

The fourth phase of the tool investigated the maturity of Company A's internal operations with regards to a SM paradigm. Figure 7-6 below serves as a reference and the enlarged version along with the details of the application page can be seen in Appendix A.5

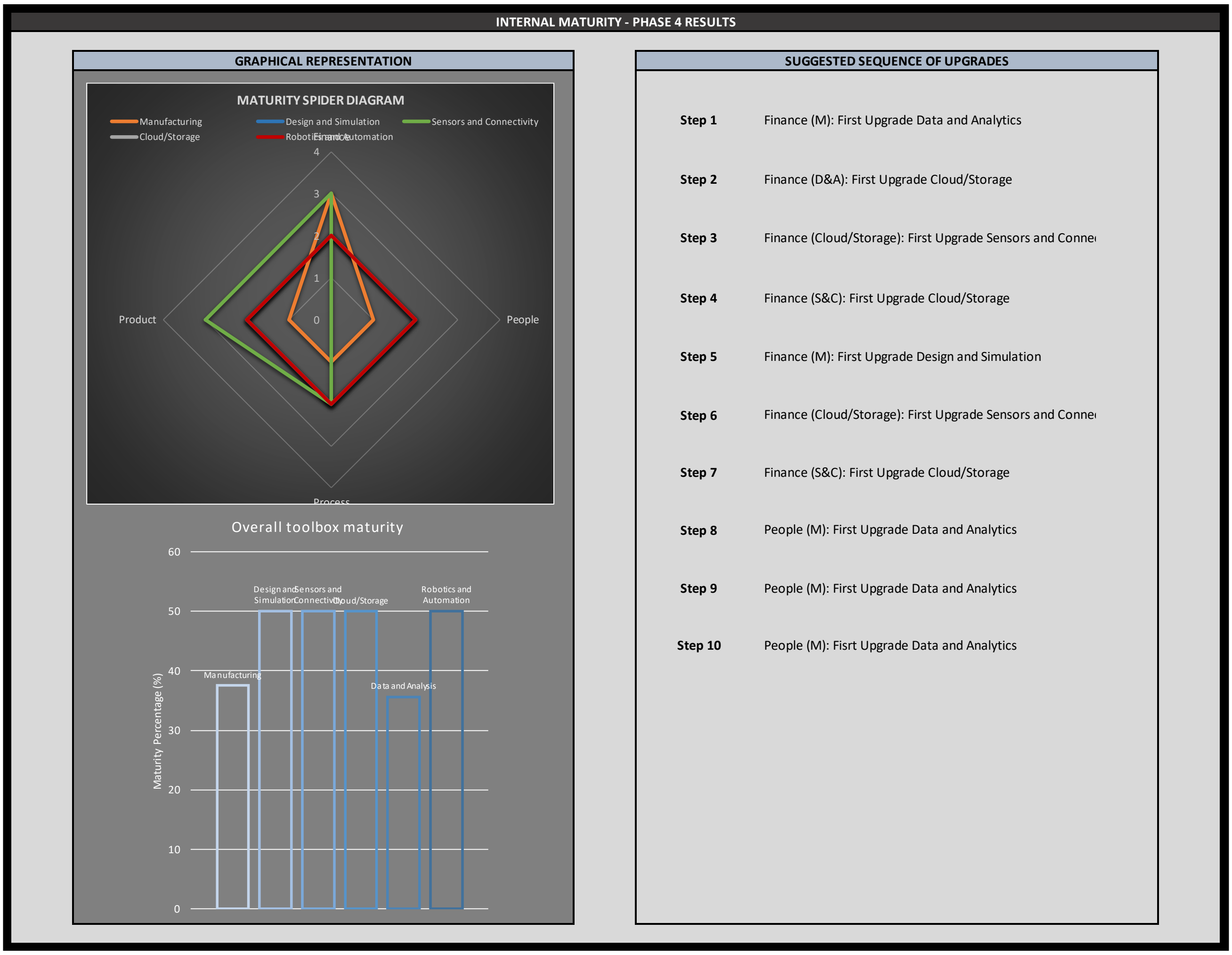


Figure 7-6: *Company A - Phase 4 (SM^{3}E) simulation results*

Figure 7-6 above shows three different outputs, all of which must be considered before drawing any conclusions about the maturity of Company A's internal operations. The analysis starts by investigating the overall maturity level of the various toolboxes. The above figure shows that the *Manufacturing* and *Data & Analytics* toolboxes have the lowest maturity of 38%. To understand the low average maturity score, the spider diagrams must be investigated.

While Figure 7-6 above shows all the spider graphs in one figure, the individual spider graphs can be viewed in Figure 7-7 on the following page. Figure 7-7 shows that the *Manufacturing* and *Data & Analytics* toolboxes have the most skewed maturity ratings with a high *Finance* dimension maturity but very low maturities for the other organizational dimensions. This not only explains the low overall maturity of those toolboxes, but also shows Company A which of the dimensions need improvement.

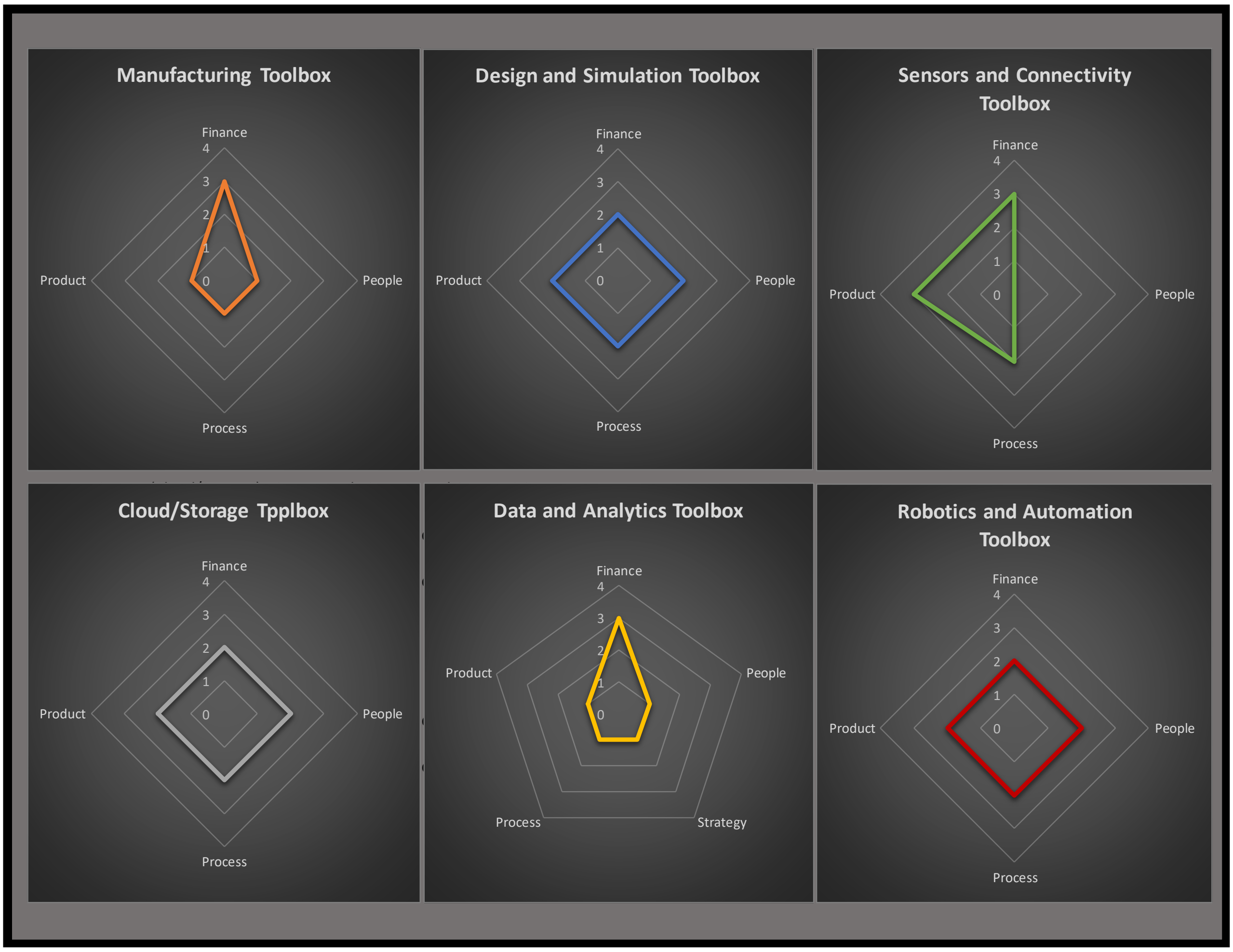


Figure 7-7: *Company A - Phase 4 simulation spider graphs*

Company A believed that Phase 4 of the tool accurately reflected their enterprises position. They have only recently started their transition towards adopting data-driven manufacturing and SM innovations, which is reflected in their overall maturity ratings not surpassing 50%. It is important to understand that the maturity percentage of Phase 4 is not necessarily fundamentally "good" or "bad", but rather shows the company their position relative to the most advanced SM capabilities currently available. It is, therefore, imperative that serious consideration is given to the risk vs reward of further SM innovation adoption. Please see Section 5.3 for an in-depth explanation of this phenomena. However, while it is not necessarily required to improve maturity to the highest levels, it is still recommended that the enterprise tries to reduce the disparity between their organisational dimensions of the *Manufacturing*, *Sensors and Connectivity* and *Data and Analytics* toolboxes.

7.3 Final Simulation Validation Feedback

This section reflects on the qualitative feedback that was gained from the discussion held with Company A's representatives after the simulation was completed. The discussion was focussed around four questions and the answers can be viewed below:

Question 1: ***What insights have you gathered about the tool?***

Company A believes that the tool approaches the problem appropriately and logically. They were satisfied with how the output data was represented and found the decision support tool to be useful. They felt that the tool accurately reflected their position, and that they could gather useful road mapping information from the tool. They believed that the Phase 1, 2 and 3 of the tool was universally very useful, not only in terms of technology adoption, but also for the development of their novel manufacturing process. They believed that Phase 4 of the tool is geared more towards digital technologies but that it was useful for road mapping of operations.

Question 2: ***What are the shortcomings of the tool?***

Company A believed that, if the technology under investigation is not digitally geared, then Phase 4 of the tool is less important than the other phases, however, they would still include Phase 4 in the analysis as a road mapping tool. Company A also believed that the tool could be difficult to use without training or guidance, but that this can be fixed by improving the user interface.

Question 3: ***What additions must be made?***

Company A was generally satisfied with the tool and believed that adding too many additional features could result in a cumbersome tool. They did, however, suggest that the toolbox system of Phase 4 can be confusing at times and suggested the addition of a predefined upgrade process for the toolbox maturities.

Question 4: ***What type of data is required before using tool****?*

Company A believed that, before using the tool, the user must understand the various definitions of specific tool aspects and requirements. They also believed that the user must have knowledge of the technology in question and the company operations.

Based on the responses above, the researcher is inclined to believe that the decision support tool developed in this project successfully fulfilled its purpose of supporting the decision-making process of an enterprise during the adoption of novel manufacturing technologies. Additionally, the simulation also showed that the tool developed in this project can be used for road-mapping purposes, by helping enterprises to estimate their current position and also show future steps that must be followed to achieve an improved position. Finally, the simulation showed that the tool is not only useful for decision support during manufacturing technology adoption, but that some applicability also translates to the adoption and implementation of novel manufacturing processes. The applicability of the tool for novel manufacturing processes was not in the original scope of the project, however, it can now be considered as an additional research contribution.

Chapter 8: Conclusion

This chapter provides the reader with an overview of the research process that was followed in the pursuit of creating a decision support tool that can assist decision making during adoption of novel manufacturing technologies. This is done by first summarising the research steps and then reflecting on the project by providing concluding remarks about some of the research steps' results. This chapter also shows how and where the project answered the appropriate research questions and objectives. Finally, this chapter discusses the project's limitations and suggested future work that can be done to improve on the project.

8.1 Overview of Research Process

Figure 8-1 below reiterates the design process followed in this project and defined in Chapter 2. It shows the three distinct design cycles that were completed, along with the design activities of each design cycle.:

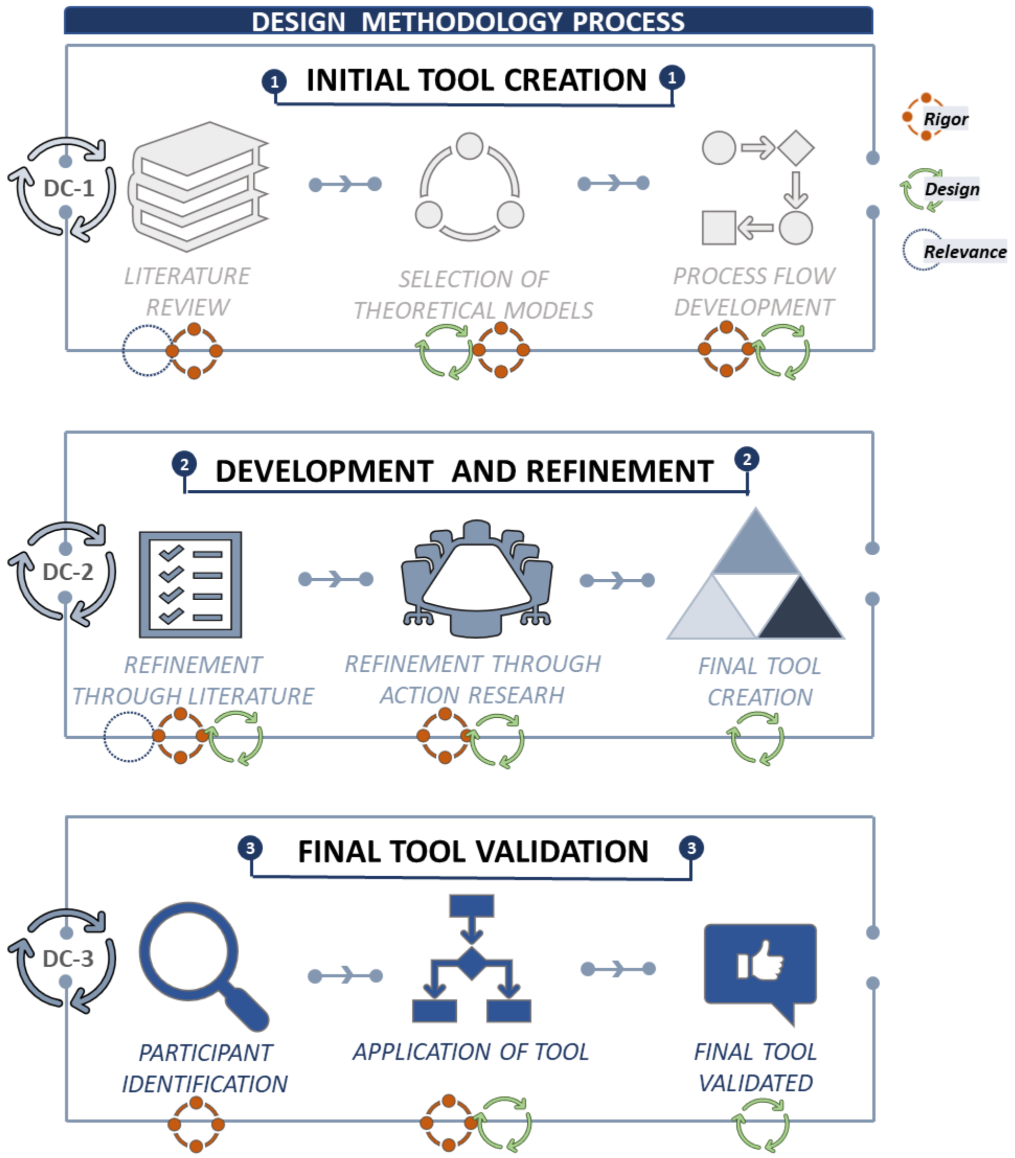


Figure 8-1: *Overall thesis design process*

Ultimately, the goal of the research project was to design and develop a decision support tool that has both academic and practical value. In essence then, the various activities completed in this project was in service of the development triangle shown in Figure 8-2 below. This triangle guided the development process.

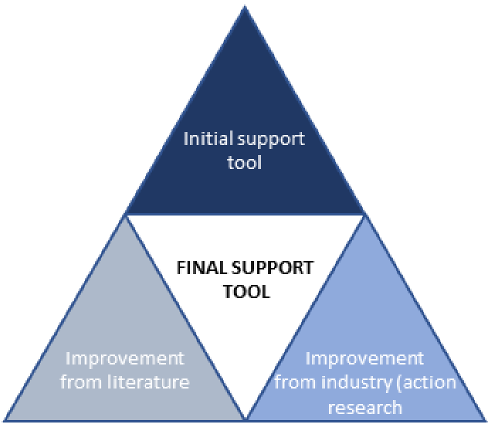


Figure 8-2: *Decision support tool development triangle*

8.1.1 Literature refinement process

The literature refinement phase was the first refinement step following the creation of the initial decision support tool and added a crucial layer of rigor to the project. The literature refinement phase was added since, after the initial tool creation, the support tool consisted simply of four existing theoretical models arranged in a logical process flow. These four theoretical models selected for building the decision support tool are summarised in Table 8-1 below, and their inclusion is argued in Chapter 3:

Table 8-1: *Theoretical models selected for the development of a decision support tool*

Model Name	**Acquisition Question**	**Source**
A Readiness Level Model for New Manufacturing Technologies (MTRL)	Is the technology ready?	(Peters, 2015)
Long Valley of Death: Foundation for Innovation	Is the infrastructure surrounding the technology mature enough?	(Ward et al., 2017)
Technology Readiness and Risk Assessment: A New Approach	Is it worth pursuing further development?	(Mankins, 2009)
SM^{3}E Manufacturing Maturity Model	Are the internal operations mature enough to receive the technology?	(Mittal, Romero and Wuest, 2018) (Mittal, Romero and Wuest, 2018) (Mittal et al., 2018) (Mittal et al., 2019)

While these models were selected from an extensive literature body due to their superior capability of answering the required decision support questions, some of them were originally designed for a slightly different purpose from the one required for this project's application context. The literature refinement stage was therefore used to refine and tailor the existing model dimensions to better fit the new application context of the decision support tool. The SM^3E model, which is used in Phase 4 of the decision support tool, required the most refinement from literature. Chapter 5, therefore, provides a detailed description of the refinements that were made.

The literature refinement stage introduced additional literature bodies that dealt with SM innovations and adoption considerations. Most notably the refinement stage investigated how specific data outputs of an enterprise can be used as a measurement of maturity. The result of this investigation was the identification of specific SM innovation requirements that must be met before maturity can be improved. It was discovered that these innovations generate unique data, which can be used as a measurement metric for maturity. From this literature refinement stage, the decision support tool was updated to include more specific maturity descriptors that provide the user with clear instructions on the type of data the enterprise must generate and the associated innovation that must be adopted to facilitate the data generation at each level of maturity. Ultimately, the literature refinement stage proved to be useful in aligning the contextual requirements of the selected theoretical models to the new contextual requirements of the decision support tool developed in this project, by providing clarity of descriptors and logical maturity progression standards.

8.1.2 Action research refinement process

The action research phase followed the literature refinement stage. While literature refinement is useful to increase the applicability of the tool, an overreliance on literature can lead to shortcomings during practical applications, since literature source identification can be influenced by the researcher's personal biases. To add an additional layer of rigor, experts in various fields of manufacturing, innovation adoption, and theoretical model use in decision support were interviewed and asked to rate various aspects of the proposed decision support tool in a process known as scientific-technical action research (Masters, 1995). Table 8-2 below summarises the experts that were interviewed:

Table 8-2: *Summary of experts interviewed during action research*

Subject matter/Industry Expert	**Abbreviation**
Additive Manufacturing PhD	AdM_PHD
Additive Manufacturing (cemented carbide) Specialist/PhD	AdM_S
Asset Management and Manufacturing Expert	AM&M
Business Intelligence Engineer	BIE
Carbide Manufacturing and Distribution Expert	CM&D
Management Consulting and Manufacturing Expert	MC&M
Digital Transformation in Manufacturing Expert	DTM

The action research phase was extensive with multiple conclusions drawn and refinements made to the proposed decision support tool based on the ratings and comments provided by the interviewees. These results can be seen in Chapter 6 as all the detail cannot be included in this section. The most notable action research rating results were the *Need (N)* vs *Need Addressed by Tool (NAT)* result, along with the *Overall Tool Score (O)*. For *Need* vs *NAT* the interviewees indicated that there is not only a strong need for a decision support tool such as the one proposed in this thesis but also that the proposed tool successfully addressed the need, given that some refinement requirements were met. Furthermore, the *Overall Tool Score (O)*given by the interviewees was an average 76.7%, which categorises the tool according to the following definition as defined in the rating legend of Chapter 6: *Significant research contribution is made, and tool delivers its base purpose while introducing useful additional functionalities. Some practical application is immediately available, but some refinement is required before the tool is fully industry-ready.*

Reflecting on the results lead to the conclusion that this project successfully identified and addressed the need for a decision support tool while also making significant research contributions. However, the action research phase was included as a refinement phase and, while the two main metrics discussed above were acceptable, the interviews did reveal certain improvements that had to be made to the tool before it would be fully ready for practical application. A curious observation of the action research phase was the variation in responses depending on the interviewee's area of expertise. In some cases, interviewees with an intricate knowledge of the analysis area would scrutinize and challenge the ratings more than the other interviewees. While this could logically be expected, it did create scenarios in which the opinion of some experts would carry more weight than others depending on the analysis area. In such cases, it was still useful to include the comments of the other interviewees as it created an interesting image of how the tool's dimensions were perceived from both an expert's and general user's viewpoint. The action research phase did, however, include multiple experts in a variety of fields, which provided a well-rounded distribution of feedback.

Ultimately, the action research phase successfully aggregated the various comments of the experts and communicated the results effectively using graphs, ratings and qualitative comment analysis. From the action research phase, some additions and improvements were made to the tool as can be seen in Chapter 6. Most noticeably, many of the refinements dealt with clarification of the maturity descriptors and improvement of the logic around maturity progression requirements. These additions along with the refinements from literature proved to be useful in creating a well-rounded and practical tool as was discovered in the final tool validation stage and is discussed in the following section.

8.1.3 Final tool validation

The final tool validation case study was done by simulating a real-world scenario and applying the tool to an existing manufacturing enterprise. While the ultimate goal of this tool is to be used in the cemented tungsten carbide AM industry, there are currently no commercial applications of cemented carbide AM technologies. The tool was, however, developed as a general-use decision support tool for the adoption of most novel manufacturing technologies. Validation of the tool using some other novel manufacturing technology would therefore be sufficient in proving the tool's efficacy for use in the cemented carbide industry. For this project's simulation, an enterprise, Company A, was selected as they had been investigating a specific use case of novel manufacturing technology, and subsequent novel manufacturing process, adoption even before the genesis of this project. They were, therefore, willing to apply the tool developed in this project to help with the decision support of the adoption process. Due to confidentiality restrictions, Company A could only reveal that they are investigating the adoption of a new forming manufacturing technology along with the subsequent development of a novel manufacturing process. This use case could therefore validate the proposed decision support tool on both a technology and process level. Validation of the tool Furthermore, for the simulation Company A provided two representatives in the CEO and the Operations Manager. The CEO is also the founder a successful consulting company that specialises in software consulting solutions and decision support. They were, therefore, the ideal candidates for the tool's implementation and scenario simulation.

The tool was applied successfully and to the satisfaction of the participants. Company A believed the tool accurately reflected their position while also being useful for the development of an innovation adoption and operational improvement roadmap. During the simulation, Company A's representatives expressed their interest in some of the tool's dimensions that they have previously neglected to consider. The tool was therefore useful for baselining and highlighting critical considerations that some users might not be aware of. An interesting observation was made during the final internal maturity phase of the tool where Company A seemed to score low in many of the SM orientated maturity rankings. When asked by the researcher whether Company A felt that these scores were unfairly harsh or inaccurate, Company A responded by saying they felt the tool was accurate as they are aware of- and have been suspecting a lack of maturity for some of their internal dimensions. In fact, the tool helped to pinpoint where exactly Company A should focus their resources to improve said dimensions, thus cementing the tool's usefulness for decision support.

Some final critiques of the tool that should be noted was that Phase 4 of the tool is not necessarily as applicable for the analysis of technologies that are not digitally geared, however, Company A still believed that Phase 4 of the tool provided useful baselining information that can be used regardless of the technology's digital capabilities. Lastly, Company A believed Phase 4 can be difficult to implement without the guidance of the researcher, but that self-implementation could be possible with an improved user interface.

8.2 Overview of Research Questions

The main research question for this project asked: *What should comprise a decision support tool[1] for use by manufacturing enterprises[2] during the novel manufacturing technology adoption phase known as "The long valley of death"[3]? How can one achieve the above by integrating and adjusting established theoretical model[4] concepts of maturity and readiness indexes?*

First of all, the main research question was answered successfully as is proven by the creation, refinement, and validation of a successful decision support tool for the adoption of novel manufacturing technologies. Additionally, the project showed that the tool can also be effective in cases where a new manufacturing process is implemented. Successful validation of the tool implies that the tool can ultimately be used for decision support in the cemented tungsten carbide AM industry, once these technologies have viable commercial applications. Next, multiple secondary research questions (SRQ) stemmed from the main question, each of which is listed and answered below:

SRQ 1.1: ***What is the input of such a tool?***

The inputs of the decision support tool are varied and rely heavily on the application domain knowledge of the user and their qualitative interpretation of the problem. This project showed, however, that decision support can be provided by inputting the following: Firstly, the tool requires the input of readiness criteria that estimate how long development will take to bridge each level of technology readiness up until the desired TRL is reached. Next, the tool requires the input of external maturity criteria which describe the maturity level of Supply Chain, Technology, and Product dimensions. Then, the tool requires inputs that estimate the probability that a novel technology will be developed successfully by a third party. This input along with a technology need input is then used to estimate the risk of future R&D projects. Lastly, the tool requires maturity level inputs for various internal operations of a manufacturing enterprise. These inputs rely on the type of data generated by the various operations.

SRQ 1.2: ***What is the output of such a tool?***

This project showed that the adoption of novel manufacturing technologies is a function of multi-varied, complex, and uncertain variables. It is, subsequently, extremely difficult, if not impossible, to output a binary "Yes or No" answer with a decision support tool. Ultimately, such a tool uses qualitative inputs to try and create an output that brings structure to the adoption process. It guides the user through multiple considerations and possible influencing factors in order for them to combine the tool outputs with their pre-existing knowledge and generate an informed opinion. The final output uses quantitative percentage ranges along with bar graphs and spider graphs to present the various risks and probable outcomes in a logical and comprehensible way.

SRQ 1.3: ***What is the preferred process flow of such a tool?***

This project showed that the preferred process flow of such a tool is to first answer how long it will take a novel technology to reach the desired TRL. Next, the tool investigates, once the technology is at a desired TRL, what is the maturity of the external dimensions that an enterprise relies on during their day-to-day operation. Then, once the user understands TRL and the external maturity, the tool answers what is the probability of the third party successfully completing the R&D efforts within the given timeframe. The last part of the process flow investigates if the internal operations of an enterprise are mature enough so they can identify which dimensions need to be improved before adopting a new technology.

SRQ 1.4: ***Which interface can be used for such a tool?***

This project showed that Microsoft excel can be used to create a user interface. The availability of VBA along with the @Risk excel plug-in allows for the creation of a powerful analysis tool. However, other programming languages can be used, Microsoft excel is just extremely accessible to most individuals and enterprises.

SRQ 2.1: ***What sizes of enterprises are relevant to the study?***

This project showed that small to medium-sized enterprises prefer self-help tools as it is less costly than outsourcing consultation services. This tool was therefore developed for use by SMEs.

SRQ 2.2: ***How far down the production network are criteria still relevant?***

This project considered factors from the supply chain that supports the novel technology being adopted to the final product produced by the technology.

SRQ 2.3: ***How does Smart Manufacturing fit into the application context?***

This project showed that the incorporation of SM elements is fundamental to the sustained success of manufacturing enterprises. The project also explored critical risk/reward factors that must be considered before investing in the adoption of SM innovations. A selection process chart was developed to help with the selection of appropriate SM innovation aspirations.

SRQ 3.1: ***What is the long valley of death?***

This question was answered in detail in the literature review of Chapter 3. To summarise: The term "Valley of death" is frequently used in the manufacturing realm to describe the gap between academic innovation and market commercialisation of a new technology. The gap represents a phase during innovation development where academic funding and interest for further development have been exhausted but the development is not yet significant enough to attract commercial involvement in the project. In their 2017 paper, Ward et al. argue that overlapping the "Valley of Death", is a "Long Valley of Death" (Ward *et al.*, 2017). They suggest that most institutions view the valley of death as a Manufacturing Readiness Level (MRL) issue, specifically the transition between MRL 4 and 6 where, in reality, the true problem starts even earlier and concludes later down the innovation timeline.

SRQ 3.2: ***How can LVoD be used in a decision support tool?***

This project shows that by understanding and analysing the factors that feed into market failure associated with the LVoD, a user can make more informed decisions. This was done by incorporating the maturity criteria developed by Ward for the LVoD into a tool (Ward *et al.*, 2017).

SRQ 4.1: ***Which readiness indexes are relevant to the study?***

After an extensive literature search, four possible models were identified for use as a readiness index in the decision support tool. After conducting a selection process, as seen in Chapter 3, the Manufacturing Technology Readiness Level (MTRL) model developed by Peters was chosen as the most applicable model (Peters, 2015).

SRQ 4.2: ***Which maturity models are relevant to the study?***

After an extensive literature search, seven possible maturity models were identified for use in the decision support tool. Three of the models dealt with maturity considerations of the LVoD and four models dealt with manufacturing maturity. After a selection process was completed, as seen in Chapter 3, The LVoD: Foundation for Innovation maturity model (Ward eta l., 2017) was selected to address the LVoD, and the SM^{3}E model (Mittal, Romero and Wuest, 2018) was selected to address manufacturing maturity of SMEs.

SRQ 4.3: ***Are there other theoretical models that can be useful to the study?***

During the extensive literature search, the possible advantage of including a risk analysis tool was identified. Two possible risk estimation models were chosen and after a selection procedure, as seen in Chapter 3 the TRRA model developed by Mankins (2009) was selected.

8.3 Project Contributions

This project made contributions in the fields of novel manufacturing technology adoption, decision support tools, maturity, and readiness. The main contribution of the project was the successful development of a decision support tool that can support an enterprise's decision-making during the adoption and exploitation of novel manufacturing technologies. Additionally, the tool proved to be useful not only for the adoption of novel manufacturing technologies but also for novel manufacturing processes. In such a case, the novel manufacturing process in its entirety is considered to be the "technology" under investigation. With this contribution, the researcher believes they have successfully addressed a gap in the research, as discussed in Chapter 1, and thus, to the knowledge of the researcher, this project provides the first practically applicable tool that can support novel technology adoption decision making from an early stage of technology R&D through to the final operational phase of an enterprise. The researcher believes this tool will be useful to the cemented tungsten carbide AM industry once the available cemented carbide AM technologies have viable commercial applications.

The project also made a number of secondary contributions, one of which was the development of an innovation selection process as shown in Chapter 5.3. This process outlines the critical considerations before adopting new SM innovations for the purposes of maturity improvement. This process is critical for road mapping and strategizing activities as it aids in the investigation of possible investment risks associated with innovation adoption. It is recommended that the innovation selection process be consulted during the use of Phase 4 of the proposed decision support tool. Some other secondary contributions this project made relates to the literature review which provides the reader with a detailed perspective on current readiness, maturity and innovation adoption literature. Overall, the project provides the reader with a logical, stepwise research document that can not only be replicated but also built upon for future work.

8.4 Project Limitations

For this project, time constraints were a major limitation. Designing, developing and testing a tool with full industry-ready capabilities will require a comprehensive commercial effort that will take longer than the time designated for this project. Therefore, the tool developed in this project, while still highly applicable, serves more as an academic proof-of-concept and provides a baseline from which future, more intricate commercial tools can be developed.

Another limitation of this project relates to the method of validation that was used. Since the tool fundamentally deals with technologies that have not yet been adopted, it is extremely hard to prove that the output of the tool generated during the simulation phase in Chapter 7, will accurately reflect future adoption efforts. The researcher tried to negate this limitation by creating a non-binary tool that, instead of outputting "yes" or "no", outputs a variety of information that must be combined with the user's expertise to generate an informed opinion. Thus, as long as the tool accurately reflects the current position of the enterprise and technology, the validation was successful.

One final project limitation is the fact that the tool defines maturity levels with relation to certain SM innovation adoptions. With time, some innovations that are currently associated with a high level of maturity could become commonplace in the industry, thus no longer representing the highest form of maturity. The tool must, therefore, be refined continuously to align with industry requirements otherwise it can become outdated as maturity requirements increase.

8.5 Future Work

This thesis provides the reader with a structured and logical document that outlines the entire process of creating a decision support tool for novel manufacturing adoption. By clearly defining the various development activities it makes it easier for future researchers to not only replicate but improve upon the process. While multiple reasonable measures were taken during this project to ensure the development of an applicable and value-adding tool, the nature of academic work lends itself to future improvements and developments. For this thesis, such future work should focus on further refinement of the various dimensions and descriptors of the tool phases. The addition of extra intermediate phases can also improve the applicability of the tool. Furthermore, future researchers could use the tool to develop standard practices and procedures for improving external and internal maturity. Lastly, Phase 3 of the tool developed in this thesis can be expanded significantly to include more detailed risk analysis methods. The following suggestions can be implemented in future work:

Include Capability Levels: Future researchers should consider the addition of a capability level analysis that follows the readiness analysis. This provides a measurement of the technology's proven stage of capability within a practical setting.

Include Six Sigma/DMAIC requirements: Future researchers should investigate the use of Six Sigma and DMAIC methods as a measure of maturity or operational capability.

Improve risk analysis: The risk analysis phase of the proposed tool can be improved by future researchers by studying additional risk analysis techniques. Implementing a modified Delphi technique, for instance, could be beneficial for scenarios where the available knowledge is limited.

Customize data-driven descriptors across organisational dimensions: The decision support tool developed in this thesis uses data-driven maturity descriptors in Phase 4 of the tool. In the toolboxes, the data-descriptors are the same across all organizational dimensions for each level of maturity. This was a deliberate design choice as customization of each maturity level of every maturity level in all the toolboxes will take a monumental research effort when combined with the development of an entire tool. Since this project established the basic functionality of the decision support tool, it would be possible for future researchers to focus purely on the data descriptors.

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Appendix A

Decision Support Tool Supporting Content

This appendix provides the supporting content for the proposed decision support tool developed in this project. The content of this Appendix is as follows:

- **Section A.1:** Tool Overview of Data Page
- **Section A.2:** Tool Phase 1 – MTRL
    - Section A.2.1: @Risk User Manual
    - Section A.2.2: Phase 1 Output
- **Section A.3:** Tool Phase 2 – LVoD
- **Section A.4:** Tool Phase 3 – TRRA
- **Section A.5:** Tool Phase 4 – SM^{3}E
    - Section A.5.1: Phase 4 Navigation Page
    - Section A.5.2: Phase 4 Toolboxes

A.1 Overview of Data Page

A.1. Overview of Data Page

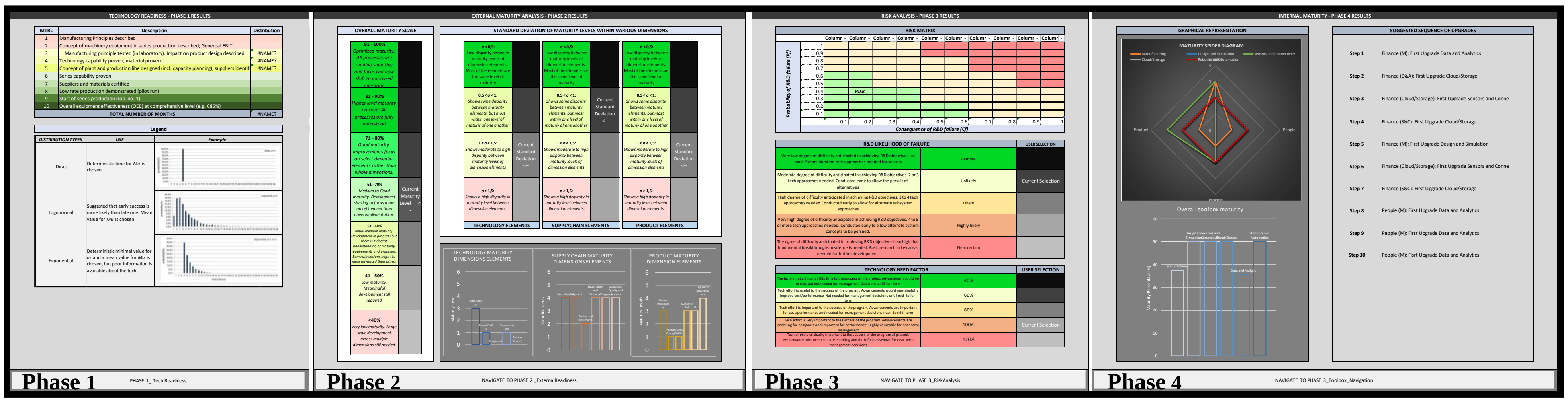


Figure A-1: *Decision support tool interface - Overview of Data page Company A simulation results*

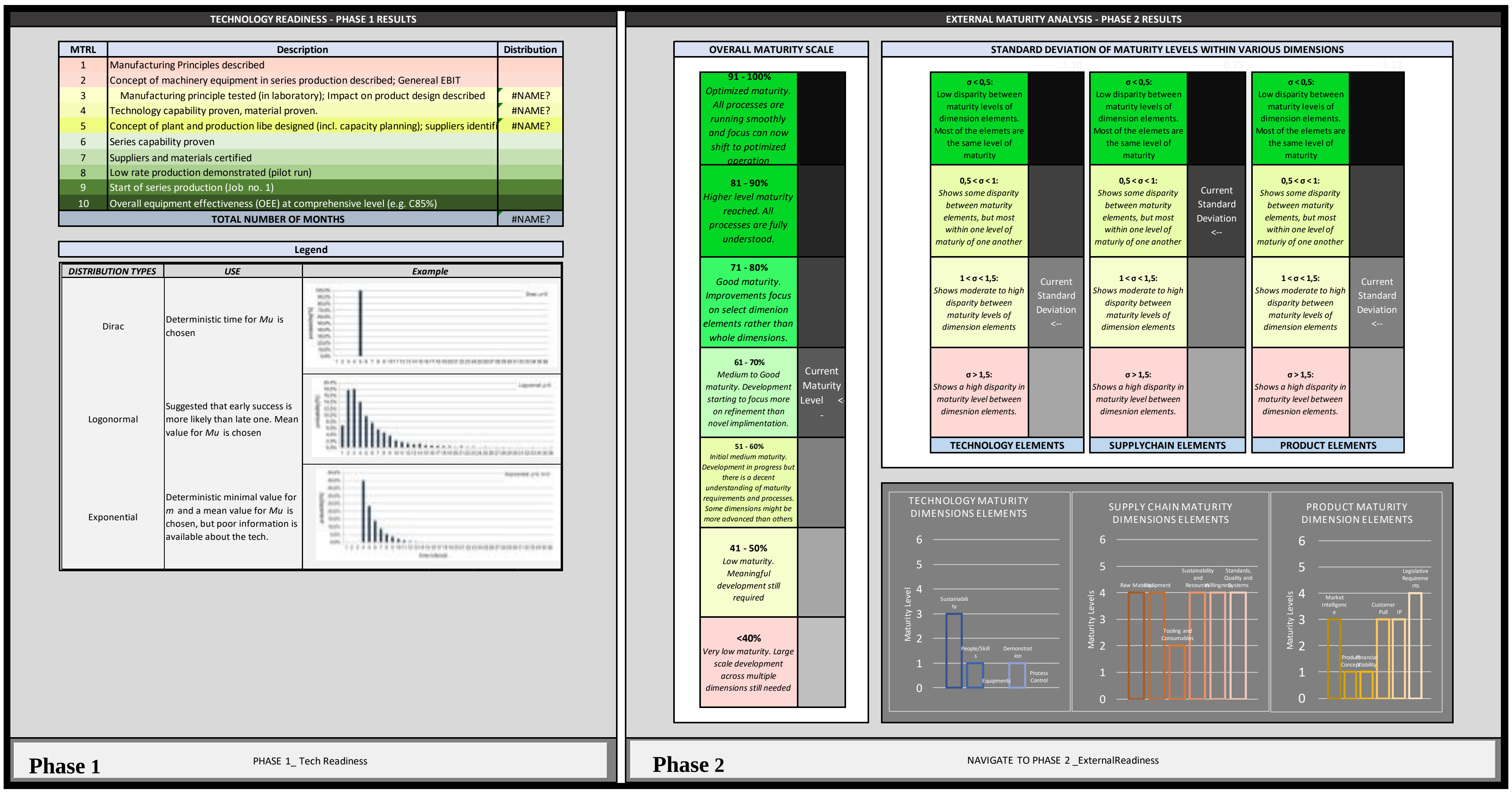


Figure A-2: *Enlarged image of the Overview of Data page - Phases 1 and 2 Company A simulation results*

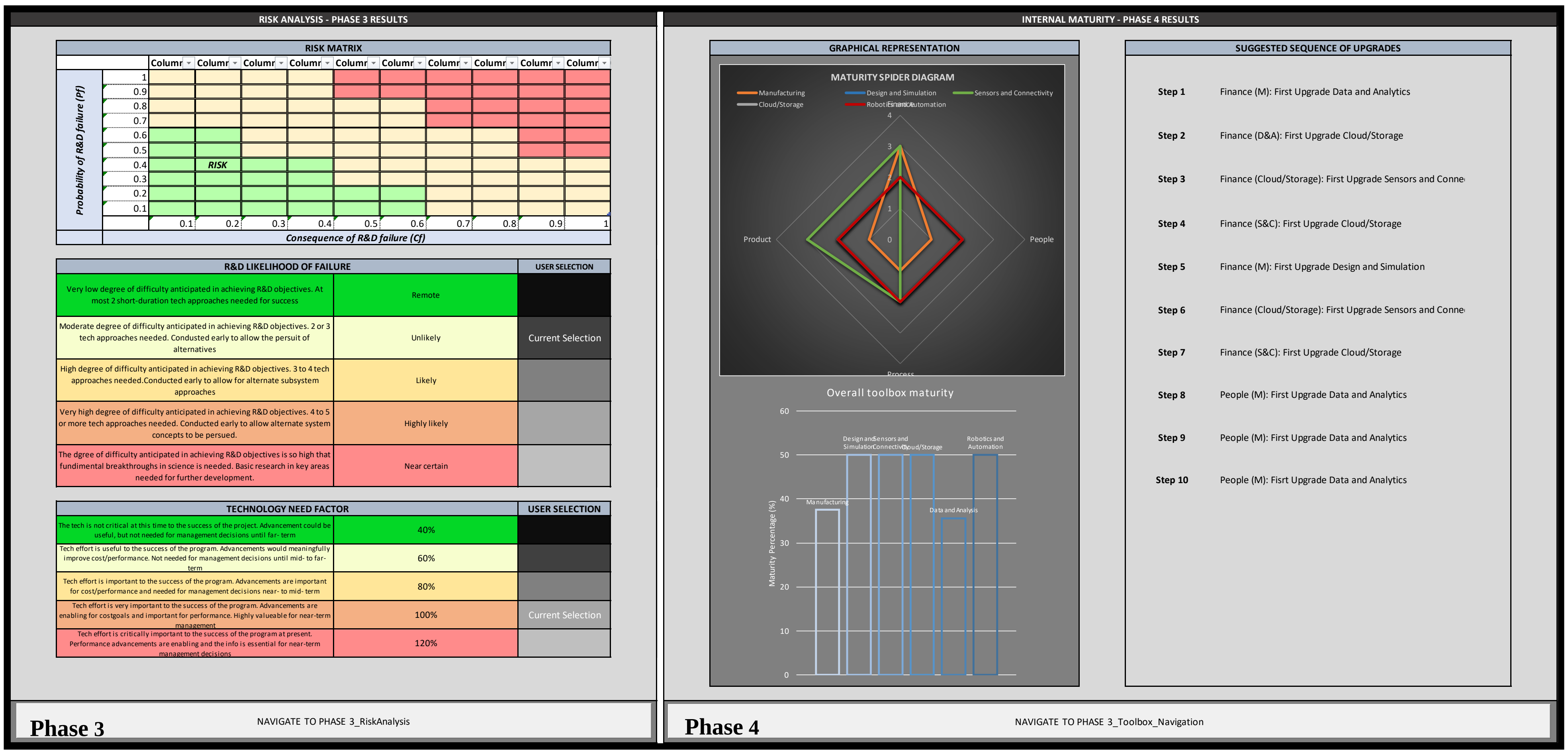


Figure A-3: *Enlarged image of the Overview of Data page - Phases 3 and 4 company A simulation results*

TECHNOLOGY READINESS - PHASE 1 RESULTS

MTRL	Description	Distribution
1	Manufacturing Principles described	
2	Concept of machinery equipment in series production described; Genereal EBIT	
3	Manufacturing principle tested (in laboratory); Impact on product design described	
4	Technology capability proven, material proven.	
5	Concept of plant and production libe designed (incl. capacity planning); suppliers identifi	
6	Series capability proven	5
7	Suppliers and materials certified	3.03825363
8	Low rate production demonstrated (pilot run)	5.18436578
9	Start of series production (Job no. 1)	
10	Overall equipment effectiveness (OEE) at comprehensive level (e.g. C85%)	
TOTAL NUMBER OF MONTHS		13.22261941

Legend

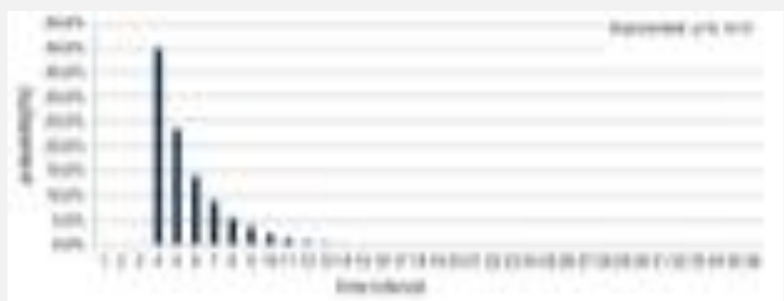
DISTRIBUTION TYPES	*USE*	*Example*
Dirac	Deterministic time for *Mu* is chosen	
Logonormal	Suggested that early success is more likely than late one. Mean value for *Mu* is chosen	
Exponential	Deterministic minimal value for *m* and a mean value for *Mu* is chosen, but poor information is available about the tech.	

Figure A-4: *Phase 1 final tool overview page - Company A simulation results*

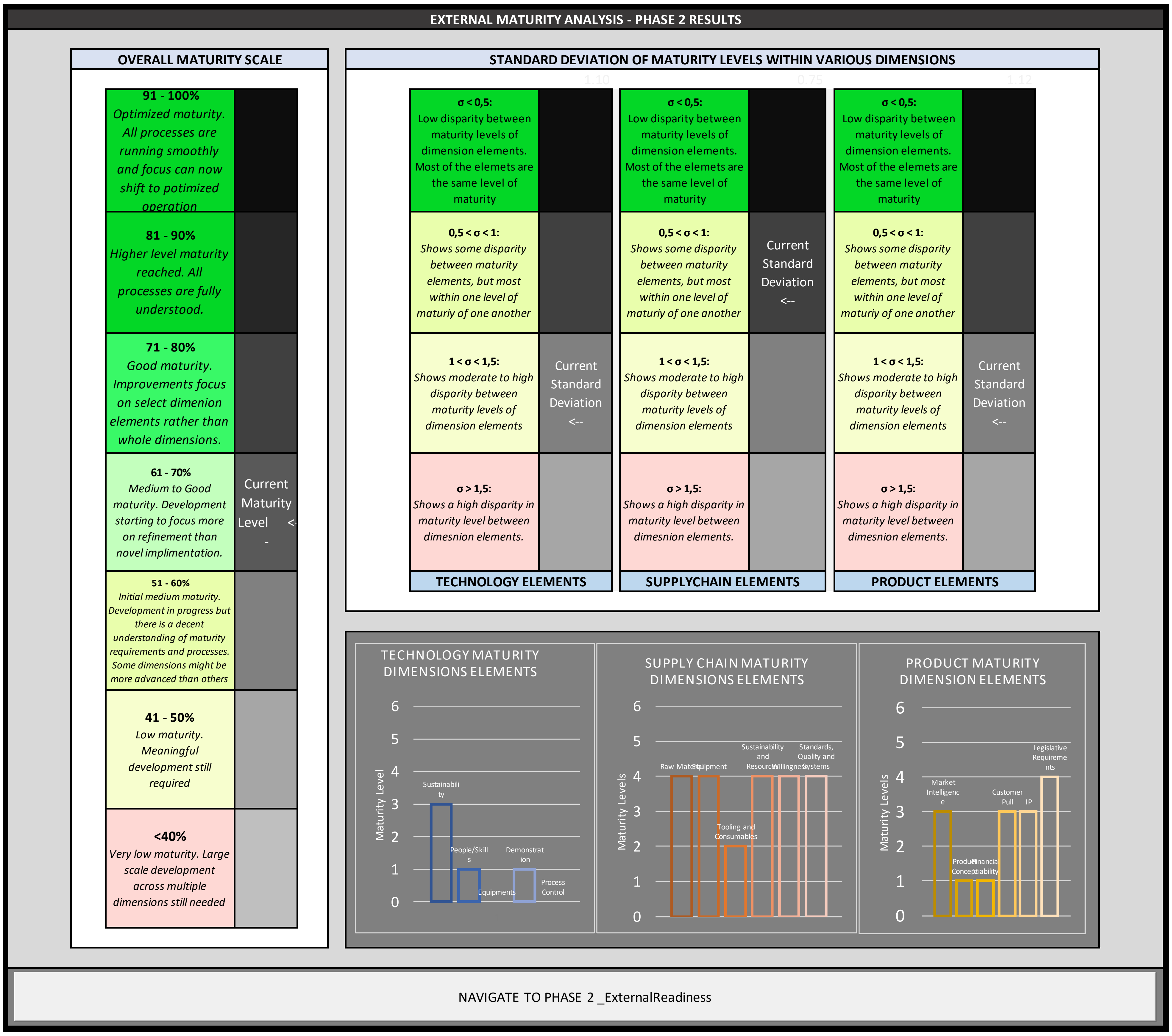


Figure A-5: *Phase 2 final tool overview page – Company A simulation results*

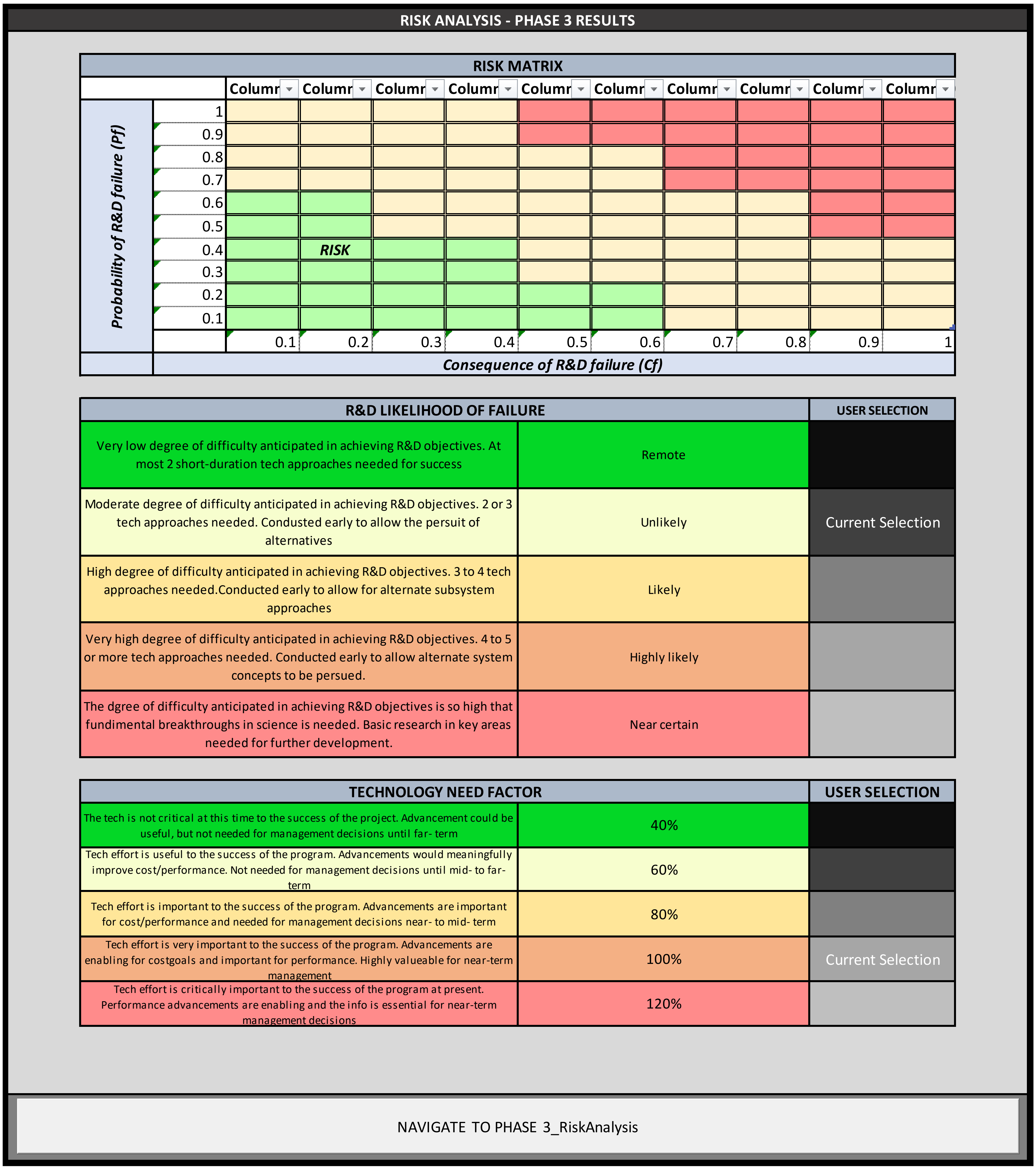


Figure A-6: *Phase 3 final tool overview page – Company A simulation results*

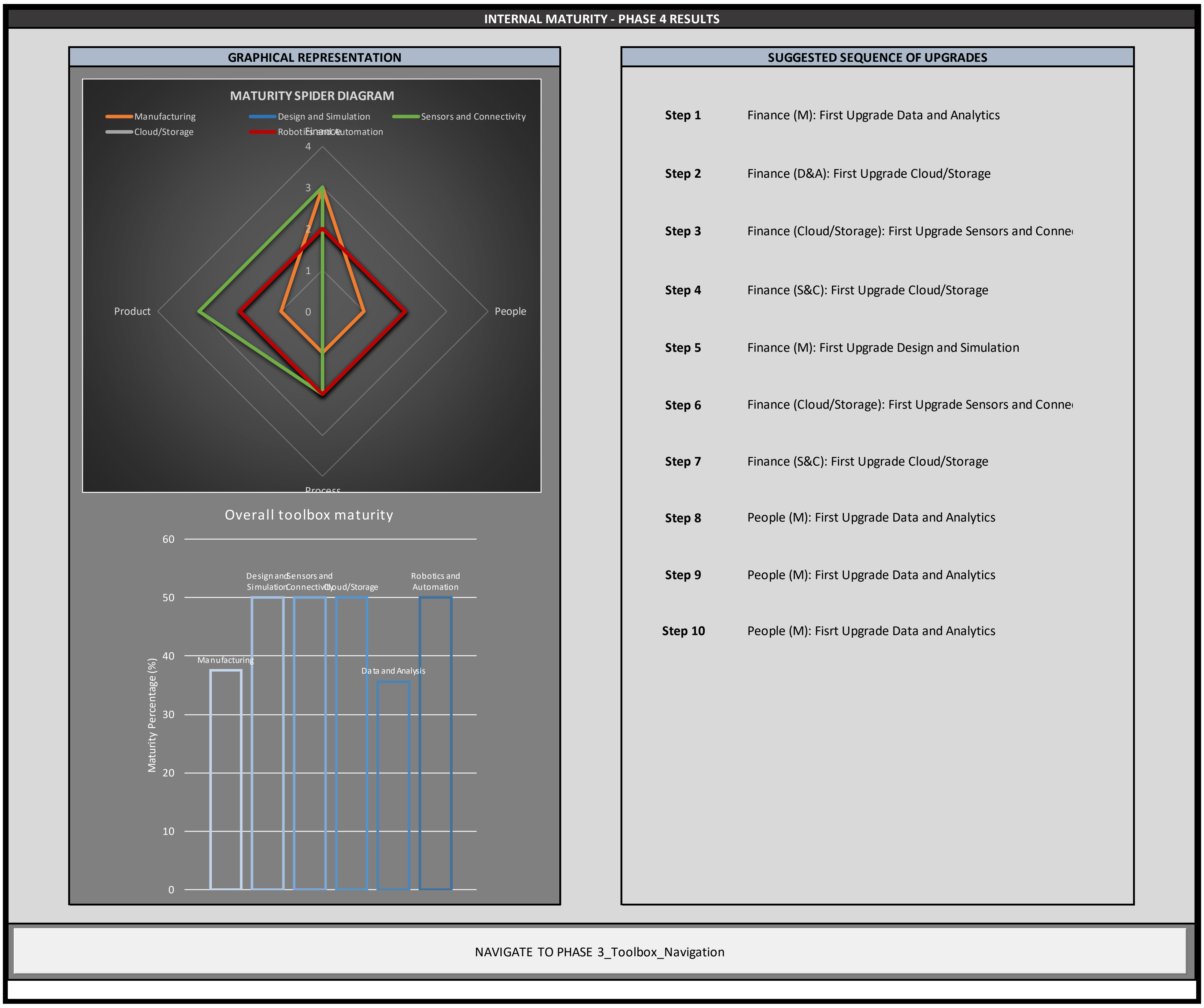


Figure A-7: *Phase 4 final tool overview page – Company A simulation results*

A.2 Tool Phase 1 – MTRL

A.2.1 @Risk User Manual

A.2.1 @Risk User Manual

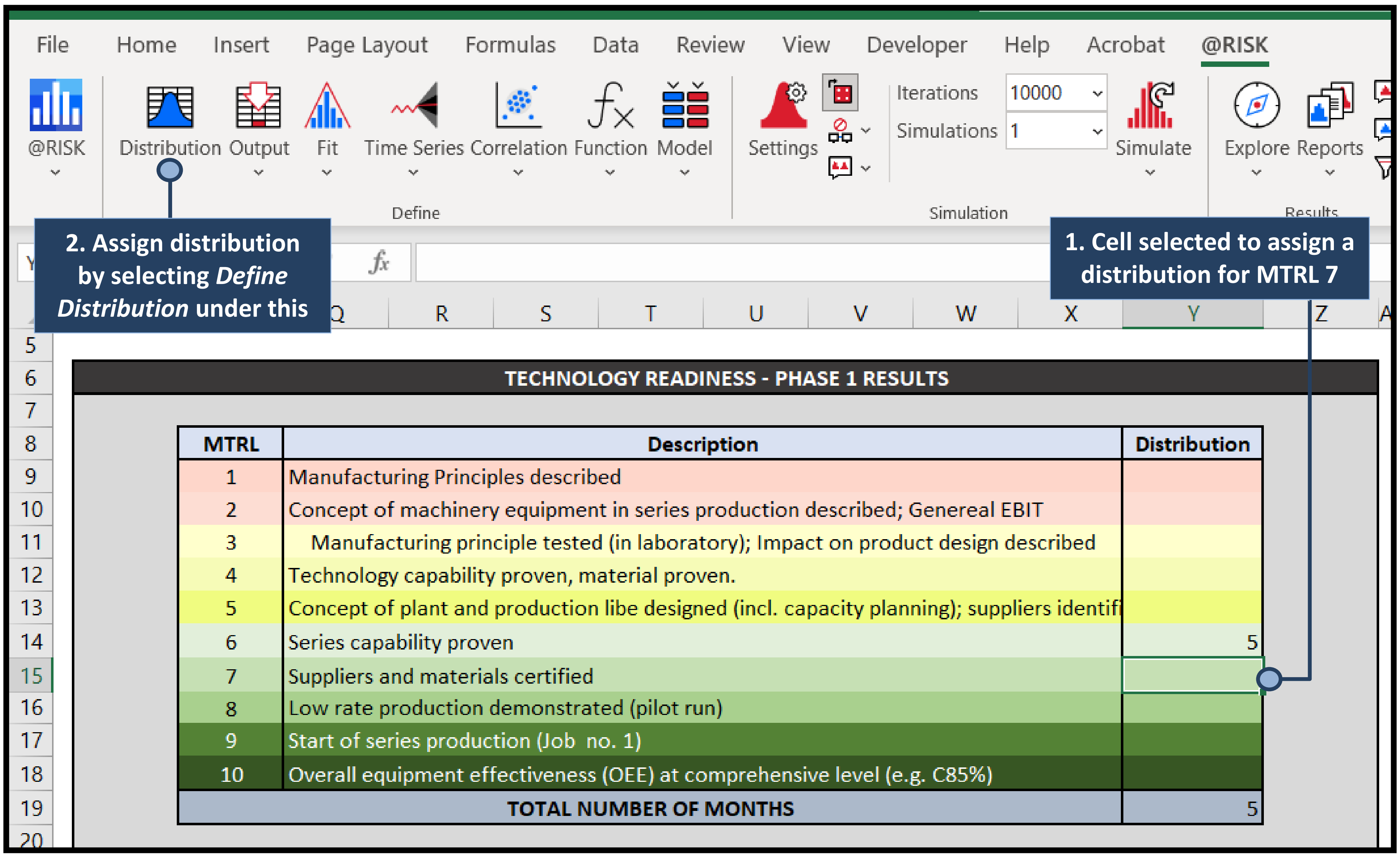


Figure A-0-8: *@Risk user manual – Assigning distributions*

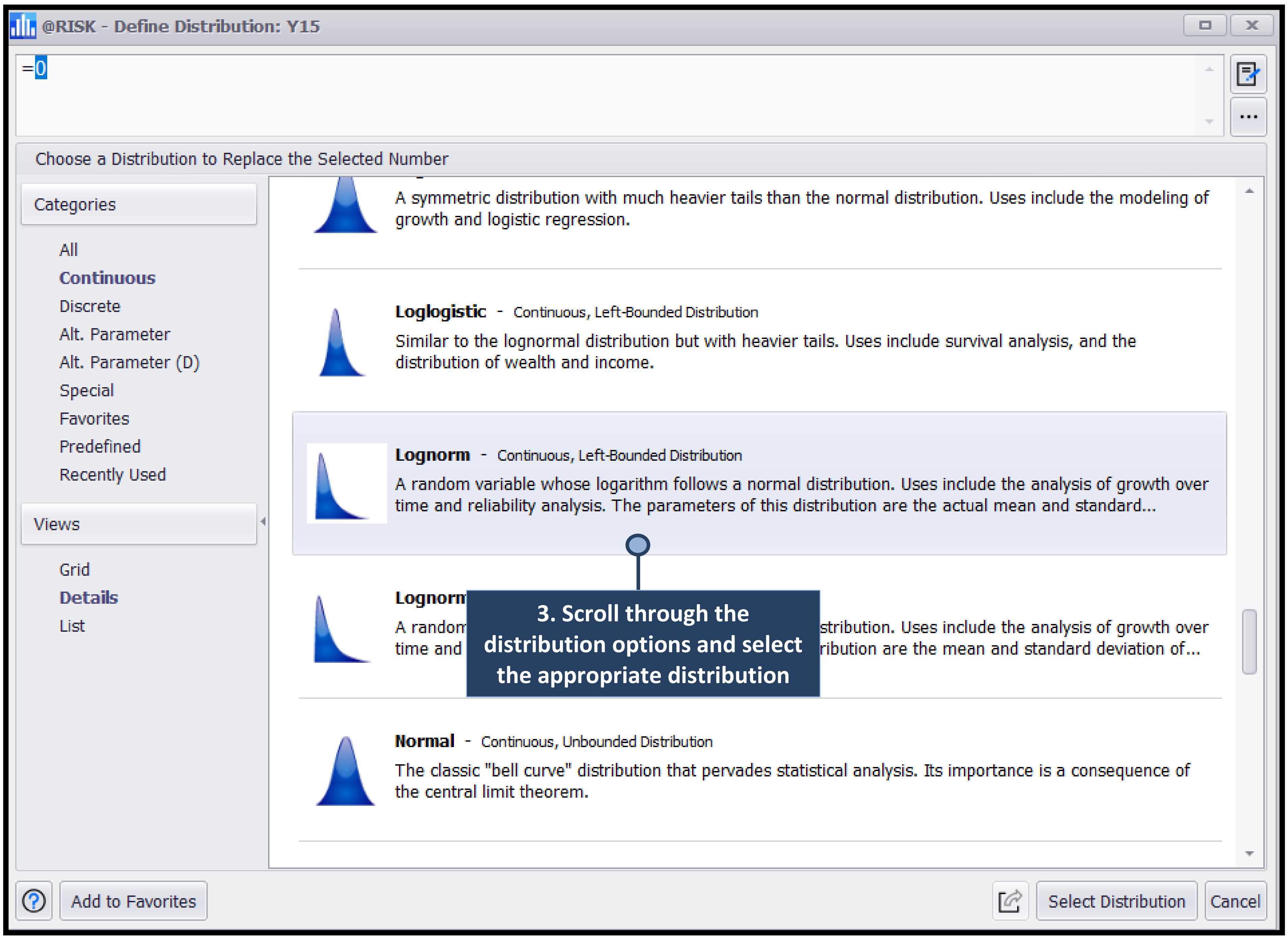


Figure A-9: *@Risk user manual – Selecting distributions*

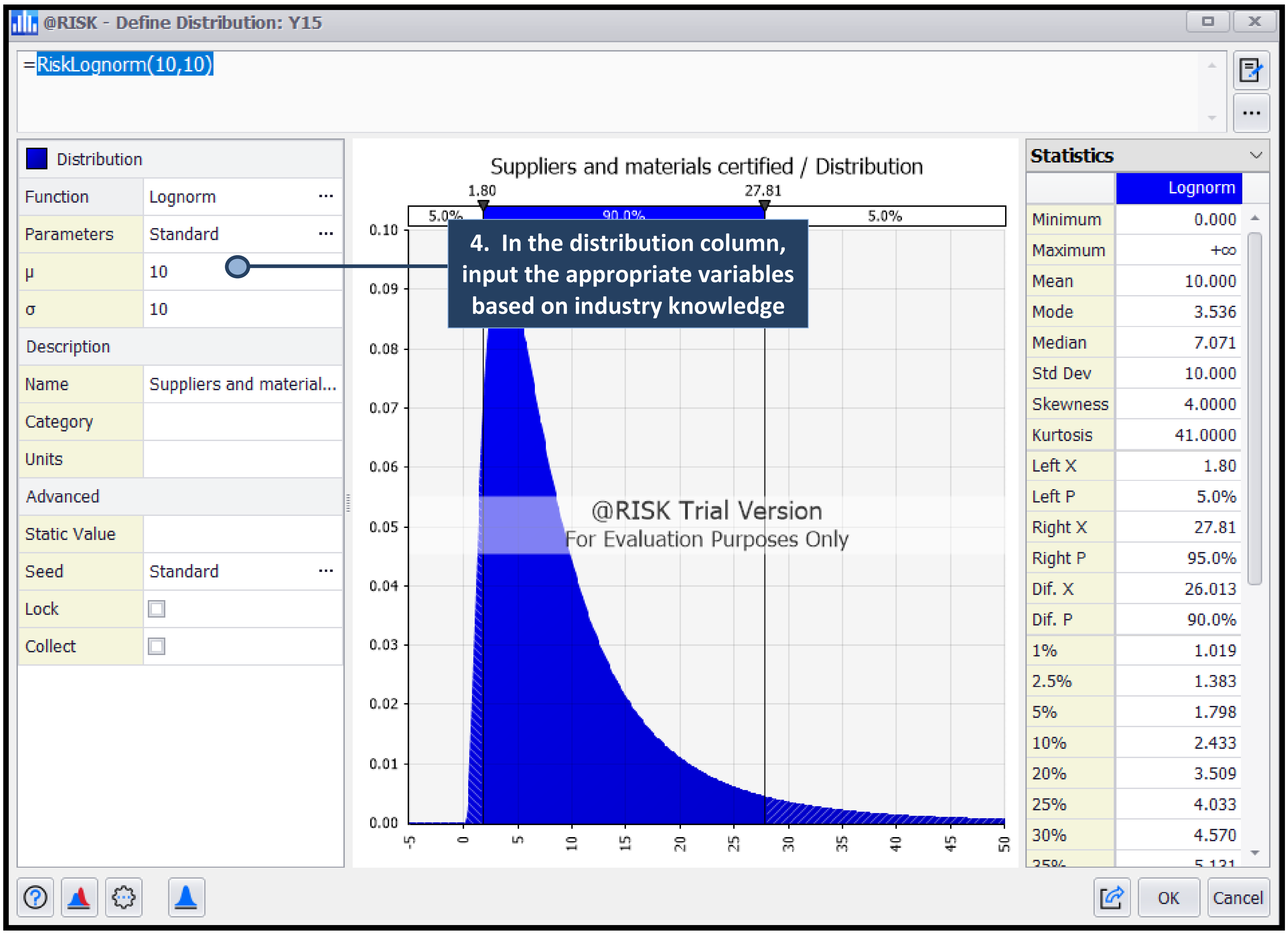
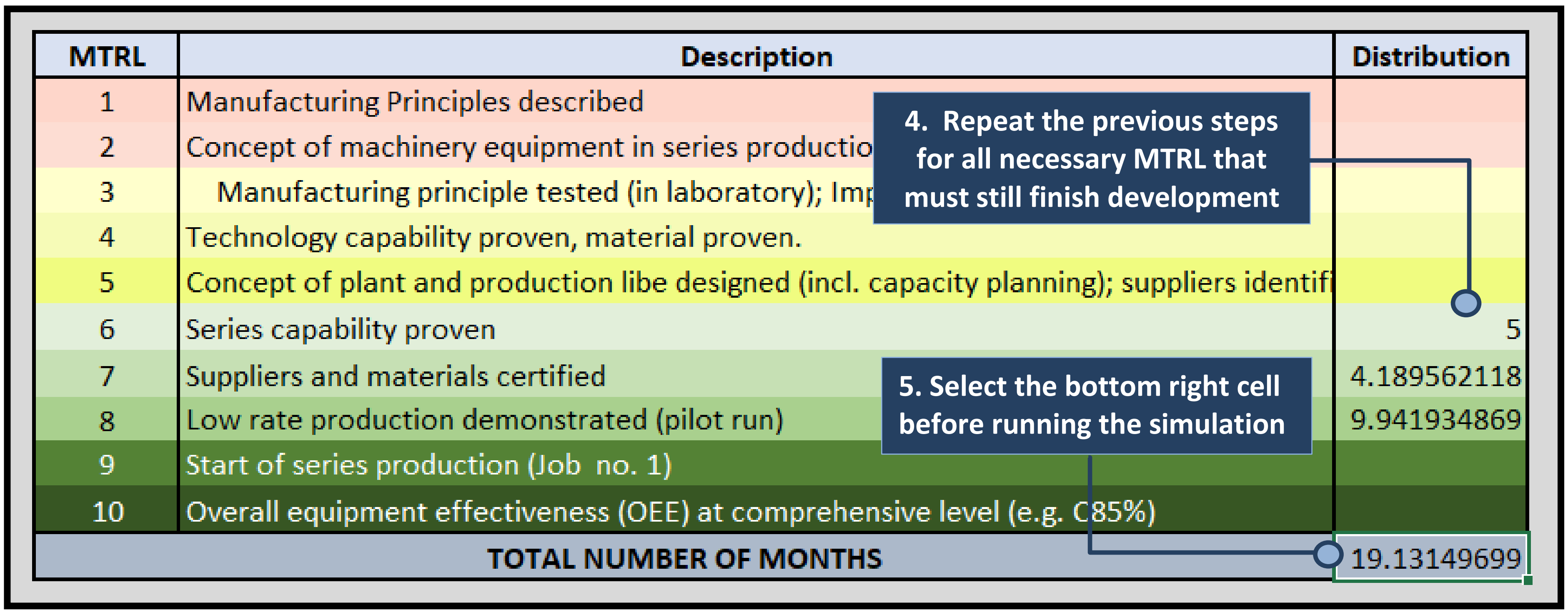


Figure A-10: *@Risk user manual – Selecting distribution variables*



MTRL	Description	Distribution
1	Manufacturing Principles described	
2	Concept of machinery equipment in series productio	
3	Manufacturing principle tested (in laboratory); Imp	
4	Technology capability proven, material proven.	
5	Concept of plant and production libe designed (incl. capacity planning); suppliers identifi	
6	Series capability proven	5
7	Suppliers and materials certified	4.189562118
8	Low rate production demonstrated (pilot run)	9.941934869
9	Start of series production (Job no. 1)	
10	Overall equipment effectiveness (OEE) at comprehensive level (e.g. C85%)	
	TOTAL NUMBER OF MONTHS	19.13149699

Figure A-11: *@Risk user manual – Selecting output distributions*

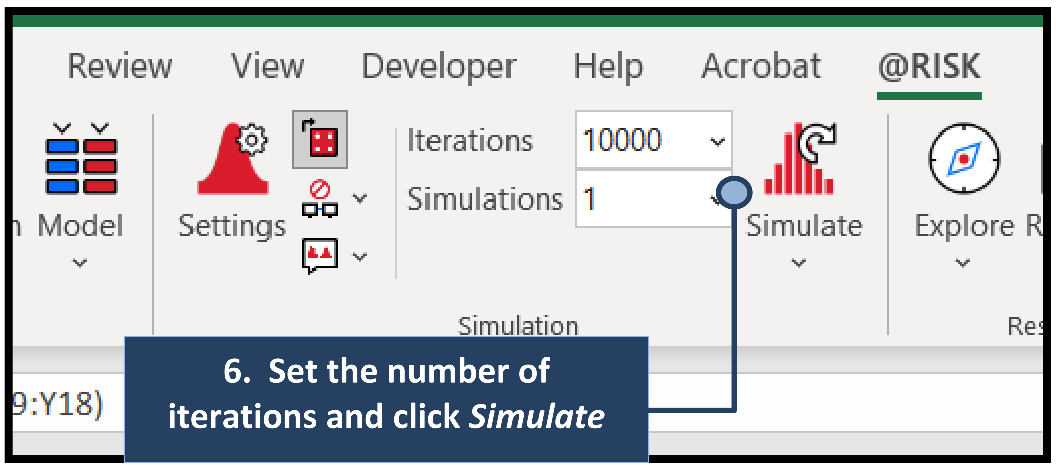


Figure A-12: *@Risk user manual – Running simulation*

A.2.2 Phase 1 Output

TECHNOLOGY READINESS - PHASE 1 RESULTS

MTRL	Description	Distribution
1	Manufacturing Principles described	
2	Concept of machinery equipment in series production described; Genereal EBIT	
3	Manufacturing principle tested (in laboratory); Impact on product design described	3,099852075
4	Technology capability proven, material proven.	12,00840917
5	Concept of plant and production libe designed (incl. capacity planning); suppliers ic	9,485300626
6	Series capability proven	
7	Suppliers and materials certified	
8	Low rate production demonstrated (pilot run)	
9	Start of series production (Job no. 1)	
10	Overall equipment effectiveness (OEE) at comprehensive level (e.g. C85%)	
TOTAL NUMBER OF MONTHS		24,59356187

Legend

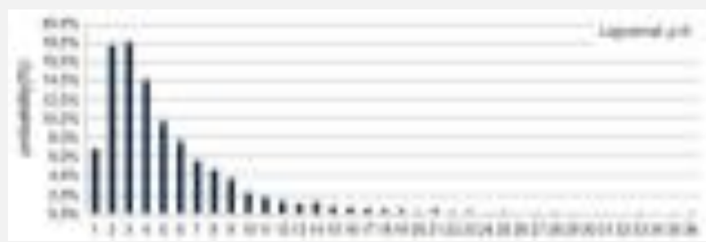
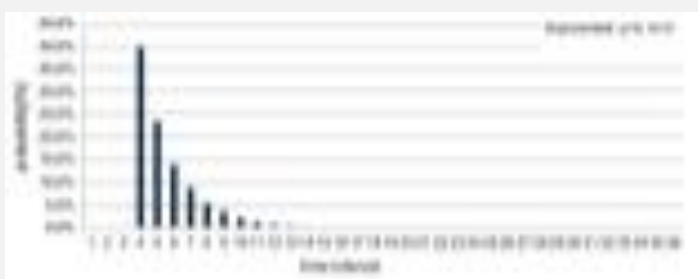
DISTRIBUTION TYPES	*USE*	*Example*
Dirac	Deterministic time for *Mu* is chosen	
Logonormal	Suggested that early success is more likely than late one. Mean value for *Mu* is chosen	
Exponential	Deterministic minimal value for *m* and a mean value for *Mu* is chosen, but poor information is available about the tech.	

Figure A-13: *Phase 1 final tool application page - Company A simulation inputs*

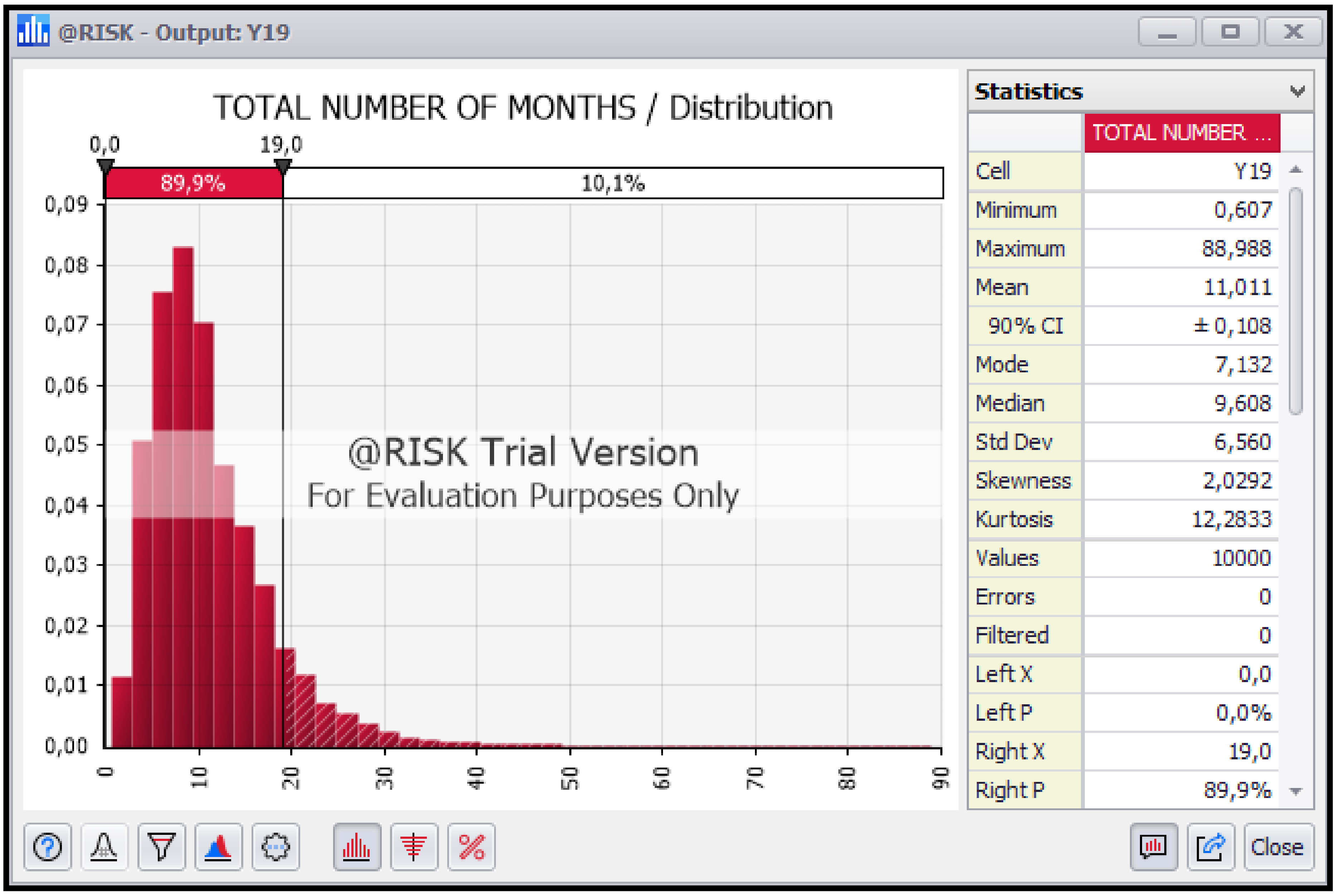


Figure A-14: *Phase 1 final tool application page - Company A simulation results*

A.3 Tool Phase 2 – LVoD

A.3. Tool Phase 2 - LVoD

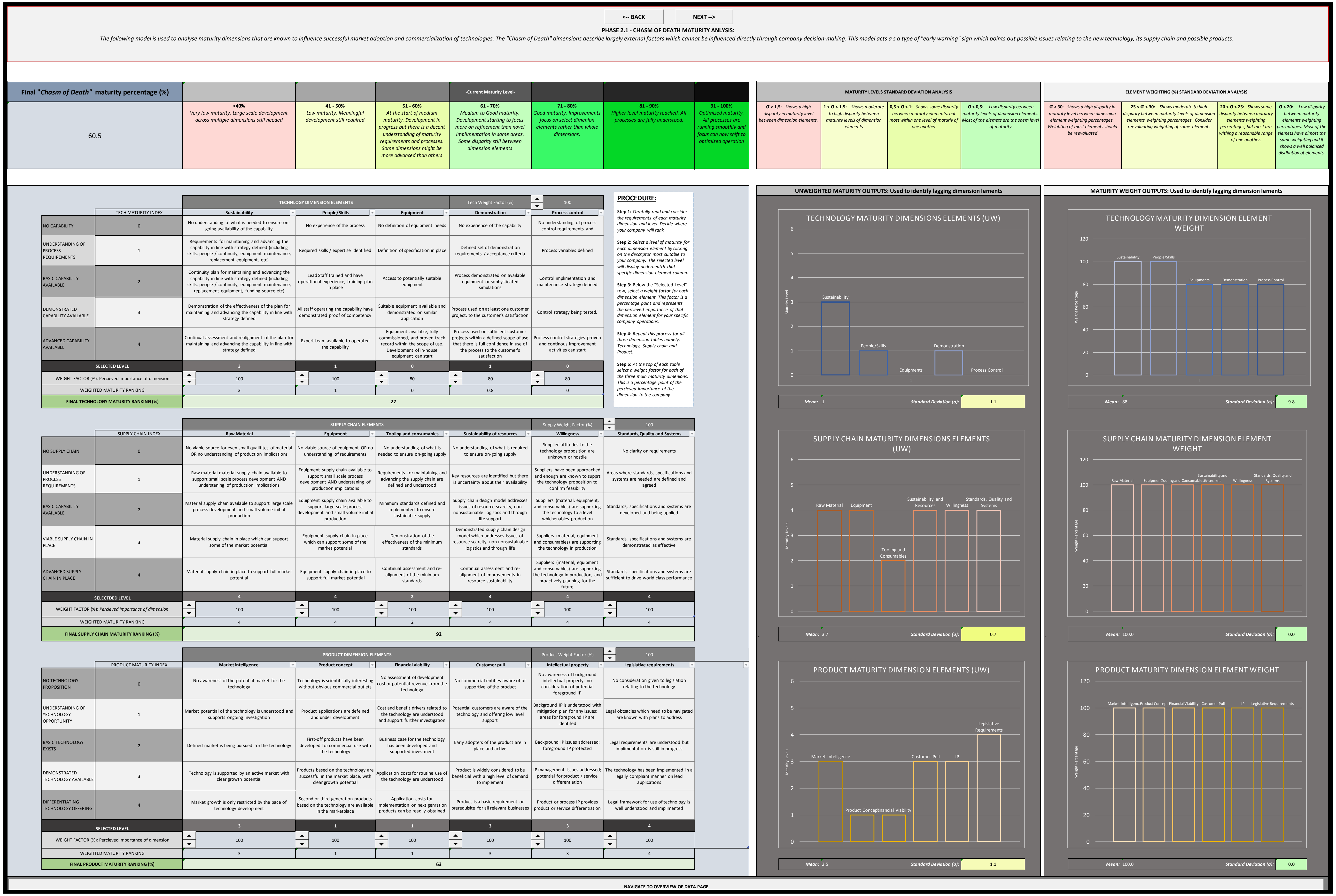


Figure A-15: *Phase 2 final tool application page – Company A simulation results*

	TECH MATURITY INDEX	TECHNOLOGY DIMENSION ELEMENTS Sustainability	People/Skills	Equipment	Tech Weight Factor (%) Demonstration	100 Process control
NO CAPABILITY	0	No understanding of what is needed to ensure on-going availability of the capability	No experience of the process	No definition of equipment needs	No experience of the capability	No understanding of process control requirements and
UNDERSTANDING OF PROCESS REQUIREMENTS	1	Requirements for maintaining and advancing the capability in line with strategy defined (including skills, people / continuity, equipment maintenance, replacement equipment, etc)	Required skills / expertise identified	Definition of specification in place	Defined set of demonstration requirements / acceptance criteria	Process variables defined
BASIC CAPABILITY AVAILABLE	2	Continuity plan for maintaining and advancing the capability in line with strategy defined (including skills, people / continuity, equipment maintenance, replacement equipment, funding source etc)	Lead Staff trained and have operational experience, training plan in place	Access to potentially suitable equipment	Process demonstrated on available equipment or sophysticated simulations	Control implimentation and maintenance strategy defined
DEMONSTRATED CAPABILITY AVAILABLE	3	Demonstration of the effectiveness of the plan for maintaining and advancing the capability in line with strategy defined	All staff operating the capability have demonstrated proof of competency	Suitable equipment available and demonstrated on similar application	Process used on at least one customer project, to the customer's satisfaction	Control strategy being tested.
ADVANCED CAPABILITY AVAILABLE	4	Continual assessment and realignment of the plan for maintaining and advancing the capability in line with strategy defined	Expert team available to operated the capability	Equipment available, fully commissioned, and proven track record within the scope of use. Development of in-house equipment can start	Process used on sufficient customer projects within a defined scope of use that there is full confidence in use of the process to the customer's satisfaction	Process control strategies proven and continous improvement activities can start
SELECTED LEVEL		3	1	0	1	0
WEIGHT FACTOR (%): Percieved importance of dimension		100	100	80	80	80
WEIGHTED MATURITY RANKING		3	1	0	0.8	0
FINAL TECHNOLOGY MATURITY RANKING (%)		27				

PROCEDURE:

Step 1: *Carefully read and consider the requirements of each maturity dimension and level. Decide where your company will rank*

Step 2: *Select a level of maturity for each dimension element by clicking on the descriptor most suitable to your company. The selected level will display underneatrh that specific dimension element column.*

Step 3: Below the "Selected Level" row, *select a weight factor for each dimension element. This factor is a percentage point and represents the percieved importance of that dimension element for your specific company operations.*

Step 4: *Repeat this process for all three dimension tables namely: Technology, Supply chain and Product.*

Step 5: *At the top of each table select a weight factor for each of the three main maturity dimenions. This is a percentage point of the percieved importance of the dimension to the company*

Figure A-16: *Phase 2 final tool application page – Company A simulation Technology dimension results*

		SUPPLY CHAIN ELEMENTS				Supply Weight Factor (%)	100
	SUPPLY CHAIN INDEX	Raw Material	Equipment	Tooling and consumables	Sustainability of resources	Willingness	Standards,Quality and Systems
NO SUPPLY CHAIN	0	No viable source for even small qualitites of material OR no understanding of production implications	No viable source of equipment OR no understanding of requirements	No understanding of what is needed to ensure on-going supply	No understanding of what is required to ensure on-going supply	Supplier attitudes to the technology proposition are unknown or hostile	No clarity on requirements
UNDERSTANDING OF PROCESS REQUIREMENTS	1	Raw material material supply chain available to support small scale process development AND understaning of production implications	Equipment supply chain available to support small scale process development AND understaning of production implications	Requirements for maintaining and advancing the supply chain are defined and understood	Key resources are identified but there is uncertainty about their availability	Suppliers have been approached and enough are known to supprt the technology proposition to confirm feasibility	Areas where standards, specifications and systems are needed are defined and agreed
BASIC CAPABILITY AVAILABLE	2	Material supply chain available to support large scale process development and small volume initial production	Equipment supply chain available to support large scale process development and small volume initial production	Minimum standards defined and implemented to ensure sustainable supply	Supply chain design model addresses issues of resource scarcity, non nonsustainable logistics and through life support	Suppliers (material, equipment, and consumables) are supporting the technology to a level whichenables production	Standards, specifications and systems are developed and being applied
VIABLE SUPPLY CHAIN IN PLACE	3	Material supply chain in place which can support some of the market potential	Equipment supply chain in place which can support some of the market potential	Demonstration of the effectiveness of the minimum standards	Demonstrated supply chain design model which addresses issues of resource scarcity, non nonsustainable logistics and through life	Suppliers (material, equipment and consumables) are supporting the technology in production	Standards, specifications and systems are demonstrated as effective
ADVANCED SUPPLY CHAIN IN PLACE	4	Material supply chain in place to support full market potential	Equipment supply chain in place to support full market potential	Continual assessment and re-alignment of the minimum standards	Continual assessment and re-alignment of improvements in resource sustainability	Suppliers (material, equipment and consumables) are supporting the technology in production, and proactively planning for the future	Standards, specifications and systems are sufficient to drive world class performance
SELECTDED LEVEL		**4**	**4**	**2**	**4**	**4**	**4**
WEIGHT FACTOR (%): *Percieved importance of dimension*		100	100	100	100	100	100
WEIGHTED MATURITY RANKING		4	4	2	4	4	4
FINAL SUPPLY CHAIN MATURITY RANKING (%)		**92**					

Figure A-17: *Phase 2 final tool application page – Company A simulation Supply Chain dimension results*

	PRODUCT DIMENSION ELEMENTS				Product Weight Factor (%)	100
PRODUCT MATURITY INDEX	Market intelligence	Product concept	Financial viability	Customer pull	Intellectual property	Legislative requirements
NO TECHNOLOGY PROPOSITION — 0	No awareness of the potential market for the technology	Technology is scientifically interesting without obvious commercial outlets	No assessment of development cost or potential revenue from the technology	No commercial entities aware of or supportive of the product	No awareness of background intellectual property; no consideration of potential foreground IP	No consideration given to legislation relating to the technology
UNDERSTANDING OF YECHNOLOGY OPPORTUNITY — 1	Market potential of the technology is understood and supports ongoing investigation	Product applications are defeined and under development	Cost and benefit drivers related to the technology are understood and support further investigation	Potential customers are aware of the technology and offering low level support	Background IP is understood with mitigation plan for any issues; areas for foreground IP are identifed	Legal obtsacles which need to be navigated are known with plans to address
BASIC TECHNOLOGY EXISTS — 2	Defined market is being pursued for the technology	First-off products have been developed for commercial use with the technology	Business case for the technology has been developed and supported investment	Early adopters of the product are in place and active	Background IP issues addressed; foreground IP protected	Legal requirements are understood but implimentation is still in progress
DEMONSTRATED TECHNOLOGY AVAILABLE — 3	Technology is supported by an active market with clear growth potential	Products based on the technology are successful in the market place, with clear growth potential	Application costs for routine use of the technology are understood	Product is widely considered to be beneficial with a high level of demand to implement	IP management issues addressed; potential for product / service differentiation	The technology has been implemented in a legally compliant manner on lead applications
DIFFERENTIATING TECHNOLOGY OFFERING — 4	Market growth is only restricted by the pace of technology development	Second or third generation products based on the technology are available in the marketplace	Application costs for implementation on next genration products can be readily obtained	Product is a basic requirement or prerequisite for all relevant businesses	Product or process IP provides product or service differentiation	Legal framework for use of technology is well understood and implimented
SELECTED LEVEL	3	1	1	3	3	4
WEIGHT FACTOR (%): Percieved importance of dimension	100	100	100	100	100	100
WEIGHTED MATURITY RANKING	3	1	1	3	3	4
FINAL PRODUCT MATURITY RANKING (%)	**63**					

Figure A-18: *Phase 2 final tool application page – Company A simulation Product dimension results*

Final "*Chasm of Death*" maturity percentage (%)				-Current Maturity Level-			
60.5	**<40%** *Very low maturity. Large scale development across multiple dimensions still needed*	**41 - 50%** *Low maturity. Meaningful development still required*	**51 - 60%** *At the start of medium maturity. Development in progress but there is a decent understanding of maturity requirements and processes. Some dimensions might be more advanced than others*	**61 - 70%** *Medium to Good maturity. Development starting to focus more on refinement than novel implimentation in some areas. Some disparity still between dimension elements*	**71 - 80%** *Good maturity. Improvements focus on select dimenion elements rather than whole dimensions.*	**81 - 90%** *Higher level maturity reached. All processes are fully understood.*	**91 - 100%** *Optimized maturity. All processes are running smoothly and focus can now shift to optimized operation*

Figure A-19: *Phase 2 final tool application page – Company A simulation final maturity results*

MATURITY LEVELS STANDARD DEVIATION ANALYSIS				ELEMENT WEIGHTING (%) STANDARD DEVIATION ANALYSIS			
σ > 1,5: *Shows a high disparity in maturity level between dimesnion elements.*	**1 < σ < 1,5:** *Shows moderate to high disparity between maturity levels of dimension elements*	**0,5 < σ < 1:** *Shows some disparity between maturity elements, but most within one level of maturiy of one another*	**σ < 0,5:** *Low disparity between maturity levels of dimension elements. Most of the elemets are the saem level of maturity*	**σ > 30**: *Shows a high disparity in maturity level between dimesnion element weighting percentages. Weighting of most elements should be reevaluated*	**25 < σ < 30:** *Shows moderate to high disparity between maturity levels of dimension elements weighting percentages . Consider reevaluating weighting of some elements*	**20 < σ < 25:** *Shows some disparity between maturity elements weighting percentages, but most are withing a reasonable range of one another.*	**σ < 20:** *Low disparity between maturity elements weighting percentages. Most of the elemets have almost the same weighting and it shows a well balanced distibution of elements.*

Figure A-20: *Phase 2 final tool application page – Company A simulation standard deviation results*

Figure A-21: *Phase 2 final tool application page – Company A simulation results*

A.4 Tool Phase 3 – TRRA

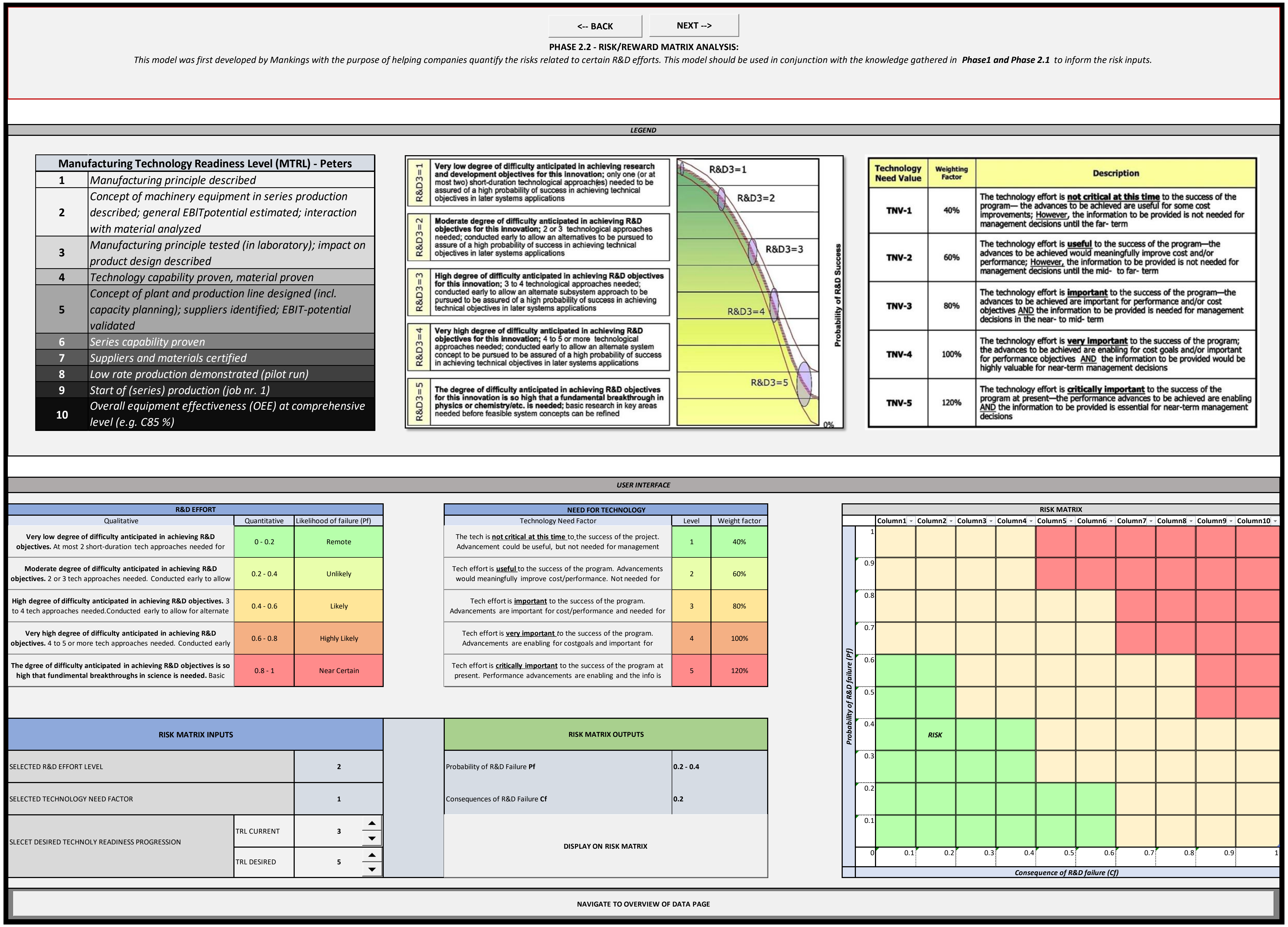


Figure A-22: *Phase 3 final tool application page – Company A simulation results*

R&D EFFORT		
Qualitative	Quantitative	Likelihood of failure (Pf)
Very low degree of difficulty anticipated in achieving R&D objectives. At most 2 short-duration tech approaches needed for	0 - 0.2	Remote
Moderate degree of difficulty anticipated in achieving R&D objectives. 2 or 3 tech approaches needed. Conducted early to allow	0.2 - 0.4	Unlikely
High degree of difficulty anticipated in achieving R&D objectives. 3 to 4 tech approaches needed.Conducted early to allow for alternate	0.4 - 0.6	Likely
Very high degree of difficulty anticipated in achieving R&D objectives. 4 to 5 or more tech approaches needed. Conducted early	0.6 - 0.8	Highly Likely
The dgree of difficulty anticipated in achieving R&D objectives is so high that fundimental breakthroughs in science is needed. Basic	0.8 - 1	Near Certain

NEED FOR TECHNOLOGY		
Technology Need Factor	Level	Weight factor
The tech is **not critical at this time** to the success of the project. Advancement could be useful, but not needed for management	1	40%
Tech effort is **useful** to the success of the program. Advancements would meaningfully improve cost/performance. Not needed for	2	60%
Tech effort is **important** to the success of the program. Advancements are important for cost/performance and needed for	3	80%
Tech effort is **very important** to the success of the program. Advancements are enabling for costgoals and important for	4	100%
Tech effort is **critically important** to the success of the program at present. Performance advancements are enabling and the info is	5	120%

RISK MATRIX INPUTS		
SELECTED R&D EFFORT LEVEL		**2**
SELECTED TECHNOLOGY NEED FACTOR		**1**
SLECET DESIRED TECHNOLY READINESS PROGRESSION	TRL CURRENT	**3**
	TRL DESIRED	**5**

RISK MATRIX OUTPUTS	
Probability of R&D Failure **Pf**	**0.2 - 0.4**
Consequences of R&D Failure **Cf**	**0.2**
DISPLAY ON RISK MATRIX	

Figure A-23: *Phase 3 final tool application page – Company A simulation input results*

A.5 Tool Phase 4 – SM^{3}E

A.5.1 Phase 4 Navigation Page

A.5.1. Phase 4 Navigation Page

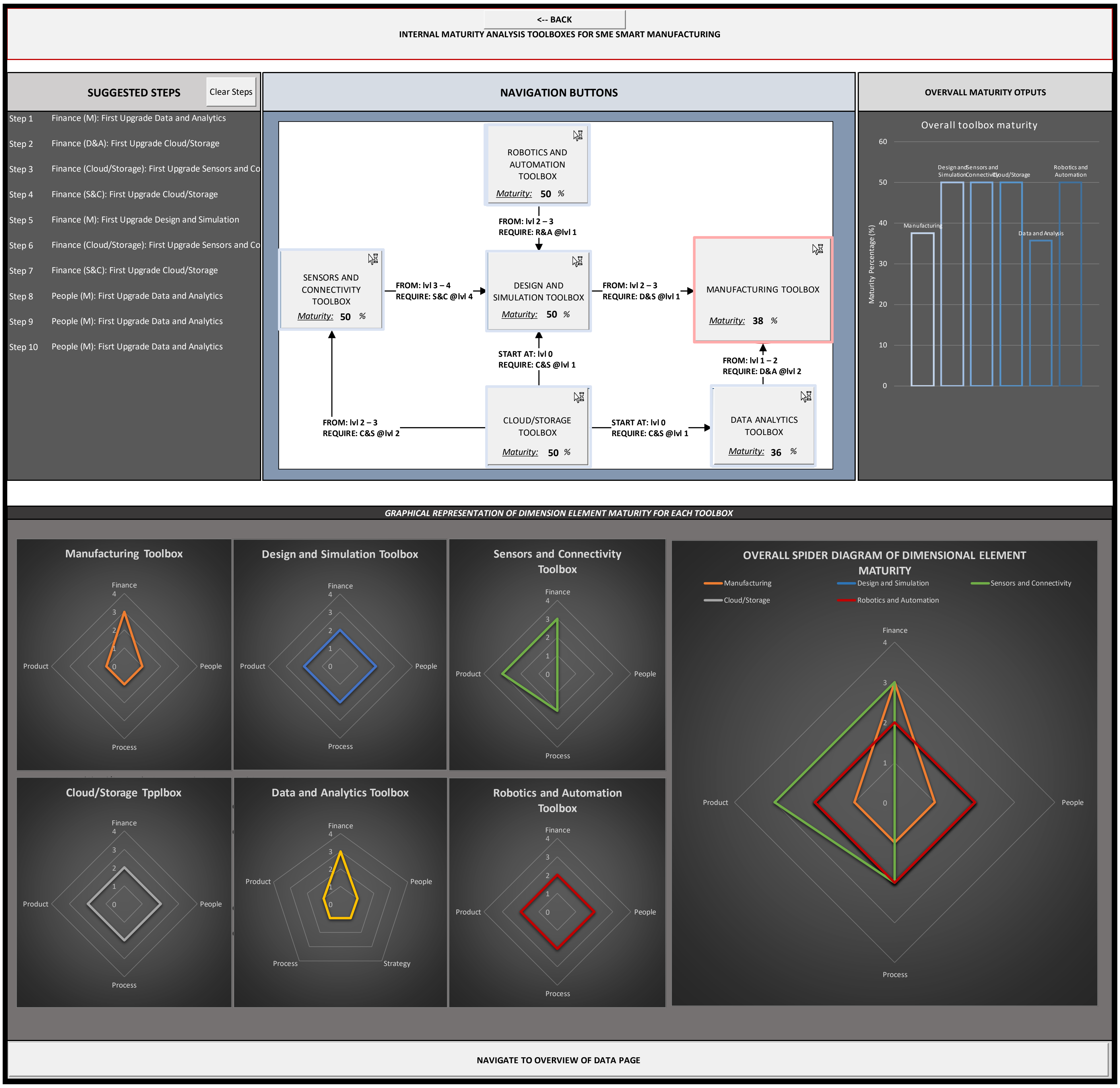


Figure A-24: *Phase 4 final tool navigation page – Company A simulation results*

A.5.1. Phase 4 Navigation Page

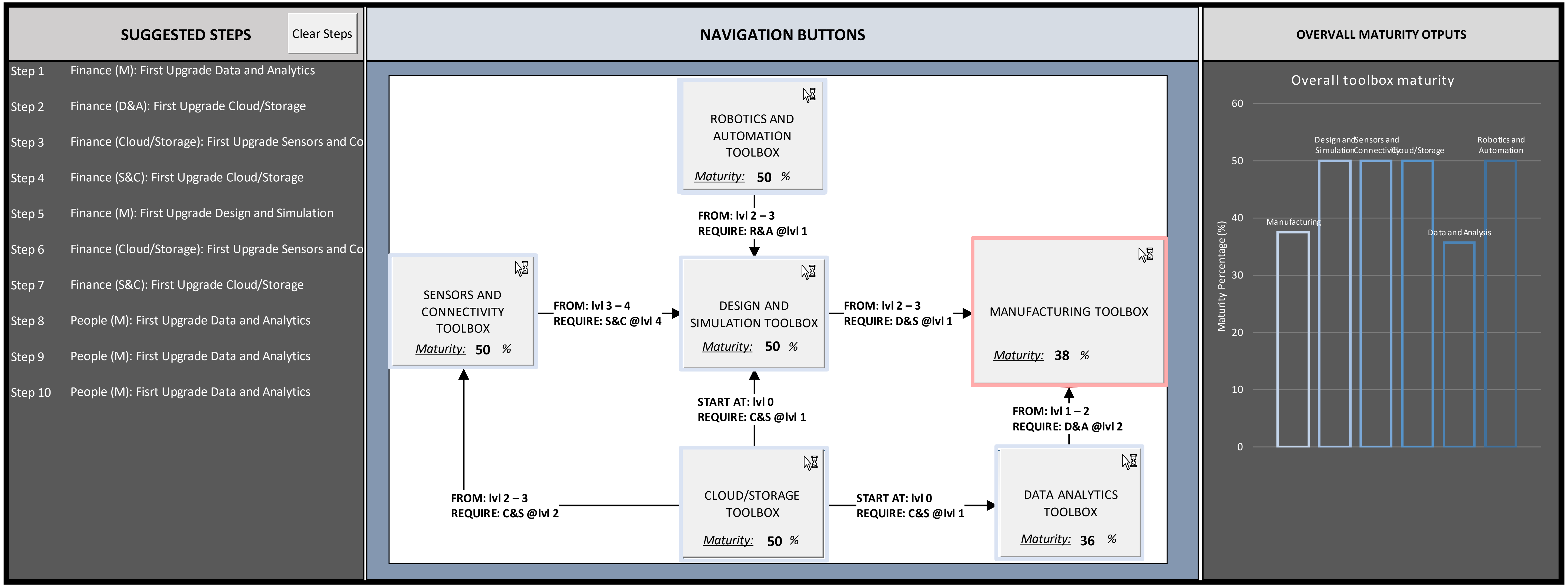


Figure A-25: *Phase 4 final tool navigation page – Company A simulation results*

A.5.1. Phase 4 Navigation Page

Figure A-26: *Phase 4 final tool navigation page – Company A simulation results*

A.5.2 Phase 4 Toolboxes

A.5.2. Phase 4 Toolboxes

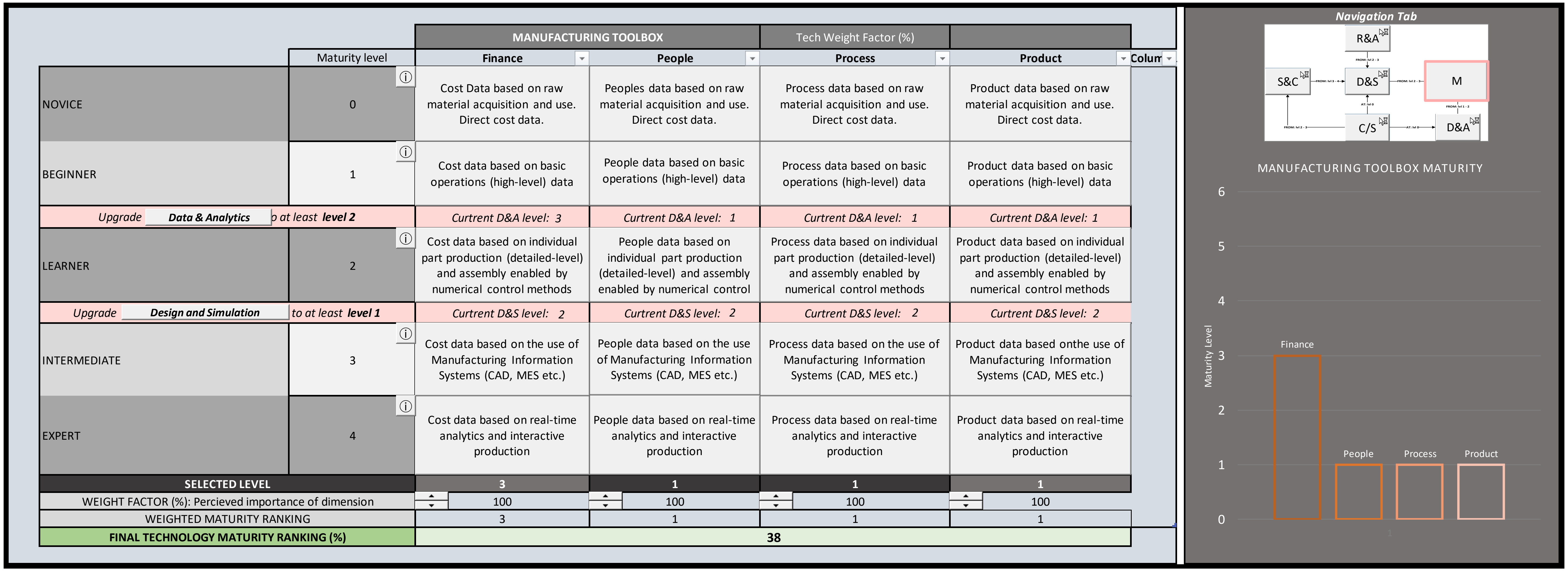
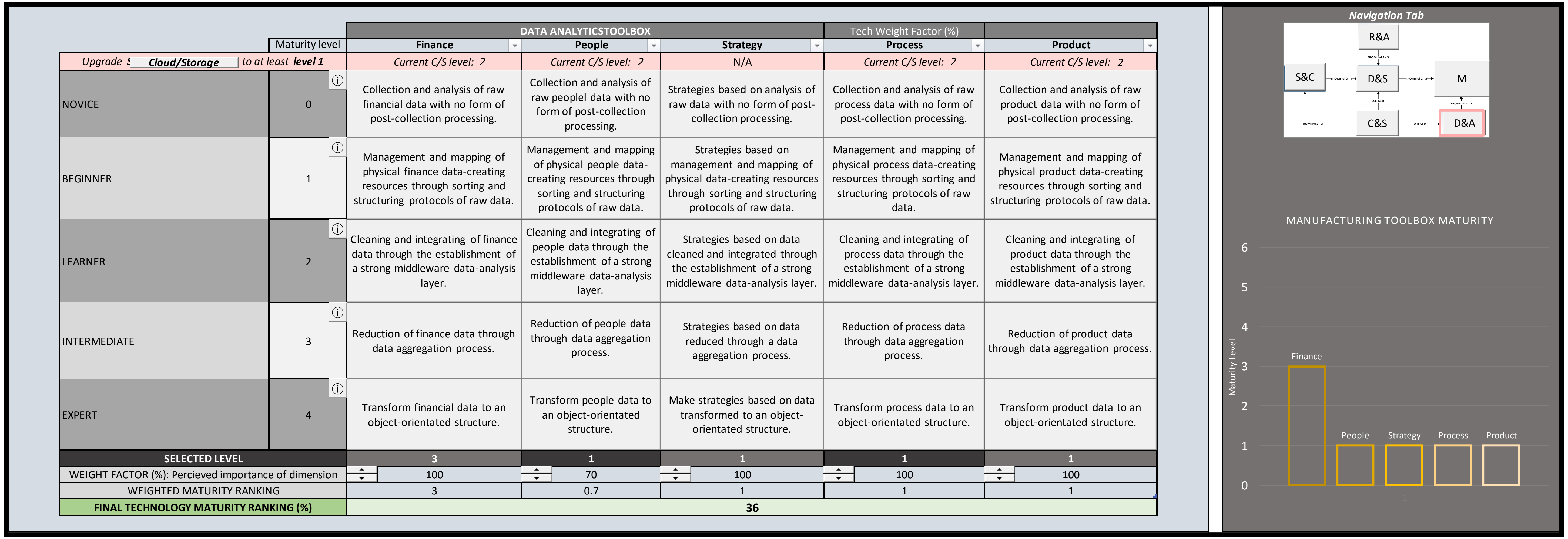


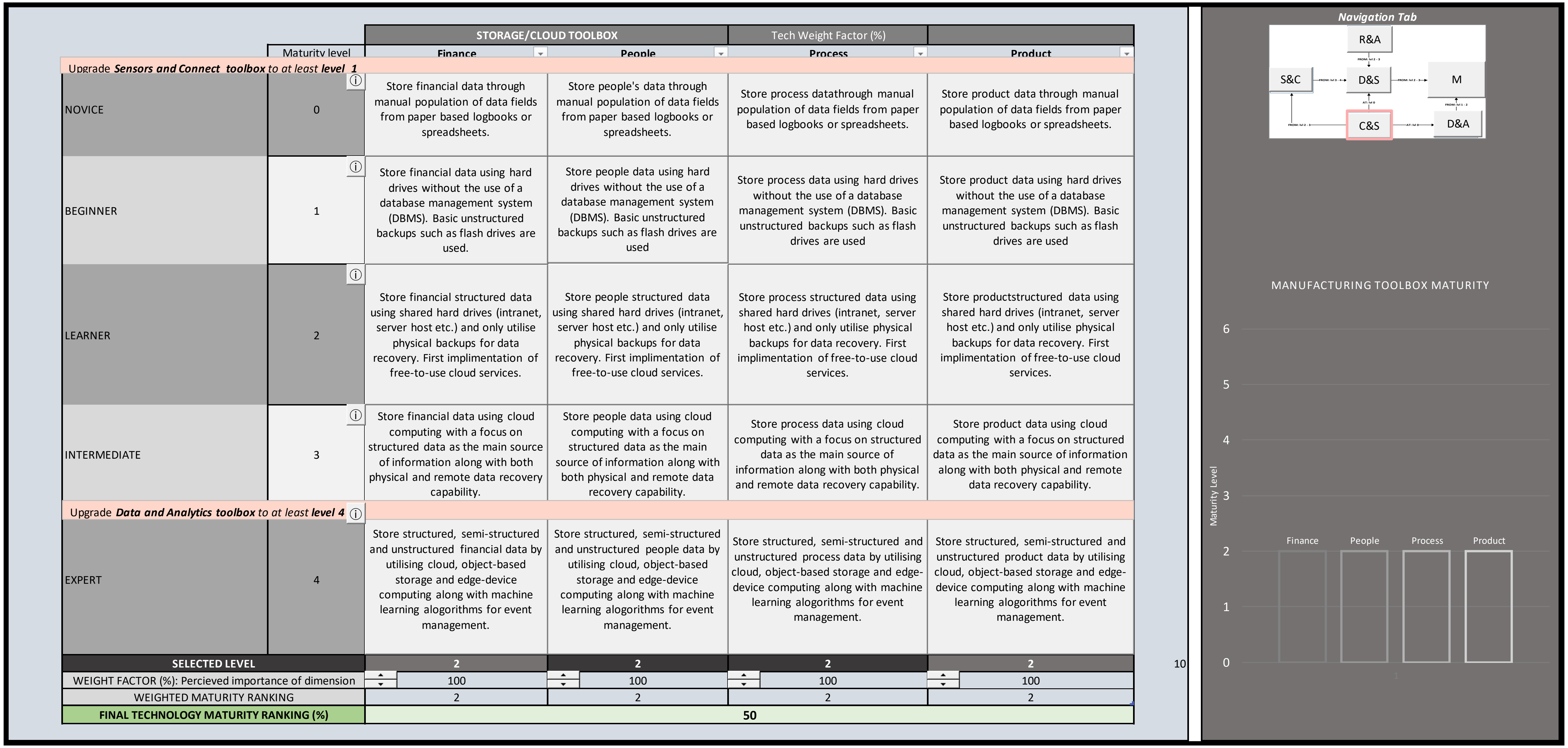
Figure A-27: *Phase 4 final tool application page – Company A Manufacturing toolbox simulation results*

A.5.2. Phase 4 Toolboxes



		DATA ANALYTICSTOOLBOX			Tech Weight Factor (%)	
	Maturity level	Finance	People	Strategy	Process	Product
Upgrade ***Cloud/Storage*** *to at least* ***level 1***		*Current C/S level: 2*	*Current C/S level: 2*	N/A	*Current C/S level: 2*	*Current C/S level: 2*
NOVICE	0	Collection and analysis of raw financial data with no form of post-collection processing.	Collection and analysis of raw peoplel data with no form of post-collection processing.	Strategies based on analysis of raw data with no form of post-collection processing.	Collection and analysis of raw process data with no form of post-collection processing.	Collection and analysis of raw product data with no form of post-collection processing.
BEGINNER	1	Management and mapping of physical finance data-creating resources through sorting and structuring protocols of raw data.	Management and mapping of physical people data-creating resources through sorting and structuring protocols of raw data.	Strategies based on management and mapping of physical data-creating resources through sorting and structuring protocols of raw data.	Management and mapping of physical process data-creating resources through sorting and structuring protocols of raw data.	Management and mapping of physical product data-creating resources through sorting and structuring protocols of raw data.
LEARNER	2	Cleaning and integrating of finance data through the establishment of a strong middleware data-analysis layer.	Cleaning and integrating of people data through the establishment of a strong middleware data-analysis layer.	Strategies based on data cleaned and integrated through the establishment of a strong middleware data-analysis layer.	Cleaning and integrating of process data through the establishment of a strong middleware data-analysis layer.	Cleaning and integrating of product data through the establishment of a strong middleware data-analysis layer.
INTERMEDIATE	3	Reduction of finance data through data aggregation process.	Reduction of people data through data aggregation process.	Strategies based on data reduced through a data aggregation process.	Reduction of process data through data aggregation process.	Reduction of product data through data aggregation process.
EXPERT	4	Transform financial data to an object-orientated structure.	Transform people data to an object-orientated structure.	Make strategies based on data transformed to an object-orientated structure.	Transform process data to an object-orientated structure.	Transform product data to an object-orientated structure.
SELECTED LEVEL		**3**	**1**	**1**	**1**	**1**
WEIGHT FACTOR (%): Percieved importance of dimension		100	70	100	100	100
WEIGHTED MATURITY RANKING		3	0.7	1	1	1
FINAL TECHNOLOGY MATURITY RANKING (%)		**36**				

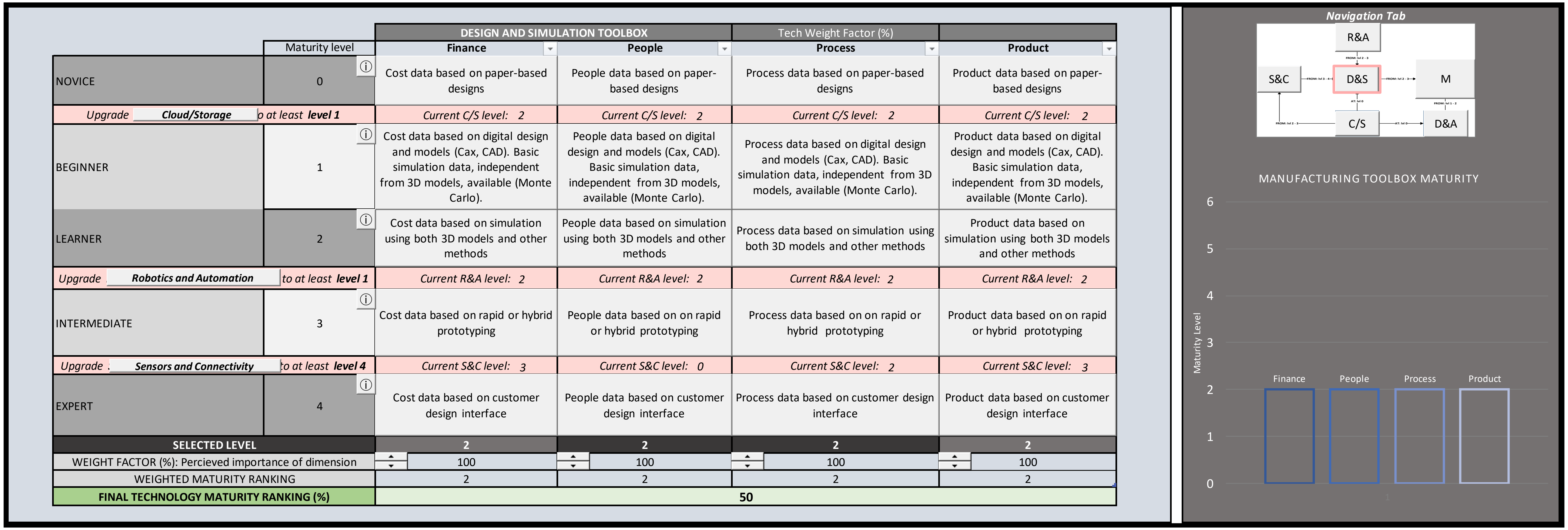
Figure A-28: *Phase 4 final tool application page – Company A Data and Analytics toolbox simulation results*



		STORAGE/CLOUD TOOLBOX		Tech Weight Factor (%)	
	Maturity level	Finance	People	Process	Product
Upgrade ***Sensors and Connect*** *toolbox to at least* ***level 1***					
NOVICE	0	Store financial data through manual population of data fields from paper based logbooks or spreadsheets.	Store people's data through manual population of data fields from paper based logbooks or spreadsheets.	Store process datathrough manual population of data fields from paper based logbooks or spreadsheets.	Store product data through manual population of data fields from paper based logbooks or spreadsheets.
BEGINNER	1	Store financial data using hard drives without the use of a database management system (DBMS). Basic unstructured backups such as flash drives are used.	Store people data using hard drives without the use of a database management system (DBMS). Basic unstructured backups such as flash drives are used	Store process data using hard drives without the use of a database management system (DBMS). Basic unstructured backups such as flash drives are used	Store product data using hard drives without the use of a database management system (DBMS). Basic unstructured backups such as flash drives are used
LEARNER	2	Store financial structured data using shared hard drives (intranet, server host etc.) and only utilise physical backups for data recovery. First implimentation of free-to-use cloud services.	Store people structured data using shared hard drives (intranet, server host etc.) and only utilise physical backups for data recovery. First implimentation of free-to-use cloud services.	Store process structured data using shared hard drives (intranet, server host etc.) and only utilise physical backups for data recovery. First implimentation of free-to-use cloud services.	Store productstructured data using shared hard drives (intranet, server host etc.) and only utilise physical backups for data recovery. First implimentation of free-to-use cloud services.
INTERMEDIATE	3	Store financial data using cloud computing with a focus on structured data as the main source of information along with both physical and remote data recovery capability.	Store people data using cloud computing with a focus on structured data as the main source of information along with both physical and remote data recovery capability.	Store process data using cloud computing with a focus on structured data as the main source of information along with both physical and remote data recovery capability.	Store product data using cloud computing with a focus on structured data as the main source of information along with both physical and remote data recovery capability.
Upgrade ***Data and Analytics toolbox*** *to at least* ***level 4***					
EXPERT	4	Store structured, semi-structured and unstructured financial data by utilising cloud, object-based storage and edge-device computing along with machine learning alogorithms for event management.	Store structured, semi-structured and unstructured people data by utilising cloud, object-based storage and edge-device computing along with machine learning alogorithms for event management.	Store structured, semi-structured and unstructured process data by utilising cloud, object-based storage and edge-device computing along with machine learning alogorithms for event management.	Store structured, semi-structured and unstructured product data by utilising cloud, object-based storage and edge-device computing along with machine learning alogorithms for event management.
SELECTED LEVEL		**2**	**2**	**2**	**2**
WEIGHT FACTOR (%): Percieved importance of dimension		100	100	100	100
WEIGHTED MATURITY RANKING		2	2	2	2
FINAL TECHNOLOGY MATURITY RANKING (%)		**50**			

Figure A-29: *Phase 4 final tool application page – Company A Cloud and Storage toolbox simulation results*

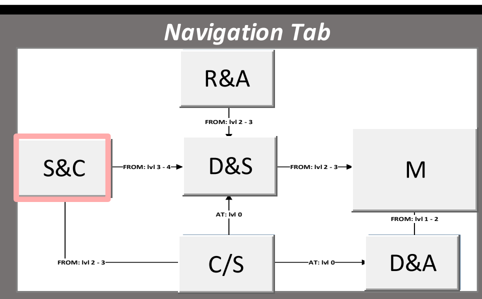
A.5.2. Phase 4 Toolboxes



	Maturity level	DESIGN AND SIMULATION TOOLBOX Finance	People	Tech Weight Factor (%) Process	Product
NOVICE	0	Cost data based on paper-based designs	People data based on paper-based designs	Process data based on paper-based designs	Product data based on paper-based designs
Upgrade Cloud/Storage to at least level 1		Current C/S level: 2	Current C/S level: 2	Current C/S level: 2	Current C/S level: 2
BEGINNER	1	Cost data based on digital design and models (Cax, CAD). Basic simulation data, independent from 3D models, available (Monte Carlo).	People data based on digital design and models (Cax, CAD). Basic simulation data, independent from 3D models, available (Monte Carlo).	Process data based on digital design and models (Cax, CAD). Basic simulation data, independent from 3D models, available (Monte Carlo).	Product data based on digital design and models (Cax, CAD). Basic simulation data, independent from 3D models, available (Monte Carlo).
LEARNER	2	Cost data based on simulation using both 3D models and other methods	People data based on simulation using both 3D models and other methods	Process data based on simulation using both 3D models and other methods	Product data based on simulation using both 3D models and other methods
Upgrade Robotics and Automation to at least level 1		Current R&A level: 2	Current R&A level: 2	Current R&A level: 2	Current R&A level: 2
INTERMEDIATE	3	Cost data based on rapid or hybrid prototyping	People data based on on rapid or hybrid prototyping	Process data based on on rapid or hybrid prototyping	Product data based on on rapid or hybrid prototyping
Upgrade Sensors and Connectivity to at least level 4		Current S&C level: 3	Current S&C level: 0	Current S&C level: 2	Current S&C level: 3
EXPERT	4	Cost data based on customer design interface	People data based on customer design interface	Process data based on customer design interface	Product data based on customer design interface
SELECTED LEVEL		2	2	2	2
WEIGHT FACTOR (%): Percieved importance of dimension		100	100	100	100
WEIGHTED MATURITY RANKING		2	2	2	2
FINAL TECHNOLOGY MATURITY RANKING (%)		50			

Figure A-30: *Phase 4 final tool application page – Company A Design and Simulation toolbox simulation results*

		SENSORS AND CONNECTIVITY TOOLBOX		Tech Weight Factor (%)	
	Maturity level	Finance	People	Process	Product
NOVICE	0	Maually collect cost data	Maually collect people's data	Maually collect process data	Maually collect product data
BEGINNER	1	Local collection of cost data via offline sensors.	Local collection of people data via offline sensors.	Local collection of process data via offline sensors.	Local collection of product data via offline sensors.
Upgrade ***Storage*** *to at least* ***level 1***					
LEARNER	2	Sensory cost data transferable to a single storage point and interface.	Sensory people data transferable to a single storage point and interface.	Sensory process data transferable to a single storage point and interface.	Sensory product data transferable to a single storage point and interface.
Upgrade ***Cloud/Storage*** *o at least* ***level 2***		*Current C/S level: 2*	*Current C/S level: 2*	*Current C/S level: 2*	*Current C/S level: 2*
INTERMEDIATE	3	Cost data collected and transferred via a Wireless Sensor Network (WSN)	People's data collected and transferred via a Wireless Sensor Network (WSN)	Process data collected and transferred via a Wireless Sensor Network (WSN)	Product data collected and transferred via a Wireless Sensor Network (WSN)
EXPERT	4	Cost data collection through an optimised WSN that utilises hierarchical sensor-level inference (smart sensors) and machine learning	People's data collection through an optimised WSN that utilises hierarchical sensor-level inference (smart sensors) and machine learning algorithms	Process data collection through an optimised WSN that utilises hierarchical sensor-level inference (smart sensors) and machine learning algorithms	Product data collection through an optimised WSN that utilises hierarchical sensor-level inference (smart sensors) and machine learning algorithms
SELECTED LEVEL		**3**	**0**	**2**	**3**
VEIGHT FACTOR (%): Percieved importance of dimensio		100	100	100	100
WEIGHTED MATURITY RANKING		3	0	2	3
FINAL TECHNOLOGY MATURITY RANKING (%)		**50**			



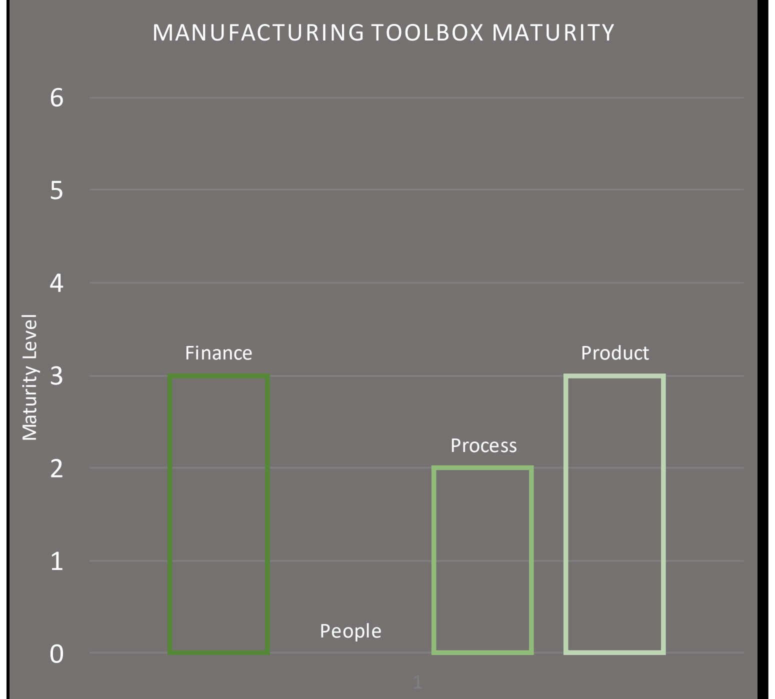


Figure A-31: *Phase 4 final tool application page – Company A Sensors and Connectivity toolbox simulation results*

A.5.2. Phase 4 Toolboxes

		ROBOTICS AND AUTOMATION TOOLBOX		Tech Weight Factor (%)	
	Maturity level	Finance	People	Process	Product
NOVICE	0	Cost data based on manually-operated machines	People's data based on manually-operated machines	Process data based on manually-operated machines	Product data based on manually-operated machines
BEGINNER	1	Cost data based on non-programmable machines	People's data based on non-programmable machines	Process data based on non-programmable machines	Product data based on non-programmable machines
LEARNER	2	Cost data based on programmable machines	People's data based on programmable machines	Process data based on programmable machines	Product data based on programmable machines
INTERMEDIATE	3	Cost data based on collaborative robotic networks via cluster computing.	People data based on collaborative robotic networks via cluster computing.	Process data based on collaborative robotic networks via cluster computing.	Product data based on collaborative robotic networks via cluster computing.
EXPERT	4	Cost data based on collaborative robotic networks via cloud computing and AI driven digital twins.	People's data based on collaborative robotic networks via cloud computing and AI driven	Process data based on collaborative robotic networks via cloud computing and AI driven digital twins.	Product data based on collaborative robotic networks via cloud computing and AI driven digital twins.
SELECTED LEVEL		**2**	**2**	**2**	**2**
VEIGHT FACTOR (%): Percieved importance of dimensio		100	100	100	100
WEIGHTED MATURITY RANKING		2	2	2	2
FINAL TECHNOLOGY MATURITY RANKING (%)		**50**			

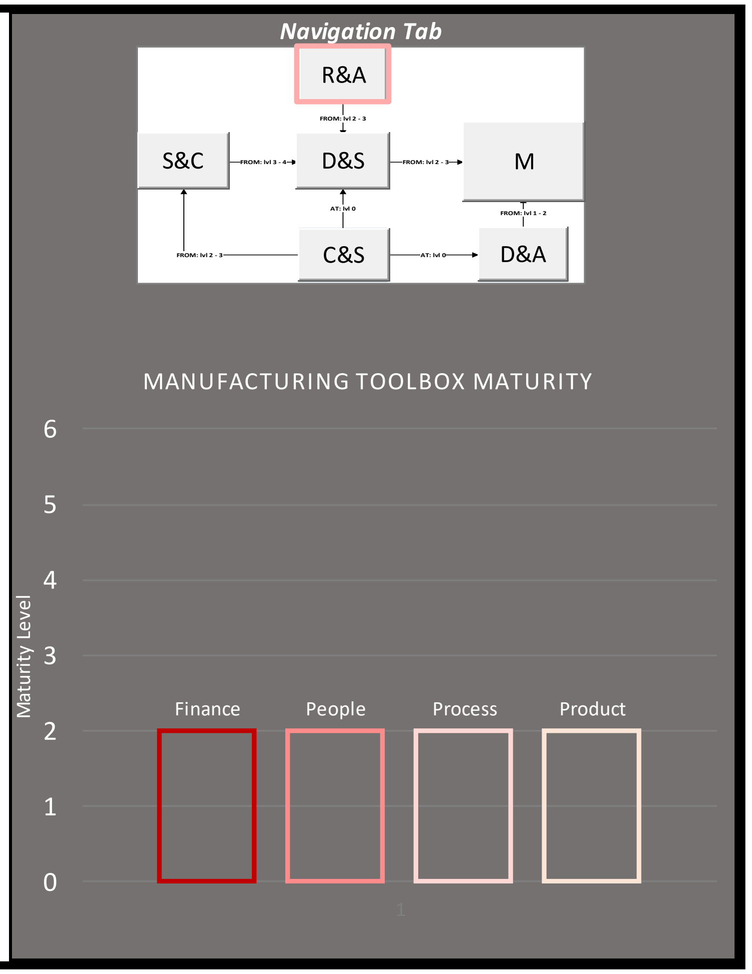


Figure A-32: *Phase 4 final tool application page – Company A Robotics and Automation toolbox simulation results*

Appendix B

Action Research Tool Supporting Content

This appendix provides the supporting content for the proposed decision support tool developed in this project. The content of this Appendix is as follows:

- **Section B.1:** Interviewee Expertise
- **Section B.2:** Overall Tool Interview Questions
- **Section B.3:** Tool Phase Interview Questionnaire
    - Section B.3.1. Phase 1 Interview Questions
    - Section B.3.2. Phase 2 Interview Questions
    - Section B.3.3. Phase 4 Interview Questions

B.1 Interviewee Expertise

Table B-1: Interviewee experience summary

Expert	Knowledge Domain	Years of Experience	Qualification
AdM_PHD	Additive manufacturing of metals	9yrs	PhD in Engineering
AdM_S	Additive manufacturing of cemented tungsten carbide	6yrs	PhD in Engineering
AM&M	Reliability engineering, Asset management and Operational risk assessment with a focus on Manufacturing domain	24yrs	M. Engineering
BIE	Specialises in smart manufacturing innovation integration	3yrs	B. Engineering
CM&D	Hard- and superhard material research, production, marketing and application engineering	34yrs	BSc. Physics; MSc. Engineering
MC&M	Manufacturing and digitally assisted manufacturing consultation	35yrs	Bsc. Engineering; MBA
DTM	Operations manager for a manufacturing enterprise.	8yrs	M. Engineering; MBA

Table B-2: *Interviewee abbreviations*

Subject matter/Industry Expert	**Abbreviation**	**Eligibility Criteria**
Additive Manufacturing PhD	AdM_PHD	(b) (d)
Additive Manufacturing (cemented carbide) Specialist/PhD	AdM_S	(d)
Asset Management and Manufacturing Expert	AM&M	(a) (c)
Business Intelligence Engineer	BIE	(a) (c)
Carbide Manufacturing and Distribution Expert	CM&D	(b) (c)
Management Consulting and Manufacturing Expert	MC&M	(a) (b) (d)
Digital Transformation in Manufacturing Expert	DTM	(a) (c) (d)

B.2 Overall Tool Interview Questions

Rating Descriptor	Score
Need for such a tool	3
Need addressed by proposed tool?	3
Relevance of Phase 1	4
Difficulty of impimentation of phase 1	2
Relevance of phase 2	4
Difficulty of implimentation of phase 2	2
Relevance of phase 3	2
Difficulty of implimentation of phase 3	1
Relevance of phase 4	4
Difficulty of implimentation of phase 4	3
Overall tool rating	82

Figure B-1: *Example of overall tool rating interview template*

OVERALL DECISION TOOL QUESTIONS
Is this tool useful for guiding SME's during novel manufacturing technology adoption? Rate 0 - 4 and expand on your rating with a comment.
Was the information provided by the support tool adequate to inform decision making? Rate 0-4 and expand with a comment
Should any additions/subtractions be made to the support tool? What are they?
Does the support tool display and communicate data and information in a concise and understandable way? Rate from 1-4 and expand with a comment
How useful is the process flow of the tool (Rate 1-4)?
How difficult is it to impliment the tool (Rate 1-4)?
Any final comments?

Figure B-2: *Example of overall tool rating qualitative response template*

B.3 Tool Phase Interview Questions

B.3.1. Phase 1 Interview Questions

B.3.1. Phase 1 Interview Questions

QUESTIONS SURROUNDING THE READINESS ANALYSIS

TECHNOLOGY READINESS DIMENSION *(-Click for More info-)*

Tech Readiness Relevance (Rate relevance 0-4)	
How relevant is tech readiness for acquisition	4
How relevent is the model for a starting point of tool	3
How usefull is the chosen section for decision support?	4

Tech Readiness Qualitative Response
Which functionality would you remove/add and why?
Rather start with push pull need. Is it necessary. Could invest in R&D

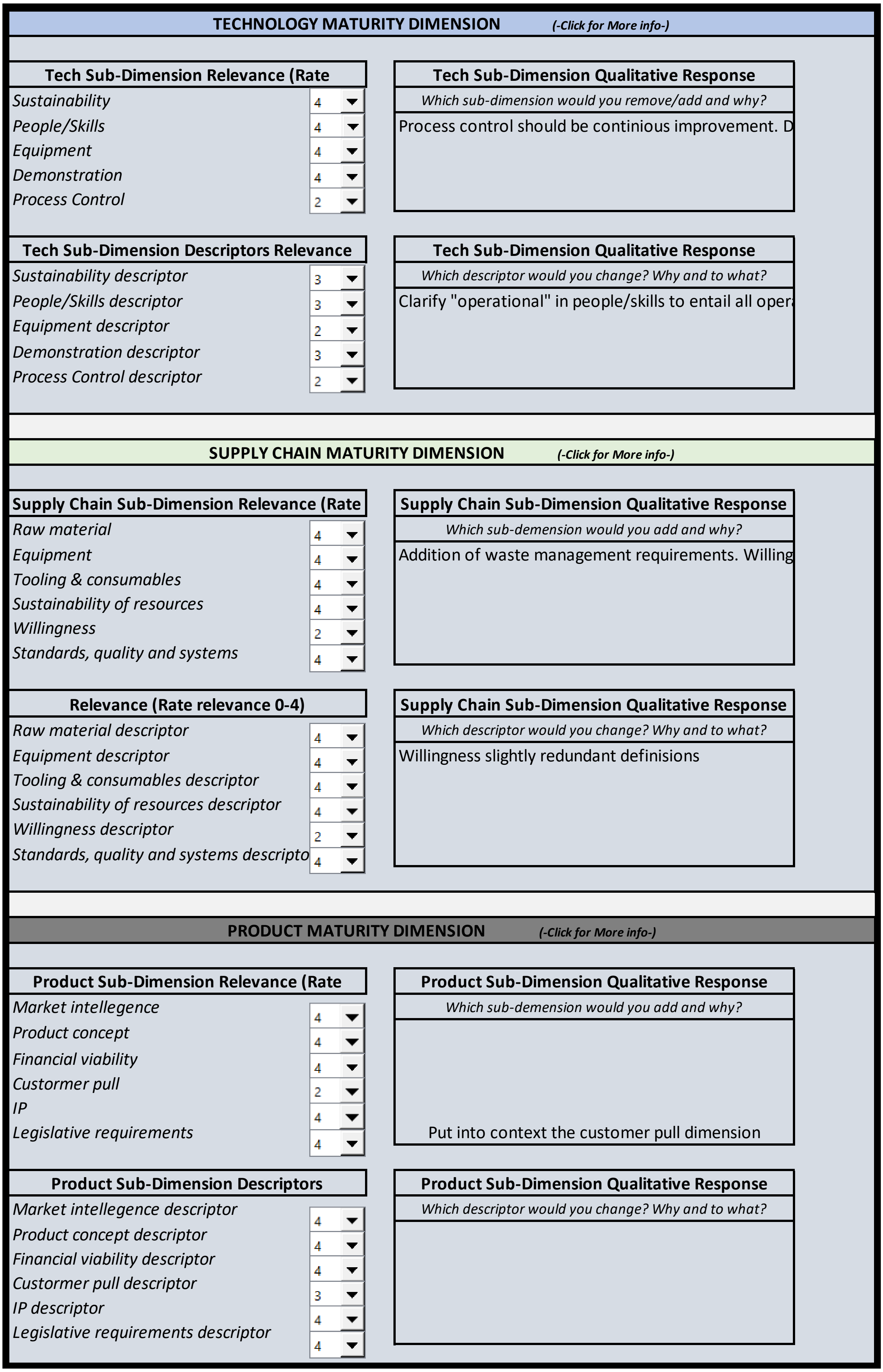
Tech Readiness difficulty of implimentation (Rate relevance 0-4)	
How difficult will it be to impliment a readiness analysis	2

Tech Readiness Qualitative Response
Clarify?
Clarify the objectives of why the technology must be acquired.

Figure B-3: *Example of Phase 1 rating interview template*

B.3.2. Phase 2 Interview Questions

B.3.2. Phase 2 Interview Questions



TECHNOLOGY MATURITY DIMENSION *(-Click for More info-)*

Tech Sub-Dimension Relevance (Rate	
Sustainability	4
People/Skills	4
Equipment	4
Demonstration	4
Process Control	2

Tech Sub-Dimension Qualitative Response

Which sub-dimension would you remove/add and why?

Process control should be continious improvement. D

Tech Sub-Dimension Descriptors Relevance	
Sustainability descriptor	3
People/Skills descriptor	3
Equipment descriptor	2
Demonstration descriptor	3
Process Control descriptor	2

Tech Sub-Dimension Qualitative Response

Which descriptor would you change? Why and to what?

Clarify "operational" in people/skills to entail all opera

SUPPLY CHAIN MATURITY DIMENSION *(-Click for More info-)*

Supply Chain Sub-Dimension Relevance (Rate	
Raw material	4
Equipment	4
Tooling & consumables	4
Sustainability of resources	4
Willingness	2
Standards, quality and systems	4

Supply Chain Sub-Dimension Qualitative Response

Which sub-demension would you add and why?

Addition of waste management requirements. Willing

Relevance (Rate relevance 0-4)	
Raw material descriptor	4
Equipment descriptor	4
Tooling & consumables descriptor	4
Sustainability of resources descriptor	4
Willingness descriptor	2
Standards, quality and systems descripto	4

Supply Chain Sub-Dimension Qualitative Response

Which descriptor would you change? Why and to what?

Willingness slightly redundant definisions

PRODUCT MATURITY DIMENSION *(-Click for More info-)*

Product Sub-Dimension Relevance (Rate	
Market intellegence	4
Product concept	4
Financial viability	4
Custormer pull	2
IP	4
Legislative requirements	4

Product Sub-Dimension Qualitative Response

Which sub-demension would you add and why?

Put into context the customer pull dimension

Product Sub-Dimension Descriptors	
Market intellegence descriptor	4
Product concept descriptor	4
Financial viability descriptor	4
Custormer pull descriptor	3
IP descriptor	4
Legislative requirements descriptor	4

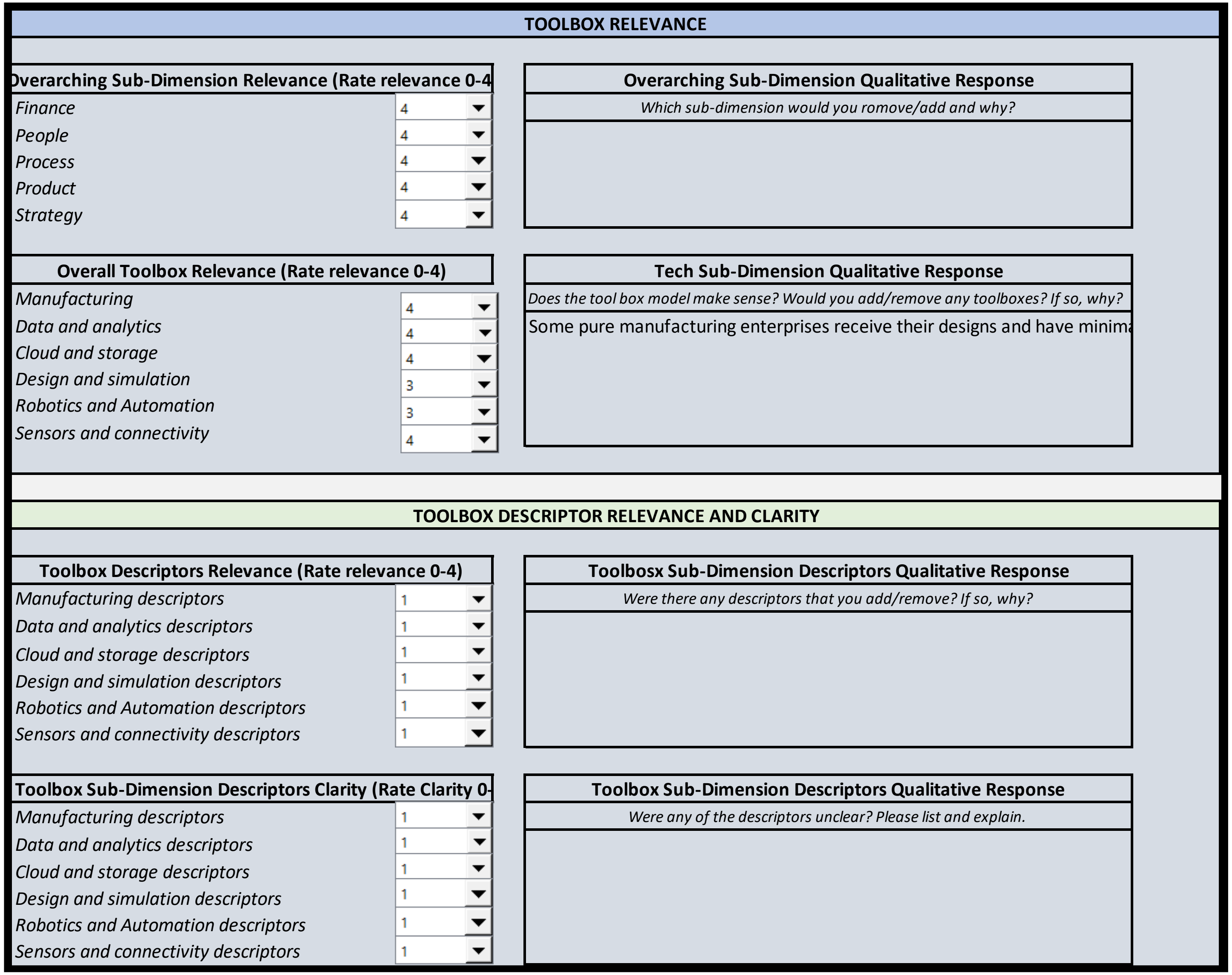
Product Sub-Dimension Qualitative Response

Which descriptor would you change? Why and to what?

Figure B-4: *Example of Phase 2 rating interview template*

B.3.3. Phase 4 Interview Questions

B.3.3 Phase 4 Interview Questions



TOOLBOX RELEVANCE

Overarching Sub-Dimension Relevance (Rate relevance 0-4	
Finance	4
People	4
Process	4
Product	4
Strategy	4

Overarching Sub-Dimension Qualitative Response

Which sub-dimension would you romove/add and why?

Overall Toolbox Relevance (Rate relevance 0-4)	
Manufacturing	4
Data and analytics	4
Cloud and storage	4
Design and simulation	3
Robotics and Automation	3
Sensors and connectivity	4

Tech Sub-Dimension Qualitative Response

Does the tool box model make sense? Would you add/remove any toolboxes? If so, why?

Some pure manufacturing enterprises receive their designs and have minim

TOOLBOX DESCRIPTOR RELEVANCE AND CLARITY

Toolbox Descriptors Relevance (Rate relevance 0-4)	
Manufacturing descriptors	1
Data and analytics descriptors	1
Cloud and storage descriptors	1
Design and simulation descriptors	1
Robotics and Automation descriptors	1
Sensors and connectivity descriptors	1

Toolbosx Sub-Dimension Descriptors Qualitative Response

Were there any descriptors that you add/remove? If so, why?

Toolbox Sub-Dimension Descriptors Clarity (Rate Clarity 0-	
Manufacturing descriptors	1
Data and analytics descriptors	1
Cloud and storage descriptors	1
Design and simulation descriptors	1
Robotics and Automation descriptors	1
Sensors and connectivity descriptors	1

Toolbox Sub-Dimension Descriptors Qualitative Response

Were any of the descriptors unclear? Please list and explain.

Figure B-5: *Example of Phase 4 rating interview template*

B.3.3 Phase 4 Interview Questions

GENERAL USE QUESTIONS
Does the toolbox model provide a satisfactory framework for an internal maturity analysis (0-4)?
Are there any glaring issues regarding the toolbox model that should be changed or investigated?
Should any additions be made to the toolbox model? What are they?
Any final comments?

Figure B-6: *Example of Phase 4 qualitative response template*

B.3.3 Phase 4 Interview Questions

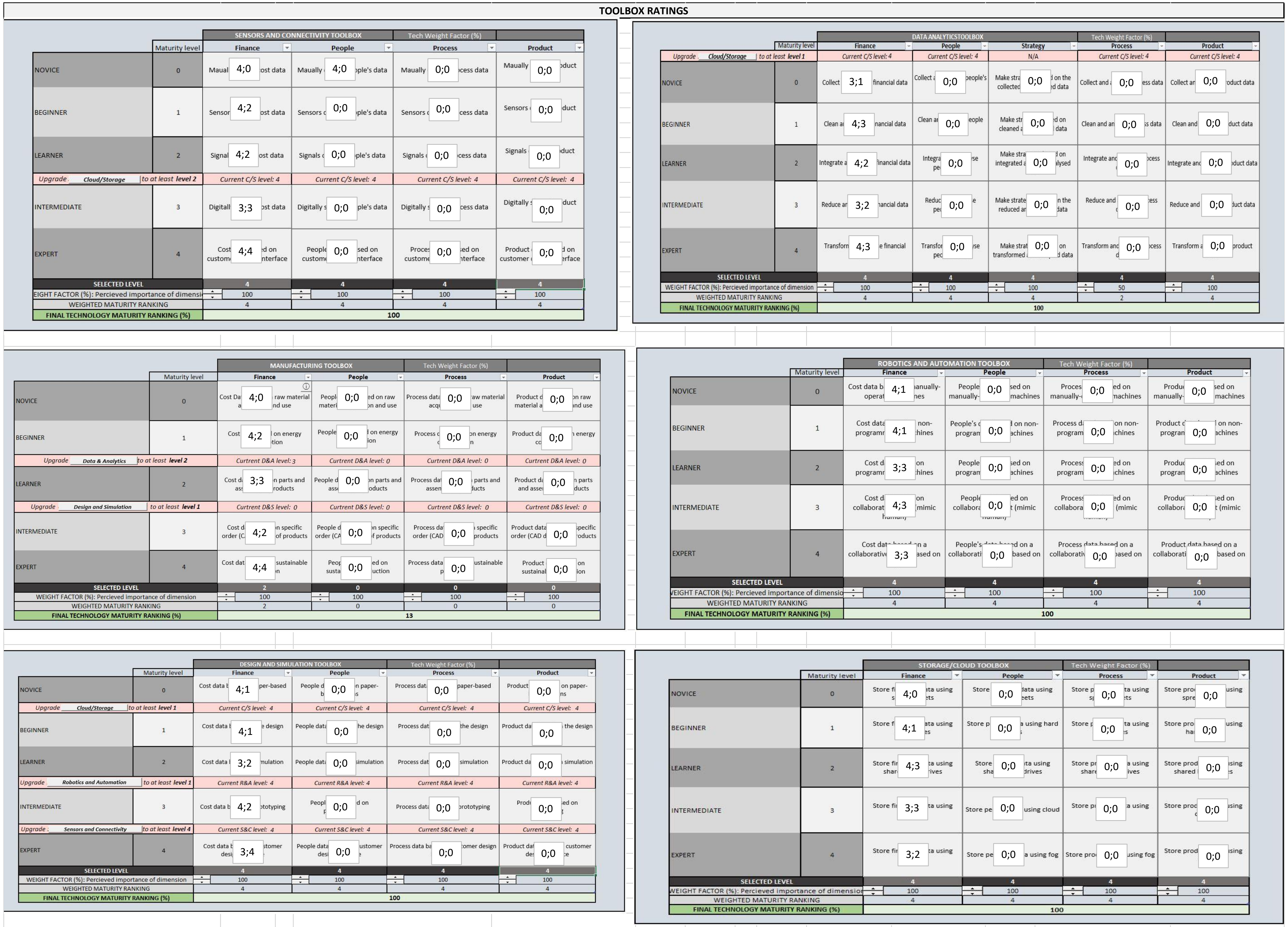


Figure B-7: *Example of Phase 4 rating interview template*