Gordon Institute of Business Science
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Cost benefits through asset life cycle management in South African Industries

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A research project submitted to the Gordon Institute of Business Science, University of Pretoria, in partial fulfilment of the requirements for the degree of Master of Business Administration.

Module: MBA Research Proposal

Nature of study:

The nature of the study takes the form of quantitative research

7 March 2023

PLAGIARISM DECLARATION

I Khulekani Mavundla, student no. 17382302 declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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Abstract

A four-fold research problem incorporating a lack of middle of life management for assets, incorrect manufacturing life-cycle benchmark for assets, effects of cost cutting practices and insufficient methods for sustainably retaining asset lifecycle costs to a minimum were investigated. The study intended to understand the relationship as well as the moderating effects between Manufacturing Asset Life-cycles (MALC) management and inherent cost benefits. The literature review's confirmation of theoretical concerns to exist in asset life-cycle management literature and various forms of articulating associated concepts, helped propel the study forward to generate two hypotheses; *H1* suggesting that *MALC-m leads to CB-real* and *H2* hypothesising that TCO-mr moderates CB-real from manufacturing asset life-cycle management. After quantitatively collecting nominal and ordinal data, inferential statistical tests were conducted to test the latter hypotheses using Spearman's rank order correlation on the ordinal data. Results that emerged disproved the two hypotheses, with *H2* findings confirming a new emergent relationship to suggest that **access to quality TCO asset data**, moderates creation of CB-real. Another contribution to theory were the two conceptual models in chapter 5, figure 6-3 and 6-4, presenting a **life-cycle stage and time continuum-based model for viewing MALC-m input data** as well as **life-cycle stage and time continuum-based model for viewing MALC-m application outcomes.** The two models work in synchrony with each other as they look at the same principles, just from different views

Table of Contents

Abbreviations

MALC-m	Manufacturing asset life cycle management
ibpMALC-m	Internal business process manufacturing asset life cycle management
ebpMALC-m	External business process manufacturing asset life cycle management
CB	Cost benefit
CB-real	Cost benefit realisation
CBA	Cost benefit analysis
BCR	Benefit cost ratio
TCO	Total cost of ownership
TCO-mr	Total cost of ownership measurement readiness
OEM	Original equipment manufacturer
VM	Value management
AM	Asset Management
PHM	Prognosis and health management
LCB	Life cycle benefits
LCC	Life cycle cost
LCCA	Life cycle cost analysis
CM	Circular Manufacturing
EIS	Enterprise information systems
VCM	Value creation mechanism
BOL	Beginning of Life
MOL	Middle of Life
EOL	End of Life

1. Research problem

It is very common for manufacturing entities to focus strategy and resource attention towards the design and construction stages of a manufacturing organisation's life-cycle, but neglect the operational phase of assets, where output can be optimised (Zarte, Pechmann & Nunes, 2019). Operational functions as well as assets to be utilised are usually designed and integrated adequately enough that life spans of assets can be pre-predicted (Vogl, Weiss & Helu, 2019). Secondly, predicted life spans of manufacturing assets are usually wrongfully assumed to be equivalent to asset useful lives, which are derived from accounting tax lives (Mutha, Bansal & Guide, 2021). These predicted asset life spans are sometimes perceived to not achieve their life expectancy according to stipulated useful lives (Vogl et al., 2019; Mutha et al., 2021). This is therefore problematic because it is usually mentioned that with substandard life-spans, the financial benefits expected from assets may be hindered; in the form of higher life cycle costs or substandard manufacturing asset availability (Vogl et al., 2019). To make matters worse, using a substandard reference duration to benchmark an asset life-cycle leaves the system vulnerable to a series of sub-optimal performance, including the possibility of confusing mediocre performance (Mutha et al., 2021) with acceptable end of "useful life" (p. 3004).

Subsequent to imprecise asset life-span boundaries that manufacturing organisations often find themselves benchmarking towards (Mutha et al., 2021), there are at least two other problems that this study is concerned about. Within the business practice plagued with costs cutting initiatives, the third layer of the problem prevails as manufacturing equipment suppliers are often negotiated into low profit margins (Zou et al., 2021). This sometimes results in manufacturers going to extremes in order to resuscitate their profitability, leading to actions resembling the employ of substandard design inputs, such as haphazard material selection, poor design processes or minimal quality assurance processes (Zou et al., 2021). As a consequence, the latter short-cuts result in a higher probability of premature failures, leading to higher maintenance, operational and possibly phasing out costs, which come with an increased likelihood for health and safety incidents (Zou et al., 2021). With suitable pre-procurement life-cycle cost analysis and forecasting and calculation based decision making against causes and effects of products with substandard life cycle costs could be executed with better predictability (Zou et al., 2021).

The fourth layer of the problem is related to the reality that practical processes for managing manufacturing assets accurately enough to keep asset ownership costs to an objective minimum, are not well understood in literature (Animah, Shafiee, Simms, Erkoyuncu & Maiti, 2018). The shortfall has been argued to come from a lack of strategic integration of timeous asset performance data throughout the asset's life-span, including cost of this performance on a real time basis, with the day-to-day decision making (Vogl et al., 2019). Instead of the latter effort being through a system that is designed with a strategic purpose to steer manufacturing assets of an organisation towards enabling the company's goals, this function is generally dealt with organically. As a result, end of life decisions often end up being left to the subjective judgement of asset maintenance custodians (Animah et al., 2018) such as operational specialists, "engineers and inspectors" (p. 311).

The issue is not with the lack of trust for the industry experts but rather the reason that the latter mentioned approach (status quo) is not strategically driven but rather managed with discretion as it emerges, implying that it is situationally controlled. This risks producing unrepeatable outcomes or even poor quality decisions (Animah et al., 2018), especially as the organisation's decision makers change. The research therefore aims to shine the light on a discussion that may lead to alleviating barriers that deprive manufacturing organisations with the necessary opportunity to know when to focus or remove resources in making asset life cycle based decisions. In the context of this study, having a clear asset philosophy based rationale implies that decisions made have at least taken into account cost-benefits involved in manufacturing assets, continuously over their life cycles as well as the risks presented when choosing those decisions.

1.2. Purpose statement

The purpose of the study is to understand the relationship as well as the moderating effects between Manufacturing Asset Life-cycles (MALC) management and inherent cost benefits. The intention is to fulfil a contribution towards theory as well as practice in the manufacturing industry.

1.2.1. Construct and variables of interest unpacked

One of the primary constructs of interest, in relation to the research purpose, has to do with management of life cycle of manufacturing assets. This construct unpacked, simply relates to interventions put in place in order to ensure optimum asset utilisation (Berlak, Hafner & Kuppelwieser, 2021). A difference to organic management of manufacturing assets is that with MALC-m, the asset is used to facilitate manufacturing activities and its management is executed with a strategic infusion that is paced to deploy specific actions to prompt outcomes at various asset life-spans (Roda et al., 2020). Another main construct of interest is cost benefits in relation to the process utilising or ownership of manufacturing assets. In addition to the typically acclaimed effects on immediate costs that affect bottom line, Roda et al. (2020) perceives the process of MALC management to account for cost effects on **externalities as well. The latter incorporates effects on** health and safety, risk, equipment efficacy, environmental and social impact at the least, even if someone else absorbs the costs outside of the organisation, MALC-m is concerned with the impact of that absorption on the manufacturing activity of the value chain.

1.3. Value for theory

In literature, it is only right that the pragmatic element of useful life of an asset be revisited in order for subsequent theory and practice to hopefully re-align back to pre-1960's view that based these forecasts on insight shared by original equipment manufacturers (OEMs) (Mutha et al., 2021).

The cost of sub-standard asset replacement in Industry literally resembles loss of financial gain (Mutha et al., 2021). This is due to the fact that the discarded value poses a potential loss of opportunity. With South Africa being plagued with chronic de-industrialisation (Bhorat, Steenkamp, Rooney, Kachingwe & Lees, 2018) utilisation of operational systems that accurately outline the extent of asset productivity as well as its impact (), become increasingly crucial. Considering literature outlining very limited practical understanding of asset life cycle tracking in Manufacturing (Vogl et al., 2019), as a grounding step, it is imperative that industry leaps in the direction of familiarity with theories relating to how this could be achieved, especially in developing countries such as South Africa.

Within the fourth and perhaps the succeeding industrial revolutions, where manufacturing assets are expected to exhibit cyber-physical integration in the form of smart manufacturing (Kusiak, 2018), this research has opportunity to add to educational insight from developing an industry perspective or just facilitate a theoretical dialogue. As with the conceptual intent of modern manufacturing, nature of information may potentially transcend to knowledge that can be used to form a basis of understanding by manufacturing asset custodians/users who aim to be more effective at achieving more competitive asset utilisation, both at cost efficiency and utilisation effectiveness (Kusiak, 2018).

1.4. Value for business

It is also said, arguably, that the goal of business is to create value for stakeholders (Dembek, York & Singh, 2018). On the other hand it is proven that organisations' primary output is usually discovered to be associated with financial gains (Pretorius, 2019), whilst advocating stewardship in the social and environmental domains (Zarte et al., 2019). This is said with an understanding that some organisations don't concern themselves much with socio-economic effects of their business operations (Zarte et al., 2019) and equivalently, the only environmental initiatives are primarily to fulfil regulatory obligations. Improved asset life cycles are associated with various benefits from the environmental domain of value creation (Carvalho, Chaim, Cazarini & Gerolamo, 2018), as well as some costs savings (Vogl et al., 2019). **This study therefore seeks to explore curiosity** around the holistic relationship between manufacturing asset life cycle management (MALC-m) and financial value creation, through cost benefits realisation (CB-real). Another perspective for business value draws from modern business models which no longer sell products but instead frame their value proposition towards customers and clients in terms of *magnitude of asset usage* (Graessler & Yang, 2019). In such business models, a life cycle costing method becomes critical (Graessler & Yang, 2019) as it enables sellers and service providers to account for instantaneous real time costs of being in possession of manufacturing assets.

The research problem frames useful lives as being regularly incorrectly outlined from tax lives as well as not being forecasted from OEMs scientific predictions in a lot of cases (Mutha et al., 2021). In the quest of outlining potential value for business, it is necessary to articulate how the latter framing of the research problem links to the subject of deriving value from MALC-m, which is further framed in Chapter 2 of the study. The problem statement, framed in chapter 3, discusses the time-line goal post or minimum time-boundaries to which manufacturing asset life spans could be managed and benchmarked to if certain level of financial gains are retrievable. The study itself adds to the body of work that seeks to learn the extent to which there are costs benefits if MALC-m is performed consistently, throughout all stages of the asset's lifespan, aspiring towards sustaining the asset to reach or exceed the scientifically forecasted life expectancy. Figure 1-1 illustrates the business level disconnection between accounting asset life and real asset life span according to OEMs.

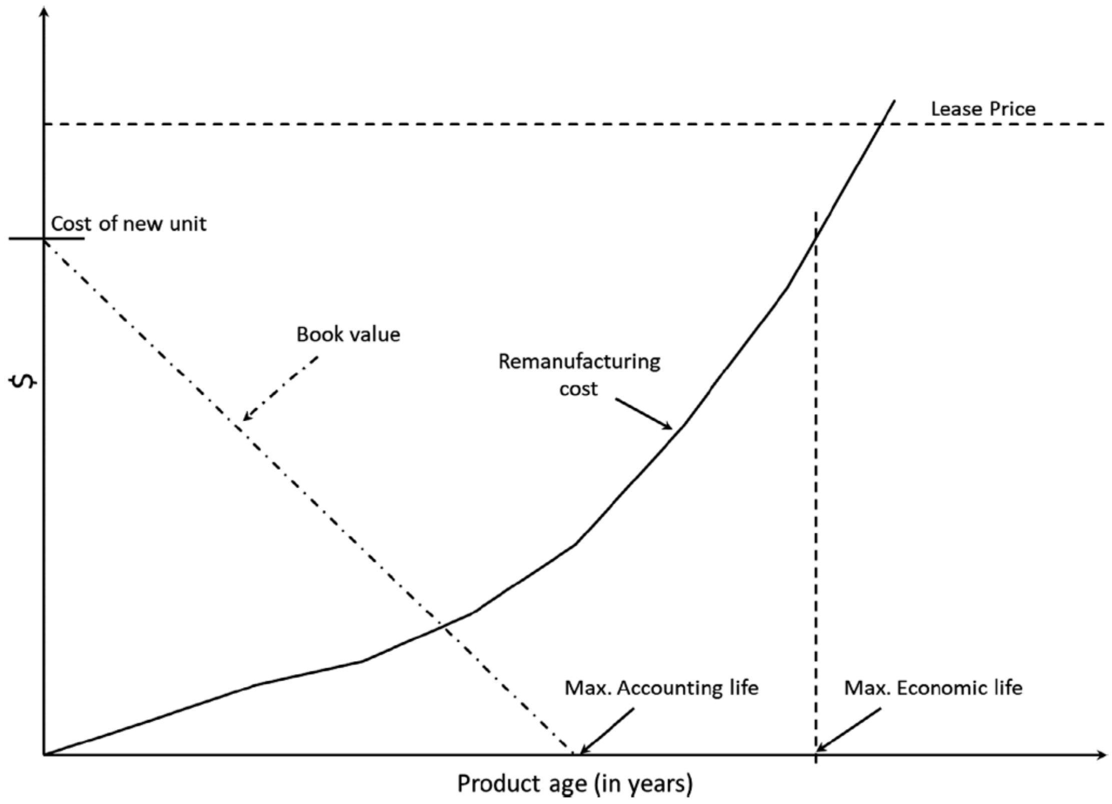


Figure 1-1

Note. Distinguishable economic and accounting lives of the same business asset. From "Managing the inter-functional tension between accounting and financial profits…" by Mutha et al., 2021, *Production and Operations Management*, *30*(9), p. 2995. (https://doi.org/10.1080/09537287.2019.1625079/). Copyright 2021 by Production and Operations Management.

1.4.1. Value for manufacturing organisations of the future

From a perspective that seeks to address needs of manufacturing entities going into the future, decision making that is driven by data has been argued to be one of the key competencies needed for organisations transcending into smart manufacturing (Ahmed, Jeon, & Piccialli, 2022; Kusiak, 2018,). As a subset of the fourth industrial revolution, application of smart manufacturing methodologies (Kusiak, 2018) aims to support the creation of extra-ordinary performance in industrial operations (Ahmed et al., 2022) and thus shows to possess key attributes for successful manufacturing entities of the future. This study therefore proves to be relevant as it provides opportunity for the application of asset data and information to optimise asset life-cycles in a way that enhances cost benefits as a form of financial value. It also triggers discussions of incorporating other industry 4.0 pillars of automisation such as deep learning and machine learning. The discussion of improving manufacturing asset life-cycles where cost benefits prevail is synonymous with asset productivity as it translates to deriving operating profits from assets (Amoa-Gyarteng, 2021). Since data and engineering predictability prevailed as two of the six pillars of smart manufacturing (Kusiak, 2018), alongside "materials, sustainability" (p. 510) amongst other aspects, concepts that promote predictability in manufacturing settings appears to be linkable to useful approach value.

1.4.2. Macroeconomic level value for manufacturing industry

At a macroeconomic level, less than 20 nations in the world regulate about 80% of global value contribution from the manufacturing sector (Andreoni & Tregenna, 2020). For manufacturing sector's value contribution to be sustainable, it needs to exist in at least three domains that is presently known in literature, namely; economic development, social prosperity and environmental stability (Zarte et al., 2019). Whilst other research studies are progressing in the other two domains of value addition (Zarte et al., 2019); this study intends to investigate how manufacturing asset life-cycle management can influence the economic dimension through cost value addition in manufacturing settings. The ultimate goal is the possible contribution of knowledge towards alleviation of the vastly prevalent technology trap visible in low and middle income countries (Andreoni & Tregenna, 2020).

Having introduced the intent of the study as well as the nature of problems that it aims to address in theory, the remainder of the document contains the following sections;

- **Chapter 2** - Literature and theory review
- **Chapter 3** - Research questions and hypotheses
- **Chapter 4** - Research design and methodology
- **Chapter 5** - Results
- **Chapter 6** - Discussions
- **Chapter 7** - Conclusion
- **Appendix A1** - A consistency matrix
- **Appendix A2** - Proposed research questions, coded into indicator questions
- **Appendix A3** - A Gantt chart for research journey
- **Appendix A4** - Flowcharts for LCC decision making

- **Appendix A5-1 & A5-2** - Survey digital reach on business social media
- **Appendix A5-3** - Validity tests
- **Appendix A5-4** - Reliability tests

2. Literature and theory review

We cannot begin to speak about a relationship between manufacturing asset life-cycles and cost benefits without incorporating the initial relation of the two constructs that is generally pre-conceived before acquisition of manufacturing assets. Prior to acquisition, during the budgeting phase of a project, life-cycle costing is executed whereby life cycle cost (LCC) benefits are commonly argued (Galar, Sandborn, & Kumar, 2017) in order to justify viability (or inviability) of the investment decision (Roda, Macchi & Albanese, 2020. It is critical to distinguish that *life-cycle cost benefits analysis* used at these initial stages are only estimations and are used to support the decision making process (Mutha et al., 2021). On the other hand, the existence or non-existence of cost benefits of optimising MALC (through managing) explored in this research was aimed to be cumulatively determined in hindsight or real-time (Galar et al., 2017) throughout the life-span of the asset (Roda et al., 2020).

2.1. Introduction

A few theoretical concepts have been developed when it comes to supporting the process of managing asset life-cycles in manufacturing industries and a wide amount are discussed in this literature review section. Such concepts include the value management of assets, total cost of (asset) ownership management, prognosis health management, life cycle cost analysis, cost benefit analysis, cost benefit ratio based decision making, circular manufacturing using user-supplier integration methodology and various industry standards for MALC management amongst a few. Among all surveyed theory none discuss the cost returns of the holistic endeavour of implementing a MALC management program, irrespective of benefit stance being the purchaser or manufacturer of manufacturing industry assets.

2.2. Research Grounding Theory - TCO

A total cost of ownership (TCO) concept is proposed as the research grounding theory, largely for its capability to account for both direct and indirectly implicated costs (Remko, 2020; Seth, Nemani, Pokharel & Sayed, 2018) of asset utilisation or custodianship over its entire life cycle. LCC of a manufacturing asset is almost indistinguishably compared to TCO in the sense that they both refer to the cost of utilising or just keeping an asset over its life-span (Roda et al., 2020). The difference, however lies in the strategic view of actual asset related costs over the operation phase that TCO connotes (Roda, Macchi & Albanese, 2020), as opposed to pre-investment decision making estimates which usually come with LCC. A TCO development framework is displayed in figure 2-2.

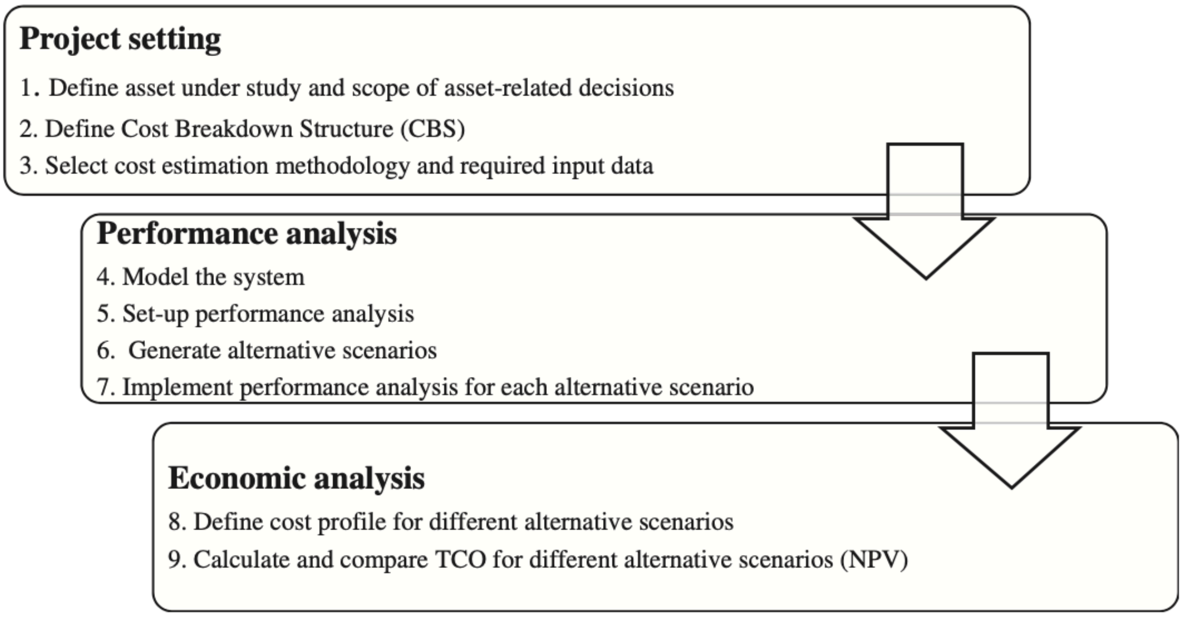


Figure 2-2:

Note. Framework for TCO development. From "Building a Total Cost of Ownership model to support manufacturing asset lifecycle management" by Roda et al., 2020, *Production Planning & Control 31*(1), p. 27. (https://doi.org/10.1080/09537287.2019.1625079 /). Copyright 2020 by Production Planning & Control.

2.2.1. Benefits of TCO

Advantages of employing TCO on MALC are argued to incorporate a capability to enhance management's understanding of how new technology aligns to the business goal (Berlak et al., 2021). Management's clarity on asset performance levels can help influence decisions of selection of assets or systems to utilise under varying economic and market conditions (Pretorius, 2019).

2.2.2. Shortcomings of TCO

Conceptually, the TCO model does have its own short-comings, such as the assumptive view that all attributable value can be interpreted as costs (Seth et al., 2018). Another limitation in the application of TCO is the need to control and preserve a consistent, good quality of asset data (Seth et al., 2018). Even though a good enterprise resource planning (ERP) software or computerised maintenance management system (CMMS) can assist with provision of a consistent in-feed of asset data, physical assets without real time information sampling into TCO models may still require data exporting via spreadsheets. Information manipulated from exported spreadsheets could still introduce human error and attribute Seth et al.

(2018) risk of poorly maintained asset data. Roda et al. (2020) outline culture, asset data related reasons as well as framework utilisation issues as primary barriers of TCO model applications industry. Remko (2020) on the other hand attributes the gap between conceptual research and empirical application as the reason for poor risk resilience in supply chain, with 44% found to not have scenario mitigation plans at the beginning of the COVID-19 pandemic. The latter shortcomings relate to implementation problems rather than TCO concept insufficiencies.

2.3. Asset management relation to value management

Asset management (AM) is contrasted to value management (VM) through the characteristic that AM aims to align assets to the company's strategy, whilst VM is concerned with value improvement that extends beyond financial gains (Ghazali & Anuar, 2017). This is a view that tends to see a company's strategy to be primarily concerned with financial gains. Value management is designed to be an overarching superset of asset management, whereby VM seeks to reach an improved realisation of fit between utilisation of physical assets and the organisations' strategy (Ghazali & Anuar, 2017).

Unfortunately, organisations tend to focus their strategies towards decisions that involve implementation of new products, processes and services as well as stages that priorities re-engineering and remanufacturing of the latter entities (Zarte et al., 2019). Whist doing so, organisations do not focus enough on decisions that favour optimised value output during organisational life-cycle stages of planning manufacturing as well as execution (of manufacturing) (Zarte et al., 2019). Poor application of sustainable manufacturing decisions is attributed to insufficient knowledge about the subject as well as the lack of standards for sustainability indicating factors for properly managing manufacturing operations (Zarte et al., 2019). Whilst manufacturing is reported to be in shortfall of measurement standards and *know-how,* this body of work demonstrates that at least theoretical tools for harnessing potential benefits that may emerge out of MALC have been proven to exist. The concern however dwells more with the knowledge about the output value or potential of utilising such tools in the manufacturing industry.

2.4. Prognosis health management perspective

The aspect of continuous monitoring of asset costs within the total cost of ownership concept draws the TCO itself to be classifiable as a subset of a smart decision management methodology that Vogl et al. (2019) refers to as the prognosis health management (PHM). PHM is a system that utilises asset performance data at both current and historical states to enable "intelligent decision making" (Vogl et al., 2019, p. 79). One of the methods that the PHM employs to enable this smart decision making through data processing, is the incorporation of sensor-measured data (Yucesan, Dourado & Viana, 2021). The TCO methodology is conceptually a subset of PHM (Vogl et al., 2019) as it is a cost/benefit attributing method in the "engineering immune system" (p. 88) methodology which uses PHM to ensure absolute elimination of asset failures in its area of application (Yucesan, 2021).

2.5. Asset LCC and TCO industry standards

Besides the IEC60300-3-3 which seemed to be too general and basic when it comes to consolidating LCC, there are also a few industry specific standards that cater to LCC and TCO concepts, which have been critiqued for lacking validity and practicability (Vogl et al., 2019). The latter mentioned industry standards have been articulated and summarised in table 1-1 below, in terms of their scope of industry application, aspect of asset life cycle cost benefit that they focus on managing, as well as the limitations it possesses.

Table 1-1:

STANDARD	INTENDED INDUSTRY	ASPECT BEING MANAGED	LIMITATIONS
EN60300–3-3	General	Analysis of LCC	Too general (Vogl et al., 2019; Graessler & Yang, 2019)
ISO 15663-2	Oil and gas	Calculation of LCC-benefit estimates for end of life decision making	Industry specific (Animah et al., 2018)
SEMI E35-0618	Semiconductor industry (Woodhouse et al., 2019)	Cost effectiveness of manufacturing equipment per unit of production	Industry specific, argued to be most practical (Vogl et al., 2019)
VDMA 34160	General (Graessler & Yang, 2019)	Detailed list of subcomponents influencing LCC of machines	
VDI 2884	General (Graessler & Yang, 2019)	Comprehensive selection of LCC in the form of operating costs and investment cost	
ASTM E917 – 17	Construction		Industry specific
ISO 15686–5:2017	Construction		Industry specific

STANDARD	INTENDED INDUSTRY	ASPECT BEING MANAGED	LIMITATIONS
APPA 1000-1	Construction		Industry specific
NATO - ALCCP-1	Military		Industry specific

Even through there are various paradigms within which to view life-cycle phases of manufacturing assets, such as procurement, design, manufacturing, utilisation and phasing out (Zou et al., 2021), this study narrowed the life-cycle phases down to a simpler phases. This section specifically adopted a three phase perspective of classifying asset life-cycles management under beginning of life, mid-life and end of life management (Roda et al., 2020; Polenghi, Acerbi, Roda, Macchi & Taisch, 2021).

2.5.1. Beginning of life management of assets

This stage of a MALC was deemed to be the most crucial as it presents opportunities to infuse decisions that will have implications on the assets entire life cycle (Polenghi et al., 2021), irrespective of the quality of decision made or the implication effected. One approach towards the beginning of life asset management incorporates triangulation of information from multiple equipment suppliers for each manufacturing stage to arrange equipment information to feed a TCO estimation model (Woodhouse, Smith, Ramdas & Margolis 2019). The latter philosophy is accepted in the semiconductor industry and prescribed in the SEMI E35-0618 standard that is specifically designed for the sector (Woodhouse et al., 2019). Another view suggests a pre-design phase consideration of mobility costs over an asset's lifecycle, preceding decisions to design for energy effectiveness through modularity and reduced weight (Graessler & Yang, 2019). The understanding of LCC enables designers to factor in the right influence leading to selection and configuration of inputs that can influence better cost effective operational phases of their products. From an industry standards point of view, Graessler & Yang deem EN60300–3-3 to be "the most promising" for estimating LCC on light weight and is usable by both original equipment manufacturers (OEMs) and users. In their analysis, Graessler & Yang (2019) consider ownership costs, cost of procurement as well as disposal as categories of costs that are incurred within life cycle stages of semi-conductors. In addition to Graessler & Yang's procurement management and disposal, Zou et al. (2021) use LCC factors to quantify decision making based on whether the project is classified under "operation and maintenance" (p. 435) or modernising and overhauling within power plants in China. Industry specificity from Zou et al. (2021) occurs through their methodology of determining individual equipment's cost rates and cost ratios as a time based proportion of initial investment as well as and standard cost ratios and indices as a proportion of their comparable asset classes.

2.5.2. Mid life asset management

Methods that are ready to be used for LCC in manufacturings industries still remain in shortage, to an extent that in major economy such as China, LCC application is still deemed to be under-utilised, especially for assets that are not simple to quantify (Zou et al., 2021).

2.5.3. End of life asset management

Where management of MALC calls for end of life decision making, managers' strategic judgement needed relates to identifying, assessing and choosing the most relevant of the available strategic options relating to this stage (Animah et al., 2018). The effort of managing MALC at this asset life cycle stage incorporating the latter mentioned methodology may also yield answers suggesting against taking developmental action, such as *shutting the manufacturing operation down,* depending on the firms' identified constraints (Animah et al., 2018). This could happed even with the avoidable, unforeseen cost of risk, environmental degradation, social or health and safety as articulated by Animah et al. (2018), could possibly show unattractive relative to short term financial gains. The latter is likely to occur especially to those with less regard for risk, environment and human safety relative to their bottom line profits (Zou et al., 2021), for as long as they show lack of tangible cash inflow results. This therefore further reinforces the curiosity from research question no.1 which the study has used *H1* to test (MALC management leads to CB realisation).

2.6. Harnessing cost benefit from MALC

Given evidence that *cost benefit* is one of the key sources of competitive advantage in any business (Rui, Zhang & Shipman, 2017) a different way to pose the purpose of the study would be to use Vartanova & Kolomytseva (2019) lens to establish if managing MALC is by any chance a business process or capability that improves the cost dimension of competitive advantage. Even though almost 30 years ago, Porter (1996) cautioned that a strategic advantage can only come from a competitive advantage that can be sustained, Rui et al. (2017) defined c*ompetitive advantage* as the amount of knowledge assets and company-wide relations that underpin a company's uniqueness. *Knowledge assets* in the company's possession incorporate "knowledge, experience and organisational relations" (Rui et al., 2017, p. 137). Similarly if MALC could be proven to enhance cost benefits, it would inherently constitute a source of a cost oriented competitive advantage and therefore may be regarded as a key capability to have. One of the approaches followed when establishing key capabilities from which MALC cost benefits may be harnessed, is a simple, four stage process adapted from Rui et al. (2017) which suggests identifying a potential key capability, measuring it, evaluating and finally “diagnosing” (p. 137) it.

2.6.1. Identification

Not all assets are expected to yield an equivalent rate of costs when their life-cycles are optimised. For the sake of relevant results, a proper discrimination process is required in order to qualify or disqualify assets of significant relevance to a specific manufacturing operation. Ideally the entire system of assets should be assessed, thereby possibly eliminating the need for discriminating, which has potential to suppress cumulatively significant effects of compounding individually insignificant cost benefits.

2.6.2. Measurement

In the quest to discover whether the identified unit of analysis, *MALC management*, does yield cost benefits or not, the period of analysis needs to be measured (or possibly simulated) over the life-span of the asset. In the context of the study, there at least need to be a measurement in pursuit of a sought after manufacturing asset life-span (MALS), when a practical application of the critical research outcomes get to be trialled.

2.5.3. Evaluation of MALC and cost benefit creation

The evaluation of cost benefit creation would have to incorporate benchmarking of cumulative or real-time MALC costs and manufacturing asset life spans against the MALC costs and MALS initially forecasted during the decision making stage. For instance, in the context of oil industry’s offshore assets, Animah et al. (2018) proposed the use of a benefit-cost ratio (BCR) which relates life cycle benefits (LCB) to life cycle costs in order to account for all benefits in financial form then discriminate according to gain. Even though it is possible to use cost benefit analysis (CBA) in isolation to assess financial advantages of a specific strategy, literature has argued this to yield bias (Aurland-Bredesen, 2020). Considering the idea that BCR is a holistic ratio of benefits to costs expressed in their individual net present values (Animah et al., 2018), Aurland-Bredesen (2020) argues for it’s benefits in the face of a catastrophic risk, where strategy options have an element of interdependency, resulting in comparability. In such a case, the ultimate cost benefit is the one showing on the higher boundary whereas the lower boundary of comparison becomes a mere minimum option and the mid-range exhibiting other viable options that could be chosen if choices' discrimination are not on the basis of cost benefits.

2.6.4. Diagnostic of financial value creation

It is critical to consider the idea that diagnosing MALS is a relative process whereby MALS as an absolute construct means very little. Exception to the latter prevails when MALS is measured for data analysis or mere information gathering purposes. During the diagnosing phase, a deficit between MALC during the operational phase against MALS during the decision making phase would have constituted an unoptimised MALC. A surplus of the latter respective MALC to MALS relation would imply an optimised MALC.

Financial gains from asset utilisation can either be from value derivation or reduction in costs (cost efficiency). Benefits attributed to unlocking optimum longevity from MALC can therefore also be hypothesised to exist in at least the latter mentioned dimensions. One of the few suggested systems for optimising asset life-cycle outputs incorporates the use of asset management plans (AMPs), which should incorporate asset registers as one of their inputs (Bonthuys, Van Dijk & Cavazzini, 2019). In their South African municipal asset optimisation study, Bonthuys et al. (2019) outlined the feasibility of using a systemic AMP model that leverages technical, operational, and financial functional disciplines to manage asset life cycles. In contrast to the total cost of ownership model by Roda et al. (2020) which was presented at a system design point of view, Bonthuys et al. took a pragmatic application approach towards improving output of an asset over its life cycle. For both their novelty, the TCO approach (Roda et al., 2020) and AMP/AR practical exploitation (Bonthuys et al., 2019) could be bricolaged as building blocks to a far more robust conceptual model. Overlaying the latter models as an option could have enabled the study to carry perspectives from system design level as well as execution level, respectively. If this view were to be pursued, a strategy level tool would be outstanding in order to complete the organisational hierachical decision structure. Due to limitations in available time as well as requirements of the MBA study, the TCO management remains the grounding theory being pursued for the study.

2.7. Fourth industrial revolution perspective

Given the fourth industrial revolution (4IR) as the figurative industrial climate for assets, Carvalho et al. (2018) mentioned interoperability, decentralisation, virtualisation, real-time capabilities, modularity and service orientation to be the core elements in demand for operations to realise asset longevity. The criticality for the latter elements stems from being design principles that were reported to have the highest capability to lead organisations towards sustainable manufacturing (Carvalho et al., 2018) within the technology context. Given 4IR as the context within which the study aimed to understand characteristics of assets life cycles, the seven enablers needed to be explored in order to gain understanding of opportunities and risks that they provide. Similar to CM, the 4IR perspective was kept in mind but was not pursued as a conceptual tool for developpping the required solutions

2.8. Circular manufacturing perspective

Conceptually, circular manufacturing (CM) emanated from the circular economy (CE) thinking (Acerbi & Taisch, 2020). One of the clearer interpretations of CE articulated it as an *industrial approach that is created to have regenerative capacity for resource. This principle,* when applied in manufacturing using sustainability oriented strategies, it is then approached as CM (Acerbi & Taisch, 2020; Polenghi et al., 2021) for sustainable value development. The paradigm of viewing OEM's equipment (or intangible services) as products was challenged by Polenghi et al. (2021) towards an asset based view whereby the seller adopts an asset supplier perspective and the user takes an asset user ontological stance. The former would generally be in such a uni-directional way that OEMs only serve as providers of information, products, data, etc., and customers become mere consumers of products and support.

Polenghi et al. proposed the employ of interoperable data-based enterprise information systems (EIS) among the reformed asset supplier and asset user paradigms, throughout the MALC in order to enhance their circularity. The latter thinking posed a challenge on the viability of potential benefits from the implementation of ALC management from both asset suppler and user perspective and hence the pursuit of the studies' purpose of exploring the link between MALC management and cost benefits of implementation.

Nussholz (2018) theorised a new hybrid perspective of CM that is centred on value management as a principle. The perspective approaches a realisation of CM through interactive planning and execution of innovative value creation mechanisms at each and every life-cycle of an asset (Nusshol, 2018). Nussholz not only consolidated a view that proposes that CM is not philosophically different from VM, since they are both focused on harnessing value creation mechanisms over life-spans. Nussholz also agreed with the stakeholder approach that (Ghazali & Anuar, 2017) undertakes in attempt to aggregate towards reaching balanced outcomes for relevant individuals (or organisations). Acerbi & Taisch (2020) ended up doing more than just articulating the regenerative capacity of manufacturing assets to be a prerequisite for CM. They followed up with an applicable model overlaying various circular manufacturing processes with life-cycle stage based tools and activities required in the CM application process (Acerbi & Taisch (2020). This is a significant leap in the direction of bringing the proposed applicability of CM model (or any of the typically philosophical MALC-m concepts), down to demonstrating the *how* part, rather than just the strategic intent level (the why part) and leaving implementation open to practitioners' intuition. Figure 2-2 displays

	BoL							MoL		EoL			
	Technical requirements	Technical Drawings	User Manual	Assembly and Disassembly Instruction	Material Composition	Energy, Water, and Material Consumption for production	Commissioning strategy	Maintenance plan	Product Conditions	Product residual value	Reusable Entities	Energy, Water, and Material Consumption for regeneration	Remanufacturing plan
Circular Design	x	x	x				x						
Cleaner Production						x							
Disassembly		x		x							x	x	
Recycling		x	x	x	x				x	x		x	
Remanufacturing		x	x	x					x	x		x	x
Resource efficiency						x		x					
Reuse									x	x	x		
Servitization								x	x				
Waste Management					x				x	x			

Figure 2-2:

Note. Framework for Mapping Data families for CM stratgy during (M)ALC-m. From "A literature review on circular economy adoption in the manufacturing secto" by Acerbi, F., & Taisch, M. (2020). r, *273*, (123086.https://doi-org.uplib.idm.oclc.org/10.1111/jiec.13187). Copyright 2020 by *Journal of Cleaner Production*.

The CM concept is still new in literature, and despite a very promising pragmatic approach identifiable from CM methodologies, it is still not easy to develop business propositions to sell its adoption to manufacturing organisations. A reason for the latter is aligned with latest publication in the topic still identifying CM to have higher short term costs when compared to the status quo due system change costs that CM comes with (Baldew, 2023). For such a reason, and considering the cost cutting plague in industry (Zou et al., 2021). CM methodology in its organic design, was parked and not pursued further in this study, even though its spill-over effects towards MALC-m and TCO applications were not neglected where-ever they re-emerged.

2.9. Theoretical principles consolidation

The problem remained, yet again, that theory still needed to enhance practice with the decision tools to determine accurately as soon as the total cost of ownership surpasses the economic value expected from the asset. Graessler & Yang (2019) summed up the understanding that at *beginning of life* stage, cost benefits during design manifest from information management, costing expertise, "sophisticated preparation and constant maintenance" (p. 1051). It therefore goes without question that effort is indeed required and there may be an element of complication in the process of **MALC management** if sophistication and constant looking after are deemed as suitable descriptors for the process (Roda et al., 2020; Graessler & Yang 2019). MALC management is only one construct of the study. In the context of cost besefits, Graessler & Yang (2019) outlined CBA to be unique to a product (asset) and organisation, in addition to being highly variable in line with the expertise of the person executing the analysis. Irrespective of a contrary argument to the latter, proving objectivism of a quantitatively structured benefit cost ratio analysis within oil and gas manufacturing (Animah et al., 2018), such vast inconsistencies in theory alignment further depicted a potential lack of external validity (Zyphur & Pierides, 2017) and repeatability in application of the **cost benefit** analysis methodologies paired.

Besides the application in reviewed manufacturing sectors during *beginning of life* stage being in semi-conductor industry (Woodhouse et al., 2019; Graessler & Yang 2019), power manufacturing in China (Zou et al., 2021) or *end of life* decision making being in offshore oil and gas (Animah et al., 2018), the race has been towards quantification of LCC. The latter literature has been found to focus a lot on the development of TCO methodologies to determine LCC for manufacturing assets.

With both MALC management and cost benefits as constructs of the study, proven to be at least complicated constructs (if not complex) (Roda et al., 2020), the theoretical discussion presented by this research to examine moderating variables for MALC management as well as the relationship between the constructs was thus due.

2.10. conceptual model formulation

Given the above-mentioned constructs of interest within this study, the below framework incorporates a conceptualised potential link of the research variables and the nature of their individual relationships with one another as characterised in the literature review.

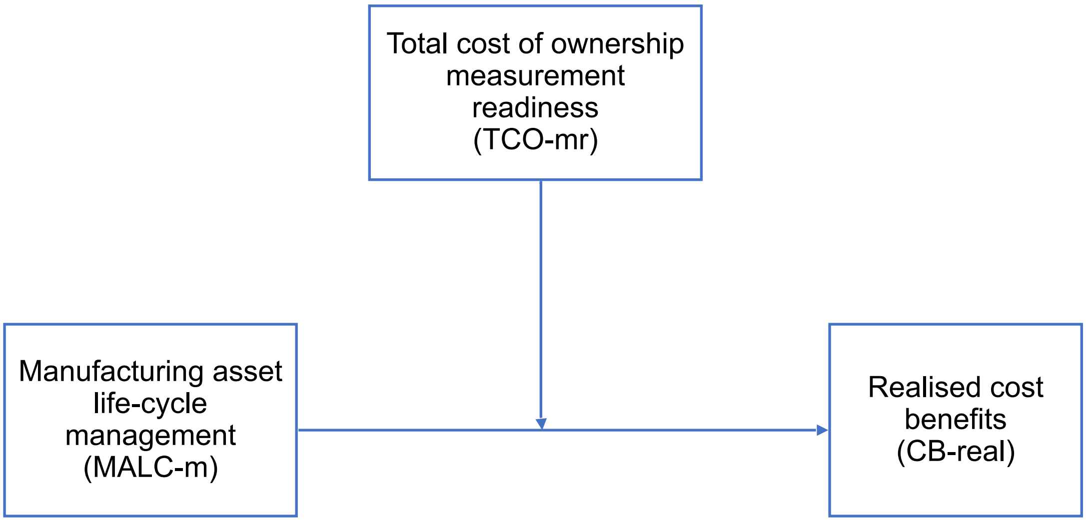


Figure 2 – 1: Conceptual model derived from the literature review

All shortcomings mentioned in this section are feasible to overcome, given the correct context, a sufficiently pragmatic system (plan) in place and a good enough managerial drive to follow through execution. The need for more studies merging the gap between empirical application and conceptual theory in manufacturing industries (Remko, 2020) was therefore further reinforced. Specific attention was drawn towards life-long asset exploitation due to the embedded potential financial advantage of leveraging every monetisable value.

Holding true of the proposed conceptual framework (as a prerequisite), would have implied that the study proved the value to practically exist in the whole trouble of ensuring TCO measurement readiness on MALC-m as well pursuing management of the same assets as a strategic initiative. Reliable predictability of the latter cross over point may be one of the most useful outcomes in the process of MALC management, as it would enhance the decision making of whether to pursue asset replacement or continue maintaining as well as to forecast when the replacement action may be needed.

2.10. Conclusion

In reflection to the reviewed literature, the constructs of interest have been reinforced to the initial intention of the study with a slight focus. The variables have been narrowed to incorporate manufacturing asset life-cycle management (denoted as MALC-m henceforth), the realised cost benefits (referred to as CB-real) as well as the eligibility or readiness of an organisation to measure total cost of ownership measurement (TCO-mr). Given the literature assessments regarding the concepts of MALC management and inherent cost benefits, this chapter has outlined and expanded the level of thinking. It has outlined that, not only does the practice of MALC management address problem layer of imprecise benchmarks leading to substandard MALS, MALC also tends to be in excess in some asset cases. In the context of MALC over-extension during end of life, new problems may emerge, which further reinforced a need to strategically manage MALC in order to declare best suitable end of life strategies for the organisation's context.

3. Research questions and hypotheses

This study is proposed with an aim to develop learnings that will establish answers or literature discussions for the following two research questions reflected as RQ1 and RQ2.

3.1. Research Questions

Research Question 1 (RQ1) - What is the nature of relationship between asset life cycle improvement and cost benefit in a manufacturing environment?

In their study with a setting in middle income countries (including South Africa), Andreoni & Tregenna (2020) suggests “constraints in terms of… technological competitiveness” (p. 324) relative to value output. Value creation mechanisms (VCM) are variables with capacity to affect value creation from manufacturing assets (Pakkanen, Juuti & Lehtonen, 2020). The following statements is therefore hypothesised;

Hypothesis 1 (*H1*) - Manufacturing asset life cycle management leads to costs benefits realisation

H1 therefore leads to the following conditions to be tested;

- **Alternative hypothesis (H_{1a})** - Manufacturing asset life cycle management leads to realisation of costs benefits
- **Null hypothesis (H_{10})** - Manufacturing asset life cycle management does not lead to realisation of costs benefits

Research Question 2 (RQ2) - What are the most critical moderating factors for the relationship between manufacturing asset life cycles and cost benefit?

Considering an understanding that the effect in value could be moderating amongst other possibilities, the two research questions are therefore extrapolated. The future of manufacturing incorporates various uses of data to perform maintenance functions that will be directed at improving equipment availability and reducing life cycle costs (Vogl et al., 2019). This notion was also used to extrapolate hypothesis 1 and 2. RQ2 is informed by Kyriaki, Konstantinidou, Giama & Papadopoulos (2018) recommendation to further study “life cycle analysis and life cycle costs analysis” (p. 3073) of certain manufacturing assets.

Hypothesis 2 (*H2*) - TCO measurement readiness moderates creation of cost benefits from MALC

H2 therefore leads to the following conditions to be tested;

- **Alternative hypothesis (H_{2a})** - TCO measurement readiness moderates creation of cost benefits from MALC
- **Null hypothesis (H_{20})** - TCO measurement readiness does not moderate the creation of cost benefits from MALC

If this were true, it would be outlining that MALC management is a value creation mechanism through which CB-real would be the resultant cost dimension of competitive advantage (Rui et al., 2017). TCO may therefore be a tool for outlining where the value is being created or destroyed for better decision making when it comes to manufacturing assets.

3.2. Conclusion

If hypothesis *H1* were to be found true, different implications of attaining the cost benefit would need to be assessed. Such considerations incorporate the feasibility of implementing a management system (Bonthuys, Van Dijk & Cavazzini, 2019) for MALC towards optimisation, implementing a system to quantify costs or (non-financial) organisational impact of implementing as well as the inherent "return on investment" (p. 9). If *H2* were found to be true, then actual application of MALC-m using a pragmatic tool would have been tested for viability.

4. Research design and methodology

The purpose of the study was to understand the relationship as well as mediating and moderating effects between Manufacturing Asset Life-cycles (MALC) management and inherent cost benefits within manufacturing organisations. The intention was to fulfil a contribution towards theory as well as practice in the manufacturing industry. The study followed a descriptive research design which will execute a mono quantitative methodological choice and utilise surveys a data collection method. The study occured over a cross-sectional time horizon, whereby non probabilistic purposive sampling methods will be in effect.

4.1. Research design

The study aimed to generate results that could have a positive contribution to knowledge and therefore a good formulation of research design is there to improve the probability of the latter calibre of output as well as the overall quality of research (Sovacool, Axsen & Sorrell, 2018). In the quest of producing a study that has “rigour, novelty” (Sovacool et al., 2018, p. 12) and good writing “stye” (p. 12); not much novelty and style could be displayed within the research design, however the chapter is a critical foundation for rigour (Saunders, Lewis & Thornhill, 2016). Limitations to significant advancement of novelty within this chapter is due to the reason that the chapter would be more of an integration of constituents from a well studied research science (Zyphur & Pierides, 2017). Whilst good writing style had to be demonstrated consistently throughout the study; rigour, in the context of this research design, was be applied by means of explicating (selecting and applying) suitable research approaches whilst tending to stipulate imperfections in reasonable detail.

4.1.1. Purpose of research design

Due to the fact that both research questions asked questions that sought to interrogate *“what”* the relationship was between the two constructs as well as *“what”* the influencing factors were (Saunders et al., 2015), the purpose of the study therefore emerged to be **descriptive**.

4.1.2. Philosophy

Considering the justification stipulated in *section 4.1.4.* of this study, explaining the methodological choice, it may be appreciated why the study is deemed to be quantitative in nature. The notion that quantitative methods are generally known to be associated with objective paradigms (Sovacool et al., 2018), as well as the research questions’ nature that seeks to understand the objective relation between two constructs, made the research philosophy that of a positivist.

4.1.3. Approach selected

The data collection method (also stipulated under strategy) was that of surveys, which by its nature of being a predeterminable structured approach, made the methodological choice to be quantitative (Saunders et al., 2016). Similar to the general execution of quantitative research, this study aimed to test theory through the use of data, which then deemed the approach to theory development as deductive (Saunders et al., 2015).

4.1.4. Methodological choices

The research aimed to converge the understanding of the relationship between manufacturing asset life cycles (optimisation) and cost benefits within manufacturing organisations. There were immovable academic duration and work-life constraints that the author was subjected to, which limited flexibility towards embarking on long duration research. This implies that there was unfortunately not sufficient time-horizon capacity to triangulate towards subjecting findings into a further inductive or deductive study. If the research were to be followed up with another inductive study, the method would have been mixed (Saunders et al., 2016). Similarly, the study would have been multi-method if another deductive study were to be embarked on. As a result of the above justification, a mono-method research was adopted whereby data was collected using one method, which became quantitative according to research approach and philosophy selection.

4.1.5. Strategy

As was with the generic nature of quantitative research, where a **deductive** approach to theory would be undertaken, the aim was to converge the descriptive understanding of the relationship nature between the two given constructs as well as their moderating factors. An ideal, tried and tested strategy to adopt in order to execute research with the latter conditions was a quantitative survey (Sovacool et al., 2018).

4.1.6. Time horizon

In an ideal quest for methodological novelty, a longitudinal method would have provided opportunity for more rigorous and reliable results (Sovacool et al., 2018). Despite the reality that technology has provided reasonable opportunities to track the same respondents for data collection at more than one point, longitudinal methods still remain unfavourable for the author as they require a time frame that was not available for the MBA (Sovacool et al., 2018). As a result of this, the time horizon selected for this study was **cross sectional**, whereby data was only collected at a single point in time for the sampled population (Sovacool et al., 2018).

4.2. Proposed research methodology

One of the primary objectives of this section was to argue and defend selected aspects of the proposed research methodology. Consequentially, the research methodology section also aimed to govern means towards achieving *relational validity* (Zyphur & Pierides, 2017). Relational validity was meant to determine if the methodology and results ethically connect the researchers purpose to the methodological choice and the actual execution of the study (Zyphur & Pierides, 2017).

4.2.1. Population

Firstly we acknowledged optimised asset life cycles as outcomes of sustainable decision making processes (Caetani, Ferreira & Borenstein, 2016; Zarte et al., 2019), which in their nature are strategic endeavours (Caetani et al., 2016). The population eligible to provide valuable data in understanding moderating factors between manufacturing asset life cycles and cost benefits within manufacturing organisations was therefore likely to be professionals whose duties are associated with asset utilisation, asset care and assessment of asset value derivation. In relation to the above as well as the derivation in (Roda et al., 2020; Zarte et al., 2019), the target population was therefore derived to include production/process managers/engineers, operations managers, accountants, business managers, maintenance and plant managers. The latter groups are generally personnel who influence performance at systemic level and sometimes even at strategic level as MALC management and implementation has to take place at the latter organisational levels respectively.

4.2.2. Unit of analysis and reliability of responses

As discussed under the population section, the units of analysis, derived from Zarte et al. (2019) included three tiers of professionals. Tier 1 comprised of **asset utilising professionals** such as production and operations managers. Tier 2 comprised of **professionals who looked after assets** such as maintenance engineers and plant managers and lastly the third tier incorporates **professionals who are associated with synthesising of value derivation**, such as accountants and business managers. The categorical partitioning of respondent tiers is intended to aid in the understanding of different levels of expertise among responses **in order to improve reliability** of results and the research as a whole.

4.2.3. Sampling method and size

Zyphur & Pierides (2017) outlined that if a research aims to understand certain aspects of a certain population, then "representativeness of the sample" (p. 8) should be focused on instead prioritising traditional categorising. The argument for example is that, if the aim of research is to study certain aspects of a population that does not prefer to be identified with gender, it is not even ethical to statistically describe the group under male or female categories (Zyphur & Pierides, 2017). Under this paradigm, positivist declarations that only see random sampling (for instance) to be possible if preceded by "a full population list" may exclude some population dynamics. Long existing statistical definitions appeared to instil dogmatic behaviour upon researchers (Zyphur & Pierides, 2017) by disregarding the probable postmodernist perspective of the natures reality (Saunders et al., 2015). It is due to the latter principles that the researcher approached the population and sampling with a co-creator's perspective whilst using ethics as the guiding principles instead of long standing statistical definitions (Zyphur & Pierides, 2017).

The nature of research questions probed a quantitative research study in multidisciplinary fields (finance, asset management and operational effectiveness), therefore it was improbable for the study to have a complete identification of the target population. This in essence implied that there was no sampling frame and without a sampling frame, traditional sampling suggests that the technique could not be a probabilistic sampling method (Saunders et al., 2016; Zyphur & Pierides, 2017). The latter, combined with the fact that the research strategy of choice was a quantitative survey; depicted the sampling method to become complex enough to justify being informed by researchers' discretion relative to research questions. Even though yet again, the researcher aimed to deviate from the typical nature of applicability to small samples as discussed by Saunders et al. (2016), discretional selection was in line with a **non-probabilistic**, **purposive sampling method** (Saunders et al., 2016). Another sampling method that was utilised, took into consideration that research participants were also going to be largely accessed through social media searches (such as LinkedIn) as well as researchers' personal contacts. Traditionally this nature of sampling appeared to favour the two non-probabilistic volunteer sampling methods that were used. The first was a *volunteer sampling method* called **self selection sampling** which will incorporated volunteering of participants to partake in the study, following publicising of the survey (Saunders et al., 2016). The second *non-probabilistic, volunteer sampling method* to be used, called **snowball sampling***,* incorporated word of mouth (including digitally transferred) invitations that diverge from the researcher outwards, via his direct contacts. The size of the sample incorporated all accessible Manufacturing Industry professionals, who fell within the three tiers of units of analysis mentioned in section 4.2.2.

As result of the above, **a full population list could not be provided** as it would have cast a limit on the cascading effects of the intended snowball sampling and further constrain the dynamic nature of the self selection method selected, especially if there were to be a shortfall in the number of responses received versus intended. The researcher targeted a minimum of number of 120 responses in order to achieve validity and repeatability of results.

4.2.4. Measurement Instrument

For RQ1 and *H1,* which sought to learn the relationship nature of the constructs; both nominal and ordinal data was incorporated as inputs since the two constructs were perceived from a continuous data point of view (Saunders et al., 2016). This was by virtue of expectation based on the literature review undergone thus far. In the questionnaire, the anticipation was practically drawing from professionals' experience-based perception to inform how MALC management as the independent variable, influences the three dimensions of cost benefit which include profits, costs and investments (Zarte et al., 2019). RQ2 and *H2* In their nature, were expected to correlate a perceived moderating factor, interpreted as a value creation mechanisms in Pakkanen et al. (2020). Using parametric description of the nominal data (Saunders et al., 2016), second measurement method was generated. All attainable VCM’s were be subjected to descriptive statistics.

4.2.5. Data gathering process

Firstly it was acknowledged that, by virtue of the data gathering process entailing the use of primary data from actual research subjects, the research may be categorised as empirical (Lei & Candès, 2021). Informed by quantitative research as the methodological approach as well the research strategy of choice being a survey, the method of gathering data had to become structured (Saunders et al., 2016) and pre-existing (Sovacool et al., 2018). In order to answer RQ1 and RQ2, which sough to investigate a convergent relationship nature between the constructs (Sovacool et al., 2018), remote (telephonic or digital) data collection methods were sufficiently effective (Saunders et al., 2016). The chosen primary data collection technique was be a **questionnaire**, following that it entailed respondents answering similar "questions in a predetermined order” (Saunders et al., 2016, p. 437). The questionnaire design was not adopted from a previously used survey instrument but rather designed by the researcher from a predominant use of a total cost of ownership framework by Roda et al. (2020). Questionnaires were created using online tool called *Google Forms,* instead of others such as *Survey Monkey* because of fluency and ease of access and usability by the researcher as well as respondents according to the author's understanding. The questionnaire was distributed using various methods, including email, online posting of link on platforms such as LinkedIn as well as digital communication tools such as *iMessage* and *WhatsApp*.

4.2.6. Analysis approach

By virtue of the quantitative nature of data, the analysis was undertaken using statistical methods (Sovacool et al., 2018). RQ1 sought to explain the nature of the relationship (between MALC management and cost benefits) and by it's explanatory nature, it aimed to analyse the influence of the independent variable on the dependent, which in turn assimilated a bi-variate analysis (Sovacool et al., 2018). Sovacool et al. explains bivariate analysis to yield a reasonable level of rigour, and so this would satisfy the quality intentions of the formulated research design. The bivariate analysis sought is a statistical method that is of inferential nature (Lei & Candès, 2021; Sovacool et al., 2018). Methods of testing inferences that are relatable to the research questions were considered. Variables that can be distinguished or ranked are referred to as nominal and ordinal (respectively), as opposed discrete variables, which are characterised by countability (Calonico, Cattaneo & Titiunik, 2015). A correlation test called the *Spearman's Rank Order Correlation test*, which deals with ordinal data sets (Schober, Boer & Schwarte, 2018) was used since MALC management, TCO-mr and cost benefit were asked in an ordinal data format (Calonico et al., 2015; Chatterjee, 2021; Saunders et al., 2016). It was initially planned that if found necessary, a comparison of any two independent nominal data sets such as perspectives of *tier 1* (asset users) relative to views of *tier 2* professionals, a Chi^2 test would be selected. If more than two independent groups of ordinal data sets needed to be compared, a non parametric statistical test such as the Friedman's analysis of variance (Friendman's ANOVA) test would have been embarked on. For RQ2, which sought to converge empirically understood moderators of the relationship, the same Spearmans rank correlation test statistics was used to categorise the most agreed upon benefits. For this part, the survey needed to contain nominal and ordinal data.

4.2.7. Quality controls

As mentioned in the research design section, one of the main aims at achieving quality incorporated explicating suitable research approaches. Triangulation of theoretical perspectives from literature, statistical analysis methods (whereby descriptive and inferential statistics) as well as purpose of design (descriptive and explanatory) aimed to also enhance chances of a better quality output in the study (Sovacool et al., 2018). Furthermore quality of data collected was pursued through ensuring that the purposive sample and self selected samples of different natures of professionals were as heterogeneous as possible (Saunders et al., 2019). Unfortunately this homogeneity was not achieved, so the Chi^2 test and the Friendman's ANOVA could not be run.

4.2.8. Limitations

Even though the research aimed to study the relationship between asset life cycle and cost benefit, a moderating effect was also hypothesised. Considering the nature of constructs, that they have one dependent variable, it was initially not clear whether the relationship incorporated depended, independent, moderating, mediating, controlling or confounding variables. In other words it may have emerged that by virtue of the hypotheses and conceptual framework, a change of course would be needed after the study. The limitation therefor was that; an optimisation model using a single objective, may constrain the outcome of the study to not more than one possible outcomes (Caetani et al., 2016).

At this the research design stage of the study there had yet been very minimal interaction between research design, methodology and the actual real research (Zyphur & Pierides, 2017). Therefore the research methodology still had potential to assimilate a mere researcher passive representation of already existing research techniques and general processes as opposed to methodology co-creation (Zyphur & Pierides, 2017), which needed to be the objective. Fortunately the outcome was not as such

4.3. Conclusion and Ethical considerations

The questionnaire creation tool selected favoured the authors' experience, there is still a chance that there was bias towards the tools (by researcher) as they may have not been as favourable to respondents and thus hinder the rate of response. Input from consultation with successful researchers such as supervisors yielded more pragmatic reasoning rather than mere researcher perception. By virtue of the researcher being from an Engineering profession, there was a very high possibility of him having a large proportion of professionals from his traditional functional background which may skew data towards a coverage error (Sovacool et al., 2018). In hindsight this prevailed, based on the homogenous expertise of respondents achieved.

During data collection, names of participants were not requested and thus even during the self selection sampling, the researcher was not be able to identify an individual respondents’ data. This enhanced protection of respondents **anonymity**. An informed consent was given by each respondent through acceptance of a consent statement written in English at the beginning of a survey. If a respondent opted not to proceed with the survey, there were going to be any penalties nor prejudice as a consequence of their decision and such declaration was mentioned in the consent statement.

4.3.1. Information control and data retention

At the end of the research project, a research report will be provided to Gordon’s Institute of Business Science (GIBS). As a deontological consequence of University rules, the report will ethically form part of proprietary information for the business school as well as the University of Pretoria. Access to any further publications derived from the report including the report itself will have to be pursued via the business school. Besides the Universities’ obligation to retain information for a regulated amount of years, the researcher also voluntarily commits to retain all data in a secure, private cloud (“iCloud”) for a period of more than 10 years.

5. Results

5.1 Introduction

In the interest of the document's readability, survey questions were re-coded and each referred to in terms of identities ranging from ID1 up ID43….

5.2. Survey

The research was conducted to follow through a research design that intended to follow *self selective sampling* and *snowball sampling* as the two forms of non-probabilistic purposive sampling methods of choice to reach potential respondents. The survey was re-iteratively sent out to a digital network of 1620 followers, where it received an approximate amount of 2831 screen displays, referred to as impressions in the social media program, as displayed on Appendix A5-1. The research was subsequently electronically mailed (emailed) to another primary sample of at least 260 manufacturing workers and thereafter further emailed to another sub-sample of approximately 40 managers.

5.2.1. Self selective sample size: digital mini-focus group

Four weeks after initially sending out the questionnaire, digital social media connections were contacted directly using two methods. At first, three groups of 31 to 38 research subjects (per group) where added to sub-focus groups, whereby the survey was posted (for the second time). In the latter iteration queries, completion responses and gratitude messages arising were communicated openly. This method of probing sub-collective respondents was only trialled on business social media contacts in an ascending alphabetical order, with names starting with letters from *A* until *H*.

The response rate was found to hover around 3-5% per mini-focus group, which was mathematically decent enough for the researcher to pursue with all 1620 contacts in his network, in order to boost the number of responses. The latter focus group-based self selective sampling was nonetheless put on hold, primarily because a vast number of participants remaining silent and a few immediately leaving the group. Even though neither the people who remained silent nor left groups were asked of their individual reasons for acting as such, it was indicated that they either did not have interest or were agitated by the idea of being added to a digital group without prior request. Guided by a moral compass to retain and grow professional networks instead of the contrary, the researcher opted not to act repulsively towards his entire business social networks and forfeited the mini-focus groups at week six of data collection.

5.2.2. Self selective sample size: digital social media direct messaging

The second self selective sampling approach embarked on, within the digital social media based data collection process, was sending the remainder of respondents (who meet criteria of the intended research population) individual direct messages on the latter mentioned digital social media. At least 500 direct messages were sent during this round of iteration. The rate of response was slightly less from this approach, as it was at a maximum of 3%. All data collection processes embarked on were actioned sequentially with not less than a week apart in order to learn the most effect data collection process.

5.2.3. Snowball sample size

In hindsight, observations from the data collection process showed the minimum quantifiable snowballed sample size to equate to 2831 of total digital social media screen displays, less 1620 followers from the same platform, which equates to minimum of 1211 snowballed sample size.

5.3. Responses

The collective primary quantified sample size summed up to a minimum of 1920 potential respondents, which comprised of 1620 people from the original followership sample when added to the approximate 300 manufacturing workers. The data collection time horizon took place over a 10 week period, from 9 December 2022 to 23 February 2023. The rate of response was however 64 respondents, which included one responded who declined the statement of consent. The number of responses was relatively low compared to the researchers ideal minimum target of 120 responses.

5.3.1. Questionnaire structure

The questionnaire consisted of 42 questions, which in the questionnaire design, were characterised by identification numbers (ID) from one to 43 and incorporated three categories of survey questions. The first category was found in the very first question and was of *consent acknowledgement* nature. If respondents could opt not to give consent, the survey would immediately end. The second questions' category were of demographic nature and sought to understand the level of expertise that the respondents had, relative to the constructs being investigated. Out of the 42-question survey, the study had seven demographic questions. The remainder and greater proportion of the questionnaire was made up of 37 likert scale framed, theory building questions.

Within the 37 questions, eleven measured MALC management construct within three phases of MALC phases, namely; beginning of life (BOL), middle of Life (MOL) and end of life (EOL). Nine other questions intended to assess respondents perception of what constituted cost benefits. Eight questions succeeding the latter, measured indicators for total cost of ownership readiness through the extent to which respondents experienced problems related to data access limitations. These ended up being the first set of questions within the survey that were framed using negative reinforcement. The last seven questions measured TCO adoption in relation to its measurement readiness (three questions), cost value/benefit realisation (three questions) as well as in relation to MALC phases. The seven TCO adoption indicator questions incorporated three negatively reinforced questions.

5.3.2. Respondents demographics

All respondents had the experience of working with manufacturing assets at different stages of asset life-cycles. Only one respondent had sole experience works with end of life life-cycle. Figures 5-1, 5-2 and 5-3 illustrate some of the respondents demographics.

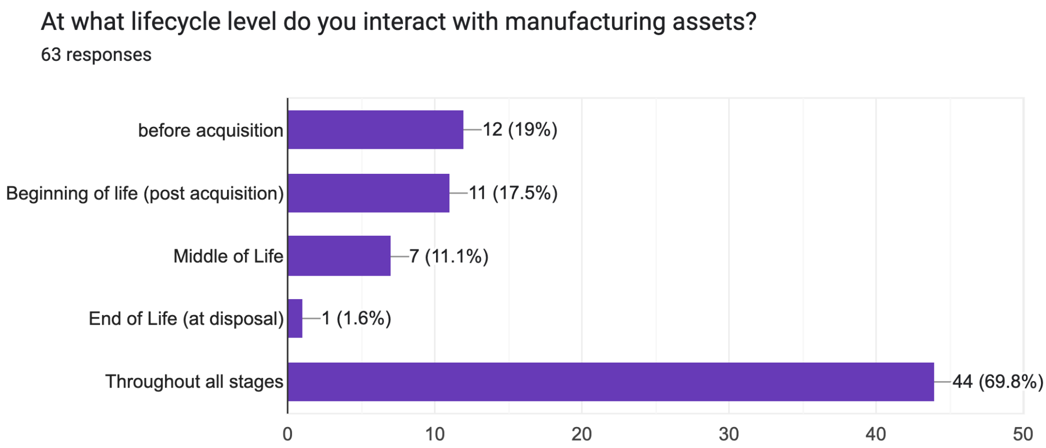


Figure 5-1: Respondents Life cycle stage interaction with assets

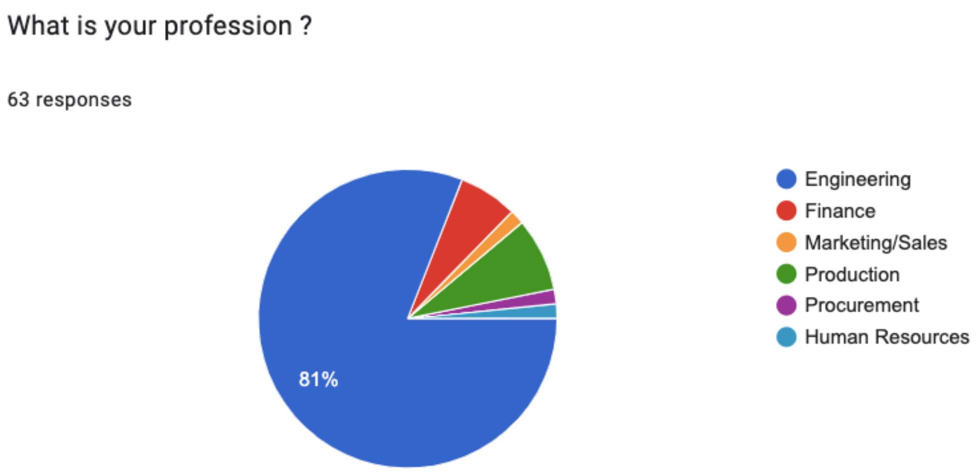


Figure 5-2: Respondents functional background

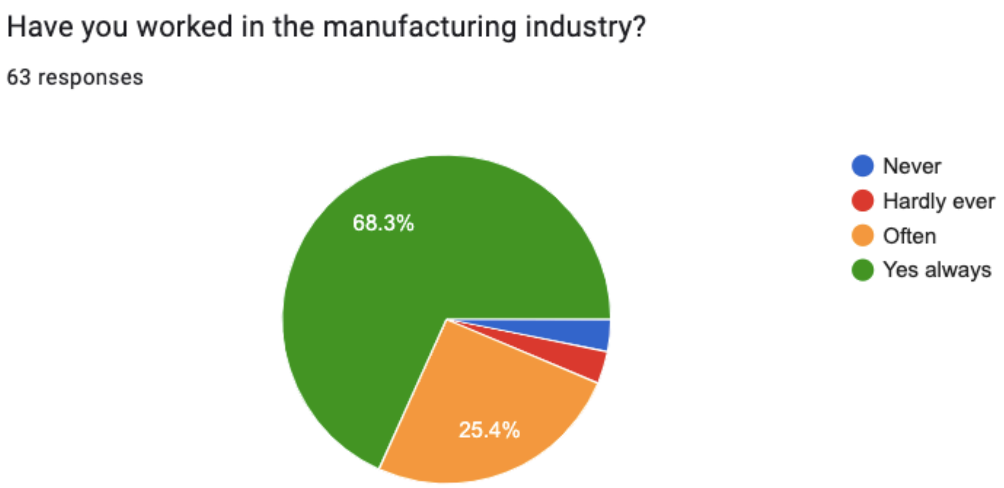


Figure 5-3: Respondents familiarity with Manufacturing industry

5.3.3. Data coding

With the exclusion of questions that aimed at gathering respondents nominal and ordinal demographic data, all scores were coded to ascend in a positively reinforcing order. Practically this meant that scoring was ranked with the lowest number denoting the least favourable outcome (towards the context of the question) and the highest number representing the best favourable outcome, in an ordinal manner. Similarly, questions that were contextually framed from a stance of reinforcing the negative, which were found from ID 28 to ID 37 in the context of the current study, had to be coded in an order where an agreeing response would receive the lowest score and the contrasting would achieve the highest ordinal score.

5.4. Inferential statistics: Research Question 1

The first research question aimed at investigating *the nature of relationship between asset life cycle management and cost benefits* within a South African manufacturing environment. The question further led to hypothesis *H1. H1* suggested that; *Manufacturing asset life cycle management leads to costs benefits.* Of significant importance, was the understanding of what constituted the variables to be tested in order to eventually answer the research questions. For *H1, v*ariables of interest were **MALC-m** as the dependent variable and **cost benefits**, as the independent variable. This meant that inferential statistical tests had to be run based on the two constructs (MALC-m and cost benefits) in order to test the study's first hypothesis.

5.4.1. Validity tests - Hypothesis 1

All questions informing a specific construct were grouped together and summed with an item (variable) specific total score, such as that displayed on the last column in **table 2**. As an illustrative example, the three questions addressing CB-real construct were coded as ID40, ID41 and ID42 then a construct specific total score was correlated to all individual questions. For both of the constructs used to test hypothesis *H1*, a validity test was done using a *2-tailed Spearman's Correlation* test. The results for CB-real were as such that statistical significance was attained on all questions at a 95% confidence level, when compared to total score of the variable being measured.

Table 2: Correlation test for CB-real validity

Correlations					
		ID40	ID41	ID42	CB-real Total
ID40	Pearson Correlation	1	.058	.164	.504
	Sig. (2-tailed)		.652	.199	<.001
	N	63	63	63	63
ID41	Pearson Correlation	.058	1	.641	.814
	Sig. (2-tailed)	.652		<.001	<.001
	N	63	63	63	63
ID42	Pearson Correlation	.164	.641	1	.851
	Sig. (2-tailed)	.199	<.001		<.001
	N	63	63	63	63
CBrealTotal	Pearson Correlation	.504	.814	.851	1
	Sig. (2-tailed)	<.001	<.001	<.001	

MALC-m variable also had its informing questions grouped from ID9 to ID19 and summed to form a variable specific total, which was further correlated to the latter research questions. As such, a similar test (to that for CB-real) was run for MALC-m variable, whereby the construct value's total was found to have statistical significance when correlated to all individual questions at a 95% confidence level. The output values were reflected on table A5-1 in Appendix A5-3.

5.4.2. Reliability tests (Internal consistency) - Hypothesis H1

Based on the thinking that the two research questions incorporated four research constructs being informed by a number of indicator questions in the questionnaire, reliability of the questions had to be assessed. Cronbach's Alpha tests were run to determine the internal consistency of each group of survey questions relative to the variables that they sought to test from respondents. For CB-real, as a construct that appears in both hypotheses H1 & H2, the first run of Cronbach's alpha was 0.57, as tabulated in the first column of table 3. Considering the fact that the latter value was lower than 0.7, it thus could not be accepted to indicate suitability of the group of survey questions in representing the variable of interest (Taherdoost, 2016). A cause of such a relatively low Cronbach's alpha had to be determined.

Table 3: Cronbach's Alpha - CB-real variable

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.570	.548	3

Upon further analysis, reviewing *specific item-total statistics* results, the initial Cronbach's Alpha (CA) could be improved to a value above the recommended 0.7 threshold (Taherdoost, 2016), as declared in the last cell of row no.1 of table 4. In reference to item total statistics table, the latter CA improvement could be achieved if research question coded as ID40 could be deleted from the likert scale group of questions attempting to assess CB-real.

Table 4: Item-Total statistics (of Cronbach’s Alpha’s) - CB-real

Item-Total Statistics					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
~~ID40~~	~~6.9683~~	~~3.257~~	~~.122~~	~~.031~~	.781
ID41	7.6508	1.908	.490	.413	.278
ID42	7.5397	1.801	.584	.427	.107

Survey question ID40 expected respondents to choose an answer from a five-point likert scale, for a statement declaring; *“I believe that cost benefits may result from a system that continuously assesses the total cost of owning (TCO) different assets”.* Indeed after the second iteration, following the deletion of ID40, an improved CA value of 0.781 was achieved as opposed to the previous sub-optimal value of 0.57 as denoted in both the forecast in table 4. Table 5 displays CA from the second iteration results.

Table 5: Cronbach’s Alpha - CB-real (iteration 2)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.781	.781	2

The reason that survey questions coded as ID41 and ID42 were not considered for deletion, is that the column stipulating “*Cronbach Alpha if item Deleted*” reflected that the indicator questions’ group would result in reduced CA’s of 0.278 and 0.107 respectively if the latter were to be removed.

For MACL-m, the Cronbach’s alpha showed to be well above 0.7, with a value 0.9 (and thus all 11 eleven questions’s likert scale responses showed to contain an internal consistency when it came to informing the construct. Due to the good CA value, *item total statistics* table illustrated in Appendix A5-4, were no longer reviewed for further iterations as it had already exhausted its means to inform the understanding of whether the likert scale used (in its entirety) to inform the variable, was reliable or not.

Table 6: Cronbach's Alpha - MALC-m variable

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.900	.901	11

5.4.3. Factor analysis for MALC-m construct

After computation of the factor analysis, the *correlation matrices* for both CB-real and MALC-m variables were found to contain all comparisons with at least one correlation factor that is greater than 0.3 (Watkins, 2018). For MALC-m, in table 7, all correlations that computed above 0.3 were allocated into highlighted cells.

Table 7: Correlation Matrix - MALC-m

	ID9	ID10	ID11	ID12	ID13	ID14	ID15	ID16	ID17	ID18	ID19
ID9	1.00	0.45	0.37	0.37	0.35	0.25	0.08	0.11	0.22	0.27	0.21
ID10	0.45	1.00	0.62	0.70	0.49	0.53	0.38	0.37	0.34	0.40	0.31
ID11	0.37	0.62	1.00	0.67	0.56	0.57	0.47	0.53	0.44	0.41	0.31
ID12	0.37	0.70	0.67	1.00	0.57	0.57	0.60	0.46	0.48	0.52	0.31
ID13	0.35	0.49	0.56	0.57	1.00	0.62	0.50	0.71	0.39	0.46	0.36
ID14	0.25	0.53	0.57	0.57	0.62	1.00	0.61	0.66	0.41	0.49	0.50
ID15	0.08	0.38	0.47	0.60	0.50	0.61	1.00	0.57	0.44	0.55	0.49
ID16	0.11	0.37	0.53	0.46	0.71	0.66	0.57	1.00	0.47	0.44	0.35
ID17	0.22	0.34	0.44	0.48	0.39	0.41	0.44	0.47	1.00	0.58	0.51
ID18	0.27	0.40	0.41	0.52	0.46	0.49	0.55	0.44	0.58	1.00	0.62
ID19	0.21	0.31	0.31	0.31	0.36	0.50	0.49	0.35	0.51	0.62	1.00

The *Kaiser-Meyer-Olkin Measure of Sampling Adequacy* reflected to be 0.868, which was well above 0.5 and thus was well acceptable (Watkins, 2018). The corresponding Bartlett's Test of Sphericity in table 8 showed to have a p value <0.001 which implied statistical significance at a confidence level of 95%.

Table 8: KMO and Bartlett's Test - MALC-m

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.868
Bartlett's Test of Sphericity	Approx. Chi-Square	360.776
	df	55
	Sig.	<.001

Given acceptance of *Kaiser-Meyer-Olkin* number and statistical significance of Bartlett's Test of Sphericity, the eigenvalues were reviewed to understand the number of sub groups that MALC-m indicator questions could be grouped into. There were only two groups with eigenvalues >1, in the column summing up total eigenvalues in table 9). From this, it was concluded that the eleven informing question for MALC-m could be reformed into a collective of two distinctive constructs. The cumulative percentage that the two question groups represented was 62.588% of the total questions' variance scores and thus were suitable enough to inform the broader contexts that the 11 indicator questions attempted to measure.

Table 9: Total variances explained - MALC-m

Total Variance Explained									
	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.633	51.210	51.210	5.633	51.210	51.210	3.974	36.126	36.126
2	1.251	11.377	62.588	1.251	11.377	62.588	2.911	26.462	62.588
3	.999	9.079	71.666						
4	.671	6.097	77.763						
5	.585	5.318	83.081						
6	.447	4.062	87.143						
7	.374	3.400	90.543						
8	.330	3.001	93.544						
9	.296	2.690	96.234						
10	.241	2.187	98.421						
11	.174	1.579	100.000						

Table 10 shows the selection of specific survey questions using coded identity descriptors for MALC-m construct (ID9 to ID19), and the allocated reformed (new) construct groups identified as components numbered one and two. The logic utilised to allocate questions to reformed groups was based on the higher absolute value of the two components (with the component matrix) through the *principal component analysis method.* As indicated in table 10, only question coded as ID9 was allocated into its own sub-indicator group and the rest of the indicator questions coded as ID10 to ID19 were allocated to another group.

Table 10: Component Matrix - MALC-m

Component Matrix[a]		
	Component	
	1	2
ID9	.427	.617
ID10	.711	.469
ID11	.767	.298
ID12	.804	.265
ID13	.774	.082
ID14	.805	-.073
ID15	.742	-.321
ID16	.739	-.206
ID17	.668	-.265
ID18	.729	-.291
ID19	.623	-.424

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

As such, the two sub-variables that MALC-m indicator questions were apportioned into were; **external business process manufacturing asset life-cycle management** (ebp MALC-m) for ID9 and **internal business process manufacturing asset life-cycle management** (ibp MALC-m) for ID10-ID19. Table 11 illustrates the latter survey questions' new sub-variables allocation whilst demonstrating context commonalities.

Table 11: New sub-variables grouping for TCO-mr from EFA

ID	Survey Question	New sub-variable
29	There is no database and systematic asset data collection at my workplace that I can get access to	Data access barrier
30	There is a Lack of access to asset data at my work-place	Data access barrier
31	I experience a Low quality of asset data from suppliers/asset providers at work	Processing and support barrier
32	I experience Resource constraints (e.g. cash/time constraints) when it comes to reviewing asset performance at work	Processing and support barrier
33	Cost of finding the right asset performance data is too high at work	Processing and support barrier
34	There is Lack of universal methods and standard formats for continuously modelling the total cost of asset utilisation at work	Processing and support barrier
35	I experience Short term perspectives when it comes to asset lifecycle management at work	Processing and support barrier
36	I experience Lack of attention towards long term (> 3 years) asset management in my organisation	Processing and support barrier
37	I experience a Lack of total cost of asset ownership (TCO) adoption obligation at work	Processing and support barrier
38	There is a Lack of top management commitment to keep track of the actual total cost of asset utilisation (per asset)	Processing and support barrier

5.4.4. Factor analysis for CB-real construct

Again, for CB-real, the correlation matrix was also reviewed (with ID40 excluded), as displayed in table 12 and all correlation matrix values were found to be >0.3, thus indicating acceptability of pursuing the next level of factor reduction (Watkins, 2018).

Table 12: Correlation Matrix - CB-real

Correlation Matrix			
		ID41	ID42
Correlation	ID41	1.000	.641
	ID42	.641	1.000

The *Kaiser-Meyer-Olkin Measure of Sampling Adequacy* of 0.5 was on the margin against the same benchmarked value for declaring acceptability to pursue factor analysis for CB-real (Watkins, 2018). The corresponding *Bartlett's test of sphericity* showed to have statistical significance with a p-value <0.001 (see last column's sig. value on table 13) at a confidence level of 95%.

Table 13: KMO and Bartlett's Test - CB-real

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.500
Bartlett's Test of Sphericity	Approx. Chi-Square	32.013
	df	1
	Sig.	<.001

The table of *total variables explained* (named table 14), shows only one eigenvalue variance with a value >1 and thus ID41and ID42 could be consolidated into one sub-group. The name of the sub-group was kept the same as the originally intended construct, which was still referring to *cost benefits realised* (CB-real). The interpretation of variances from table is linked to the understanding that a single grouping of the survey questions, accounts for 82.05% of the variances existing for CB-real construct measurement. Due to there being only two reliable questions for CB-real construct and them only belonging to the same sub-group, there was no need to review the *components matrix* since its pragmatic relevance would have been to allocate a group per survey question based on the higher absolute value of each component.

Table 14: Total variances explained - CB-real

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.641	82.050	82.050	1.641	82.050	82.050
2	.359	17.950	100.000			
Extraction Method: Principal Component Analysis.						

5.4.5. Spearman’s rank correlations (SRC)

It is necessary to reflect on the fact that the independent variable, manufacturing asset life-cycle management (MALC-m) was reduced from 11 indicator questions down to two subgroups (ebpMALC-m and ibpMALC-m). Given the latter, a correlation was investigated to understand both ebmMALC-m and ibpMALC-m relative to real cost benefits (CB-real). This was done using Spearman’s rank correlation test, as it is designed to examine for association between ordinal data sets (Schober et al., 2018).

5.4.6. MALC-m versus CB-real

Table 15 below displays results from permutations that were run between informing questions for MALC-m (ebmMALC-m and ibpMALC-m) when measured against this for CB-real.

Table 15: Spearman's rank correlation - MALC-m versuss CB-real

Correlations					
			ebpMALC	ibpMALC	CBrealTot
Spearman's rho	ebpMALCm	Correlation Coefficient	1.000	.376**	.132
		Sig. (2-tailed)	.	.002	.301
		N	63	63	63
	ibpMALCm	Correlation Coefficient	.376**	1.000	.200
		Sig. (2-tailed)	.002	.	.115
		N	63	63	63
	CBrealTotal	Correlation Coefficient	.132	.200	1.000
		Sig. (2-tailed)	.301	.115	.
		N	63	63	63

**. Correlation is significant at the 0.01 level (2-tailed).

Analysing the association test between epb-MALC-m and BC-real a positive correlation factor of 0.132 was more indicative of a weak positive relationship with a p-value (0.301) >0.05, not showing statistical significance. For ipb-MALC-m and BC-real, a Spearman's rho factor of 0.2 resulted, which was more indicative of a weak positive relationship and a p-value (0.115) >0.05, not showing statistical significance

5.5. Inferential statistics: Research Question 2, hypothesis 2

Hypothesis *H2* suggested that *total cost of ownership measurement readiness moderates creation of cost benefits (from MALC management).* Reflecting on the fact that for *H2*, the independed variable was still **MALC-m** whereas **TCO measurement readiness (TCO-mr)** was hypothesised as the moderating variable. **Cost benefits realisation (CB-real)** was yet again, hypothesised as the dependent variable. Inferential statistics still had to be run to test for relationships between these constructs. Fortunately MALC-m is a common independent variable (between *H1 and H2)* and thus had already been assessed for validity and reliability (including a factor analysis). Permutations therefor only had to be run for TCO-mr in order to prepare for testing of hypothesis *H2.*

5.5.1. Validity tests - TCO-mr

Table A5-2 shows TCO-mr convergent validity test results that were achieved through computation of a *2-tailed Spearman's Correlation* test (Taherdoost, 2016) *on* the IBM SPSS software. The results of all ten indicator questions' correlation showed statistical significance (with p-values <0.001) at a 95% confidence level when compared to item total scores of the tested TCO-mr construct.

5.5.2. Reliability tests (Internal consistency) - Hypothesis H1

For the TCO-mr construct, a Cronbach's alpha of 0.87 was found, as tabulated in table 16**.** Considering the fact that the latter value was higher than the minimum recommended 0.7 (Watkins, 2018), it was accepted to indicate suitability of the group of indicator questions in representing TCO-mr and therefore the *item total statistics* table illustrated in Appendix A5-4, were no longer necessary to review in the context of deciding on a question to delete.

Table 16: Cronbach's Alpha - TCO-mr variable

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.870	.868	10

5.5.3. Factor analysis for TCO-mr construct

The correlation matrix for TCO-mr variables were found to contain all comparisons with at least one correlation factor that is greater than 0.3, as per highlighted cells' allocation in table 17**.**

Table 17: Correlation Matrix - TCO-mr

Correlation Matrix											
		ID29	ID30	ID31	ID32	ID33	ID34	ID35	ID36	ID37	ID38
Correlation	ID29	1.00	.672	.366	.247	.338	.311	.302	.304	.385	.308
	ID30	.672	1.000	.298	.338	.378	.372	.262	.218	.258	.385
	ID31	.366	.298	1.000	.479	.296	.362	.479	.420	.483	.449
	ID32	.247	.338	.479	1.000	.355	.375	.404	.531	.467	.637
	ID33	.338	.378	.296	.355	1.000	.171	.312	.204	.166	.264
	ID34	.311	.372	.362	.375	.171	1.000	.490	.548	.465	.441
	ID35	.302	.262	.479	.404	.312	.490	1.000	.671	.419	.516

	ID36	.304	.218	.420	.531	.204	.548	.671	1.000	.500	.589
	ID37	.385	.258	.483	.467	.166	.465	.419	.500	1.000	.608
	ID38	.308	.385	.449	.637	.264	.441	.516	.589	.608	1.000

With the correlation matrix factors warranting advancing further with factor analysis steps, the *Kaiser-Meyer-Olkin Measure of Sampling Adequacy* further measured 0.816, which is better than the unacceptability threshold of 0.5 (Watkins, 2018). *Bartlett's test of sphericity* (shown in table 18 below) measured sufficiently, with a statistically significant p-value <0.001 at 95% confidence level.

Table 18: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.816
Bartlett's Test of Sphericity	Approx. Chi-Square	256.798
	df	45
	Sig.	<.001

A sufficient correlation matrix as well as acceptable KMO and Bartlet's factors warranted proceeding with delving deeper into the factor analysis method. A review of variance totals with eigenvalue numbers greater than one was assessed in order to understand the number of possible re-grouping of the indicator questions for TCO-mr. Within the assessment it was discovered that two groups account for 59.419% of the total variances (see table 19, *cumulative%* column) and thus common construct perspectives had to be deduced in order to re-name survey question (ID29 to ID38) within their new grouping.

Table 19: Total variances explained - TCO-mr

Total Variance Explained									
	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.63	46.323	46.323	4.632	46.323	46.323	3.808	38.079	38.079
2	1.31	13.096	59.419	1.310	13.096	59.419	2.134	21.339	59.419
3	.860	8.600	68.019						
4	.740	7.400	75.419						
5	.638	6.384	81.803						
Extraction Method: Principal Component Analysis.									

Within the *component matrix* in table 20, it was discovered that informing questions for the TCO-mr variable would be categorised between ID29 and ID30 as well as another sub-group comprising of ID31 to ID38.

Table 20: Component Matrix TCO-mr

Component Matrix[a]		
	Component	
	1	2
ID29	.597	.606
ID30	.586	.658
ID31	.687	-.036
ID32	.725	-.132
ID33	.471	.454
ID34	.678	-.142
ID35	.731	-.231
ID36	.761	-.364
ID37	.719	-.203
ID38	.789	-.193
Extraction Method: Principal Component Analysis.		
a. 2 components extracted.		

In review, it was discovered that ID29 and ID30 were associated with restrictions relating to *database* and *systematic asset data collection,* respectively. In turn, their new sub-variable group was collectively named as **data access barriers**. Interpreted in the holistic context of the study, the latter sought to assess an effect of the **absence of data access barriers.** Questions coded from ID31 to ID38 were re-grouped into a new sub-variable, referred to as **processing and support barriers.** This was due to the fact that ID31 to ID38 questions were concerned about issues such as to low quality of asset data, resource constraints, cost of asset performance data, TCO modelling standards, short term perspectives/lack of attention towards long term management, lack of TCO adoption obligation and poor top management commitment. Again, in the context of the study, the latter sought to assess an effect of the **absence of processing and support barriers.**

5.5.4. TCO-mr versus CB-real

A Spearman's rank order correlation displayed in table 21, yielded that the **absence of data access barriers** have a **statistically significant** relationship with **CB-real**, having a p-value of (0.035)<0.05. The correlation factor between the latter however shows a weak correlation (Schober et al., 2018). The relationship between **absence of processing and supporting barriers** has an extremely poor correlation factor of 0.019 (Schober et al., 2018) alongside a **statistically insignificant** relationship with **CB-real**, having a p-value of (0.883)>0.05.

As a reflective review, the relationship between **absence of data access** and **absence of processing and supporting barriers** does have statistical significance with a p-value<0.001

Table 21: SRC - Absence of data access versus CB-real

Correlations					
			DataAccessBarriers	ProcessingandSupportBarriers	CB-real
Spearman's rho	DataAccessBarriers	Correlation Coefficient	1.000	.413**	.266*
		Sig. (2-tailed)	.	<.001	.035
		N	63	63	63
	ProcessingandSupportBarriers	Correlation Coefficient	.413**	1.000	.019
		Sig. (2-tailed)	<.001	.	.883
		N	63	63	63
	CBrealTotal	Correlation Coefficient	.266*	.019	1.000
		Sig. (2-tailed)	.035	.883	.
		N	63	63	63
**. Correlation is significant at the 0.01 level (2-tailed).					
*. Correlation is significant at the 0.05 level (2-tailed).					

5.6. Conclusion

All statistical tests that were intended to be interpreted, were run and are further discussed in the subsequent section and then later concluded on in the last section of the research report. Inferential statistics were done using IBM SPSS Statistics version 28.0.0.0 and descriptive statistics were consolidated using google forms.

6. Discussion

A reflection is made that the research pursued a research design that intended to gather data through self-selective sampling and snowball sampling as the two forms of non-probabilistic purposive sampling methods of choice in order to reach potential respondents. The collective primary quantified sample size summed up to a minimum of 1920 potential respondents, which comprised of 1620 people from the original followership sample when added to the approximate 300 manufacturing workers. In the calculation conducted in *section 5.2.2.* of the previous (results) section, the snowballed sample size was shown to equate to a minimum of 1211 potential respondents. The data collection time horizon took place over a 10 week period, from 9 December 2022 to 23 February 2023. Despite such a sample size and wide snowballing reach, the response rate stayed as low as 64 responses, whereby only 63 were usable.

This discussion section therefore interprets results from quantitatively assessed responses gathered from 63 respondents and pairs them against a comprehensively conducted literature review in Section 2 of the current study.

6.1. Reflection on the research objectives

After surveying available, relevant and accessible literature within the academic setting of the author (scholar), research constructs' relationships of interest were narrowed down to MALC-m when paired with CB-real as well as the moderating influence of TCO-mr on CB-real. The study's conceptual framework was interpreted from a variable's perspective in figure 6-1 to recap on the hypotheses that were tested in Chapter 5.

Relations projected through the first hypothesis, are reflected as *H1* in figure 6-1 and those reflected through the second hypothesis of the study are reflected at *H2*. Hypothesis *H1* aimed to aide in answering RQ1 and *H2* aimed at driving the study towards answering RQ2. The relations that were tested and reflected on throughout the results section (Chapter 5) had an aim to test two effects. The first was the effect of the independent variable (MALC-m) on the dependent variable (CB-real) as was the inquisitive stance of RQ1. The second sought after outcome from the results was the assessment of the effect caused by the moderating variable (TCO-mr) on the relationship between the independent variable (MALC-m) and the dependent variable (CB-real). Similar to the former, the latter was also in pursuit of answering research question 2.

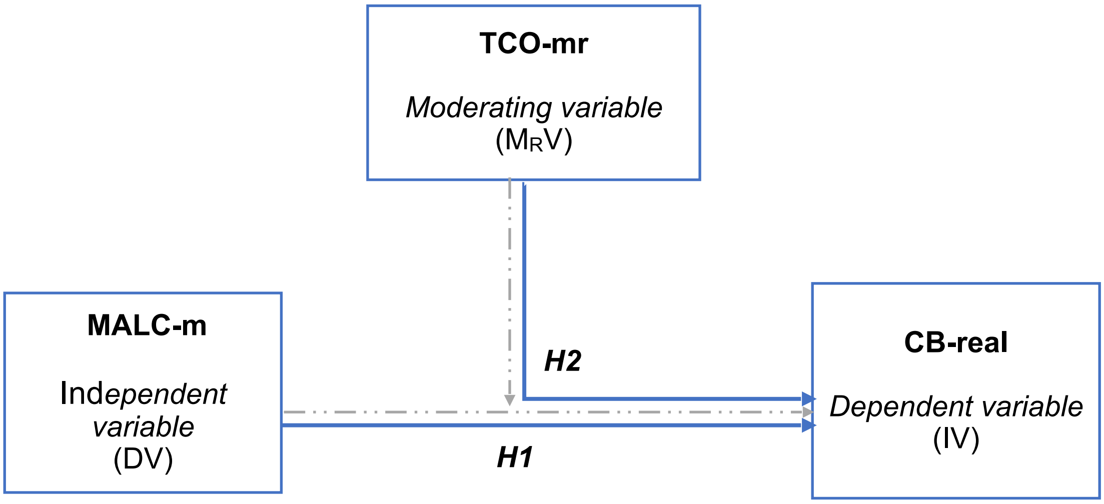


Figure 6-1: Conceptual framework illustrating hypotheses *H1* and *H2.*

6.2. Statistical tests methodology

For each of the research questions or hypotheses, a similar sequence of data review was followed. At first a review was done per research construct, in the methodology followed from item one to three in figure 6-2 below. After each set of constructs had been tested for external factor analysis, the variables' set were then subjected to their intended statistical tests for hypothesis.

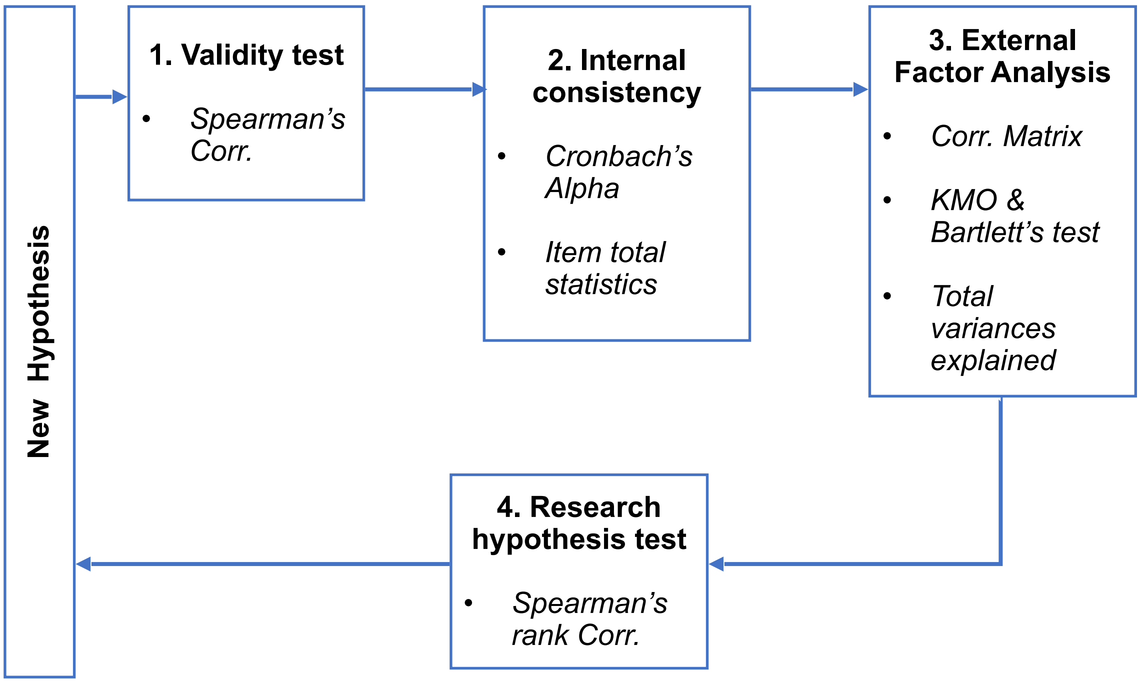


Figure 6-2: Cycles of statistical tests run on survey results

6.3. Literature concepts discussion

From the review of literature, seven key theoretical concepts emerged. Out of the seven concepts, three appeared to be philosophical paradigm based and relied on the application of other concepts to realise fruition of benefits and four were pure objectively theorised techniques. The remainder, were four objective theories of significant association with the study, which incorporated the total cost of ownership framework (TCO), Life-cycle costing (LCC), life-cycle benefits (LCB) and a concept concerned with computation of cost benefits (CB). Narrowed down in reference to figures 6-3 and 6-4, CB is theorised to emanate from either a difference between LCB an LCC or a factored ratio of these concepts (Animah et al., 2018).

6.3.1. Discussion of overarching philosophical concepts from literature

Circular manufacturing (CM) emerged as a value driven ontological stance (integrating both asset manufacturer and user) from which other conceptual theory is applied (Polenghi et al., 2021). Prognosis health management (PHM) appeared to be utilising past and present-state asset data (from technologies such as sensors) to assess reliability of asset-based systems, thereby enabling intelligent systems to facilitate failure avoidance (Vogl et al., 2019, p. 79). Value management (VM) on the other hand also proved to be philosophically driven as opposed to being an input based, technically executable concept (Ghazali & Anuar, 2017), especially when considering its “objectives over solutions” (p. 69) paradigm. VM outcomes-based approach supports application of various asset management practices that pursue organisational strategies (Ghazali & Anuar, 2017).

6.3.2. Objective concepts’ link to overarching theories

It is of theoretical understanding that an open ended array of AM practices that VM sets to represent, could range widely from various maintenance strategies (Zou et al., 2021) to asset design and configuration strategies (Graessler & Yang, 2019). The VM approach has been proven to incorporate various strategic value derivation methodologies and techniques as long as they are concerned with proposing value, creating it, ensuring ways to deliver and capture (Nusshol, 2018). Such include the analysis of LCC, LCB as well as the integrating CB ((Animah et al., 2018; Nusshol, 2018;). Even though by virtue of desired objectives, TCO framework can be utilised to accomplish VM objectives, it is fundamentally theorised as a sub-section of PHM methodologies (Vogl et al., 2019). Figures 6-3 and 6-4 show plots illustrating how theories from the literature review fit along a typical MALC as well as their relationship relative to one another.

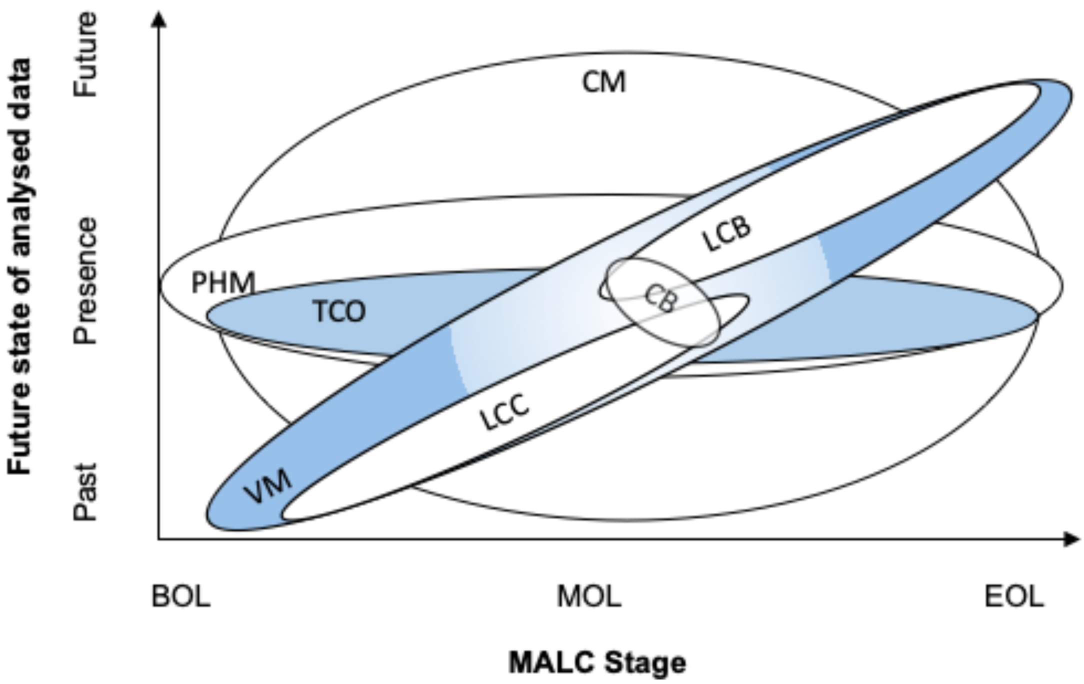


Figure 6-3: Graph showing future state of asset data for theoretical concepts against MALC stage

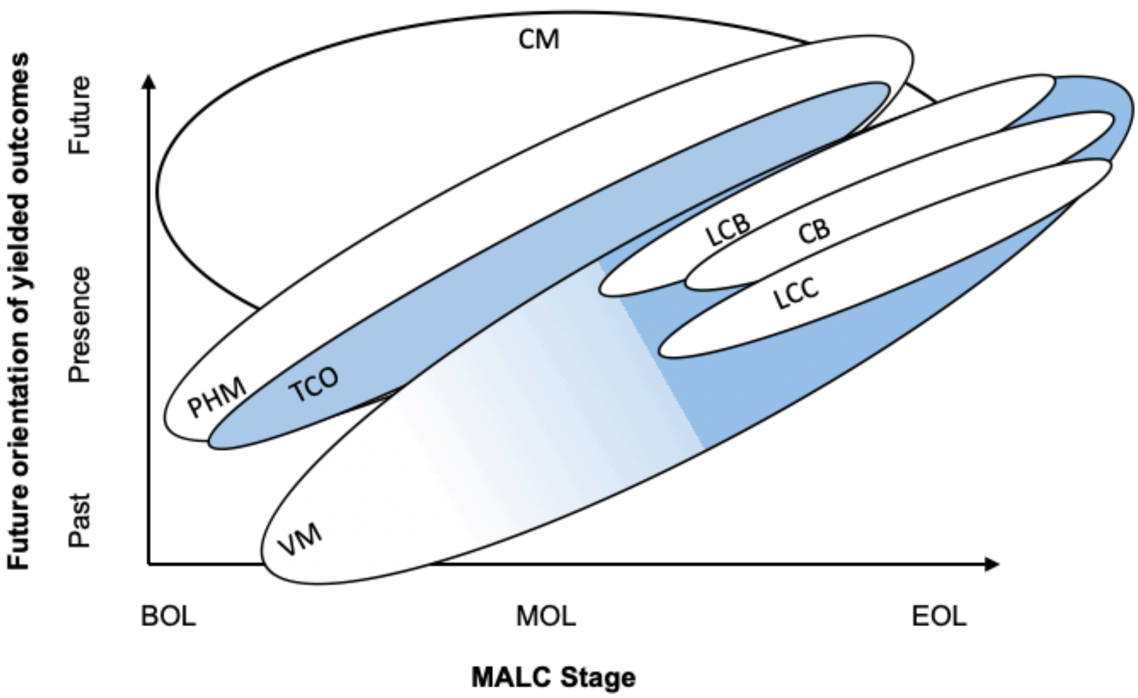


Figure 6-4: Graph showing future state of asset data for theoretical concepts against MALC stage

The study aimed to consolidate theoretical concepts of studied literature (from the literature review section) and then graphically illustrate them into two perspectives showing how they relate to each other over various stages a typical life-cycle of a manufacturing asset (MALC). The first graph, shown in figure 6-3 maps them according relative age of their input data requirements (referred to as *future state of analysed data)* along various stages of a MALC. The second plot, in figure 6-4, maps the studied literature concepts according to relative time horizons and various MALC stages at which their application is expected to yield desired outcomes (from application of theory).

6.3.3. Literature summary conclusion

Of important relevance, is a correct interpretation of figure 6-3 and 6.4 with respect to relative association of theoretical concepts. As an example, figure 6-3 demonstrates CM as a stand alone framework with capabilities to process data from the past, present and future throughout all MALC stages. On the other hand, even though CM yielded outcomes (illustrated in figure 6-4) are still explicable over all MALC stages (as input data was), their contribution can only be accounted for in the present and future (unlike CM data sourcing which can still come from the past).

In addition to the demonstrated time horizons of input data and theory application outcomes, it is critical to reflect that the three philosophical frameworks (CM, PHM and VM) represent different schools through which MALC could be managed. This implies that all inherent attributes of figure 6-3 and 6-4 are considered to be inherent contributors to MALC-m construct. The pragmatic application of the former schools of thought according to the study's interests has been through implementation and execution of the four objective concepts (LCC, LCB, CB and TCO). As an example, through the systemic application of LCC, LCB or CB, value management is practiced (Nusshol, 2018) and through a holistic application of TCO, some aspects of PHM would be in effect (Vogl et al., 2019). From the latter analogy, it starts to emerge that MALC-m is a broad concept, incorporating a broad number of methodology application options.

6.4. Research Question 1

RQ1 was framed to investigate the *nature of relationship between asset life cycle management and cost benefits in a manufacturing environment* and thus, studied hypothesis *H1* interest with MALC-m relationship towards CB-real.

6.4.1. Hypothesis *H1* MALC-m

The variable total score for all survey questions designed to inform MALC-m, characterised by a sequential coding from ID9 to ID19, yielded a moderate to high correlation factor with each of the individual questions for the variable. The lowest correlation factor against MALC-m variable total score was 0.435 and belonged to ID9. This implied that, even though ID9 indicator question was statistically significant at a 95% confidence level (p-value < 0.05), it was also the least compatible out of the 11 indicator questions. On reliability statistics, survey questions informing MALC-m holistically achieved a Cronbach's alpha of 0.9, eliminating the need to remove any survey question through the use of item total scores, especially ID9, that had been found to be less compatible with the rest (surprisingly).

When reviewing the external factor analysis (EFA), in an attempt to assess whether there were common sub-constructs that the informing question (ID9 to ID29) could be grouped into, MALC-m correlation matrix (measured using Spearman's correlation) did not prohibit from continuing with EFA. Neither did the KMO (0.868) showing a "meritorious" correlation (Watkins, 2018, p. 277) and Bartlett's test (that yielded p-value<0.001). Eventually, the survey questions were characterised into two sub-groups, through eigenvalue grouping on the total variances explained and the components matrix table. The capabilities unlocked by the strongly correlated KMO number as well as a statistically significant Bartlett's test allowed the IV to be subjected to the principal common factor evaluation (based on eigenvalue variances) and the common factor review (based on component analysis), both which constitute the external common factor analysis (Watkins, 2018). In practical essence, this implied that the indicator questions for the IV could be compressed into new collectives comprising of common themes that they collectively represented.

Through the employ of total variances explained table as well as the components' matrix, MALC-m indicator questions were re-analysed to understand the contexts within which they could be re-grouped. It was noted that ID9, phrased as "*at the beginning of asset life (purchasing stage), does your company evaluate for selection of suppliers*", referred to **BOL stage MALC-m** of **external business processes**. Given the understanding that ID10 to ID19 also referred to various stages of MALC it thus emerged that, asset life cycle stages were not the differentiating factor. MALC-m was very rigidly common in all of the questions belonging to both new sub-groups. ID10 to ID19, referring to; *evaluation of all purchasing options, effects of budget definition, economic preferences for asset design/reconfiguration, maintenance strategies/methods, continuous improvement,* *disposal, repurposing* and *recycling,* all asked about MALC-m at different stages of ALC based on Roda et al. (2020) potentialities for asset decision. All the latter however, had contexts which sought to address MALC capabilities that are internal to asset user organisation and thus were interpreted as an **internal business examining** sub-group.

From this point, the latter, ibp MALC-m as well as the former ebp MALC-m, started being the two lenses through which MALC-m was approached, especially leading towards understanding how the two new sub-groups can correlate with CB-real construct from hypothesis *H1*. Figure 6-5 maps MALC stages at which the various MALC-m informing processes were tested to exist from the survey questionnaire. The graph (6-5) also illustrates various anticipated life cycle stage associations with cost benefits as the dependent variable which the group of questions (ID9 to ID19) sought to understand the correlation with.

With only one question being externally focused in terms of business processes, out of the 11 that were derived from Roda et al. (2020) and asked from responders, an expectation was put that much less focus had to be payed towards ebpMALC-m as to that given towards ibpMALC-m.

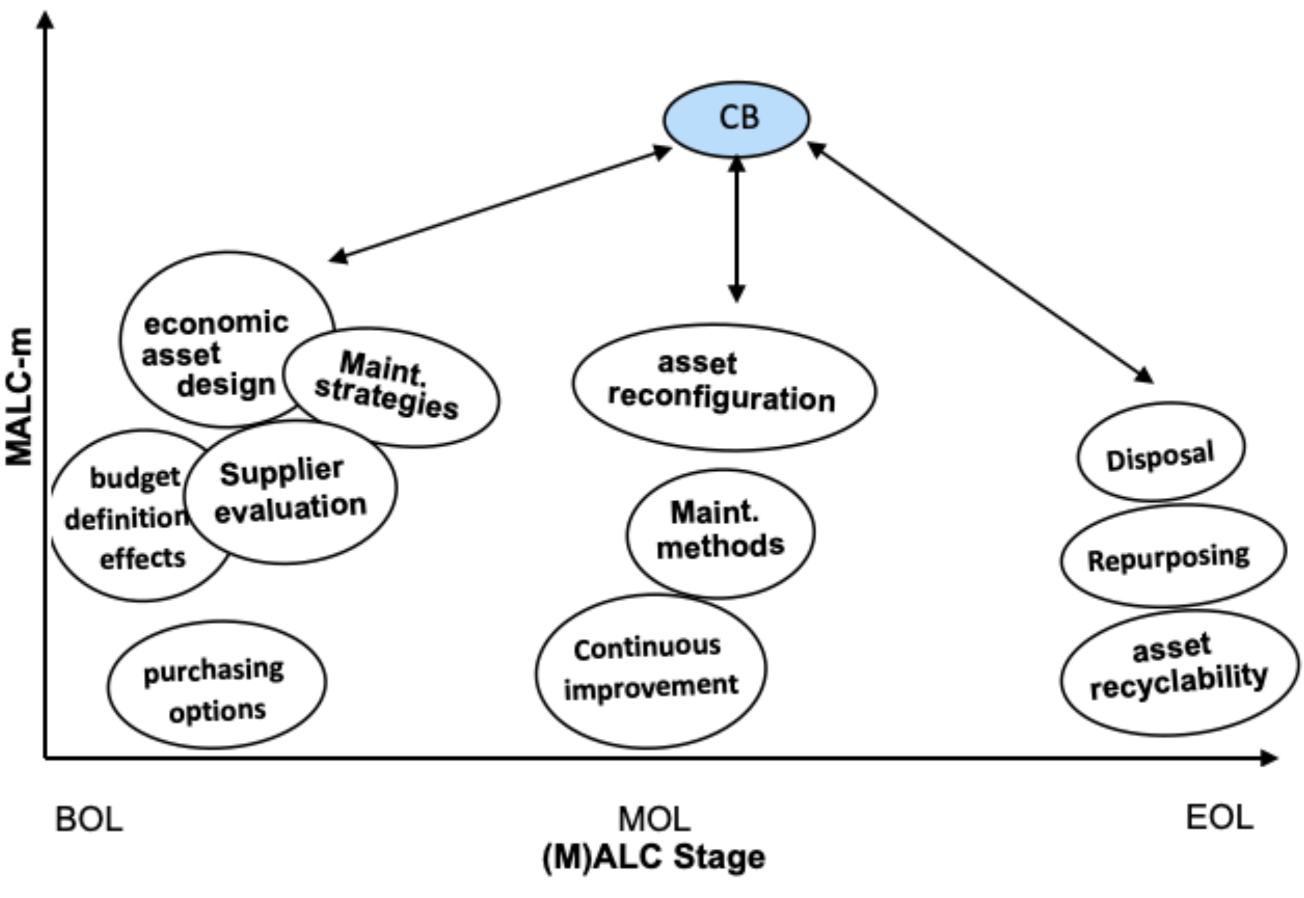


Figure 6-5: MALC-m informing questions

From a literature perspective, the differentiation of ebpMALC-m against ibpMALC-m (from inferential statistics results), implied that MACL-m as an independent variable must be viewed with value chain based holistic perspectives (Polenghi et al., 2021). Furthermore, if MALC-m is associated with a source of competitive advantage, then by inherent classification it must be embedded with distinguished business knowledge assets and relational capabilities (Rui et al., 2017). At the current stage of results review, this meant that for MALC-m to be evaluated as a potential source of competitive advantage for the conceptual framework's DV, both internal and external business oriented type of knowledge assets and relational capabilities needed to be payed attention to.

6.4.2. Hypothesis *H1* CB-real

For the DV, a variable total score was run for all attributable survey questions that were designed to indicate the attainment of CB-real within a hypothetical organisation. This time, the questions were characterised by a sequential coding from ID40 to ID42. Similar to MALC-m construct, the variable total score yielded a moderate to high correlation factor with each of the individual questions for the CB-real construct. The minimum correlation factor against CB-real variable total score was 0.504 (for ID40), yet again implying that it was also the least compatible out of the three indicator questions for the study's DV when contrasted with the constructs' (other) informing survey questions. Despite having lowest correlation factor in relation to ID41 and ID42, ID40 still reflected to be a moderately valid question for informing CB-real. The remainder of survey questions informing ID41 and ID42, which reflected correlation factors of 0.814 and 0.851, reflected much better validity of the indicator questions. All questions assessed for validity against the construct through the *2-tailed Spearman's Correlation* test were found to be statistically significant at a 95% confidence level, with all p-values being less than 0.001.

On reliability statistics, survey questions informing CB-real initially achieved a moderate Cronbach's alpha of 0.57, which Taherdoost (2016) interprets to be below the subjective acceptability value of 0.7. The initial CA value was challenging the internal consistency of the item set (indicator questions). The item total statistics table had to be followed as a guide in order to understand a method to increase the internal consistency of the construct's informing questions. As such, the item total statistics for CB-real reliability suggested deletion of ID40 survey question, which after execution resulted in a Cronbach's alpha of 0.781. The latter improvement in CA value restored the survey answers' internal consistency from the two remaining survey questions.

Referring to Cronbach's alpha computation for CB-real, a reflection ought to be made that ID40 was declared was then declared a trivial question relative to the responses from the group of questions that tried to measure the same variable. This was due to the fact that all likert scale responses proved ID40 to be unreliable for use in measuring the same variable as survey questions ID41 and ID42. ID 40 asked respondents about their organisations' experience of asset life spans being longer than accounting tax lives. In literature, tensions have been theorised to exist between commercial practitioners' perspectives and manufacturing practioners' financial decision making regarding re-manufacturability of original equipment manufacturer's products such as manufacturing assets (Mutha et al., 2021). In practical interpretation, 81% of the respondents were professionals from technical backgrounds and only 9% were from commercial backgrounds (finance, procurement and marketing collectively). Considering the latter fact it is possible that a question regarding asset useful lives may have been posed ambiguity to the majority of respondents, thus creating an internal inconsistency with likert scale responses from the other survey questions (ID41 and ID42) informing the CB-real variable.

6.4.3. Statistical test results for *H1* (MALC-m versus CB-real)

Table 15 in section 5, displays results from permutations computed between informing questions for MALC-m when measured against an aggregated average of indicator questions for CB-real. This implies that ebp-MALC-m and ipb-MALC-m were subjected to an analysis of association test whereby they represented the MALC-m variable and an average of ID41 and ID42 responses represented CB-real.

6.4.4. ebp-MALC-m versus CB-real

The relationship of ebp-MALC-m against CB-real was executed using a Spearman's rank correlation test. As a result, a positive correlation factor of 0.132 was found. This was indicative of a weak positive relationship (Schober et al., 2018) as well as a p-value of 0.301, which is greater than 0.05, thus **not** showing **statistical significance**. The absence of statistical significance between ebp-MALC-m against CB-real implied that there was not a correlation found between responses from the informing survey questions for ebp-MALC-m (coded as ID9) when measured against averaged responses for CB-real (ID41 and ID42). At this stage, if the second (and last) statistical test for the second indicator questions' sub-group for MALC-m yielded not to be statistical significant, when tested for correlation relative to the CB-real variable, the results would be disproving of research hypothesis *H1*. Such result would fully represent evidence informing rejection of the alternative hypothesis (H_a) and rather fail to reject the null hypothesis (H_0) presented from chapter 3 of the study.

6.4.5. ibp-MALC-m versus CB-real results

The second relationship that had to be computed using the Spearman's rank correlation test was the relationship between ibp-MALC-m and CB-real. Even though there was **no statistical significance** with a p-value of 0.115 (<0.05) in the relationship between ipb-MALC-m and CB-real, a correlation factor of 0.200 still showed a weak correlation (Schober et al., 2018).

6.4.6. MALC-m and CB-real discussion

At this point, data started challenging the value management's principle of a dominant focus on the organisation's internal business processes (Ghazali & Anuar, 2017). The correlation effect of CB-real with epb-MALC-m whilst not correlating ipb-MALC-m may also be indicative of two counterintuitive interpretations. Firstly, it could be a justification explaining a conundrum presented by Zarte et al. (2019), thereby presenting a reason for some manufacturing organisations' survival even when they do not focus enough on internal value maximising activities relating to their manufacturing assets. In addition, respondents view could have been of a paradigm, critiqued by Mutha et al. (2021), that cost benefits are linked to accounting profits in such a way that MALS is thought of in relation to asset acquisition costs and depreciation could mean less output value expectation from an asset. The study on the other hand adopted a stance that, if an asset has already been acquired, past expenses of acquisition are viewed as sunk costs and cost benefits are said to be in effect when MALS extension costs (beyond asset useful lives) are more economic than all alternative options (Mutha et al., 2021). The latter presents a perspective through which survey questions informing the cost benefit realisation (CB-real) construct were formulated, which is a concept that was adopted from Mutha et al. (2021) findings on "usecycles" (p. 2339) and remanufacturing perspective.

Secondly, it may be due to a poorly represented CB-real construct through the group of informing survey questions. Both survey questions that remained for CB-real actually refer to life extension of manufacturing assets. ID41 refers to MALS exceeding accounting tax lives whereas ID42 refers to MALS exceeding OEM projected life spans. There is a possibility that respondents' interpretation of ID41 and ID42 was not aligned with a CB-real manifestation from external business practice based MALC-m. A retrospective reassessment of survey question ID40, (that was eventually removed), shows the question to be asking regarding respondents' perception of CB-real from TCO-application. To illustrate the misdirection from the latter dominance, ten questions which were not statistically significant out of eleven, were inwards looking (towards an asset utilising manufacturing organisation). The only external business practice based survey question, representing ebp-MALC-m, was found through the spearman's rank correlation to be inconsistent with the construct was externally focused.

6.4.6. MALC-m and CB-real conclusion

A survey question group comprising of one indicator question representing ebpMALCM-m variable proved to have a poorly correlated relationship that is not statistically significant with CB-real. Another group representing the second MALC-m sub variable (ibpMALCM-m) also did not achieve statistical significance with the DV. Hypothesis *H1* testing through the application of Spearman's rank order correlation rejected the alternative hypothesis H_{1a}, thereby failing to reject the null hypothesis (H_{10}).

6.5. Research Question 2

With the relationships concerning RQ1 tested and discussed, the second objective of the study intended to establish the answer to RQ2, which is concerned about whether or not TCO measurement readiness moderates creation of cost benefits from MALC-m. As reflected in section 3 of the study; inferential statistics tests conducted in Section 5 aimed to test two possibilities. The possibilities are whether **H_{2a}**, hypothesising that *TCO measurement readiness moderates creation of cost benefits from MALC,* holds true or **not.** Results, declaring the opposite of H_{2a} would be affirming holding true of the statement for the null hypothesis (H_{20}).

6.5.1. Hypothesis *H2* TCO-mr

In order to test H_{2a} and H_{20}, both moderating (TCO-mr) and dependent variables (CB-real) for the study's conceptual framework had to be examined for construct validity as well as reliability (Taherdoost, 2016; Watkins, 2018). Referring back to the conceptual model for the study, the DV (CB-real) is common for both RQ1 and RQ2. The latter implies means that, only the moderating variable still needed to be discussed from the questionnaire results prior to consolidation of the conclusive meaning of the findings.

Survey questions informing TCO-mr construct were coded as ID29 to ID38 then a construct specific total score was correlated to all individual questions. A test for *convergent validity* was yet again run, to examine validity of the construct (Taherdoost, 2016). This was done using a *2-tailed Spearman's Correlation* test whereby the results showed statistical significance (with a p-value less than 0.001) on all questions at a 95% confidence level when compared to item total scores of

TCO-mr variable. In Appendix A5-3, table A5-2 tabulates proof of the latter validity of TCO-mr likert scale questions in representing the construct. The range of correlation factors of the indicator questions for TCO-mr construct against the item (variable) total score showed the survey questions to have a moderate (0.500) to strong correlation (0.783) when interpreted using Schober et al. (2018) correlations' table. The lowest correlation value was for ID33 survey question, which asked a negatively reinforcing question regarding the *cost of finding the right asset performance data* being too high at the respondent's workplace. This, yet again, implied that ID33 was also the least convergent out of the three indicator questions for the study's DV when contrasted with the constructs' (other) informing survey questions.

After execution of reliability statistics, survey questions informing TCO-mr holistically, achieved a Cronbach's alpha of 0.9. The latter high reliability CA represented a high internal consistency of the research questions in measuring their common TCO-mr construct (Taherdoost, 2016). Acceptability of the construct's CA eliminated the need to remove any survey question through the use of item total scores.

When the EFA was reviewed, in pursuit of evaluating whether there could be common sub-variable representation that indicator questions (ID29 to ID38) could be grouped into, TCO-mr correlation matrix (measured using Spearman's correlation) permitted continuation with EFA. The KMO factor of 0.868 showed a "meritorious" correlation (Watkins, 2018, p. 277). Bartlett's sphericity test, that yielded a statistically significant p-value of less than 0.001 (at 95% confidence interval), confirmed that the correlation matrix was indeed not random. Similar to MALC-m and BC-real variables, the survey questions for TCO-mr were also characterised into two sub-groups, through eigenvalue grouping on the total variances explained and the components matrix table. In the new grouping, survey questions ID29 and ID30, which reflected database accessibility restrictions were grouped into **data access barriers.** Survey questions coded from ID31 to ID38, on the other hand, reflected problems associated with effectual execution of TCO and thus were re-allocated as **processing and support barriers**. Both regrouped sub-variables for the TCO-mr construct, are reflected in table 11 under the results section (5) of the study.

A reflection ought to be made that **data access barriers** as well as **processing and support barriers** were narrowed down from indicator questions for total cost of ownership measurement readiness (TCO-mr) through a factor analysis process. When reviewed in terms individual subgroups, the association relationship between the narrowed down individual sub-groups in relation to TCO-mr is displayed in table 21 with values of discussion highlighted in blue.

6.5.2. Absence of data access barriers versus CB-real

As a suitable method for testing associations between ordinal data sets, a Spearman's rank correlation test was conducted in order to test the two variable sets informing the relationship between TCO-mr and CB-real. The first relationship that had to be analysed through inferential statistics was between **data access barriers' absence** (TCO-mr) versus CB-real. The outcome showed **statistical significance** with a p-value of 0.035 (less than 0.05), at a 95% confidence level. A correlation factor of 0.266 was however representative of a weak correlation between the two (Schober et al., 2018).

6.5.3. Absence of processing and support barriers versus CB-real

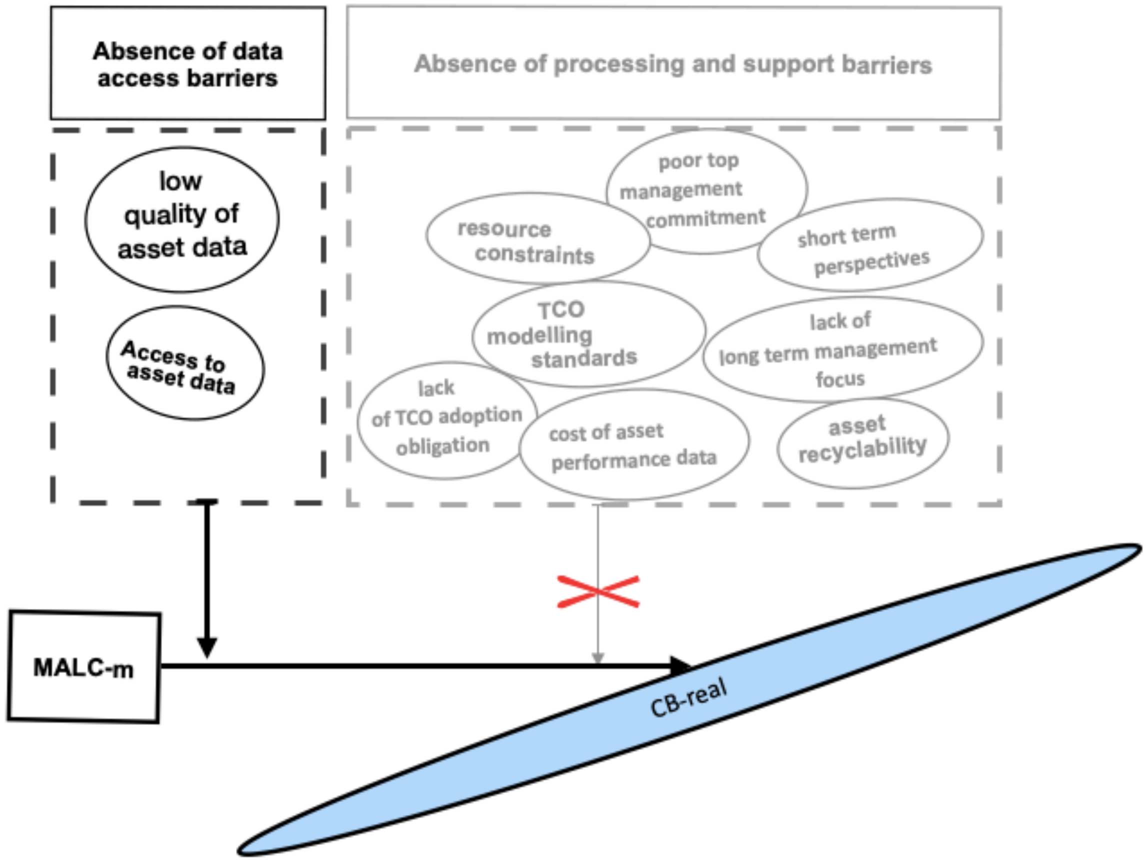
The second relationship that had to be analysed in order to attain better clarity of association between the moderating variable and DV, was through a Spearman's rank order test on the lack of **processing and support barriers** in comparison with **TCO-mr.** The outcome yielded a correlation factor of 0.019, which was "negligible" (Schober et al., 2018) as well as a p-value of 0.883 (far greater than 0.05), thus concluding the correlation as **not statistically significant.** As a point of interest, the correlation between the two sub-variables for TCO-mr (*lack of data access barriers* and *processing and support barriers)* yielded a statistically significant Spearman's rank correlation (of 0.413), with a p-value less than 0.01 at 95% confidence level.

6.5.4. TCO-mr and CB-real discussion

Referring to the holistic results of TCO-mr and CB-real**,** which were assessed through execution of a Spearman's rank correlation test on TCO-mr sub-variables, **absence of processing and support barriers** and **absence of data access barriers,** against CB-real, the results were as represented in figure 6-6. The lack of statistical significance on the *absence of processing and support barriers* when measured against CB-real implied that indicator questions for the latter sub-variables (ID31 to ID38) do not have a moderating influence on CB-real.

Figure 6-6: Resultant model for TCO-mr and CB-real

One of the theorised main short-comings of the TCO methodology, from literature is the assumptive view that all value extracted from assets can be interpreted in terms of costs (Seth et al., 2018). Given this notion, one could possibly relate that linking elements of the *absence of processing and support barriers*' sub-variable (such as



TCO modelling standards or lack of management focus) could pragmatically be a difficult process to comprehend, unless one has adopted Seth et al. cost translatability assumption. The problem with the latter paradigm of absolute costs translatability of all asset values, is that it is not always true (Seth et al., 2018) and as an example, various individuals' translation linking management's commitment to CB-real may have constituted inconsistent meanings. Even when individuals are exposed to literature knowledge, their judgement in essence determines the choice of selecting and applying it, thereby introducing new potential risk factors if opting not to apply (Remko, 2020). Even when humans have made the choice to apply theory, interpretation of how to implement is sometimes left vulnerable to paradigm, bias or even random inconsistency which can risk errors in application of the TCO framework (Roda et al., 2020). Ultimately, the lack of correlation between *processing and support* with CB-real, is very much attributable through PHM and TCO literature when one considers the nature of indicator questions that informed the moderating sub-variable. Alternatively, it is also possible that the questionnaire failed to frame the informing equations for (the moderativeng variable) in a relatable manner

In terms of **absence of data access barriers**' association with CB-real, computed using the SCR test referred to above and resulting in statistical significance, it is therefore deduced that indicator questions ID29 and ID30 collectively moderate the relationship between MALC-m and CB-real.

H2 statistically significant sub-portion of results, outlining that *access to asset data,* which is *good quality (asset data)* aides in better attainment of cost benefits (CB-real) from the process of managing MALC (MALC-m) is congruent with literature. The former finding from the statistically significant portion of *H2* results, affirms Seth et al. (2018) view that another major limitation in the application of TCO is the need to control and preserve a consistent, good quality of asset data. In terms the study's findings, this may be viewed as "controlled and preserved consistent, good quality asset data" for TCO has been proven to have capabilities to improve CB-real if MALC-m is in execution. The latter is yet again congruent with Vogl et al. (2019) notion that, lack of strategic integration of timeous asset performance data causes inefficient LCC of owning assets. Considering a view by Polenghi et al., (2021) that MALC-m is most crucial to apply at BOL stage since that is where decisions made will have the greatest impact over the entire life span of the asset, perhaps data access and data quality should be managed more from this MALC stage. It should be noted that, one of the applied methods for harnessing CB-real from MALC-m incorporates identifying key capabilities, measuring them, evaluating and lastly applying diagnostics in declaration to where value creation really lies (Rui et al., 2017). The latter approach is proposed as an implementation methodology, from the outcome of study's correlated relations from the findings. Rui et al. approach to harnessing CB-real through access to quality data for TCO, is very much aligned with the prognosis and health management concept of reducing time and costs of maintenance through using technology for intelligent sensing, analysing applying prognosis assets or diagnosing (Vogl et al., 2019).

6.5.5. Conclusion

Despite some sub-variables for a common construct showing a mixed outcome of no statistical significance on results for one group and statistical significance on results for another, results for this research are interpreted using constructs that were initially hypothesised, in their total capacity. Taking *H1* this into consideration, whereby the relationship between MALC-m and CB-real had both sub-variables for MALC-m not statistically significant against the DV, the study rejected the alternative hypothesis (H_{1a}) and rather failed to reject the null hypothesis (H_{10}).

For *H2*, despite a partial statistical significance attained on one of the two sub-variables' correlation (lack of data access barriers when compared to CB-real), the research also rejected the alternative hypothesis (H_{1a}) and failed to reject the null hypothesis (H_{10}). A new finding however emerged from the statistically significant, correlation that, access to quality asset data, moderates the realisation of cost benefits through the process of managing manufacturing asset life-cycles.

7. Conclusion

The purpose of this research had two dimensions. The first was to develop an understanding regarding the relationship between manufacturing asset life-cycle management and cost benefits realisation. The second dimension of the study's purpose was to understand activities that can improve, or degrade the relationship. (between MALC-m and CB-real). As the study was associated with a masters level of academic enrolment, its purpose was intended for pursuit through a hybrid approach. The approach incorporated immersion in theory as well as actual research, based on primary data.

7.1. The problem summarised

The study attempted to address a research problem that came in four layers. The first problem layer was that manufacturing industry practice focuses a lot of resources towards design and construction stages of an asset (within the BOL stage) whilst neglecting the operational (MOL) phase, which is where life-spans could be optimised.

The second problem stemmed from a paradigm that challenges the industry's view of what constitutes a good benchmark for manufacturing asset life spans. The view of basing a good MALS benchmark from accounting useful lives (derived from tax lives) is critiqued for incorrectness (Mutha et al., 2018) which results in hindering of financial benefits through higher LCC, promotion of substandard MALS and reduced manufacturing asset availability (Vogl et al., 2019). The research adopts a literature paradigm by Mutha et al. (2018) that seeks to address the latter problem layer through using OEM MALS benchmarks as references for optimum asset life spans.

The third layer of the research problem is concerned with an inherent risk of sub-standardly designed manufacturing assets by OEMs at the face of asset users' constant push for lower prices, within the cost cutting plague in business (Zou et al., 2021).

The fourth problem layer comes from a reality that practical processes for managing manufacturing assets towards accurately minimising costs of ownership are not well understood in literature (Animah et al., 2018). This problem layer is theoretically argued to stem from a lack of strategic integration of timeous asset performance data over assets' life-spans (Vogl et al., 2019), leading to decisions such as EOL strategies being left to operational practitioner's intuition. Without repeatable conceptual research, the likelihood is that, the gap of strategic application of TCO theoretical methodologies is even worse than predicted by Remko (2020).

Concerned with the four layered research problem, the study then pursued an attempt to answer the following research questions:

- Research Question 1: What is the nature of relationship between manufacturing asset life cycle management and cost benefits in a Manufacturing environment?
- Research Question 2: What are the most critical moderating factors for the relationship between manufacturing asset life cycles and cost benefits?

7.1. Main Conclusions for *H1*

Given the results for *H1* that rejected the alternate hypothesis (H_{1a}), which hypothesised that, Manufacturing asset life cycle management leads to realisation of costs benefits, there a various ways to interpret the outcome. Firstly, from a critical realist's ontological stance, adopted in the interpretation of the outcome exactly as it emerges (Saunders et al., 2015). The study's results have been accepted as they were presented from the research instrument and analysed through the data analysis software, which was *IMB SPSS Statistics*.

7.1.1. Ambiguity of CB-real indicator questions

Alternatively, as discussed in Chapter 6, it is possible that the research instrument itself was not interpreted in the manner that the researcher aimed to present it. As an example, the two informing survey questions for the *cost benefits realisation* construct were framed in terms of respondents' workplace experience with asset life spans surpassing tax lives and OEM life-spans. The research instrument design saw the latter optimised lifespans as good indicators for Mutha et al. (2018) financial value derivation, which in terms of MALC value management, translates to cost benefit when computed using tools such as cost benefit ratios (Animah et al., 2018).

In the latter view of possible misinterpretation of CB-real informing survey questions by respondents, the supposed conclusion would have interpreted the results as having tested and accepted a (different) null hypothesis that *MALC-m does not lead to improved life-spans*. This would then be an illogical statement, factually disputable through literature. As an example, the argument for optimising asset ownership to surpass MALS benchmarked by OEMs as opposed to accounting tax lives (Mutha et al., 2018) and the objective EOL benefit cost ratio concept, which is an analysis case study conducted by Animah et al. (2018), both nullify the former illogical statement. It would typically be the 81% proportion of the study's respondents (from engineering backgrounds) who would typically pursue asset management to surpass not only the accounting tax life but also the OEM specified life-spans through the employ of maintenance strategies (Vogl et al., 2019). Mutha et al. (2018) also finds the accounting perspective, to be dominant within the accounting practitioners and to also be in contradictory "tensions" (p. 2995) with operations functions such as end of life phase manufacturing practitioners (which would generally comprise of technical professionals). It is thus found to be unlikely that 81% of engineering professionals or practitioners would knowingly agree to a notion that managing asset life-cycles yields reduced life-spans. An argument for the latter comes from a reality that they are theorised to favour maintenance strategies and asset longevity concepts such as prognosis health management (Vogl et al., 2019) and circular manufacturing (Acerbi & Taisch, 2020) to name a few. From the latter retrospective disproof, the cost benefit realisation questions could have not been interpreted as improved manufacturing asset life-spans.

7.1.2. Complexity of MALC-m construct

Considering the derived MALC-m theoretical application of frameworks plotted in figure 6-3 and 6-4, showing MALC-m to comprise of at least four theoretical concepts (LCC, LCB, CB, TCO) and not less than three philosophical concepts (PHM, VM and CM), it is not hard to accept that management of MALC is a complex phenomenon (Roda et al., 2020). In addition to all the complex infusion of theory by MALC-m, the concept takes place continuously, (Roda et al., 2020; Polenghi et al., 2021), whereby in the context of this study (and the derived framework) is applied over a trisected life-cycle an asset. Given provable complexity of MALC-m construct in its independent capacity, it is possible that the study's indicator questions may have not covered all the relevant subcomponents concepts, thus leading to misrepresentative results.

7.1.3. Type I and Type II error proofing

Besides statistical probabilities, both hypotheses of the study could not have been subjected to a type I error, meaning a mistake of rejecting the null hypothesis instead of a correct decision of failing to reject it (Franke, G., & Sarstedt, 2019), since the studies' results failed to reject both null hypotheses H_{10} and H_{20}. The only other chance of a type I error, as mentioned above would have been through statical tests, however the p-values are indicative of the likelihood that each of the two spearman's tests could have committed the latter mentioned error (Franke, G., & Sarstedt, 2019).

In the essence of protecting the results interpretation from a type II error for *H1 (or H2)*, which would cause failure to reject the null hypothesis (H_{10} or H_{20}) in a situation where the correct recourse would have been to reject H_{10}, the researcher made use of reviewers for the report, such as the Supervisor and other scholars. Sources of type II errors could have stemmed from a few reasons in the practical context of study. These reasons could have ranged anywhere from statistical randomness despite a p-value>0.05 (Franke, G., & Sarstedt, 2019) to pure human error from unnoticed mismanagement of data by the researcher (Seth et al., 2018). Type II errors could have also stemmed from an unintended bias from the study's point of view or that of respondents, especially with such an unintended high homogeneity of respondents from engineering professions (reaching a proportion such as 81%).

7.1.3. Limited response rate

The low rate of responses experienced, resulting in 63 usable responses for the quantitative study, may also have been a contributing factor towards failure to reject both null hypothesis (H_{10} and H_{20}). Again, the highly homogenous group of participants in addition to the low response rate, could have resulted in skewness of results towards the attained, resultant outcomes.

7.2. Main Conclusions for *H2*

The results for *H2*, resulted in a partial statistical significant relationship, through the use of a Spearman's rank order correlation test, which was undertaken on the two sub-variables. **Absence of data access barriers** when correlated to **CB-real** yielded **statistical significance** with a low (but acceptable) rho-value of 0.266 and a p-value of 0.035 (less than 0.05). **Absence of processing and support barriers** on the other hand was found to be statistically insignificantly related to CB-real, with an unacceptable Spearman's rho of 0.019 (Schober et al., 2018) and a p-value 0.883. The research as a result, rejected the alternative hypothesis (H_{2a}) and failed to reject the null hypothesis (H_{20}). A new finding however emerged from the statistically significant, correlation that, access to quality asset data, moderates the realisation of cost benefits through the process of managing manufacturing asset life-cycles. In terms of the study's classification, the new correlation may be written as **access to quality TCO asset data**, moderates creation of CB-real through MALC-m.

7.2.1. Correlation inhibiting factors

A summed up consolidation of factors in section 7.1. Incorporates complexity of MALC-m construct, type II error possibilities, possible ambiguity of CB-real indicator questions, limited response rates and low heterogeneity of respondents' backgrounds. Besides these factors that were mentioned to have potentially inhibited statistical significance, there are no other attributable factors for the lack of significant association.

7.3. Recommendations

Given experiences derived from the reiterative process of this research, a few recommendations have been proposed for practitioners and fellow scholars interested in life-cycle management of assets within manufacturing industrial settings.

7.3.1. Recommendations for practitioners

It is recommended that practitioners from all functional backgrounds within manufacturing operations, take pragmatic steps towards eliminating the gap articulated by Remko (2020), that seems to exist between conceptual research and empirical application. In the interest of MALC-m and consolidations from this study, conceptual research to be applied relates to the selection of philosophical concepts for MALC optimisation such as PHM, VM or CM. The selected concepts should be applied in relation to the company's strategic objective (Animah et al., 2018), and continuously evaluated for success (within the manufacturing organisation) using quantitative concepts such as TCO and BCR methodologies.

7.3.2. Recommendations for academics

Both practitioner categories, including manufacturing industry practitioners and academic scholars are appealed to, for further testing (theoretically and empirically), challenging and development of the two conceptual methodologies for viewing MALC-m input data and application outcomes.

It is also proposed that another iteration of a confirmatory theoretical research be embarked on to test the findings of association between this study's statistically significant correlation results. In such a study, the influence of **access to quality total cost of ownership data** should be examined against **cost benefits**, when asset life-cycle management is in executing. Other methods of articulating CB must be considered, such as benefits cost ratio.

7.3.3. Recommendations for future research

An empirically based attempt of the study, excluding all the subjective interpretations of cost benefits that the current study was subjected to, is proposed. In the proposed empirical study, elements of MALC-m would have to be tested at different magnitudes and an objectively quantifiable CB would have to be calculated or measured from real time, standard calculations. Perhaps costs benefits realisation should also be replaced with life cycle benefits and a comparison of different decision cases be plotted against benefit cost ratios (as dependent variables). The BCR concept is seen to be better suited due to the reason that it integrates LCC, which is a costs representative and LCB, which represents value derivation (Animah et al., 2018). In so doing, it would consolidated three variables; CB through BCR, LCC and LCB that are fragmented in the current study and would make a significant leap in reducing complication within the MALC-m concept. The proposed study could be approached in the form of experimental research, case study or just simple use of secondary data such as that from manufacturing operations. It is to be noted that the risk or limitation within this study attempt would most likely be access to sensitive company data, which would have to be attained with careful abidance to applicable ethical boundaries for both researcher (and their institution).

7.4. Research limitations

The study was limited to academic enrolment requirements such as a business view objective, within the manufacturing industry. This was the case as the author undertook the study in pursuit of a manufacturing industry based masters qualification in business administration. Fortunately the latter topic was in the author’s passionate area of interest, which involves managing operations sustainably, at lowest attainable asset life-cycle costs, to achieve the highest possible financial value from asset life-cycles. Other limitations of the research incorporated a limited window duration, within which to collect data as well a low survey response rate of 64 respondents relative to the ideal quantity of 120 answered.

7.5. Conclusion

The four-fold research problem and the purpose articulated in the first chapter of this research, later on led to a development of theoretical insight through the literature review section. The literature review’s confirmation of theoretical concerns to exist in asset life-cycle management literature and various forms of articulating associated concepts, helped propel the study forward. Such consolidated theory incorporated asset life cycle cost/benefits analysis, total cost of ownership methodologies, value management concepts, prognosis and health management approaches to asset care strategies and asset life-cycle phase based strategising techniques, to name the relevant few. Later, the theoretically refined research questions, were framed into two hypotheses; *H1* suggesting that *MALC-m leads to CB-real* and *H2* hypothesising that TCO-mr moderates CB-real from manufacturing asset life-cycle management. After quantitatively collecting nominal and ordinal data, inferential statistical tests were conducted to test the latter hypotheses using Spearman's rank order correlation on the ordinal data. Results that emerged disproved the two hypotheses, with *H2* findings confirming a new emergent relationship to suggest that **access to quality TCO asset data**, moderates creation of CB-real.

Another contribution to theory were the two conceptual models in chapter 5, figure 6-3 and 6-4, presenting a **life-cycle stage and time continuum-based model for viewing MALC-m input data** as well as **life-cycle stage and time continuum-based model for viewing MALC-m application outcomes.** The two models work in synchrony with each other as they look at the same principles, just from different views

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Appendix A1: Consistency Matrix

Table A1-1: Consistency Matrix

Research Questions & Hypotheses	Literature & Theory Review	Data Collection Tool	Analysis
RQ1 - What is the nature of relationship between manufacturing asset life cycle management and cost benefits in a Manufacturing	Vogl et al., 2019 Roda et al., 2020	Questionnaire	Literature
Hypothesis 1 (*H1*): Manufacturing asset life cycle management leads to realisation of costs benefits	Roda et al., 2020 Mutha et al., 2021	Questionnaire	Inferential Statistics, bi-variate analysis: Spearman's correlation test
RQ2 - What are the most critical moderating factors for the relationship between manufacturing asset life cycles and cost benefits?	Kyriaki et al., 2018 Roda et al., 2020	Questionnaire	Literature
Hypothesis 2 (*H2*): TCO measurement readiness moderates creation of cost benefit from manufacturing asset life-cycle	Pakkanen et al., 2020	Questionnaire	Descriptive statistics

Appendix A2 - Survey Questionnaire

Table A2-1: Survey Questionnaire

Reason	ID	Questions	Reference	Response options				
Introductory	**1**	Consent						
Introductory	2	Please outline your continental residence	N/A	South African	African	Non-African		
Introductory	3	What is your profession	N/A					
Introductory	4	Years of experience	N/A	0 - 2	0 - 5	5-Jan	13-20	20 & above
Introductory	5	At which of the three asset utilisation categories do your work (with assets)	N/A	Asset value synthesi sing	Asset care	Value derivation (e.g operations)		
Introductory	6	At what lifecycle level do you interact with manufacturing asset	N/A	before acquisiti on	Beginning of life (post acquisition)	Middle of Life	End of Life (at disposal)	Throu ghout all stages
Introductory	7	Do you work in manufacturing industry	N/A	Never	Hardly ever	Seldom	Often	Yes always
Introductory	8	How is your day-to-day work related to assets or asset data (information)	N/A	I never work with assets or asset informati on	I hardly work with assets or asset information	I seldom work with assets or asset information	I often work with assets or asset information	I always work with assets
BOL lifecycle stage	9	At the beginning of asset life (purchasing stage), does your company evaluate for selection of suppliers	Roda et al., 2020	Never	Hardly ever	Seldom	Often	Yes always
BOL lifecycle stage	10	At the beginning of asset life (purchasing stage), does your company evaluate for alternative purchasing options	Roda et al., 2020	Never	Hardly ever	Seldom	Often	Yes always
BOL lifecycle stage	11	At the beginning of asset life, does your company review effects of Budget definition (such as projections of future cashflows/ economic value)	Roda et al., 2020	Never	Hardly ever	Seldom	Often	Yes always

BOL lifecycle stage	12	At the beginning of asset life, does your company evaluate economic preferences for Asset design / configuration	Roda et al., 2020	Never	Hardly ever	Seldom	Often	Yes always
BOL lifecycle stage	13	At the beginning of asset life, does your company evaluate options for Maintenance methods to utilise	Roda et al., 2020	Never	Hardly ever	Seldom	Often	Yes always
MOL Lifecycle stage	14	During asset operation phase, does your organisation evaluate assets performance for Continuous Improvement	Roda et al., 2020	Never	Hardly ever	Seldom	Often	Yes always
MOL Lifecycle stage	15	During asset operation phase, does your organisation evaluate assets performance for Plant Reconfiguration	Roda et al., 2020	Never	Hardly ever	Seldom	Often	Yes always
MOL Lifecycle stage	16	During asset operation phase, does your organisation evaluate the need for reviewing Maintenance methods	Roda et al., 2020	Never	Hardly ever	Seldom	Often	Yes always
EOL lifecycle stage	17	During asset operation phase, does your organisation evaluate assets for disposal	Roda et al., 2020	Never	Hardly ever	Seldom	Often	Yes always
EOL lifecycle stage	18	During asset operation phase, does your organisation evaluate assets for re-use/repurposing	Roda et al., 2020	Never	Hardly ever	Seldom	Often	Yes always
EOL lifecycle stage	19	During asset operation phase, does your organisation evaluate assets for recycling?	Roda et al., 2020	Never	Hardly ever	Seldom	Often	Yes always
Cost Value Assessment	20	Do you associate an evaluation of different asset suppliers with possible cost benefits?	Roda et al., 2020	No	Not sure	Yes		

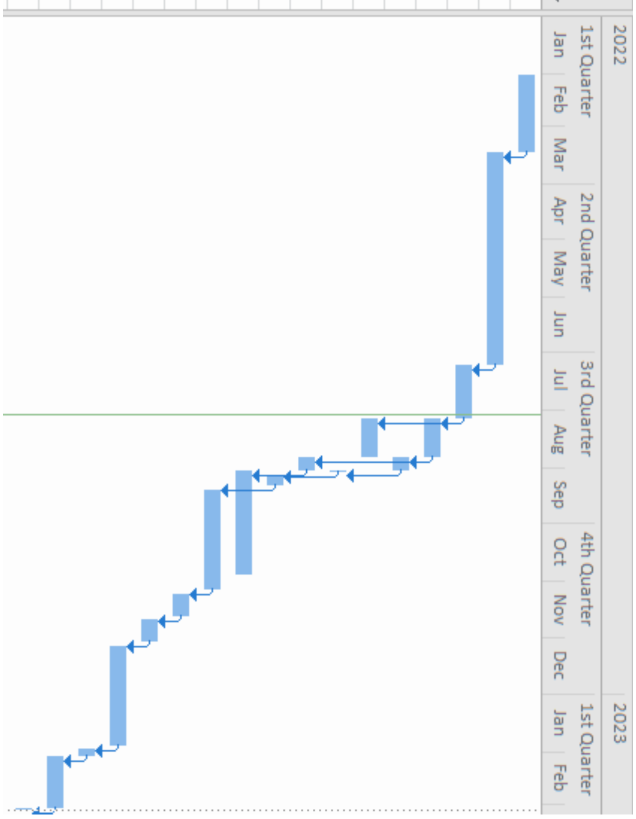
Cost Value Assessment	21	Do you associate an evaluation of alternative assets purchasing options with cost benefits as an outcome?	Roda et al., 2020	No	Not sure	Yes		
Cost Value Assessment	22	Do you associate an evaluation of Budget definition during asset acquisition with cost benefits as an outcome?	Roda et al., 2020	No	Not sure	Yes		
Cost Value Assessment	23	Do you associate an evaluation of Asset design / configuration with cost benefits as an outcome?	Roda et al., 2020	No	Not sure	Yes		
Cost Value Assessment	24	Do you associate an evaluation of Asset Maintenance methods with cost benefits as an outcome?	Roda et al., 2020	No	Not sure	Yes		
Cost Value Assessment	25	Do you associate an evaluation of Continuous Improvement (on asset utilisation) with cost benefits as an outcome?	Roda et al., 2020	No	Not sure	Yes		
Cost Value Assessment	26	Do you associate an evaluation of Plant Reconfiguration with cost benefits as a potential outcome?	Roda et al., 2020	No	Not sure	Yes		
Cost Value Assessment	27	Do you associate an evaluation of asset re-use/ repurposing with cost benefits as a potential outcome?	Roda et al., 2020	No	Not sure	Yes		
Cost Value Assessment	28	Do you associate an evaluation of “need for disposal” with cost benefits as a potential outcome?	Roda et al., 2020	No	Not sure	Yes		
Data Access problems	29	There is no database and systematic asset data collection at my workplace that I can get access to	Roda et al., 2020	No	Not sure	Yes		
Data Access problems	30	There is a Lack of access to asset data at my work-place	Roda et al., 2020	No	Not sure	Yes		

Data Access problems	31	I experience a Low quality of asset data from suppliers/asset providers at work	Roda et al., 2020	No	Not sure	Yes		
Data Access problems	32	I experience Resource constraints (cash/ time constraints)	Roda et al., 2020	No	Not sure	Yes		
Data Access problems	33	Cost of finding the right asset performance data is too high at work	Roda et al., 2020	No	Not sure	Yes		
Data Access problems	34	There is Lack of universal methods and standard formats for continuously modelling the total cost of asset utilisation at work	Roda et al., 2020	No	Not sure	Yes		
Data Access problems	35	I find it difficult to make reasonable assumptions and estimates for future cost of asset utilisation (or ownership)	Roda et al., 2020	No	Not sure	Yes		
Data Access problems	36	I experience Short term perspectives when it comes to asset lifecycle management at work	Roda et al., 2020	No	Not sure	Yes		
Data Access problems	37	I experience Lack of attention towards long term (> 3 years) asset management in my organisation	Roda et al., 2020	No	Not sure	Yes		
TCO Adoption	38	I experience a Lack of total cost of asset ownership (TCO) adoption obligation at work	Roda et al., 2020	No	Not sure	Yes		
TCO Adoption	39	There is a Lack of top management commitment to keep track of the actual total cost of asset utilisation (per asset)	Roda et al., 2020	No	Not sure	Yes		
TCO Adoption	40	My organisation manages total cost of owning assets, on a continuous basis from acquisition to end of asset life	Roda et al., 2020	No	Not sure	Yes		
TCO Adoption	41	My organisation manages total cost of owning assets, only at acquisition phase of an asset	Roda et al., 2020	No	Not sure	Yes		

TCO Adoption	42	My organisation manages total cost of owning assets, only at utilisation phase of the asset's life	Roda et al., 2020	No	Not sure	Yes		
TCO Adoption	43	My organisation manages total cost of owning assets, only at end of life	Roda et al., 2020	No	Not sure	Yes		
TCO Adoption	44	I believe that cost benefits may result from a system that continuously assesses the total cost of owning (TCO) different assets	Roda et al., 2020	No	Not sure	Yes		
TCO Adoption	45	I generally experience asset life-spans far superior than "useful lives" stipulated on tax life registers	Mutha et al., 2021	No	Not sure	Yes		
TCO Adoption	46	My organisation experiences asset life-spans that surpass those expected by original equipment manufacturers (OEMs)	Mutha et al., 2022	No	Not sure	Yes		
TCO Adoption	47	My organisation has a system for following up return of investments (ROI) originally promised during project justification phase	N/A	No	Not sure	Yes		

Appendix A3-1: MBA Research Gantt chart (schedule)

Task Name	Durati	Start	Finish
Research Idea	6 wks	Tue 22/02/01	Mon 22/03/14
Research proposal workshops and Articles reading	82 days	Tue 22/03/15	Wed 22/07/06
Research Proposal	4.2 wks	Thu 22/07/07	Thu 22/08/04
Marking of Research Proposal by Gibs	3 wks	Fri 22/08/05	Thu 22/08/25
Proposal Feedback Corrections + Ethics Submission	1 wk	Fri 22/08/26	Thu 22/09/01
Finalise Literature Review	3 wks	Fri 22/08/05	Thu 22/08/25
Ethics Submission	1 day	Fri 22/09/02	Fri 22/09/02
Fine-tuning of Research Quesstion and Data Gathering Plan	1 wk	Fri 22/08/26	Thu 22/09/01
Design Questionnaires	1 wk	Mon 22/09/05	Fri 22/09/09
Send out surveys for Data Gathering	8 wks	Fri 22/09/02	Thu 22/10/27
Break for final electives & Global module travel	8 wks	Mon 22/09/12	Fri 22/11/04
Validate and Analyse Gathered Data	2 wks	Mon 22/11/07	Fri 22/11/18
Consolidate Chapter 5 - results and Ch 6 - Consolidation of Results	2 wks	Mon 22/11/21	Fri 22/12/02
Thesis document write-up	8 wks	Mon 22/12/05	Fri 23/01/27
Write Journal article from Thesis	4 days	Mon 23/01/30	Thu 23/02/02
Buffer time for Research Interaction with supervisor & Murphy	4 wks	Fri 23/02/03	Thu 23/03/02
Final submission	1 day	Fri 23/03/03	Fri 23/03/03



Appendix A4: Flowcharts for LCC decision making

(Zou et al., 2021)

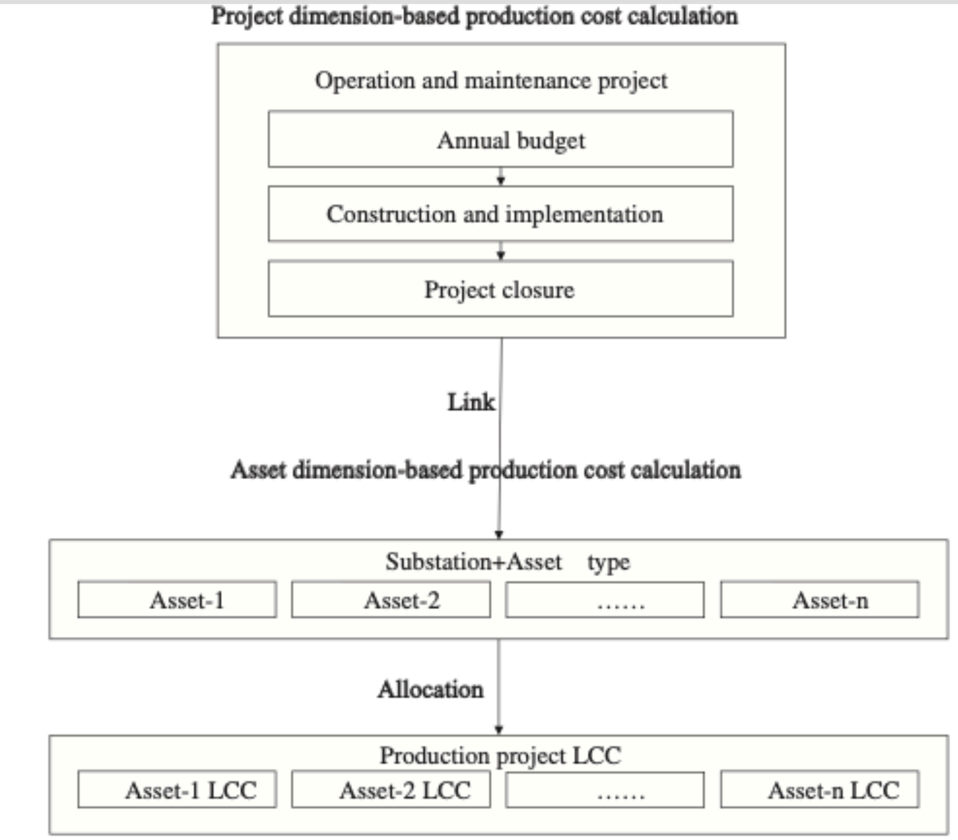


Fig. 1 LCC allocation flowchart for operation and maintenance projects

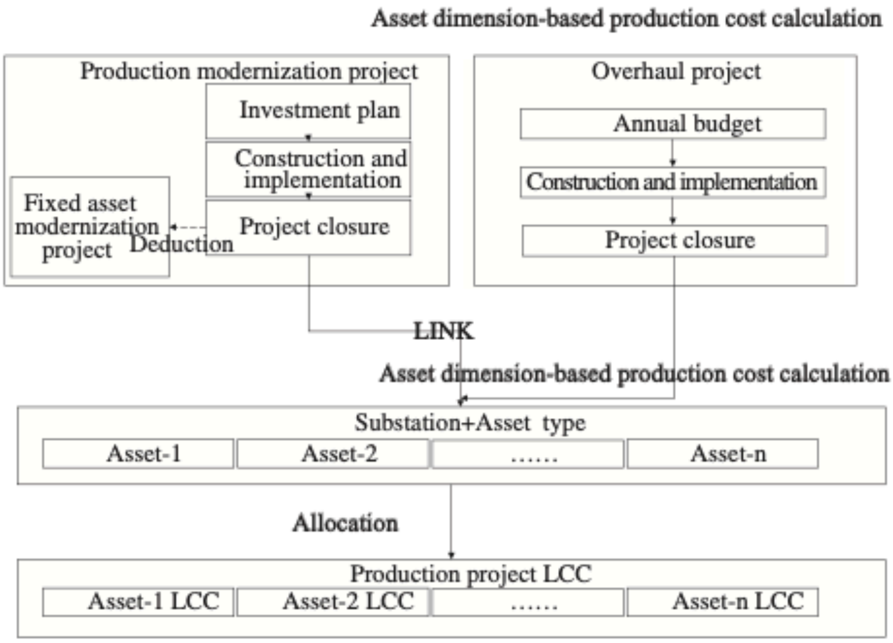
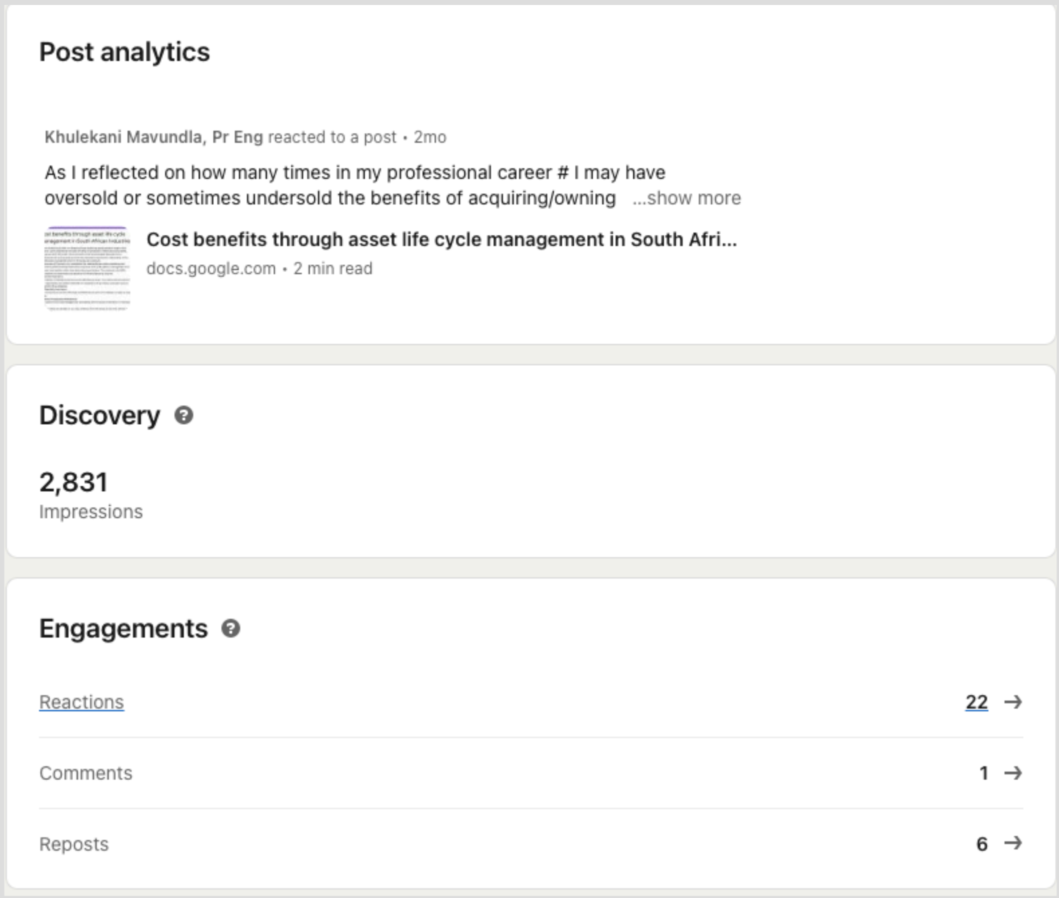


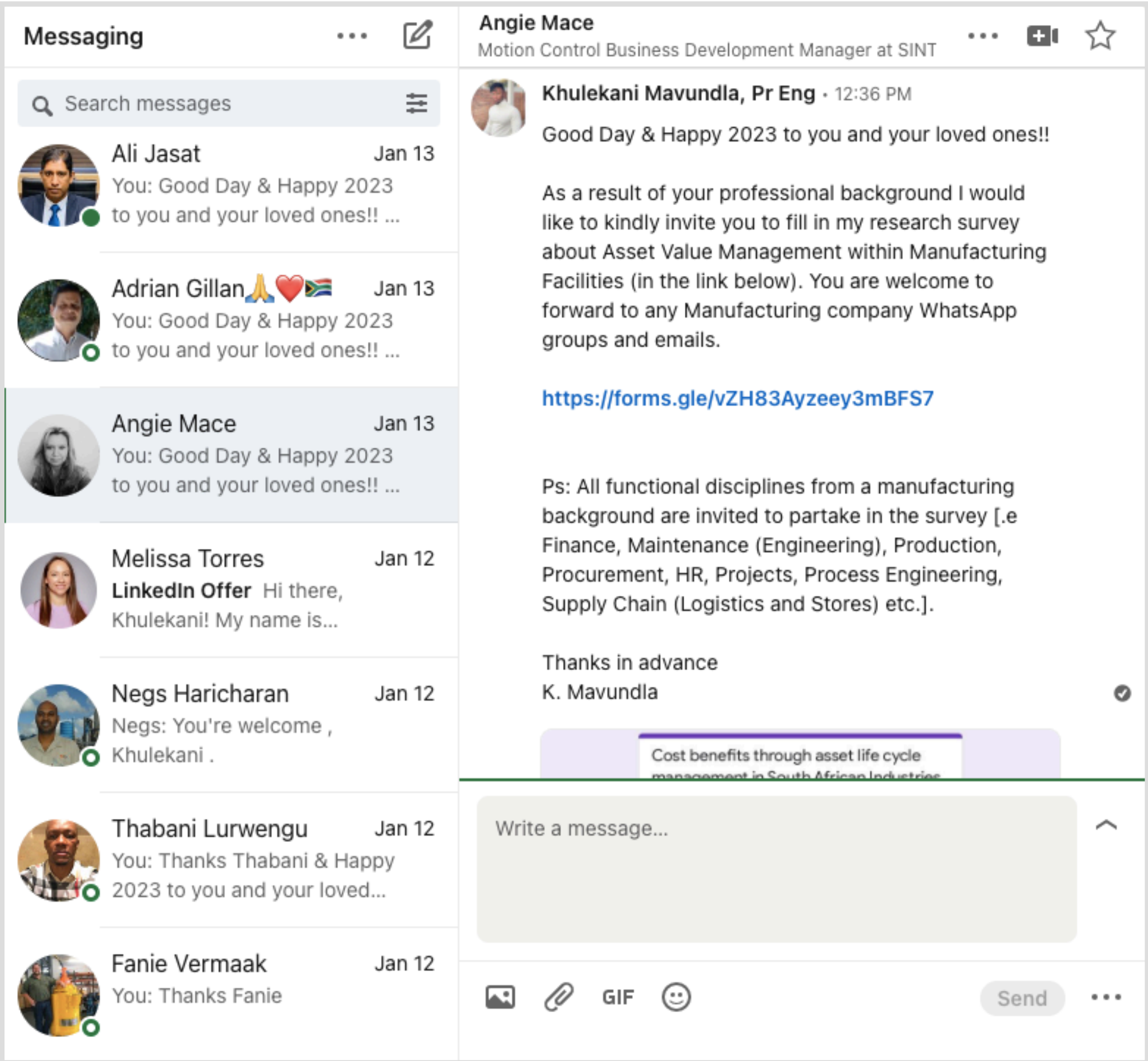
Fig. 2 LLC allocation flowchart for modernization and overhaul projects

Appendix A5 - Survey and Results

Appendix A5-1: Survey digital reach on business social media



Appendix A5-2: digital social media direct messaging



Appendix A5-3: Validity test results

Table A5-1: MALC-m variables' validity - Correlations

		ID9	ID10	ID11	ID12	ID13	ID14	ID15	ID16	ID17	ID18	ID19	MALC mTotal
ID9	Pearson Correlation	1	.448**	.370**	.367**	.346**	.245	.084	.111	.220	.268*	.205	.435**
	Sig. (2-tailed)		<.001	.003	.003	.005	.053	.515	.385	.083	.033	.107	<.001
	N	63	63	63	63	63	63	63	63	63	63	63	63
ID10	Pearson Correlation	.448**	1	.622**	.700**	.487**	.533**	.376**	.365**	.339**	.397**	.307*	.691**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001	<.001	.002	.003	.007	.001	.014	<.001
	N	63	63	63	63	63	63	63	63	63	63	63	63
ID11	Pearson Correlation	.370**	.622**	1	.668**	.559**	.568**	.470**	.525**	.444**	.407**	.311*	.745**
	Sig. (2-tailed)	.003	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001	.013	<.001
	N	63	63	63	63	63	63	63	63	63	63	63	63
ID12	Pearson Correlation	.367**	.700**	.668**	1	.565**	.567**	.598**	.457**	.475**	.516**	.308*	.783**
	Sig. (2-tailed)	.003	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001	.014	<.001
	N	63	63	63	63	63	63	63	63	63	63	63	63
ID13	Pearson Correlation	.346**	.487**	.559**	.565**	1	.622**	.495**	.708**	.386**	.456**	.361**	.758**
	Sig. (2-tailed)	.005	<.001	<.001	<.001		<.001	<.001	<.001	.002	<.001	.004	<.001
	N	63	63	63	63	63	63	63	63	63	63	63	63
ID14	Pearson Correlation	.245	.533**	.568**	.567**	.622**	1	.606**	.658**	.406**	.490**	.497**	.797**
	Sig. (2-tailed)	.053	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001
	N	63	63	63	63	63	63	63	63	63	63	63	63
ID15	Pearson Correlation	.084	.376**	.470**	.598**	.495**	.606**	1	.569**	.439**	.553**	.494**	.739**
	Sig. (2-tailed)	.515	.002	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001
	N	63	63	63	63	63	63	63	63	63	63	63	63
ID16	Pearson Correlation	.111	.365**	.525**	.457**	.708**	.658**	.569**	1	.468**	.436**	.345**	.727**
	Sig. (2-tailed)	.385	.003	<.001	<.001	<.001	<.001	<.001		<.001	<.001	.006	<.001
	N	63	63	63	63	63	63	63	63	63	63	63	63
ID17	Pearson Correlation	.220	.339**	.444**	.475**	.386**	.406**	.439**	.468**	1	.581**	.510**	.694**
	Sig. (2-tailed)	.083	.007	<.001	<.001	.002	<.001	<.001	<.001		<.001	<.001	<.001
	N	63	63	63	63	63	63	63	63	63	63	63	63
ID18	Pearson Correlation	.268*	.397**	.407**	.516**	.456**	.490**	.553**	.436**	.581**	1	.622**	.752**
	Sig. (2-tailed)	.033	.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001
	N	63	63	63	63	63	63	63	63	63	63	63	63
ID19	Pearson Correlation	.205	.307*	.311*	.308*	.361**	.497**	.494**	.345**	.510**	.622**	1	.667**
	Sig. (2-tailed)	.107	.014	.013	.014	.004	<.001	<.001	.006	<.001	<.001		<.001
	N	63	63	63	63	63	63	63	63	63	63	63	63
MALCmTotal	Pearson Correlation	.435**	.691**	.745**	.783**	.758**	.797**	.739**	.727**	.694**	.752**	.667**	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	
	N	63	63	63	63	63	63	63	63	63	63	63	64

Table A5-2: TCO-mr variables' validity - Correlations

		ID29	ID30	ID31	ID32	ID33	ID34	ID35	ID36	ID37	ID38	TCOmr Total
ID29	Pearson Correlation	1	.672**	.366**	.247	.338**	.311*	.302*	.304*	.385**	.308*	.602**
	Sig. (2-tailed)		<.001	.003	.051	.007	.013	.016	.015	.002	.014	<.001
	N	63	63	63	63	63	63	63	63	63	63	63
ID30	Pearson Correlation	.672**	1	.298*	.338**	.378**	.372**	.262*	.218	.258*	.385**	.601**
	Sig. (2-tailed)	<.001		.018	.007	.002	.003	.038	.086	.041	.002	<.001
	N	63	63	63	63	63	63	63	63	63	63	63
ID31	Pearson Correlation	.366**	.298*	1	.479**	.296*	.362**	.479**	.420**	.483**	.449**	.686**
	Sig. (2-tailed)	.003	.018		<.001	.019	.004	<.001	<.001	<.001	<.001	<.001
	N	63	63	63	63	63	63	63	63	63	63	63
ID32	Pearson Correlation	.247	.338**	.479**	1	.355**	.375**	.404**	.531**	.467**	.637**	.722**
	Sig. (2-tailed)	.051	.007	<.001		.004	.002	.001	<.001	<.001	<.001	<.001
	N	63	63	63	63	63	63	63	63	63	63	63
ID33	Pearson Correlation	.338**	.378**	.296*	.355**	1	.171	.312*	.204	.166	.264*	.500**
	Sig. (2-tailed)	.007	.002	.019	.004		.180	.013	.109	.194	.037	<.001
	N	63	63	63	63	63	63	63	63	63	63	63
ID34	Pearson Correlation	.311*	.372**	.362**	.375**	.171	1	.490**	.548**	.465**	.441**	.676**
	Sig. (2-tailed)	.013	.003	.004	.002	.180		<.001	<.001	<.001	<.001	<.001
	N	63	63	63	63	63	63	63	63	63	63	63
ID35	Pearson Correlation	.302*	.262*	.479**	.404**	.312*	.490**	1	.671**	.419**	.516**	.724**
	Sig. (2-tailed)	.016	.038	<.001	.001	.013	<.001		<.001	<.001	<.001	<.001
	N	63	63	63	63	63	63	63	63	63	63	63
ID36	Pearson Correlation	.304*	.218	.420**	.531**	.204	.548**	.671**	1	.500**	.589**	.750**
	Sig. (2-tailed)	.015	.086	<.001	<.001	.109	<.001	<.001		<.001	<.001	<.001
	N	63	63	63	63	63	63	63	63	63	63	63
ID37	Pearson Correlation	.385**	.258*	.483**	.467**	.166	.465**	.419**	.500**	1	.608**	.711**
	Sig. (2-tailed)	.002	.041	<.001	<.001	.194	<.001	<.001	<.001		<.001	<.001
	N	63	63	63	63	63	63	63	63	63	63	63
ID38	Pearson Correlation	.308*	.385**	.449**	.637**	.264*	.441**	.516**	.589**	.608**	1	.783**
	Sig. (2-tailed)	.014	.002	<.001	<.001	.037	<.001	<.001	<.001	<.001		<.001
	N	63	63	63	63	63	63	63	63	63	63	63
TCOmr Total	Pearson Correlation	.602**	.601**	.686**	.722**	.500**	.676**	.724**	.750**	.711**	.783**	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	
	N	63	63	63	63	63	63	63	63	63	63	64

Table A5-3: CB-perceived (CB-perc) variables' validity - Correlations

		ID20	ID21	ID22	ID23	ID24	ID25	ID26	ID27	ID28	CBpercTotal
ID20	Pearson Correlation	1	.469**	.550**	.437**	.511**	.501**	.480**	.433**	.081	.687**
	Sig. (2-tailed)		<.001	<.001	<.001	<.001	<.001	<.001	<.001	.529	<.001
	N	63	63	63	63	63	63	63	63	63	63
ID21	Pearson Correlation	.469**	1	.898**	.431**	.145	.437**	.692**	.577**	.268*	.789**
	Sig. (2-tailed)	<.001		<.001	<.001	.258	<.001	<.001	<.001	.033	<.001
	N	63	63	63	63	63	63	63	63	63	63
ID22	Pearson Correlation	.550**	.898**	1	.509**	.217	.460**	.687**	.565**	.242	.816**
	Sig. (2-tailed)	<.001	<.001		<.001	.087	<.001	<.001	<.001	.056	<.001
	N	63	63	63	63	63	63	63	63	63	63
ID23	Pearson Correlation	.437**	.431**	.509**	1	.477**	.285*	.518**	.478**	.323**	.698**
	Sig. (2-tailed)	<.001	<.001	<.001		<.001	.024	<.001	<.001	.010	<.001
	N	63	63	63	63	63	63	63	63	63	63
ID24	Pearson Correlation	.511**	.145	.217	.477**	1	.617**	.305*	.133	.063	.517**
	Sig. (2-tailed)	<.001	.258	.087	<.001		<.001	.015	.300	.624	<.001
	N	63	63	63	63	63	63	63	63	63	63
ID25	Pearson Correlation	.501**	.437**	.460**	.285*	.617**	1	.536**	.308*	.103	.672**
	Sig. (2-tailed)	<.001	<.001	<.001	.024	<.001		<.001	.014	.423	<.001
	N	63	63	63	63	63	63	63	63	63	63
ID26	Pearson Correlation	.480**	.692**	.687**	.518**	.305*	.536**	1	.470**	.262*	.800**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	.015	<.001		<.001	.038	<.001
	N	63	63	63	63	63	63	63	63	63	63
ID27	Pearson Correlation	.433**	.577**	.565**	.478**	.133	.308*	.470**	1	.582**	.751**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	.300	.014	<.001		<.001	<.001
	N	63	63	63	63	63	63	63	63	63	63
ID28	Pearson Correlation	.081	.268*	.242	.323**	.063	.103	.262*	.582**	1	.509**
	Sig. (2-tailed)	.529	.033	.056	.010	.624	.423	.038	<.001		<.001
	N	63	63	63	63	63	63	63	63	63	63
CBpercTotal	Pearson Correlation	.687**	.789**	.816**	.698**	.517**	.672**	.800**	.751**	.509**	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	
	N	63	63	63	63	63	63	63	63	63	64

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Appendix A5-4: Reliability test results

Table A5-4: TCO-mr reliability - item total statistics

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple	Cronbach's Alpha if Item
ID29	24.5079	78.738	.517	.545	.863
ID30	24.7619	76.765	.498	.565	.864
ID31	25.3333	74.032	.594	.396	.856
ID32	26.1746	73.114	.638	.518	.853
ID33	25.5556	79.799	.388	.255	.871
ID34	25.9365	74.189	.581	.419	.858
ID35	25.9524	73.014	.641	.539	.853
ID36	25.9365	71.318	.667	.611	.850
ID37	25.7619	72.959	.621	.502	.854
ID38	25.6508	69.489	.704	.599	.847

Table A5-5: CB-perc reliability - item total statistics

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple	Cronbach's Alpha if Item
ID20	21.8571	11.834	.602	.517	.844
ID21	21.8889	11.197	.720	.832	.832
ID22	21.8889	11.229	.758	.840	.830
ID23	21.8889	11.713	.612	.545	.843
ID24	21.8095	12.705	.420	.619	.859
ID25	21.9524	11.304	.554	.594	.848
ID26	22.0476	10.530	.715	.601	.831
ID27	21.9841	10.855	.653	.604	.838
ID28	22.1429	11.995	.342	.397	.873

Table A5-6: MALC-m reliability - item total statistics

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
ID9	39.6349	51.816	.354	.312	.904
ID10	39.7937	48.134	.627	.588	.892
ID11	39.9206	47.107	.686	.569	.889
ID12	40.1111	45.778	.727	.700	.886
ID13	40.1587	46.329	.698	.624	.888
ID14	40.0794	44.816	.738	.622	.885
ID15	40.3016	46.504	.674	.585	.889
ID16	40.2540	46.580	.658	.660	.890
ID17	40.6190	45.853	.606	.471	.893
ID18	40.6667	45.290	.680	.558	.888
ID19	40.8413	45.297	.561	.516	.898