Predicting the Financial Feasibility of Space Mining

A Quantitative Review of Lunar Oxygen Mining Cost Structure

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drawing inspiration by unevenly mirroring your path, mum

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Abstract

The first half of the 2023 has seen space mining becoming an achievable dream as it barged in the trending topics within the new space economy. AstroForge, one of the leading startups in the market niche, has announced two asteroid mining missions for the current year, demonstrating the possibility of running refinery activity in absence of gravity and scouting for potential target asteroids (AstroForge, 2023). Complementarily, an experiment run by NASA's Carbothermal Reduction Demonstration (CaRD) team developed using Johnson Space Center's Dirty Thermal Vacuum Chamber has proven the feasibility of extracting oxygen from the lunar regolith. "This technology has the potential to produce several times its own weight in oxygen per year on the lunar surface, which will enable a sustained human presence and lunar economy"; those are the words with which Aaron Paz – JSC Senior Engineer – has commented on the successful outcome of the breakthrough test (Dinner, 2023).

The following pages have been drafted inspired by those words, by decomposing such a complex matter in its foundational bricks and elements, aiming to tackle what has been historically a common issue in disruptive innovation and space ventures: cost estimation and predictive modelling.

The dissertation starts with the first chapter proposing an overview of the youthful and explosive space business sector, introducing some of the inherent complexities tackled further in the current project management studies, reviewing how innovation takes place in this industry, and proceeding with a bridge that leads to the mining sphere, where the most prominent mission designs are pondered.

There, a concluding paragraph addresses the relevance of the study as it reviews the cost prediction methods and their goodness of fit, identifying a structural inappropriateness of the current literature and the associated methods, which result in a limited practical employability.

The second chapter develops following an abductive structure and is dedicated to carefully explain the research process, focusing on both the multiple iterative stages and the derivation of the two core building blocks: the PLS-SEM-reliant predictive model and the NPV equation.

A concluding paragraph comments on the complementary and concordant outcomes of the two models, providing a countable estimation of the project cost value. Further, it continues with the implications as well as the limitations of the work, suggesting openings for further research.

1. Space sector and the new space economy: an overview

1.1. Perspectives and development

Looking at the human history, not many years have passed since the concept of “future” has left the minds of secluded visionary thinkers to meander through squares and along the streets among common people.

What the first industrialisation has introduced is the tangible and daily experienceable feeling that the surrounding might change within a dozen of years, requiring humans to scale down their whimsical utopias to short term realisable adaptation and innovation plans.

Sputnik 1, the first artificial terrestrial satellite ever launched, reached his elliptical low earth orbit about 65 years ago; therefore, it has not been long since humankind started thinking of “space” outside astronomical laboratories and embedding the concept in industrial environments. Indeed, the narrowness of the timeframe is as limited that nowadays it is not yet possible to imagine a space business completely uprooted from governmental influence. Indeed, the strong historical heritage – build from its birth as an offshoot of space and defence national departments – still lies at the financial foundation of the sector.

As the time progresses through the twenties and the thirties of the twenty-first century, space sector is preparing itself for a new golden era, this time not driven by belligerent competing forces but promoted by business, social and environmental positive purposes. What the two timespan shares is the crucial role of the moon, with 15 missions planned for the next five years, this time by eight agencies (OECD, 2019).

Considering as an example the decade running from the Lehman Brothers collapse until the covid pandemic outbreak, the inclusive movement has allowed an increase of 64% in the number of countries actively involved in financing space activities, raising the global public budget to over USD 75 billion (OECD, 2019). As a natural consequence of having more players involved, along with an increased recognition of the benefits associated with the interconnections of the space sector with other crucial industries, there is a trend of scopes expansion, crucially bringing into the conversation inclusive and disruptive innovations.

The general understanding when referring to space industrial activities comprises launchers, human space flights, global navigation systems (GNSes), space science missions, earth observation and telecommunications. The above grouping could be further categorised by the way the impact ordinary activities, and therefore by the ability of attracting private and more short-term oriented investors. In this sense, telecom, GNSes, and earth observation directly finds an interconnection with daily life, with the last-mentioned in particular being carefully regarded recently with its crucial involvement in addressing solutions to climate change. In fact, 50% of the tracked key parameters are monitored through satellite data (OECD, 2019). The remaining spheres of space activities instead produces returns which are harder to track due to their delayed realisation. According to a study reported in the OECD 2019 review, cost savings and cost avoidance are the two areas in which industries outside of space sector have primarily experienced benefits from space activities and innovations, while other disciplines such as prevention, disaster management and agriculture are being restructured by the adoption of satellite imagery, remote sensing and broadband for example (Moriconi-Ebrard, 2016). Continuing on the reasoning, it is evident how the aerospace sector, once armed and divisive, is now on a fast-paced rejuvenating transition to a more socio-economically conscious approach to its activities, accounting to the implications beyond the missions themselves. The paradigm has moved from considering technology transfers as by-products to core assets capable of decupling the value-producing potential of each space innovation effort (Olivari, 2021).

A representative case of how space foster and promotes a high pace development of other industries is given in the telemedicine programme developed by the Indian Space Research Organisation in collaboration with local authorities and public entities. There, in the last twenty years, lives have been saved by connecting isolated hospitals and mobile medical units through satellite broadbands, providing real time diagnosis in underdeveloped villages where modern health and sanity infrastructure are far from initiating their establishment (ISRO, 2017). Many other extraordinary examples could be provided on how health, medicine, environment, agriculture, and transportation industries are not only collaterally improving from a cost and efficiency view, but also from the perspective of accessibility and social inclusion.

As the downstream portion of the sector is progressively getting converted to exploitations which scopes go well beyond national primary investment priorities – which generally concern national security and scientific exploration –, also the strategic and sourcing aspects are seeing a trending growth in the involvement of private players willing to join the space industry.

Complementarily, Elvis' perspective strengthens and emphasises how allowing a material participation of private investments is a coherent and utmost required move to compensate for the discrepancy between growth paces of national research budgets and sector-specific costs, with the latter being driven primarily by the inherent complexity that arises when testing for broadening innovation (Elvis, 2016).

The co-integration of space and private entities in developing a space program happens on a slippery slope, where balancing interests and coordinating efforts to synergistically optimise the costly innovation processes becomes crucial to develop a sustainable and long-lasting ecosystem.

Historically, countries have inherited a discipline from the cold war years, were investments from the two factions have helped to leapfrog the research advancement. Meanwhile, the only sub-sphere where private businesses have managed to progressively gain a strategically dominant position refers to the telecommunication industry (Bruggeman, 2002). Crucial is to realise that the above presented division – despite clearly splitting the investments in two orders of magnitude – is not even close to appropriately depict the reality: what has to be taken into account is in fact how the whole downstream market of businesses associated with space programs directly exploits its innovations, and therefore how those individual players are in push to bust through the ceiling and join the control room. A snapshot of the current situation could consequently be synthetised in an atypical iterative activity of faded boundaries between private players and governmental monopsonists, across the supply and value chains (Szajnfarber, 2007).

1.1.1. Innovating in space: players and trends

The above roughed out industry design structure allows to understand the peculiar innovation's development, opportunities, and criticisms. As a starting point, having institutional entities holding a monopsonist role, logically leads to a centralised consolidation of both financial resources as well as it promotes a coordination of intents. It is indeed true that the field is characterised by timely-extended product lifetimes which tendentially prefer associated tools and items' improvements to be built on existing technologies, as it happens with spaceships plug ins. This structure shapes the way technological advancement develops. As a consequence, space industry offers a breeding ground where a sustainable approach towards innovation – that builds on adapting and improving preceding discoveries – flourish over a more disruptive and revolutionary model, common instead in the early stages of new business segments (Ettlie, 1984). As defined by Christensen in late nineties, disruptive innovation focusses on optimising the outputs of a specific pre-existent object, working consistently on integration and improvement (Christensen C. M., 1997). Complementarily, steering from a strategic design that has successfully served the industry growth for decades seems difficult, therefore future challenges would be primarily addressed through improving the cooperative integration between private and public investors. A minor role is so far taken by some attempting disruptions, which have the potential to accelerate the development in the field once gaining larger market shares within the new space economy: those are primarily narrowed to the micro-satellites (CubeSat) business and the space tourism.

As it happened to other industries – even some neighbouring such as the flights and aircrafts' one –, commercialisation accommodates a healthy competitive mechanism that has the strength to drive down the costs and therefore open the doors to smaller and more agile players. Thence, what is crucial in those early stages is to harmoniously build a space governance to lead and guide the projectivity (Deudney, 2020). In this regard, institutional agencies and large players step in the role of coordinating and promoting a canalised innovation that exploit the agility of start-ups and scale ups. As a leading example, the German Space Component Initiative promotes the whole value chain of special components jointly exploiting a mixture of research-oriented grants, brokering and communication activities to lead the growth of their national satellite business (Feddeck, 2016). Luckily, the above depicted dynamic does not represent an isolated case: for about 20 years the European Space Agency is running their own Business Incubator Centres, helping more than 140 new-born projects each year, and showcasing a survival rate of above nine-tenth (O'Hare, 2017). Those forms of public-private-partnerships represents a focal point to unlock manifold growth opportunities, and ultimately fully opening the market to purely private players (Anderson, 2013).

Similarly, also large private entities are heavily supporting the space segment through their internal corporate venture capital initiatives, which made the sector grow from 200 deals in 2011 to 1400 in just six years (Capital, 2019); among the others, it is worth to mention the largest contributors to the more than 3 USD billion invested in start-up equity in 2018 (Angels, 2019): Boeing HorizonX Ventures, Lockheed Martin Ventures, Airbus Ventures, Thales Corporate Ventures and Dassault System Venture Fund. Those players contribution to the new space economy represent the perfect integration between modern and usually late-stage industry dynamics to a newer business sector, as they are the firsts pursuing disruptive innovation financing and therefore going beyond the telecommunication field.

It is worth to mention how the tremendous pace at which space economy is evolving promotes the experimentation through the integration of modern approaches in neighbouring fields. As a leading example, more and more start-ups active in the industry are pondering imitating Rocket Lab and Vector Capital in the so called “reverse merger” to fasten the capital gathering, which are enabled through investment vehicles such as the special-purpose acquisition companies. Those in fact are players without any ongoing commercial activity which run for an initial public offering and once tradeable on the capital market, acquires or merges with an existing entity (Rocket Lab USA, 2021).

A recent industry breakdown by Space Capital allows to summarise the ongoing development in private investment depicted above with some key figures: $ 264 billion dollars have been invested in the last decade, with satellites (89%) and launching systems (10%) splitting almost the entire cake. Out of those, after the initial years driven by angels' promotion, venture capitalists are driving the growth, specifically targeting investments at seeds stage (70%). As an outcome, the costs per kilo delivered outside earth's atmosphere have been dramatically reduced and the SpaceX's Starship is estimated to be ten times cheaper than its predecessor from 2015. Such results enable smaller, individual, and research-driven players to proactively contribute to this new inclusive space era (Space Capital, 2022).

The globalisation of investment and funding opportunities avoids insulation dynamics that generate research duplicates and promoting instead cooperation on the largest scale (Yazici, 2019). Those funding activities are backed by a general trend of equilibration among the country-specific space budget (Bordacchini, 2018) which comes with other parallel initiatives aimed to coordinate and guide the proper exploitation of the increased available resources. On that specific matter, a new country has decided to enter the field: Luxembourg. With 238 EUR million invested between 2017 and 2021, of which half dedicated to public and private research (Luxembourg Ministry of Finance, 2017), the small European gem is a concrete candidate to lead the new expansion of the industry: space mining. Indeed, the country is the second globally – after the US – to propose a legal framework dedicated to the exploration and usage of space resources (Space Resources, 2019) and has as its primary objective the study of moon exploitation in collaboration with new Artemis program. The reason why such attention has been drawn by this specific topic is well summarised by Ian Crawford, which argues in four points how developing this apparently narrow segment might lead to a new paradigm within space business. According to the author in fact, space mining will allow to open and better maintain scientific outposts, promote scientific discoveries while simultaneously leveraging the profitability to finance scientific experiments and ultimately prepare an infrastructure for further openings in space economy commercialisation beyond satellites (Crawford, 2016). In terms of economic returns, many authors have tried to estimate the industry potential profitability after Lewis published the “manifesto” mentioning trillion of dollars hidden between the stars (Lewis J. S., Mining the Sky: Untold Riches from the Asteroids, Comets and Planets, 1996). Other than the attractiveness embedded in such a potentially lucrative business, space mining comes as a logical intuition behind the maintenance of the gross domestic product continued growth. Axiomatically, GDPs inherent potential is entangled with resource sustainable availability, as it impacts energy supply and determines the improvement room’s size for technological development. Interestingly enough, the single observation that most of the mineable resources exploited in the technological advancement are disposable on Earth in constrained amounts due to their depositional derivation from meteors, should ring a bell regarding celestial bodies involvement in the – near – future of humans’ development (World Energy Council, 2003) (Diederen, 2009).

1.2. Space mining deep dive

To better differentiate how challenges and limitations drive business perspectives, it is worth to include a few lines summarizing some simplified industrial analysis.

As a starting point, Shishko’s perspective breaks down the activities by their proceeds’ allocation. According to his definition, space mining refers to the practice of obtaining resources – both volatiles and minerals – from space bodies of various nature, with the aim of 1) exploiting those right on the spot (in-situ resource utilisation – further referred as ISRU), 2) utilising those mined assets in space elsewhere, or alternatively 3) completing the program with a mission capable of bringing back the resources on the Earth (Shishko R. F.-C., 2017). The last-mentioned category brings some unsolved criticism which involves implication of macroeconomic nature that sums up with all the engineering-associated challenges. The current literature argues how Earth-based commodity market might directly challenge such missions. Therefore, the dream of returning resources to our planet needs an “alignment of stars” to become reality (Hein, A techno-economic analysis of asteroid mining, 2020). Therefore, in line with the ultimate scope of the dissertation, the third category slides off from the spotlight and will not be investigated further.

Also, the general research prioritises ISRU, identifying ice and regolith as the major opportunities capable of generating impactful cost cutting on space projects and expeditions costs (Pelech T. M., 2019); a journey that follows several mission launched throughout the years, since Clementine approximately calculated the presence of water supply on the moon worth more than 300 million tons (LPI, 2022).

Complementarily with the introductory proceed-destination-oriented classification, a pivotal distinction has to be made among celestial bodies. In particular, literature is focused on developing asteroid mining in low-Earth-orbit (LEO) on one side, and moon mining on the other. Our natural satellite has all the right credential to attract capital required to establish the first mining facilities in the space. A crucial role in this sense is played by the synergy with other programs: the aforementioned Artemis in fact, expects a total of 37 moon-related mission to be launched within the decade that ends in 2028, culminating with an ideally permanent outpost on the lunar surface (Bergen, 2019). It could also be argued that there might exist some sort of overlaps between asteroid-oriented mining mission designs and other project involving asteroid deviation and retrieval (Sánchez, 2016), while it is undeniable how moon studies and projects sits on a much more advanced stage.

Furthermore, studies testing for resource availability sees large players prioritising lunar studies. In particular, the European Space Agency has two active projects – ESA ISRU Mission for Lunar Regolith and ESA PROSPECT (which stands for Package for Resource Observation and in-Situ Prospecting for Exploration, Commercial exploitation and Transportation) – aimed to lead the technological development by building a fil-rouge to coordinate the individuals' efforts (ESA, 2018) (ESA, 2019). in those same years, iSPACE promoted by the Japanese agency has planned two moon exploitation-oriented missions: Hakuto-R M1 and M2 (ISPACE, 2019).

Studies on asteroids are of a greater degree of complexity as for example orbit and size plays a crucial role which is as impacting as the resource availability in terms of mission decision making. Asterank has classified 16000 smaller celestial bodies orbiting on comparable routes as the one followed by our planet (Asterank, 2019) and thus falling into the category defined as Near-Earth Asteroids (NEAs). Among those, as some might even have the potential to have a hidden concentration degree of resources worth more than the median of the plants currently established on our planet (Gupta A. a., 2009), more and more research papers have been published in the recent years advancing the status of asteroids' mapping and taxonomy. Representative and pivotal is the work carried on by leading Australian scientists Xie, Bennett, and Dempster, which managed to prepare a database which reference both water and non-water mining opportunities in the 2030-2065 horizon (Xie, 2021). To distinguish further non-watery orbiting celestial bodies, astronomers uses letters: M-type represents asteroids with large availability of metals – nickel-iron and platinum, primarily – and therefore represents a primary target for mining operations, despite accounting only for a single-digit percentage of the available asteroids (Lewis J. S., 1990); deprioritised from an exploitation-oriented perspective while still aggregately relevant as they make up the 90% of the target asteroids, there are C-type and S-type, letters that respectively stands for "carbonaceous" and "stony" (Lewis J. , Asteroid Mining 101, 2014) (Mazanek, 2014). As the academic knowledge contributes on building a stronger foundation on asteroids and their potential exploitation, start-ups have started gaining interest in the niche. Exemplary is the case of Aten Engineering, which has the recognition of being the first private organisation aimed on bringing a commercial perspective on exploitation and prospecting (ASIME, 2018). In the recently published SpaceTech Trend Report, among the five recently born players in the mining segment of New Space Economy to keep under observation, almost the entirety are devolved to the asteroids (StartUs Insights, 2023).

1.2.1. Engineers' considerations

Insightful considerations are brought to the table by a purer engineering perspective: while asteroids requires an atypical drilling equipment as the weaker attractional force enables the collection of resources by simply scraping the surface (Steklov, 2019), moon's higher gravity requires a lower degree of innovative adaptation on engines and mechanisms of Earth-used machines. Moreover, the closer and constant distance allows a remote control which suffers a manageable lag factor below 3 seconds. Lastly, the absence of an atmosphere has allowed, throughout the eras, manifold asteroids to impact the surface, and therefore enriching the moon's regolith with a great variety of resources (ASIME, 2018), (McLeod, 2017). A crucial contribution to the comparison between moon and asteroids operations' technical feasibility is brought on the table by the leading institution in the study of mining: the Colorado School of Mines. They argue that the technological advancement is currently sitting on a stage that would allow imagining a concrete and realistic Moon ISRU projectivity. In particular, the model proposed suggests how sublimation and further electrolysis could be used as a valuable alternative to traditional excavational and hauling based techniques (Sowers G. e., 2018). Such evaluation are supported by other prominent authors as Lefeber (Lefeber, 2016).

1.2.2. Complementary perspectives

Before delving further in the technicalities required to navigate the complex process of mission design choice, the route towards a holistic understanding of the business encounters some challenges that have to be properly addressed. Firstly, mining is a word that still seems in breach when contextualised in a conversation with the UN Sustainable Development Goals, as it has historically been driving pollution and therefore has a negative branding that could significantly influence the general public opinion against space mining as well. Further, the above depicted observation links to another sustainability-related topic: space debris. It is in fact crucial that the space industry as a whole start bringing more and more attention to the environmentally friendly branding image through concrete initiatives. Unfortunately, not more than one tenth of the low-Earth-Orbit (LEO) satellites delivered in the current century have had a retrieval or de-orbiting plan once the operational lifetime reaches a conclusion (Frey, 2017). Once again, the integration of private entities in the industry foster its development: Cislunar Industries headquartered in Luxembourg leads a program of debris removal (Cislunar, 2019).

As already briefly introduced in the previous pages, what is currently missing is a strong established legislation, as opposed to the current “soft law” where voluntary implementation coexists in an overly balanced way with enforced and regulated norms (Chrysaki, 2020) (Undeseth, 2020). As it has been happening with the efforts oriented tackling the climate change, a weighty and consequential implementation would be represented by the establishment of improved national regulation that integrates and enforces what the UN proposes (Rathgeber, 2010).

By accommodating the digression on the legal aspects, it becomes evident how many technicalities that orbit around the concept of space mining are still undefined, sitting on a grey area of uncertainty interpretation. Historically, despite the efforts in developing and placing new milestones, UN's proposals have always had some major weaknesses: in 1967, when the Outer Space Treaty was published, there was immediately recognised an undetailed specification on item property (UN, 1967). Twelve years later, the so-called Moon Agreement, aimed to improve the granularity of regulation in exploitation management for the future, managed to attract not more than 17 signees (UN, 1979). The aforementioned Luxembourg initiatives, in concert with the US and the United Arab Emirates that are willing to "actively promote the development of a commercial off-Earth mining industry" (Banard, 2016), are supposed to coordinate and clarify the destiny of space mining industry development; nevertheless, a both legal and ethical dilemma is urging for a solution.

Garrett Hardin about fifty-five years ago introduces the "tragedy of the commons", an exaggerated form of individualism that originates in humans' egoism and rise when there is no regulated operational framework (Hardin, 1968). The goal here is to keep exploiting the profitability and enrichment desire of private entities, needed to complement institutions in modern innovation schemes, while formulating an inclusive structure of shared benefits, as no one should have individual claim over extra-terrestrial bodies. An interesting proposal seems to be naturally sprouting up from unconnected theorists and finds its origins more than 20 years ago when Marko proposes political and economic perspectives juxtaposing first capitalism and communism and then efficient versus equitable approaches on resource exploitation (Marko, 1992). From there onwards, a general agreement has been built around the idea that an innovative approach was required, ultimately leading to the condensed idea that the solution might lie in a more pragmatic engagement that relies on royalties to distribute wealth (Center for Western Priorities, 2015). A report derived from a simulation among students mocking space mining treaties discussions produced a coherently overlapping proposal where a sort of a “space bank” was drafted to partially re-distribute successful businesses’ revenues through taxation and directly re-invest those proceeds involving more and more underdeveloped countries into ground-breaking science and technology industry (Paikowsky, 2018) (Benton, 2022).

Whereas such proposals might sound dreamy and unattainable, a comparable and time-proved system could be found in the northern America. More than a “space bank”, Saletta and Orrman-Rossiter proposes a sort of “space resource fund” under the control of e.g., the World Bank, which would induce a market-based dynamics that does not oppress active scale-ups with unrewarding taxation schemes (Saletta, 2018). Their proposal mimics and is built on the observation of the Alaskan Permanent Fund, which from 1976 promotes transparency and fences off the political influence by re-investing and re-distributing in dividends the royalties obtained from resource extraction activities on their state’s soil (Bauer, 2013). Interestingly enough, here O’Brien observes how such structure derives from a libertarian ideal of an “intergenerational transfer of wealth and in the redistribution of public funds back to the private sector” (O'Brien, 1990).

What those preceding lines have helped depicting is an idyllic scenario where space mining represents an attainable and even desirable innovative industry capable of rejuvenating societal structure by disrupting the traditional resource supply chain and constraints. Also, with the purpose of further validating the comparison, the magnitude of capital required for initiating space mining belongs to a confrontable scale to the one associated with the Alaska pipeline (Kargel, 1996).

Before completing the industry review by adding dept on mission design alternatives, and therefore opening the real pandora’s vase on cost feasibility and efficiency, it is worth commenting in a brief paragraph some considerations over the environmental sustainability assessment, given the highlighted limitation on reputation and branding mentioned previously.

As a starting point, as no environmental policy on formal requirements and constraints has been enforced in order to standardise the reporting and documentation, the industry manifests itself in different approaches across the world. In concrete terms, the NASA uses an extraterrestrial adaptation of the Environmental Impact Assessment (EIA) which resonates with the culturally American-aligned higher degree of flexibility and open windows for interpretations. Furthermore, EIA concentrates the measurement and analysis in proximity of the site of influence, without accounting for the entire supply and value chains (Dallas J. A., 2020).

On the other side, the European Space Agency adopts the traditional life-cycle-assessment (LCA) to determine the footprint of each of their missions – individually – and projects – collectively – (ESA, 2016), proposing a more inclusive and holistic perspective that takes into account also the Earth-based launching site ad-hoc activities as well as the associated facilities.

As a clear consequence of this diversified scenario, it would shortly become necessary to provide a quantitative standardisation in environmental assessments, in response to the natural progression to a mature phase of the industry, and the consequent growth in the number of more concrete projects which have to be pondered in the “button rooms”. On this note, again Dallas et al. proposes a framework that consists of three main phases. Crucially, in each of those, the participation of all the stakeholders plays a key role in addressing the complex and nouvelle dynamics while ensuring the maintenance of a high level of integrity and transparency. The first two phases constitutes the foundation of environmental assessments, with the former including screening, scoping and consideration of alternatives. Here, pivotal is the role of the scoping process where major actions are juxtaposed with various potential direct and indirect consequences. The study identifies waste, dust – dangerous for the equipment as well (Park, 2008) – and contamination risks as the most frequent implications, with the last-mentioned mainly involved when considering microbial activity, which would be briefly addressed later throughout the dissertation. The second phase builds on the results of the preceding stage and focuses on evaluating the impacts and estimating potential actions to undertake with the aim of mitigating the negative externalities. This step denotes a coherent proactiveness and openness of perspective as it was for the last component of the first phase: consideration of alternatives. In both cases, the process opens the door to external inputs, avoiding the "tunnel vision" effect. The third step concludes the process with the bureaucratic formalities of a presentation statement, review, and revision. The authors also highlights how important is to already pre-establish a monitoring and auditing activity to ensure the proper execution of the plan (Dallas J. R., 2021).

1.2.3. Technical aspects in mission design

In bullet points, mining the sky is not only attainable but desirable, and water-associated sites seems to be the most attractive. Coherently, the moon finds itself representing undoubtedly a valuable candidate, - assumingly the preferred –, even though different argumentation might support alternative thesis. Legislation, ethical integration, and complementary research, despite being lagging behind in terms of concrete implementation, are consistently making substantial development and most importantly, the various stakeholders and involved entities are rowing in the same direction, paying particular intention on maintaining an inclusive perspective capable of bringing into the conversation crucial associated side questions. Before reviewing how financials are handled in the field, an ultimate degression on mining techniques is needed, as those are pivotal in understanding a bottom-up cost approach analysis.

Continuing on that note, in the traditional on-Earth mining industry it is observed a widespread adoption of a method firstly introduced thirty years ago and named after its developer, the Nicholas Mining method selection procedure (Nicholas, 1993). It uses an empirical approach reliant on historical data gathering, identifies some weighted key parameters and for each of those, assigns a valuational grade. Shortly after the official release, academia professionals from Canada's leading research institution – University of British Columbia – adjusted the Nicholas method's weighting system to accommodate and better reflect their national industry specifications and dynamics (Miller-Tait, 1995). The next step would then be to adopt a similar approach in developing a standardised method selection procedure for the space environment. Although it has to be considered how the absence of cases cuts out the opportunity of building a binary iterative series of comparisons (Just, 2020), meaningful studies could still be conducted relying on a more logic-based model, such as the one that Pelech et. al. have basted for the moon (Pelech T. M., 2021).

A fundamental contribution to this segment is brought by a contemporary and ongoing series of research competitions which enjoy being directly promoted by the NASA and have been rebranded in 2010 under the name of "Lunabotics Mining Competition". Due to the pioneering and inclusive approach undertaken with the aim of building a bridge with the private businesses, most of the studies discussed in those conference have not been peer-reviewed and therefore published yet by a leading scientific journal. Although, the annual conferences' proceedings are publicly available at www.isruinfo.com. Most of the researchers are focusing their concerns on addressing challenges related to the soil inherent characteristics, as the dust – already briefly mentioned in the paper and here defined as fine-grained with adhesive behaviour and electronical properties obtained by direct exposition to the solar wind –

may generate severe damages to the equipment. Equally significant is considering that drilling equipment would behave in a significantly different manner with the gravity on the lunar surface being 5/6 lower than the 9,8 m/s^2 experienceable on the Earth.

With the above in mind, determining an ideal excavation system represent an engineering unsolved challenge. In fact, studies have been conducted on discrete and continuous machines, with the former requiring interrupting the contact with the drilled surface among cuts in order to clear the cutting surface, and the latter benefitting of the simultaneous involvement of manifold surfaces in uninterrupted contact with the soil, performing multiple cuts and focusing on the next surface while clearing the first. Contemporarily, studies have differentiated also between partial and complete systems, referring to the absence – or presence – of in-built mobility equipment of any kind. The scientific contributors tends to agree on how continuous excavation machines seem preferable as those could compensate a lower energy required per cut – making the engine lighter – with a higher frequency rate of cuts (Agui, 2010). Coherently, research from Lunabotics tends to converge to a bucket ladder solution as the preferred choice (Mueller, 2011) and Just et al. are confirming the alternative's validity, reporting how capability of excavators, if considering the third generation developed in 2009, reaches 2400 kg/h, cutting at 15 cm and a light system of only 76 kgs that consumes less than 200W (Just, 2020).

By expanding the timeframe under analysis, other methods which are currently still away from reaching a relevant degree of technological readiness might be embedded into the discussion. A promising and particularly curious one comes from the sphere of innovations under analysis and development for the Mars exploration. In particular, a scientist from the bionanoscience department of the Dutch leading engineering institution, TU Delft, has published some promising research intercepting microorganisms and space engineering relying on their endurance to the harshest conditions. Building on antecedent studies on metal oxides metabolism systems as a mining technology (Weber, 2006) (Valdés, 2008) and

Navarrete's encouraging empirical studies on applicability to lunar regolith (Navarrete, 2013), Volger has found that the microorganism s. oneidensis is suitable for a scalable and sustainable iron production if supported through the implementation kinetic models and magnetite precipitation (Volger R. P., 2020). According to his findings, a payback within four years could be achieved only in a very limiting combination of the influencing parameters, thereby an imminent commercialisation of its theories – on mining, an analogously for his algae bioreactor and the astro-plant growth compartment (Volger R. T., 2020) – seems unprobeable.

To conclude the section, a final consideration on an ideal mineable resource is presented in a bridging review which accounts also for the financial efficiency as a determinant factor. Multiple studies confirms how lunar regolith has approximately 40% oxygen by weight (Anand, 2012) and therefore this abundancy might serve as a joining link to drive parallel industries into developing themselves around the exploitation of such resource – e.g., the propellants, or the oxygen refinery extraction. On this last note, two methods are currently mostly embedded in modelling for the moon, the carbo-thermal reduction (Gustafson, 2009) and the molten salt electrolysis (Schwandt, 2010), already introduced in the previous pages.

A couple of comparative study on the matter, presented at the Lunabotics 2022, supports how oxygen methods represent a clear opportunity to drive the growth of space exploration through mining. In synthesis, Sowers explains that given oxygen's great availability distribution on across the lunar surface, and the scalability provided by public-private-partnerships could lower the associated expenses far below the cost to bring such resource from Earth, which is estimated to be around $ 35.000,00 per kg, offering also relevant by-products in the extraction process which might be exploited in the process of establishing a permanent infrastructure on the satellite's soil (Sowers G. , 2022). Such analysis is supported by Metzger who studied the conditions to find lunar water economically competitive in LEO through a model that accounts the water extraction over water produced in the engine's lifecycle as a ratio, which sees the expenses associated to fabricating on lunar surface on the numerator, over the launch cost and other geophysical influential factors, below at the denominator. Further, the author tested such modelling in an inflated set of conditions, using as a starting point the so-called Aqua Factorem, a recently "miniaturised" version of mining expeditions which has as targets the short-term profitability, the possibility of implementation in the current socio-economic atmosphere and the availability of being scaled up in the future. In parametric terms, it considers a mass of h/w corresponding to 2500 kg, producing slightly less than 30.000,00 kg of water yearly with an assets' lifecycle of 5 years, and of course considering the sub-optimised and underdeveloped expensive transportation features currently disposable.

Proceeding towards the section end, it is valuable to report how mission designs aimed to extract oxygen from the Lunar regolith for in-situ utilisation with bucket wheels, as well as sublimation-based methods seem to be the preferred choices among the traditional mining methods. In formal terms, such pair of mission designs represents the theoretical case studies analysed in terms of cost modelling throughout the next chapter, during the empirical component of the dissertation.

Among the key characteristics of bucket-wheels, of particular relevance is the feature on the diameter, given on 2.0 m (Pelech T. M., 2019). The limited dimension is crucial as it is scaled to a size comparable to the one of a Martian or Lunar rover, therefore ensuring the feasibility of an orbital transportation. The most promising layout is named "Polaris" and has been developed by the Carnegie Mellon University. It presents some encouraging features. In fact, with a limited weight of 200 kg and an energy consumption of 0.45 W/kg, it is capable of processing 1050 kg of lunar regolith per hour (Skonieczny, 2016). Studies in lunar simulant on various bucket-wheel systems evidenced an average consumption of 0.12 W/kg (Hill, 2006).

Although the studies on electrolysis tends to be superior when compared to the bucket-wheel based extraction methods – as simply milling is required over quarrying to get started with the extraction –, it is still relevant for the purpose of the study to introduce both models when assessing the feasibility of a moon mining mission as the former presented design is challenged by the sustained external addition of reductants which is considered to be an energy intensive activity (Ehresmann, 2017).

For both methods it is important to reference that the bulk density of regolith falls within 1500 and 1790 kg/m^3 between 15 and 60 cm of depth (Schreiner, 2016). Those parameters are key to determine how much material could be extracted.

Deep diving on the techniques which does not require a heavy bucket wheel as a primary extraction tool, some numbers have been derived and could be, once again, referenced as targets for considering a mission successful. In a schematic way, different scenarios have been pondered using hydrogen reduction of ilmenite (HRI), carbothermal reduction of silicates and iron oxides, molten regolith electrolysis and molten salt electrolysis – FFC Cambridge Process –; each method provides yields at different level of optimality. The promising HRI reports a capability of extraction of 4 kg of oxygen each 100 kg of regolith (Jones, 2021). Among the various model prosed, the study presented below focuses on an experiment run by NASA's Carbothermal Reduction Demonstration (CaRD) team developed using Johnson Space Center’s Dirty Thermal Vacuum Chamber. Their efforts have proven the feasibility of extracting oxygen from the lunar regolith. "This technology has the potential to produce several times its own weight in oxygen per year on the lunar surface, which will enable a sustained human presence and lunar economy”; those are the words with which Aaron Paz – JSC Senior Engineer – has commented on the successful outcome of the breakthrough test (Dinner, 2023).

A summary study filtered through a 95% confidence interval Monte Carlo simulation, comprising also the availability of resources on the surface, reports how a range of adequate oxygen quantities would be produced at a mining rate between 30 and 65 kg/h (Cilliers, 2020). Such targets could be extended, for comparison purposes, also over the bucket-based models. Those numbers are relevant when considering what might be a target in terms of reaching a breakeven point. Switching to the revenue perspective in fact, given the required engineering transformations, it is estimated that there would be an initial yearly request on the moon surface of 1640 metric tons of propellant (Shishko R. S., 2019). There, for the purpose of an estimation, 78% of such mass is oxygen, given the traditional propulsion techniques and living aside more innovative approaches on the exploitation of hydrogen (Elon Musk, 12 August 2021). Such number represent the potential market size for a mining programme. On top of that, it is valuable to recognise that while water has also other implementations, the by-product proceeds from the extraction might be employed in the creation of other valuable assets in building lunar infrastructure, therefore the revenue stream is not meant to be limited to the propellant components themselves. Such additional benefits act as a buffer in securing some space for additional costs and general uncertainties in the estimation process.

1.3. A gap in space cost accounting and prediction

Although the preceding representation suggest the already reiterated convenience of conveying efforts towards space industrial mining, it has to be highlighted once again how such studies have not been peer-reviewed yet. This element, when contextualised in the industrial historical untrustworthiness of cost estimations – maybe even driven by a “censoring culture” on the real expenses (Prince, 2002) –, indicates how further investigation should be dedicated towards the project-specific financial planning and analysis components.

As a starting point, the previous chapters reports more than a couple of times how space mining, and by generalising also most of the current topics in the new space economy, are associated with the concept of disruptive innovation. Whereas the term is nowadays consistently present in most of the studies referring to any tech-driven project, its definition is often misinterpreted and tailored to enhance the branding of the innovation proposed by the new venture and its founders (Mochari, 2015). Re-tackling the formal definition, it has to be reported how the literature on the topic traces back to the end of last century. At that time, Clayton Christensen firstly introduced the concept by defining it as the sustained process of a smaller player capable of challenging large incumbents and consistently aiming to climb the market by targeting first the niches standing out of the spotlight. Those bordering segments are served with cost-efficient solutions which progressively spreads over the mainstream market (Bower, 1995). A more recent review from 2015, points out how when considering the scenario of new-market footholds, those labelled as disrupters distinguish themselves by their capability of creating a market where none existed (Christensen C. M., 2015).

Given the nature of the sector, any new product or service that emerges is innovation driven. Every satellite or rocket is safer, more environmentally friendly, or delivers data and services which are at least marginally improved when compared to the ones provided by the satellites previously produced. Thus, any reference to disruptive innovation has to be pondered carefully. A concept that helps clarifying and distinguishing disruption from any other innovation is brought by one of its crucial features: the continuity (Christensen C. M., 2015). Being rather a process than a single sparkle, a sound assessment to label a technological advancement as disruptive could not be performed beforehand. In other words, disruptive innovation needs to be proven by the passing of time. Nevertheless, what is clearly evident is how the availability of resources such as propellant directly extracted in orbit, completely shifts the business model under which most space ventures operate. In fact, it solves the optimisation loop on which most of launch missions are stuck. In simple terms, delivery companies aims to have as many items on their rockets as possible, in order to achieve scale and spread the fixed costs. On the other side, the weight of the payload is directly proportional to the amount of propellant required, which of course has some relevant mass too. By considering now a parallelism with the on-the-road mobility, what currently happens in the space industry is that every “car” departures for its journey not only with the tank but also the trunk filled with fuel. Space mining opens to the opportunity of having “gas stations”, dramatically changing the approach, namely, the business model, of any orbital and deep-space mission. The above depicted aspects is what validates the second component in Christensen’s roadmap (Christensen M. C., 2006), clearly removing any window for analogies with sustained and product-oriented innovation – historically dominated by large players (Christensen C. M., 1997) – and solidifying space mining positioning as an industry-relevant disruption on its business model. To further support the preceding consideration, the dynamic of disruption is enhanced here as new entrants can navigate an innovative trajectory by developing the new business model, while existing players’ weakness is evident when growth has to be achieved through strategic change over technological change (Rosenbloom, 1994).

Given the multitude of implications that the availability of resources directly in orbit can provide as a waterfall over the entire space industry, it has to be recognised how space mining has the potential of fostering the already forecasted total market growth, mirroring what has always been happening in every industry where a disruption has occurred (Gilbert, 2003).

More authors contributes by providing further theoretical frameworks that validate the positioning of such technological progress as a disruption. Space mining in fact presents a drive which gains strength from the supply side of the market, falling therefore into the bucket of innovations labelled as radical, where the offer proposed constitutes something which is not currently present in the market. The supply push is evident and widespread across the entire space industry, as its opening to private investors along with the decreasing launching costs have produced a florid proliferation of innovative new entrants which currently navigates in a truly fluid and uncertain dynamic environment which is common in the first years of expansion of supply-push processes (Utterback, 1994), (Klepper, 2000).

Given the scale, and the impact over the overall market of the technologies revolving around the space mining, of crucial relevance is the relational aspect between any individual player within the industry. It has been studied how when a disruption is in place, the interactions initially assume the shapes of a competition with the ongoing structures and then those evolve in a collaborative environment fertile to accommodate the commercialisation of the innovation (Marx, 2014). To promote such constructive dialogue, what is crucial is the establishment of a common understanding on the countable elements of the projects, which starts from a clear definition and estimation of the cost structure.

At this regard, the entire subject of cost accounting has evolved throughout the years to properly provide the right tracking and forecasting tools tailored to the perpetual evolution of the industries and their operating models. Nowadays every accounting book reports some concepts which are employed with great success in most of the sectors. Some of those are simply retrospective, such as the Activity Based Costing which focuses on the cost drivers and the respective allocation (Gosselin, 2006), while others proposes a more proactive approach by providing insights and guidance on how to increase the efficiency and effectiveness of the business, as it is the case for the Just-in-Time theory for inventory-intensive industries (Sugimori, 1977).

What is somehow lagging behind is the cost estimation component of the matter. A great summary on the topic is proposed by Drury, who categorises in a few buckets the methods pertaining to the forecasting activity (Drury, 2018). The first approach is what usually is referred to as engineering bottom-up estimation, and it relies on a technical measurement-oriented review of the input and output relationships during the process. Such iterations need to be clearly distinguishable and defined in order to truly exploit such method. Given its nature, in being item-oriented, the capability of capturing the fixed components of the cost structure is of course less accurate than the one dedicated to the variable one (Roy, 2003). By accommodating this concern, it has to be recognised how the reliability of such tool is limited to a narrowly constrained relevance range. A second tool is known as inspection of the accounts. As evident from the title, it includes a thorough financial review of the statement accounts, focused on classifying costs based on their behaviours. Such study meet some challenges in unstable and dynamic industries, especially considering its exposure to personal judgement and biases in categorising the various elements. Further, some quantitative approaches are considered. A simple tool is represented by the high-low method, which compares historical peaks and valleys to generalise an average cost expectation. A bridge to a more computational oriented techniques, is offered by the scattergraph method, which proposes the establishment of a linear relationship between the activity levels and the associated costs. Whereas it could be argued that most variable costs could be linearly approximated, the impact of overheads needs to be accounted for in shaping the relationship between costs and outputs. Moreover, even unbiasing the slope estimation could be challenging. Generally, the studies suggest its computation through a least-squares method based on a linear regression of historical inputs, which therefore limits the method's scope of applicability within the range of stable and repetitive industries where no disruption capable of changing the internal balances is expected.

A more in-depth perspective is brought by Dai et al., who propose an initial split between qualitative and quantitative tools (Dai, 2006). Starting from the last mentioned, first it is worth considering the use of parameters as proposed by Cavalieri in his study on unit manufacturing costs (Cavalieri, 2004). Further, of greatest interest result to be the analytical techniques. Those could follow the 1) operation-based approach, which simply relies on what has been presented previously as a general engineering approach, focusing solely on a pre-established and finalised design (Gupta S. K.-C., 1994). Alternatively, the 2) breakdown approach proposes a simple sum of the individual cost elements (Clark, 1997), and once again sees its applicability limited to the final stages. Third, the 3) tolerance-based cost model builds a computing tool involving minimum expenses, ideal outcome quality, and an optimised speed of elaboration (Singh, 2002). Whereas it has some interesting features as a model, it heavily relies on the expertise and the solidity of the industry.

The above depicted quantitative techniques, as already mentioned, are mirrored on the other side by qualitative tools on cost estimation. Those could be further categorised once again in two buckets, with intuitive studies on one hand and the analogical ones on the other. Starting from the former, a reliance over past experiences is clearly evident. In this first group belongs the case-based reasoning, which aims to adapt past models to the novel environment (Rehman, 1998). As it is evident from Balarman et al.'s report, spreading such approach among heterogeneous industries could be done effectively as long as the divergence of the new project is limited and constrained to certain areas when confronted with the benchmarks (Balarman, 1998). Further, there are the decision support systems, where a comparative and structured tool is used to filter design alternatives to select the best project outlook from cost efficiency perspective. Here, expert judgement plays a crucial role in ensuring a comprehensive and attainable ponderation (Kingsman, 1997). On the latter side, analogical cost estimation techniques are explored through regression analysis models (Pahl, 1996), and improved by back-propagation neural-network models (Shtub, 1993). Those once again rely on preceding experience with similar project; therefore the benchmarking is biased on previous case studies.

To properly sum up, while the cost accounting literature is progressively increasing the involvement of quantitative models in its arsenal of techniques, it has to be recognised how those still mostly rely on historical data as the primary source. Therefore, what is missing is a true leap to produce reliable forecasts in scenarios of disruption. As properly reported by Dai, the product cost estimation techniques mentioned above shares some major challenges either in their intrinsic complexity, or in the data gathering, frequently resulting in low-efficiency outcomes and therefore their direct and dry applicability in the early phases of the design cycle is weak (Dai, 2006). As an end note, the granularity and exhaustivity provided by the quantitative methods should be directed on emphasising the qualitative observations, as those are generally readily available straight in the first exploratory phases.

Refocusing now on the space field, Keller et. al. comments how the last half-century consistent scheme of underestimations within the industry has been driven by the underlying structure of the models which have been built on similar parametric regressive equations to determine the drivers (Keller, 2014). The attempts of embedding non-explanatory complexity through analogical reasonings and engineering advisory were predominantly in vain (Smart, 2006). Among the various models developed to improve the status quo throughout the years, some has been discarded due to their overreliance on dataset characterised by complex derivability due to their nature of being detail-intense, and therefore preventing the model to give pivotal insights in a timely manner – e.g., P-Beat and Process-Based by Boeing and NASA who tried to embed a dynamic resembling activity based costing from traditional accounting theory –, while other such as QUICKCOST have been discarded as collateral dynamics such as culture, organisational scale, and willingness to risk are not captured (Hamaker, 2010), whereas their role is recognised to be of great relevance (Wertz, 1996).

It is worth noting how some structural studies have been conducted in order to improve the equations, for example by Collopy et al. who by building on Prince's publications, proved how is worth shifting from the paradigm of correlation between weight – or more recently, volume – and cost, deeply anchored in the scalability theories. They instead propose to adopt the surface areas as a key linear counterpart to engage with costs, as according to their study, cost fits with a power multiplier of factor 2,2, which is closer to a bi-dimensional approximation as opposed to the three-dimensional volumetric interpretation (Collopy, 2005).

Three years later, a report by a lecturer from the International Space University proposes the "5C approach" as a study that might improve the occurrence of cost overruns. The model starts on building a reliable, and therefore engineered, cost estimation, preferring a parametric costing over the other top-down approaches reliant to imperfect analogies, and the bottom-up approach known as grassroots costing which as it was for other models, builds on a timely-inefficient granularity of details. As a second stage, it carefully addresses the life-cycle costs of the project, which is on a trend of growing relevancy – it doubled its contribution to the total costs between Apollo and Shuttle programs -. Further, a step is dedicated studying the contractual dimension, which holds a crucial role in an industry where the role assignment between public and private entities is adopting ad-hoc shapes at each stance. There, the author is mostly concerned about who is going to bear the cost increase, distinguishing primarily between cost-reimbursement contracts or fixed-price contracts, allowing in both circumstances the existence of nuances involving incentives and percentage contributions. As a second-last point, risk management is brought into the discussion, and requires as in the traditional risk management theory the implementation of mapping, adjustments, and hedging techniques over risks epi-centred in various departments – from the engineering-associated failures or risks to the managerial, financial, and legal compliancy dimensions. Lastly, recognition and credit are given to the transparency and the role of collaborative communication as an insurance mechanism (Peeters, 2008).

Another iterative approach is proposed by NASA researchers, building a different step pathway primarily intentioned to investigate the complexity of new projects. Again, the process starts with a clear proposal formulation aimed to facilitate the identification of cost drivers in the next stage.

There, a major effort has been shown and the produced matrix could be used as a reference for further cost-driver related studies. In synthesis, a first group of driver links to the launch operations – where a major cost saving might be obtained by preferring solar sails over traditional launchers, for light mass projects (Vergaaij, 2021) –, the flight systems and the mission operations; on the side, environmental, technology advancement and external factors are accounted. Subsequently, indexes are used to rank and classify the relative influence of each driver and further, in the fourth step, experts' interviews and historical data are gathered. The fifth point analyses discrepancies between the two estimations and aims to deduct a proper estimation associating a correct uncertainty slack (Peterson, 2005).

Notwithstanding the relevance of such studies, again Keller in more recent research participated by the same Collopy proposes a discording view, stating that about half of the cost positive delta is to be treated as an endogenous phenomenon similarly experienced in the aircraft parent industry, as inherent untreatable complexity originates unpredictability, and ultimately suggesting a cost controlling approach over a non-reparable predicting system (Keller, 2014). Such concerns finds support especially when estimation involves the New Space Economy and therefore disruptive innovation, which is reported to be poorly predicted by modelling on historically-build parametric functions (Rush, 2001).

Focusing specifically space mining, numerous studies have been conducted based on the concept of net present value, in order to account for the revenue-generating-side of the projectivity, targeting high internal rate of to match the high inherent risk profile, and aiming to capture the time-cost-of-money as it “puts an upper limit on the allowable mining project cycle time” (Sonter, The technical and economic feasibility of mining the near-earth asteroids, 1997, p. 637). Alternative traditional models such as the mass pay back ratio, have already been discarded long ago (Oxnevad, An Investment Analysis Model for Space Mining Ventures, 1991), considering NPVs to be methods of superior order of quality. The internal rate of return for those heavily capital-intensive missions is estimated to be at least between 20% (Andrews, 2015) and 30% (Sonter, 1997). According to those studies, a particular emphasis and relevance are associated to some key indicators such as the target locations, the materials aimed to be reclaimed, the propulsion and power sources, the engines and mining machineries, the degree of autonomy and the project scale. This approach seems superior to the NPV developed by Hein where all cost elements are compared on a unitary level (per kg) as the vast majority of the drivers have a scaled cost structure which changes in chunks and is not sensitive to marginal volume variances (Hein, A techno-economic analysis of asteroid mining, 2020).

As a consequence, with the rejuvenate confirmation stated on poor linkage between cost and weight, those would not be explored further. Another tool know as Net Smelter Return, provided by the other parent industry, earth mining, has not been studied in terms of adaptation to the space environment and therefore could not be employed within the scope of the dissertation (Pelech T. M., 2019).

Enthusiastically, numerous studies have been “NPV-approved”, in the sense that the findings obtained through such modelling encourages the further development of the industry, not only in absolute terms, but most importantly in comparison with a proven superiority over the alternative of providing such resources from Earth when the matter concerned is on water and therefore oxygen (Colvin, 2020).

Despite the general positiveness and coherence among the NPV studies, the cost component determination is still left in an alone of inaccuracy, which, whereas it consistently delivers a homogeneous overall contribution to the study of profitability, it is still far from driving a reliable product-costing analysis to be embedded in financial planning and budgeting.

On this matter, authors such as Peterson et al. and Probst et al. have made a great work of employing more dynamic and modern statistical tools capable of inspiring further research even before having its predictive potential proven. In particular, both built a semi-quantitative model to develop a relative cost of a mission through a mixture of indices and experts' iterative feedbacks. While the former concludes relying again on parametric equations (Peterson, 2005), the latter implements the Delphi technique on multiple iterative interviews and further the structural equation modelling to study "complex causal correlations of several non-observable (latent) characteristics" (Probst, 2020, p. 450).

A different approach has been developed by researchers from Bocconi University in Milan, who have chosen to adopt a wider lens to capture a panoramic view and therefore considering also the explorative preliminary phases in two probabilistic parameters, once for the resource availability and the other for the technology advancement. Also, an interesting point is that the model they developed has a specific adaptation associated with the nature of financing, for example for the public-private partnership, or for exclusively private projects. Of inspiration there is their decision to model the parameters basing their approximations on data referred to earth mines to compensate for the lack of historicity, as well as considering high-tech and venture capital on studying what kind of profitability would be desirable and subsequently accommodating an Internal Rate of Return of "just" 20%. The modelling of the scissor of outcomes has been approached through a Monte Carlo simulation, leading to a picture where private-public collaboration probably lead to a successful moon mining for hydrogen and oxygen – in agreement with the rest of the literature reviewed (Sommariva, 2020).

As already outlined by making particular reference to the work of Keller et al., the intrinsic complexity of disruptive innovation is currently dissatisfied by the traditional cost estimation models, uncapable of untangling uncertainties to ensure a prolific and meaningful estimations. By recalling what was said on different approaches to cost estimations, Trivailo et al. proposes a review of such tools – considering parametric, bottom-up and comparative analysis –, highlighting how the relevance of the speculative assessment is inversely proportional to the stage of the mission: in other words, the value added and therefore the reliance on financial estimation is greater in those initial phases of fundraising and project management, where the availability of countable elements suitable for a cost engineering review is extremely limited (Trivailo, 2012). In particular, the same paper proposes also how expert judgment estimations (EJ) might result particularly valuable in those circumstances where the availability of historical relevance is not available. It also suggest how the statistical scalability has the potential of mitigating the major weakness at which EJ is subjected, which of course relates to the personal biases of the interviewees. Among the various alternatives, Trivailo supports in particular the adoption of the Analytic Hierarchy Process (AHP) by Saaty (Saaty, 1980) and the Delphi method, favouring the former as it structures the interview outcome in a binomial series of dichotomies which smoothens the comparative pathway towards a decision. Similarly to other "ranking" methods such as the TOPSIS study or the Conjoint Analysis, AHP provides a valuable and statistically reliable explanation of the contribution relevance of each element, here, cost drivers. On the other side, if pairwise comparison elements are picked to represent certain extreme monetary values for a specific cost element, it also offers an interesting perspective on gathering together manifold experts' opinions in a numerical coefficient, indicating at which range might a reliable prediction lie and therefore driving a semi-cost engineered estimation which integrates the benefits of an EJ study.

Coherently, here is where this study belongs: in harmoniously combining various research techniques – qualitative and quantitative –, by complementarily balancing strengths and weaknesses and proposing a comprehensive analysis on the financial feasibility of moon mining already in its exploratory phases, where the alignment in economic terms serves as a ground base to develop flourishing agreements.

2. Financial feasibility of space mining: methods and findings

As a starting point, iterative and interactive models require a particular degree or rigor in order to be successful. The case-study of a space mining mission cost estimation model which is developed throughout the dissertation could be broken down in different stages, whose outcomes interlaces.

The first step, which could be referred to as a desk research – or a traditional technical literature review – starts with a background data gathering on cost drivers and their potential ranges, as well as a study on numerical parameters derived by commonalities with other missions – e.g., the cost to deliver payload to the Moon relying on a large provider in the astro-transportation industry should not significantly differ on the basis of the items transported –. This phase softly relies on an analogical reasoning by incorporating values from precedent missions. Whereas some elements are left on the side playing the role of valuable information buckets for further stages of the study, the main proceeds are condensed into a preliminary definition of cost drivers for the two mission designs.

It is worth noting that given the abductive structure of the study, whereas most of the desk research is condensed in the previous chapter, some matters have been studied in-depth on an ad-hoc basis throughout the rest of the study.

The second phase of the study is constituted by two subsequent components, brought together by their common reliance on direct external inputs, namely, interviews. The first interaction takes a more open interview structure involving solely a close group of experts – in the range of 5 to 10 interviewees –, where the initially produced cost driver specific and mission specific features are carefully pondered and improved. Further, the phase proceeds by drafting the dichotomic pairs and proposing a Likert-formatted interview involving a large group of participants with background foundations in the industry. Here, each reviewed cost driver is proposed, along with its referenced value range, for both mission designs. The relevance of this closed interviews has a double nature: on one side, it allows the development of a statistical model while on the other it provides numerical inputs for the finalisation of the study. Such interactions are explained below.

As a last component, analytical tools are embedded to clean the data and provide a consistent prediction on the overall mission economic outlay. In this segment, simple methods are involved in answering the question of which mission design could be considered as "superior" and for which reasons according to the experts. On the other side, statistical tools, integrated in the Partial Least Squares Structural Equation Modelling, study how the cost drivers interact, relying on the Likert format of the surveyed data. The derived structural model serves as a logical baseline for a computational equation which will embed the second component of the surveyed data, the countable inputs.

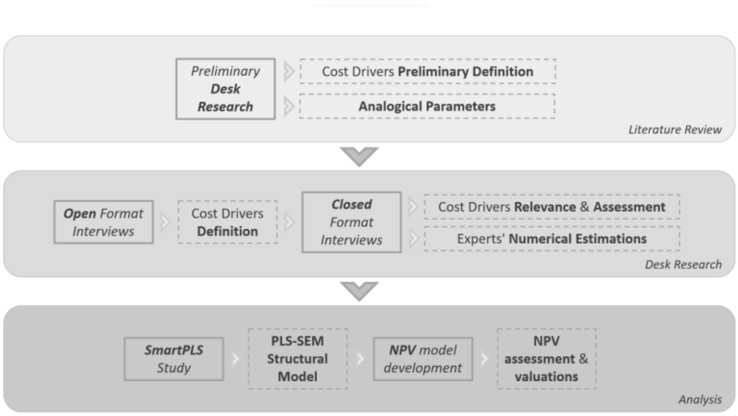

FIGURE 1 - STRUCTURE OF THE RESEARCH METHOD

To clarify, the depicted structure falls in the bucket of the so-called mixed methods, where both qualitative and quantitative approaches are combined with the purpose of enhancing reliability through triangulation and aiming for complementarity among different sources and elaborations. Further, it has to be highlighted how such variegate approach provides iterative benefits in terms of 1) initiation, by providing pitfalls that the other branch of the study can investigate; 2) development, through the cross elaboration of data; and 3) expansion, in terms of grasping elements spotted in one particular niche and broadening them by finding the room for addressment in the rest of the research tools spectrum (Greene, 1989).

2.1. Interviews

Experts' involvement at this stage takes the form of double nature. On one side, their inputs validate and ensure the relevance of the cost drivers deducted from the literature, comprising the respective value range. Complementarily, a brainstorm activity ran through open question ensures that no crucial parameters are left outside.

2.1.1. First round

The Delphi Technique

The Delphi technique introduced above both as a complementary or alternative tool to the AHP, offers interesting contribution to qualitative evaluation studies. Whereas AHP provides a superior contribution on the ranking of elements given its pairwise nature, Delphi opens to scenarios where there is a limited understanding of the matter in study (Adler, 1996). Delphi in its traditional form, uses the statistical elaboration of data in a later stage, and ensures the anonymity of the interviewed individuals, and synergises with the iterative approach with subsequent rounds that benefits, as reported above, the Likert study (Skulmoski, 2002). Differently from the traditional Delphi where either a real time or a delayed repeated interaction with two groups happens, here each subgroup has to be interviewed once, prioritising an initial distinction in two phases, where the first happen to be explorative and the second investigative. A larger sample size is dedicated to the second sphere as it could be broken down into subgroups to address disagreements and critical points.

As a point of conjunction, a publication by Norman C. Dalkey reports how the Delphi technique might be used in data interpretation. Below there is a summarisation of the approach. He firstly defines $I = \{ I_i \}$ as the referenced population, $E = \{ E_j \}$ as the – discrete or continuous – event space and $R = \{ R_{ij} \}$ as the response space, namely a collection of the individuals' responses for each event studied.

Alternatives in the event space that will manifest are represented as P = P { (E_j) }. Delphi is an aggregate study technique which studies the group response G_j on each object, which is given as a process of interconnections between the aforementioned elements – G = G [I, E, R] –. The study follows presenting some quantitative evidence supporting how EJ could be validly treated as a substitute for direct knowledge when situations with low empirical sources such as the one under analysis.

Interpretation of response could be built relying on the theory of errors derived from the physics laboratories on measurements. As a starting point, the median is used as a proxy, relying on its correspondence to the geometric mean of a lognormal distribution, which generally represents the form of the responses. The simple average of replies showcases a larger error (Aitchison, 1957). Further, the inevitable error could still be predicted on average as it plots as the linear function of the standard deviation (Dalkey, 1965).

The crucial contribution provided by the Delphi method is defined in supporting the creation of an unbiased and individual key cost driver list, and thereafter pondering each ones' contribution to the project cost and in turn feasibility. An initial interview-based interaction is conducted with a limited list of participants, whose profiles are reported below. Each interviewee is presented with a schematic representation of the previous chapters, with an enumeration of the cost drivers that have been derived from the literature, accompanied by a description and a Likert-friendly evaluation proposal. Starting from that point, the first round asks the experts to rate the relevancy of each cost driver, and freely add potential additional key elements. Redundancies are to be verified and cross-checked.

Cost Drivers, further observation

Deep diving into cost drivers, those have been discerned between the one impacting the revenue stream – namely, addressing the value of oxygen and other outcome products on the lunar surface –, and those referring to the production, from the launch to the mining engines. Among the latter, the analysis is narrowed down to the extraction mission, therefore it evaluates solely a determined segment of the value chain, without taking into account the production of propellants from the proceeds and infrastructures by refining the outcomes; it also excludes the territorial resource scouting, which is already in place, and it is progressing independently, providing publicly available data through research publications.

An interesting contribution to the research is brought by a list of coefficients presented by NASA during a lecture, where the speaker Lisa Guerra presents some derived and rounded values for different kind of challenges that might be faced by innovative space ventures, all referring to the technological readiness. In a schematic way, the below table summarize such factors which are embedded in further calculations (Sarsfield, 1998):

Complexity Factor	*Description*
0.2	System is "off the shelf"; minor modification
0.4	System's basic design exists; few technical issues; 20% new design and development
0.7	System's design is similar to an existing design; some technical issues (20%); 80% new design and development
1.0	System requires new design, development, and qualification; some technology development needed
1.3	System requires new design, development, and qualification; significant technology development with multiple contractors
1.7	System requires new design, development, and qualification; major technology development
2.0	System requires new design, development, and qualification; major technology development; crash schedule

TABLE 1 - COMPLEXITY FACTORS (SARSFIELD, 1998)

The same study offers also an historically built pie-chart approach to estimate the other cost components given some initial elements. By using the EJ approach to derive the trickiest components, it is fairly reliable to simply embed those into the pie-chart to derive some more standardised and stable elements, as the cost of the ground system and the software expenses. The below breakdown will be used as a reference.

Cost Category	*Contribution*
Launch vehicle	21%
LV integration	0.6%
Operations	8%
Ground system	2.6%
Science	1.7%
Management	4.6%
Planning and mission design	3.3%
Structural	6.6%
Thermal	0.5%
ACS	7.1%
C&DH	4.3%
EPS	5%
RF Comm	3.8%
Propulsion	3.9%
Software	1.9%
Harness	0.5%
GSE	1.1%
GFE	1%
System engineering	1.6%
Product assurance	1.1%
Parts	2.4%
Contamination	0.1%
Integration and test	3.2%
Instruments	14.3%

TABLE 2 - PARAMETRIC TABLE (SARSFIELD, 1998)

The first round and its outcomes

The set of pre-determined and literature-derived crucial cost drivers has been proposed individually and anonymously to a group of eight experts from the specific niche of space mining, associated with research institutions on space resources such as the Colorado School of Mines and new ventures engaging in the extraction of precious resources in orbit. Five of them are engineers with different specialisation, such as mining, thermomechanics, propulsion, AIT – namely, assembly, integration, and test of spacecrafts – and systems, while the remaining three specialists are a PhD candidate researcher, a mission specialist, and a spacecraft architect. Their insights have been pondered, compared, and ultimately integrated into the original list of cost drivers, crucially improving the survey structure for the subsequent phase of the study. In practical terms, the first step serves to validate the relevance of the selected key indicators and potentially leads to the inclusion of new ones as well as the removal of some redundant or less relevant indicators. Furthermore, the ranges of the numerical inputs associated with each cost driver have been reviewed and adjusted.

As a result, fourteen elements have been presented to the next stage compared to the eighteen initially proposed. The driver “Human operations in space” has been removed, as the interviewee have highlighted how manned spaceflight operation would require a fundamental restructuring of the operations design leading toward major adaptations whose implications are too complex to embed in a single modelling effort. Further, “Operational continuation” has been left out given its straight-line correlation with the energy source: in other words, as both mission designs rely on the support of nuclear energy, there is no constraint from the external conditions to cyclically interrupt the operations, as it would have been the case for engines powered by solar panels. Finally, both “On-board software complexity” and “GNC advancement” have been included in the first driver, “Technological readiness”, as those would not provide any individual consequences and grouping them together will also simultaneously fit better the conceptual framework presented in the previous pages on the complexity coefficients. Other minor adjustments have been adopted to increase, reduce, or shift some of the associated ranges, without any structural implications to the pre-proposed values. Here below it follows a comprehensive review of the selected cost drivers.

	Cost Driver	*Lower limit*	*Upper limit*	*Description*
1	Technological Readiness	Minor adjustments	Major R&D efforts	Considering a time horizon within 2030, define the technological readiness of the mission instrumentation
2	Equipment costs	Below $ 2M	Above $ 25M	Define the production costs of the mining equipment
3	Core equipment mass	Below 100kg	Above 500kg	Define the mining engine mass to be delivered on the Moon
4	Support equipment mass	Below 100kg	Above 500kg	Define the support payload mass to be delivered on the Moon, comprising battery, board computer etc.
6	Mission length	Below 1 years	Above 7 years	Define the mission duration, considering battery lifetime
7	Operational Efficiency	500 kg/h	1500 kg/h	Define the speed of regolith mining
8	Conversion Efficiency	Below 1% yield	About 10.5% yield	Define the capability of extracting oxygen from regolith
10	Human operations on ground	A small team	Large teams	Define the involvement of human operation to ensure mission success
11	In Situ resource demand	Below 800 metric tons	Above 1400 metric tons	Define the demand of oxygen for propellants per year on the lunar surface
12	Energy usage	0.20 W/kg	0.60 W/kg	Define the amount of Watt/kg would be required to extract the targeted amount
13	Battery lifetime	Standard	Major advancements	Define the level of advance of the FDIR software required (note the battery is nuclear)
14	Payload delivery costs	3500 $/kg	10000 $/kg	Define the forecasted cost per payload kg to deliver on the Lunar surface
15	Mining system complexity	Rare and solvable	Probable and mission failure-determinant	Define the incidence probability of adverse misfortunes (e.g., associated with dust damages)
16	Reprocessing complexity	Limited	Complex	Define the amount of workload needed to convert the extracted raw material into usable propellent component

TABLE 3 - COST DRIVERS: VALUE RANGES AND DEFINITIONS

2.1.2. Second Round

Likert Scales

As it is evident from the above table, the data are already structured in a Likert-friendly format, but it might be worth briefly reviewing such method. The Likert scale is a powerful tool in the sphere of psychometrics, as it captures the strength of – in this case – experts, considering their perspectives on each element, and therefore it jointly delivers patterns highlighting peaks and valleys (Likert, 1932). The scale welcomes numerical parameters, in terms of real values, as well as rank-ordered or continuous intervals of likelihood. A mixture of those approaches is also accepted to better suit each point (Dakley, 1969). Further, it is interesting to consider that the practice of "repolling", and changing the interviewees population, it is proven to magnify the study quality by reducing the uncertainties (Hartman, 1995). Minor adjustments between different interview phases are accepted to optimise the contribution of the participants. The number of interview-runs has to be adapted to the response rate. Subsequent stages are unlocked as the previous stage reaches the number of 50 respondents. On this matter, the most competent interviewees should be considered first as it could enable the embedment of their expertise as a guidance in correcting the ranges for the further stages, resulting in a constraining effect on the impact of outliers (Brockhoff, 1975) (Rohrbaugh, 1979). As a last guideline on the Likert phase of the interviews, the number of points is optimised at 7, reducible at 6 in case there is the willingness of avoiding impartial replies (Taherdoost, 2019).

Crucially is also to briefly introduce here a preliminary analytical tool on data interpretation. A standard Likert scale assumes the homogeneous weighting of the parameters. When trying to address and predict a cut-off point, the weightage is correlated to the Discrimination Index (Spearman's Correlation Coefficient) and Internal Reliability or Cronbach's Alpha. The Discrimination Index is the Spearman's correlation coefficient between responses to a particular item and scores on the total test (Barua, 2013).

The weightage is given as the factor of the observed item score multiplied by the weight assigned by the expert, the discrimination index, and the internal reliability. The cut-off then is defined as a weighted sum of each individual correlation factor multiplied by its median of individual raw score at which is subtracted the 25th percentile of Interquartile Range (IQR) (Cronbach, 1951) (Barua, 2013).

Concretising, the study reached the number of 50 interviewees. The entire experiment's population is built of employees from the space sector, with the majority being involved in Moon-related projects. Their affiliation ranges from consulting companies such as Euroconsult, a boutique specialised solely on space missions, to agency representatives from both ESA and NASA, and of course exponents from industrial manufacturer companies. Their contribution has been canalised through a Likert format interview structure, with unbiased questions asking them to rate both mission designs – the one based on thermal mining as well as the bucket wheel design – which have been previously introduced throughout the paper. Having posed the same sequence of interrogations in a pairwise format intrinsically induces a comparison among the two available designs, producing a discernible evaluation of the comparable optimality.

An integral part of the descriptive statistics of the original data is reported in the Appendix 1.

2.2. The analysis

An initial and independent assessment on the preferred mission design is conducted by simply comparing the median averages per cost driver among the two alternatives and collecting them together. The concept consistently showing better results – to exemplify, having the model "A" scoring perpetually in the lower-end values for the “energy supply” cost driver while “B” results for the same indicator revolves around the middle, suggest how that specific design A is valued as more efficient on the power demand side as opposed to its counterpart; diffused superiority of one model over the other on critical areas not only provides direction on focal improvement points, it also suggest – after some weighting – which mission design is on average preferred. A relevant feature of such method is how it does not require a direct answer: in other words, the interviewee has never be asked to express explicitly which model is in his or her view “superior”, leaving room for indistinguishable and unpolarised answers.

Some interesting and preliminary conclusions could be drawn just by looking at the descriptive statistics of the surveyed data. Whereas the two designs share some major similarities in their cost structure as it is also anticipated in the literature, there is an interesting – even though marginal – evidence on considering the bucket wheel a more fragile and unreliable method compared to its counterpart, which might be associated with the anticipated dust-related damaging threats that might be produced by greater movements on the volatile moon regolith.

2.2.1. Partial Least Squares Structural Equation Modelling

The interpretation of the evidence deduced from the Likert-based interview session are to be firstly examined through cause-effect study to ascertain the individual influence of each independent cost driver to the overall mission financial feasibility. Given the non-normality distribution of the surveyed data points in conjunction with the absence of historical reliance, partial least squares structural equation modelling emerges as the optimal statistical tool to support the analysis (Nitzl, 2016). As an alternative, while it might be argued how Covariance-Based Structural Equation Modelling could be a strong substitute, a recent paper confronting the two has evidenced how the latter performs better in hypothesis confirmation while PLS-SEM provides stronger results in prediction studies (Dash, 2021). Another argument which could be actually relevant in the expansion of the study scope and magnitude is brought by another popular method: Structural Equation Modelling (SEM) with maximum likelihood estimation (ML) is a comparable tool which still relies on bootstrap re-sampling even though solely under conditions in violation of the distributional assumptions. PLS-SEM is once again favoured as it showcases a stronger performance with limited and narrowed data sets, such as the one achievable within the scope of this study. In this sense a broader research project with multiple rounds would produce more accurate results also by implementing PLS-ML as the primary tool (Sharma, 2013). As PLS-SEM results to be the preferred analytical tool, *SmartPLS* is the software used to conduct the computations.

Deep-diving into PLS-SEM constitution, it is worth to discern a pair of iterative components where the first bridges the data gathered with each cost driver, while the structural one instead addresses the causality (Garson, 2016). Progressively, cost driver count slims down aiming to ensure the cross-unbiasedness displayed as pairwise correlation.

Targeting now the analysis, a structural model for the PLS-SEM has been developed by iteratively proceeding in consistently testing the validity and the reliability of the model itself, which is valid for both missions' cost estimation.

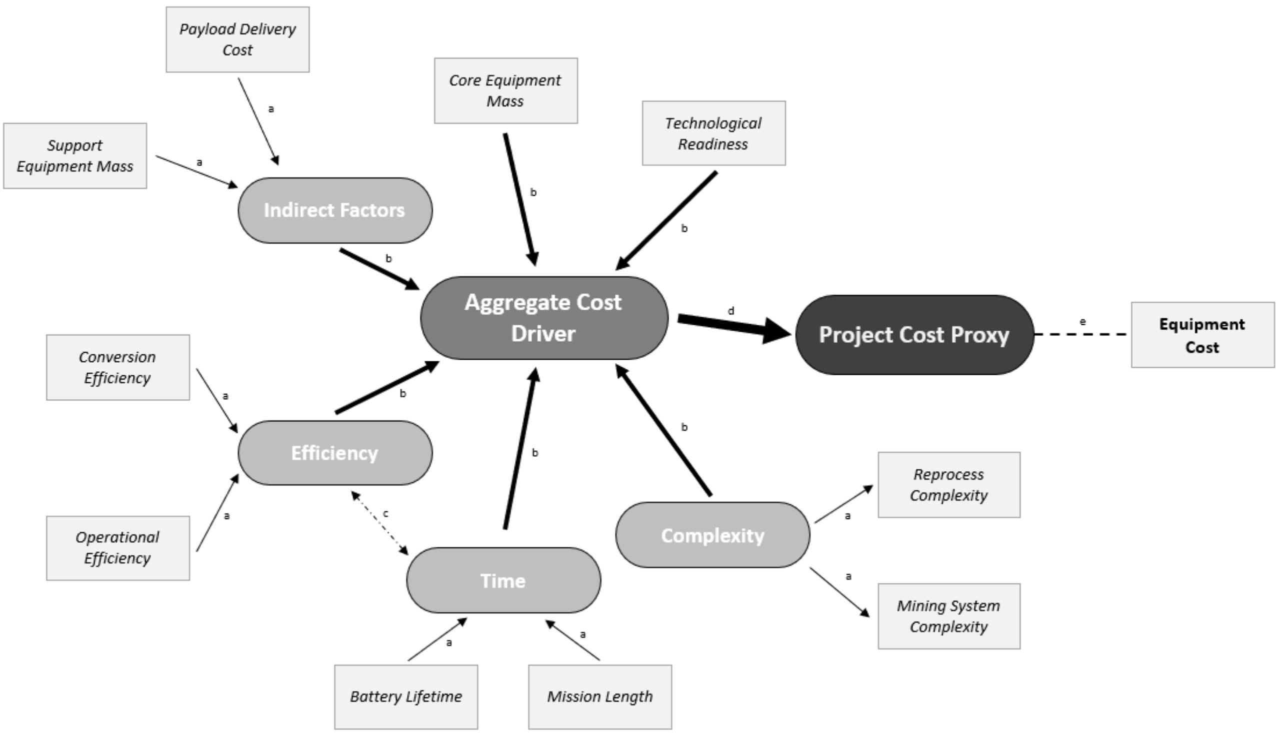

FIGURE 2 - STRUCTURAL MODEL FOR PLS-SEM

The rectangles report the observation extracted from the Likert-based interview round and therefore, by contextualising in econometric terms, those constitute the exogenous variables of the model. Three drivers have been excluded from such model for either absence of any regular or schematic pattern among the variable and the rest of the cost structure, which is the case for the ground operational support segment and the energy usage, or because it is solely associated with the revenue stream mirroring the costs, as of course it is for the request of oxygen on the lunar surface. The lighter-grey round shapes instead represents intermediate endogenous variables which are "fed" in a formative – and therefore not reflective – manner by the observations through the *a*-marked arrows. The solely exception is represented by the *Complexity* branch, where the reversed arrows represent a reflective interaction – as commonly is graphically referred to –. Such structural choice is driven by the attended expectancy of having a meaningful correlation between the two drivers for complexity. Those derived estimations together contribute through the *b* arrows – which computationally replicate the iteration produced by their *a* fellows – to what has here been called in darker grey *Aggregate Cost Driver*, the principal endogenous variable. Note that a first dotted line labelled as *c* joins *Efficiency* and *Time*. Such juncture represents a moderating effect (Becker, 2018). In simple terms, it indicates that not only a greater efficiency affects the overall cost structure on its own, but it also has a meaningful positive impact on the time consumption. The right-arm of the model sees the observed *equipment cost*, which captures the essence of the project design, connected by another dotted-line *e*, and it links to the *Project Cost Proxy* in the black background. That is the arrival point of the study, with its validity anchored to the observed *equipment cost*, it represents an estimate of the mission cost accounting for all those weighted elements that have been collected in the *Aggregate Cost Driver* and delivered through the arrow *d*. The reason why *equipment cost* is used to infer the overall project volume relies on the scheme proposed in *Table 2* by Sarsfield: the costs associated with the equipment there are reported as *operations, instruments,* and *system engineering*, which represent the major differentiator between mission designs. In fact, other elements are either too small in terms of contribution to the total cost – e.g., insurance – or have limited connection with the project's specifics – e.g., the launch costs, as it depends on which vehicle rocket is employed and not on what is transported, as long as the operations are unmanned –. Therefore, the statistical observation over the cost of the equipment could be extended to the overall project given their linear relationship. As an initial guideline on the project volumes, studies have reported how resource exploration on earth has required about $ 20 billion for the Alaskan pipeline, which is about one third of the costs associated to the Indonesian oil and gas exploration (Sonter, The technical and economic feasibility of mining the near-earth asteroids, 1997). On the other side, a more recent study has proposed the volumes for an asteroid mining starting from below $ 5 billion (Probst, 2020). Considering those estimations, the range for the project volume inference for the conversion analysis spans from $ 5 billion – derived from the comparable study – to $ 50 billion – the largest mining project developed and realised –.

Referring back to the concepts of validity, two sets of reviews have to be addressed. For those referred as formative interactions, it is relevant to keep tracking the absence of multicollinearity across the cost drivers' sample. In other words, as mentioned above, the limitation of redundancy of information is crucial to preserve and optimise the predictability power of the model. In concrete terms, the variance inflation factor is used to measure the degree to which the variance of the individual estimators is inflated because of collinearity.

$$VIF = \frac{1}{1 - R_j^2}$$

EQUATION 1 - VARIANCE INFLATION FACTOR

The reference values here starts from 1 – independence – and the threshold if generally around 5 (Hair J. J., 2017). As clearly depicted in the below tables, the VIF is constantly kept at very low levels, which validates the model.

Outer Model	BW	S
Battery Lifetime	1.105	1.206
Conversion Efficiency	1.124	1.312
Core Equipment Mass	1.143	1.136
Mission Length	1.105	1.206
Operational Efficiency	1.124	1.312
Payload Delivery Cost	1.093	1.061
Support Equipment Mass	1.093	1.061
Technological Readiness	1.143	1.136

Inner Model	BW	S
Aggregate Cost Driver -> Project Cost Proxy	1.000	1.000
Complexity -> Aggregate Cost Driver	1.530	1.679
Efficiency -> Aggregate Cost Driver	1.193	1.353
Indirect factors -> Aggregate Cost Driver	1.194	1.617
Time -> Aggregate Cost Driver	1.472	1.304
Efficiency x Time -> Aggregate Cost Driver	1.113	1.066

TABLE 4 - VIF (SMARTPLS)

Reflective junctures are addressed independently. There, the construct reliability and validity are tested by two different indicators. The composite reliability, which could be found in the literature as the omega coefficient, reports the dependability of a composite scale, which is made up of countable items jointly studying a unique underlying construct. As the components gathered for the research represents different scales, and each individually aims to assess distinct parts of the structural model, rho_c is the measure of the dependability of the composite scale. It calculated as the total of each cost driver's Average Variance Extracted (AVE) over the sum of each item's AVE and the squared correlations with each other. As a quick note, the Average Variance Extracted has been firstly introduced in the '80 and therefore is a constituent part of the classical statistical theory. Notwithstanding, its calculation is computed as per below formulation, where *k* represents the elements, *i* the error item and λ the factor loadings (Fornell, 1981):

$$AVE = \frac{\sum_{i=1}^{k} \lambda_i^2}{\sum_{i=1}^{k} \lambda_i^2 + \sum_{i=1}^{k} Var(e_i)}$$

EQUATION 2 - AVE (FORNELL & LARCKER, 1981)

The test is considered positive when the values are above a threshold of 0.7 (Hair J. F., 2019). Considering now validity, it is relevant to assess both the convergent and divergent validity. The former is easily indicated by the Average Variance Extracted, which should be greater than 0.5 (Hair J. F., 2019), while the latter requires an analysis of the Heterotrait-monotrait Ratio of Correlations (HTMT). In simple terms, having an HTMT larger than 0.9 represents a worrisome scenario where the items' correlations within the constructs are less relevant than those with other constructs (Sarstedt, 2019).

Bucket Wheel

	rho_c	AVE
Complexity	0.794	0.670

	1	2	3
1 *Complexity*			
2 *Project Cos*	0.157		
3 Efficiency	0.140	0.183	

Sublimation

	rho_c	AVE
Complexity	0.856	0.749

	1	2	3
1 *Complexity*			
2 *Project Cos*	0.575		
3 Efficiency	0.191	0.039	

TABLE 5 - CONSTRUCT RELIABILITY AND VALIDITY FOR REFLECTIVE INTERACTIONS (SMARTPLS)

By looking at the above findings, it is clear how the model fulfils the requirements and therefore such values have to be interpreted as a green flag to proceed.

The computational contribution on the structural side takes care of providing a – standardised – coefficient representative of the degree of influence of each driver on the mission cost, which is referred as π_i or factor loadings. To review such numbers, an appropriate threshold value for including the parameter would be above 0.6, while lower scores down to 0.4 might be retained as long as those does not affect the overall validity and reliability (Moores, 2006). In this specific case, the parameters reported above are those that have been retained and therefore constitutes the structural model initially introduced. The omission of the absent cost drivers happened at this stage.

	Aggregate Cost Driver		Complexity		Efficiency		Indirect Factors		Time	
	BW	S	BW	S	BW	S	BW	S	BW	S
Battery Lifetime									0.786	0.815
Conversion Efficiency					0.916	0.728				
Core Equipment Mass	0.754	0.737								
Equipment Cost										
Mining Systems Complexity			0.979	0.919						
Mission Length									0.83	0.864
Operational Efficiency					0.683	0.953				
Payload Delivery Cost							0.672	0.51		
Reprocess Complexity			0.617	0.808						
Support Equipment Mass							0.904	0.958		
Technological Readiness	0.881	0.889								

Table 6 - Factor Loadings (SmartPls)

Further relevant aspects to account for when addressing and employing the obtained model rely of course on the R^2, which is a normalised indicator – commonly used in regressive analysis – of the goodness of fit in terms of the variance component forecastable by the construct of independent variables.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y_i})^2}{\sum_{i=1}^{n}(y_i - \bar{y_i})^2}$$

EQUATION 3 - COEFFICIENT OF DETERMINATION

It is worth to mention that coherently with the previous pages, while usually R^2 utilises the arithmetic mean $\bar{y}$, here the symbol is interpreted as the geometric mean, given the explanation above. The judgemental interpretation of the parameter is therefore subjected to the nature of the study and to the personal interpretations, but of course values that revolves above the half are generally positively receipted (Hair J. J., 2017). There, solely the sublimation model officially passes the test with a value of 0.569, while the bucket-wheel stays 7-base points below at about 0.497.

In pair with π_i, f^2 is accounted to address instead whether if the magnitude of impact of each driver on the overall feasibility study is worth to be appreciated.

$$f^2 = \frac{R^2 - R^2_{excl}}{1 - R^2_{excl}}$$

EQUATION 4 - EFFECT SIZE

Such computation has to be re-iterated for each driver re-calculating the individual R^2 by removing the indicator from the formula. According to Cohen, the influence is ranked as small for values around 0.02, middle on 0.15 and great on 0.30 (Cohen, 1988).

	π_i		f^2	
	BW	S	BW	S
Aggregate Cost Driver -> Project Cost Proxy	0.516	0.323	-	-
Complexity -> Aggregate Cost Driver	- 0.193	0.139	0.049	0.009
Efficiency -> Aggregate Cost Driver	- 0.086	- 0.128	0.079	0.148
Indirect factors -> Aggregate Cost Driver	0.424	0.371	0.231	0.170
Time -> Aggregate Cost Driver	0.220	0.255	0.110	0.225
Efficiency x Time -> Aggregate Cost Driver	0.193	0.268	-	-

TABLE 7 - EFFECT SIZE (SMARTPLS)

More than the absolute values, what is relevant to evidence here is the sign of the various paths. In fact, for both models, efficiency seems to be a braking factor to the reduction of costs, as a negative value indicates an inverse relationship. Such evidence could be explained by the addition of failure threats produced by the improved interdependence among the elements on which efficiency relies on. On the same note, it is observable how complexity and efficiency showcase contradictory signs among the two mission designs, an indication that reflects how an increased complexity in the design and processes of a bucket wheel system, being a mechanical engine, is seen as a major risk factor whereas the downfalls from an increased cumbersomeness on sublimation tools are perceived as properly manageable. With that being said, a final remark goes on the validity of such estimations. As reported in the appendix, the confidence interval has to be enlarged to include those two parameters, as both falls off in relevance at the 10% threshold.

Both mission structures clearly proposes strong paths when it comes to move from the aggregate components to estimating the overall expense (first line). Of great relevance, it is worth reporting how the major driver is identified in the so-called indirect factors, which while on one hand seems logical, as the vast majority of the cost components for a project in an interconnected industry fall beyond the controllability sphere, on the other it evidences once again the degree of complexity in conducting such studies.

In the appendix there are reported the f^2 for the individual cost drivers as well, addressing their own contribution to the respective intermediate variable. For both system designs, the relevance of the technological readiness plays a major role in the overall estimation process, therefore its contribution is prioritised even over the subsequent stages of the study.

Before testing the model, is crucial to address its predictive power. A first major indicator is defined as Q^2, which defines, for those cases showcasing a positive value, a predictive relevance (Chin, 1998). The computation of Q^2 happens through a blindfolding procedure, which proceeds iteratively by a systematic removal of portions of the dataset and uses the kept numerical inputs to predict those left outside. This sample re-use tool is generally performed multiple times excluding each time different portions of the population's inputs (Geissers, 1974).

A second index is produced by verifying whether if the error produced by the PLS-SEM model are lower than those obtained through a simpler linear regression model. To conduct this comparison, the values compared are those calculated by the Root Mean Square Error (RMSE), which tests the dispersion of the residuals (Barnston, 1992).

$$RMSE = \sqrt{\overline{(f-o)^2}}$$

EQUATION 5 - ROOT MEAN SQUARE ERROR (BARNSTON, 1992)

There, *f* represents the inferred values from the model while *o* represents the observed known values.

	Q^2predict		PLS-SEM-RMSE		LM-RMSE	
	BW	S	BW	S	BW	S
Aggregate Cost Driver	0.262	0.363	0.027	0.058	0.832	0.832
Project Cost Proxy	0.018	0.115	0.014	0.022	0.982	0.982

TABLE 8 - PREDICTIVE POWER (SMARTPLS)

As it is evident from the table, while both systems positively respond to the test, the sublimation technique once again showcases a greater reliability on its study.

To validate this last assumption, a further analysis is performed relying on a more recent technique. By running a cross-validated predictive ability test (CVPAT), it is possible to explore an out-of-sample forecast to estimate the prediction error and thereafter subtracting to the obtained value the average loss of a prediction based on a naïve criterion such as the indicator averages (IA) (Liengaard, 2021). Therefore, it is deducible that scores below the 0 are acceptable.

	Avg. loss diff.		t value		p value	
	BW	S	BW	S	BW	S
Aggregate Cost Driver	-0.453	-0.726	1.384	1.87	0.173	0.068
Project Cost Proxy	-0.039	-0.202	0.172	1.778	0.864	0.082
Overall	-0.315	-0.551	1.196	2.186	0.237	0.034

Table 9 - CVPAT (SmartPLS)

Whereas on a first instance is seems enthusiastically encouraging seeing both systems scoring negative values in the test, it has also to be considered how at the 10% confidence interval, it is only the sublimation model the one capable of showing a significantly better predictive power than indicator average benchmark, whereas the scores from the bucket-wheel are not reliable within an acceptable confidence interval.

Given the above depicted review, the study continues prioritising solely the sublimation model, which not only is seen as the preferred option over multiple instances, but also it is the only one capable of consistently passing the tests on its predictive performance.

Before continuing on the development of a test format for the model, one last evidence has to be reviewed. The *Importance-Performance map analysis* (IPMA) adds value to the study by embedding the performative aspects of the constructs (Hair J. F., 2018).

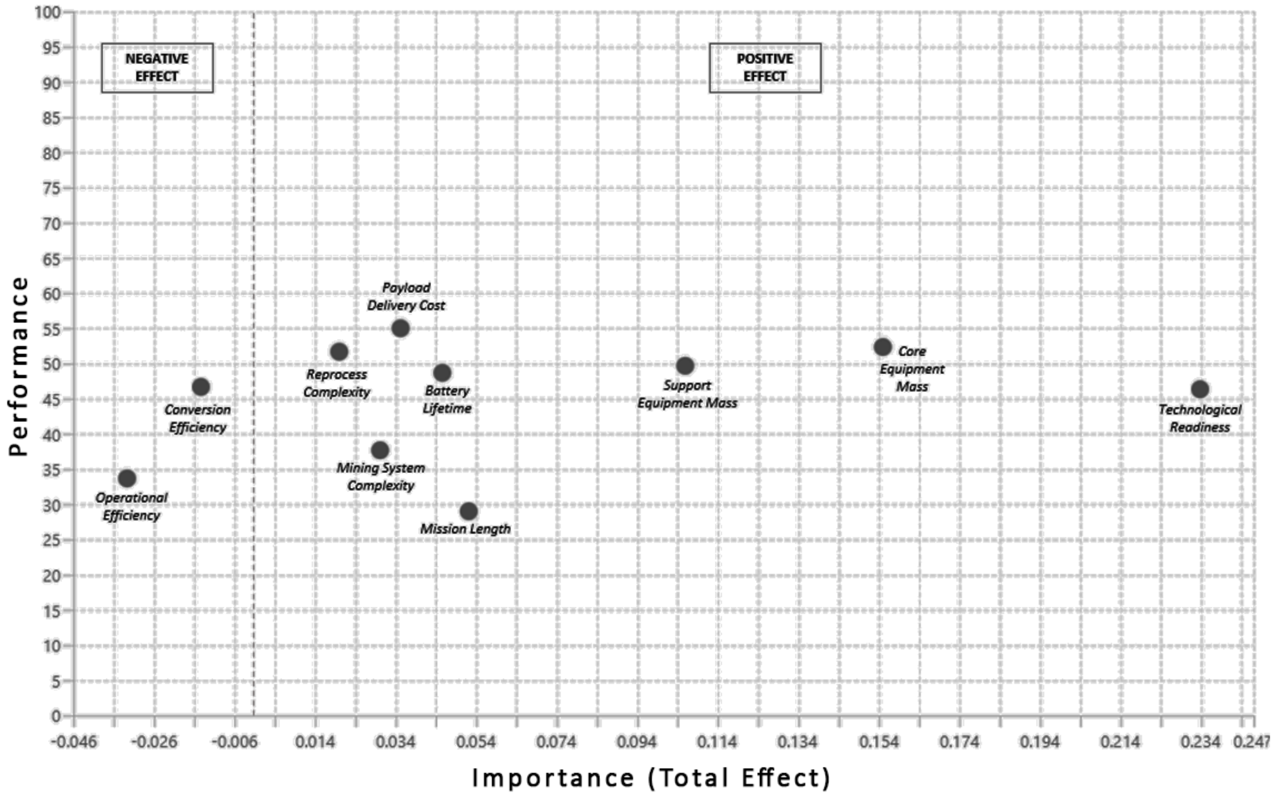

FIGURE 3 - IPMA (SMARTPLS)

Here once again it reports how efficiency contributes negatively to the overall cost optimisation, while it also provides some missing numerical inputs which are used to eventually execute the model, following the procedure indicated in the next paragraph.

PLS-SEM Predictive Cost Estimation Model

Similarly to the approach presented in Probst et al., here it is reported a way of proactively utilise the PLS-SEM to conduct estimations. As a first step, the geometric average of each cost driver is multiplied by the coefficient of the path towards the next intermediate variable. As each intermediate variable is influenced by a couple of inputs, each one is arbitrarily weighted for the half. Once reached this step, the computation continues by multiplying the obtained result by the coefficient of the path from the intermediate variables to the *Aggregate Cost Driver*. There, another factor on the importance derived from the IPMA is included. By summing the elements together, adding the geometric average of our proxy variable *Equipment Cost* multiplied by both its paths and ultimately multiplying the product by the standard deviation of the proxy variable itself, it is possible to obtain a value within a Likert scale range that could be translated into its overall volume. Below it is reported the schematic visualisation of the equation above depicted.

$$\left(\sum_i x_i \, \pi_i^{outer} \frac{\pi_i^{inner}}{2} IPMA + k\pi_k^{outer}\pi_k^{inner}\right)\sigma_k$$

EQUATION 6 - PREDICTIVE COST ESTIMATION MODEL

By properly conducting the computations, the observed results is 2.801, which appropriately reported into the parametric scale indicated above – \$ 5 to 60 billion – corresponds to \$ 30.678 B, as an estimate of the overall project volume expense.

2.2.2. Net Present Value Approach

Further preliminary study have highlighted how economic feasibility models utilising net present value seems to be the ones with a broader diffusion given a proven superior reliability. With the purpose to mirror and cross-validate the above outcomes, an ad-hoc NPV equation is proposed. The build-up formulation derives by taking a twofold inspiration, on one side from Sonter’s NPV model, initially developed for mineral asteroids' exploratory mission concepts back in the nineties (Sonter, 1997), and on the other by relying on the observation on the interaction between the cost drivers experienced during the PLS-SEM study. The numerical values used in computing the equations are either derived from the literature, where indicated, or simply utilising the geometric average of the cost drivers obtained during the second phase of the interview process.

$$NPV = pq\ \{\ C_{orb} M_{mpe} f t r e^{\Delta v / v_e} (1+i)^{-\alpha^{\frac{3}{2}}} -\ [\ z C_{man} + C_{man}\left(M_{mpe} + M_{ps}\right)]\ \} + Bn$$

EQUATION 7 - NET PRESENT VALUE FOR MOON MINING VENTURES

Each item is explained below in an orderly manner.

p is the coefficient that embodies the risks associated with the speculatory nature of the project by inferring a probability of success and is derived from the surveyed experts' perception on equipment failures filtered through PLS-SEM. There, a weight coefficient of the 40% is derived from the literature as it constrains the parameter's influence to represent failures derived from equipment-associated causes (Sommariva, 2020). [0.00 – 1.00].

q functions as the complementary counterpart of the previous indicator and reflects failures produced by external circumstances. Therefore, it accounts for the 60% of the probabilistic inflator modelling the project risk. Its numerical value is subjected to personal judgement, and it is derived through an analogical review of the literature. There, it is reported how on-earth oil extraction in the years comprised between 1999 and 2017 averages at about 60% failure rate, which on overall runs from 25% to 80% (Sommariva, 2020). As the space industry in general is known for being meticulous, as regulatory agencies undoubtedly conduct thorough evaluations before giving the green light to any individual project, it is reasonable to push the natural concerns towards the lower limit, without forgetting how the current literature is still uncertain on the mining methods. [0.00 – 1.00].

C_{orb} represents the launch cost and it is computed combining the survey findings with the historical pie-chart table on cost contributions. [$/kg].

M_{mpe} is the payload mass, jointly accounting for the mining, instrumentation, and control components and it is produced through the interviews' review. [kg].

f is the specific mass throughput ratio for the mining engine, computed as $\frac{kg\ mined/kg\ equipment}{days}$.

t expresses the length of operations. It is derived from the survey as well [days].

r mirrors the ability of the selected mining method to convert the oxygen from the mining material and its value is produced by accounting for what the survey has proposed as an output. [0.00 – 1.00].

Δv is the return trajectory associated increase in velocity. Here the major inputs are provided by a study conducted on high-thrust propulsion methods at the Delft University and the value could be rounded at 3,73 km/s on a Hohmann transfer orbital optimisation (Palmore, 1984) (Zuccarelli, 2009). [km/s]

v_e on the other side represents the propulsion system exhaust velocity. Here a straight computation is based on the formula $v_e = g_0 I_{sp}$. The former factor of standard gravity takes the value of 9.80665 m/s^2, while the latter of rocket performance impulse is approximated at 400 seconds for liquid-rocket engines using liquid oxygen and liquid hydrogen, such as the Falcon Heavy, one of the main rockets employed in the new set of Moon-associated missions. There, a third element of pressure thrust given by $(p_e - p_a)A_e$ is intentionally omitted considering an ideal scenario where the Δp approaches the zero by lowering the inner pressure to the atmospheric one at sea level (Kluever, 2003). With that being said, an appropriate estimation would give a numerical value of 3.92266 m/s2. [m/s^2].

i is the market interest rate and different perspectives have to be pondered. As a starting point, it is worth commenting how its trajectories are interlaced with external factors and any defendable analogical reasoning's relevance is constrained to a static timeframe. On one side, it is arguable how it could be associated with the internal rate of return which as reported in the previous chapters should be comprised within the range of 20-30%. On the other hand, a simpler analogical reference could be made with the 5% value proposed for interplanetary spaceships (Musk, 2016). For the purpose of the equation, it has to be said that the variable itself loses relevance on a purely arithmetic interpretation, given the interpretation of the exponential component provided right below. [0.00 – 1.00].

α is the value that reflects the semi-major axis of transfer orbit. Considering Hohmann once again (Palmore, 1984), the simplest approximation would be given by considering the half of the sum between LEO and Moon orbits, respectively about 2000 km (Hobbs, 2006) and, on average, 385000 km (Cielaszyk, 1996). By simply computing the result and scaling into the astronomical unit, which is used for the purpose of model's scalability, the numerical value of α corresponds to 0,00129346761 AU. Bridging into the conversation what briefly anticipated in the previous paragraph, by considering the factor all-together, having an exponent which value falls close to the zero leads the base value to approximately 1. [AU].

z represents a coefficient derived from the pie-chart table to synthetically infer on other costs utilising as a basepoint the PLS-SEM estimations. [0.00 – 1.00].

k is a coefficient embodying an equally balanced pair: on one side it reports the complexity factor and is modelled based on the NASA's framework reported above, while on the other – as suggested from the interviewees – it adds an additionally inflation of 20% cost increase due to spare parts and maintenance. [0.00 – 1.00].

C_{man} is the specific cost of the technological and operational equipment, studied on the statistical elaboration of the surveyed report. [$/kg].

M_{ps} refers to the raw mass of the energy supply plant. Here, the study relies on an analogical association. Most of the space ventures requiring consistent and reliable sourcing of energy have historically used a radioisotope thermoelectric generator. For this study, a particular reference is made to the MMRTG design, which produces about 2000 W of thermal power – which suits the sublimation procedure – for each 45 kgs of weight (Office of Nuclear Energy, 2008).

B is the numerical value that embodies the annual project budget and represent the unknown factor in the equation. Theoretically, it should approximately reflect the result obtained by the PLS-SEM model at the breakeven. [$].

n Lastly, this parameter codes the program length. [years].

By carefully following the above presented equation guideline, the value of B that could ensure the project feasibility and reaching the breakeven point corresponds to slightly more than $ 33.071 billion.

3. Conclusion

An immediate consideration has to be made on the research outputs. In the previous pages, a publication from Sower et al. has been cited reporting how the cost of carrying the required oxygen from the Earth to the Lunar surface would cost about 35,000.00 $/kg. By multiplying such value for the amount of mined resource used in both models, the overall cost would be of about $ 35.642 billion, which is higher than the estimated extraction costs according to both equations. While this result might seem encouraging, what is missing is some context: by simply looking at the websites of the occidental space agencies, it is clearly visible that their combined budget for the year 2022 has barely surpassed the $ 32.060 billion (NASA, 2022), (ESA, 2022).

Space agencies are known for running thousands of projects and missions per year, therefore financing in the 2024 a moon mining mission of such scale will automatically translate into an integral defunding for all the other associated activities, which stands beyond any logic. Given the observed dominance of technological uncertainty in driving the cost rise, it is expected that the overall cost for a project of this kind will drop in the incoming years, as more and more initiatives manage to contribute to the scientific development leading technological advancement. In other words, whereas the mission concept has been proven to be already a better alternative when it comes to the comparison with simply carrying the oxygen on the moon from the earth, the scale of the project makes it still unrealisable.

Nevertheless, the two models represent a clear improvement of the roadmaps used to navigate the complex and disruptive space industry. Interestingly, the two provides complementary insights, with the machine learning approach tackling how different cost components interact with each other on one side, and the Net Present Value equation functioning as a magnifying lens to spot and identify critical areas of improvement. A review of such kind is extremely valuable in the context of the New Space

Economy, where a multitude of stakeholders interact, across both the financial and operational arms of each project. The gathering of multiple investors, ranging from institutional to private funds, who fuel an orchestra of heterogeneous developers, needs the establishment of a clear product cost structure to properly harmonise the efforts and ensure a coherent and optimised approach towards the project.

Whereas the models have shown a sound and reliant structure, there is always room for improvement. On the engineering side, it is advisable to expand the number of elements considered. For example, the refining and stocking components of the process could easily constitute a bottleneck which has to be properly explored. Further, by zooming out and targeting instead the overall design of the models, it would be interesting to re-apply the approach on a different case study, within the sphere of disruptive space innovations. The reason for that would therefore be considering the potential to generalise the formulation for other mission designs where relying on historical data is not possible, in order to validate the strength of the concept of using experts' judgement and machine learning tools to extract forecasts.

Pondering on the structure of the research paper, it would be great of course to expand the sample size, which could allow either to substitute the PLS-SEM with another tool as the aforementioned PLS-ML, or to re-iterate the interview process with multiple groups of experts divided by their seniority and adapting the survey on each iteration. Thereafter, a comparison with the current result could be performed to underline the marginal impact of the population size over the model predictive power.

Furthermore, there has been only one mediating – or moderating – effect introduced. An interesting contribution could be represented by re-proposing the involvement of experts during the development phase of the model, as it can be relevant to address if there might be other influences which the statistical tools have not been able to identify.

As an end note, the study has successfully proposed alternative ways of addressing the cost forecasting issue for heavily uncertain environments in absence of historical data. While the on-field validation will not be available for some decades, I very much hope that my studies overestimate the real numbers!

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Appendix 1

Descriptive Statistics and Correlation matrices (SmartPLS)

Cost Driver	Arithmetic Mean		Geometric Mean		Median		Standard Deviation		Excess Kurtosis		Skewness		Cramér-von Mises p value		Converted Value		Unit of Measure
	BW	S	BW	S	BW	S	BW	S	BW	S	BW	S	BW	S	BW	S	
Technological Readiness	3.740	3.780	3.358	3.219	4	4	1.560	1.803	-0.349	-0.963	0.189	-0.103	0.003	0.013	0.907	0.866	Coeff.
Equipment Cost	4.540	4.860	4.238	4.672	4	5	1.526	1.312	-0.454	-0.799	-0.009	0.048	0.003	0.002	14,412,878.84	16,074,494.51	$
Core Equipment Mass	4.360	4.140	3.961	3.803	4	4	1.694	1.588	-0.640	-0.381	0.071	0.350	0.002	0.000	297.403	286.869	kg
Support Eq. Mass	3.980	3.980	3.668	3.713	4	4	1.568	1.449	-0.383	-0.652	0.579	0.402	0.000	0.003	277.882	280.835	kg
Mission Length	2.780	2.740	2.223	2.216	2	2	1.825	1.707	-0.061	-0.389	0.866	0.670	0.000	0.000	2.000	2.000	years
Op. Efficiency	3.340	3.020	2.909	2.584	4	3	1.505	1.503	-0.850	-1.302	-0.100	0.074	0.003	0.001	818.179	764.022	kg/h
Conversion Eff.	3.240	3.800	2.912	3.358	3	4	1.436	1.697	0.523	-0.558	0.732	0.248	0.000	0.020	0.040	0.047	yield
Ground Human Op.	3.820	3.720	3.256	3.180	4	3	1.926	1.919	-0.936	-0.824	0.247	0.449	0.024	0.000	-	-	-
Energy Usage	4.440	4.780	4.149	4.435	4	5	1.525	1.641	-0.517	-0.784	0.222	-0.223	0.000	0.010	0.410	0.429	W/kg
Battery Lifetime	3.840	3.920	3.444	3.502	4	4	1.641	1.671	-0.849	-0.995	0.209	0.051	0.011	0.011	-	-	-
Payload Del. Costs	4.200	4.300	3.810	3.957	4	4	1.755	1.628	-1.219	-0.968	0.256	0.126	0.000	0.006	6543.989	6702.915	$/kg
Min. Sys. Complexity	5.500	3.260	5.184	2.700	7	3	1.688	1.787	-1.185	-0.852	-0.579	0.310	0.000	0.003	-	-	-
Reprocess Complexity	5.980	4.100	5.526	3.530	7	4	1.667	1.879	2.921	-0.883	-1.917	-0.131	0.000	0.028	-	-	-
ISRU Demand	3.900	3.800	3.305	3.184	4	4	1.792	1.833	-0.880	-1.006	-0.426	-0.297	0.000	0.000	1030.508	1018.354	mt/year

Bucket Wheel	1	2	3	4	5	6	7	8	9	10	11	12	13
1 Technological Readiness	1.000	-	-	-	-	-	-	-	-	-	-	-	-
2 Equipment Cost	0.454	1.000	-	-	-	-	-	-	-	-	-	-	-
3 Core Equipment Mass	0.353	0.389	1.000	-	-	-	-	-	-	-	-	-	-
4 Support Eq. Mass	0.472	0.188	0.364	1.000	-	-	-	-	-	-	-	-	-
5 Mission Length	0.261	0.229	0.330	0.257	1.000	-	-	-	-	-	-	-	-
6 Op. Efficiency	-0.209	-0.237	-0.048	-0.201	0.049	1.000	-	-	-	-	-	-	-
7 Conversion Eff.	-0.195	-0.114	-0.183	-0.149	-0.056	0.332	1.000	-	-	-	-	-	-
8 Ground Human Op.	0.038	0.122	-0.103	0.058	0.142	0.442	0.218	1.000	-	-	-	-	-
9 Energy Usage	0.090	0.104	0.349	0.129	0.135	-0.187	-0.030	0.115	1.000	-	-	-	-
10 Battery Lifetime	0.296	0.122	0.244	0.341	0.309	-0.164	-0.187	0.225	0.396	1.000	-	-	-
11 Payload Del. Costs	0.297	0.079	0.346	0.292	-0.111	-0.230	0.013	-0.037	0.184	0.011	1.000	-	-
12 Min. Sys. Complexity	-0.368	-0.175	-0.336	-0.162	-0.484	0.232	0.264	-0.034	-0.194	-0.426	-0.115	1.000	-
13 Reprocess Complexity	-0.240	-0.035	0.116	0.115	-0.015	0.322	0.244	0.155	0.247	-0.052	0.036	0.444	1.000

Sublimation	1	2	3	4	5	6	7	8	9	10	11	12	13
1 Technological Readiness	1.000	-	-	-	-	-	-	-	-	-	-	-	-
2 Equipment Cost	0.266	1.000	-	-	-	-	-	-	-	-	-	-	-
3 Core Equipment Mass	0.346	0.269	1.000	-	-	-	-	-	-	-	-	-	-
4 Support Eq. Mass	0.549	0.304	0.401	1.000	-	-	-	-	-	-	-	-	-
5 Mission Length	0.345	0.180	0.316	0.160	1.000	-	-	-	-	-	-	-	-
6 Op. Efficiency	-0.397	-0.394	-0.211	-0.422	-0.247	1.000	-	-	-	-	-	-	-
7 Conversion Eff.	-0.243	-0.147	-0.249	-0.221	-0.115	0.488	1.000	-	-	-	-	-	-
8 Ground Human Op.	0.052	0.104	-0.184	-0.096	0.045	0.356	0.087	1.000	-	-	-	-	-
9 Energy Usage	0.261	0.450	0.319	0.309	0.280	-0.314	-0.016	0.063	1.000	-	-	-	-
10 Battery Lifetime	0.392	0.196	0.200	0.305	0.413	-0.222	-0.224	0.180	0.453	1.000	-	-	-
11 Payload Del. Costs	0.254	0.413	0.270	0.240	0.114	-0.338	-0.065	-0.056	0.167	-0.050	1.000	-	-
12 Min. Sys. Complexity	0.490	0.459	0.347	0.535	0.357	-0.397	-0.332	0.050	0.313	0.328	0.289	1.000	-
13 Reprocess Complexity	0.166	0.363	0.471	0.273	0.339	-0.142	-0.245	0.013	0.455	0.340	0.232	0.511	1.000

Appendix 2

Latent Variables Descriptive Statistics (SmartPLS)

	Median		Observed min		Observed max		Excess kurtosis		Skewness	
	BW	S	BW	S	BW	S	BW	S	BW	S
Aggregate Cost Driver	-0.069	0.045	-2.237	-1.768	2.256	2.165	-0.275	-0.603	0.093	-0.033
Complexity	0.331	0.12	-2.498	-1.623	0.919	2.141	-0.766	-0.877	-0.689	0.021
Efficiency	0.057	-0.027	-1.87	-1.625	2.241	2.004	-0.227	-1.029	0.149	-0.041
Indirect factors	-0.266	-0.134	-1.776	-1.631	2.202	2.34	-0.024	-0.384	0.763	0.594
Project Cost Proxy	-0.354	0.107	-2.32	-2.18	1.612	1.632	-0.454	-0.799	-0.009	0.048
Time	-0.043	-0.228	-1.647	-1.614	1.918	1.944	-0.994	-1.173	0.14	0.187

Latent Variables Correlation (SmartPLS)

Bucket Wheel	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1 *Aggregate Cost Driver*	1						
2 *Complexity*	-0.401	1					
3 *Efficiency*	-0.251	0.34	1				
4 *Indirect factors*	0.57	-0.132	-0.195	1			
5 *Project Cost Proxy*	0.516	-0.161	-0.189	0.181	1		
6 *Time*	0.421	-0.504	-0.141	0.254	0.221	1	
7 *Efficiency x Time*	0.296	-0.057	0.065	0.224	0.183	-0.078	1
Sublimation	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1 *Aggregate Cost Driver*	1						
2 *Complexity*	0.518	1					
3 *Efficiency*	-0.408	-0.382	1				
4 *Indirect factors*	0.618	0.526	-0.447	1			
5 *Project Cost Proxy*	0.323	0.481	-0.36	0.392	1		
6 *Time*	0.466	0.465	-0.288	0.253	0.223	1	
7 *Efficiency x Time*	0.36	0.061	0.045	0.193	-0.039	0.06	1

f^2 (SmartPLS)

f^2	Project Cost Proxy		Aggregate Cost Driver	
	BW	S	BW	S
Battery Lifetime	0.000	-0.001	-0.016	0.071
Conversion Efficiency	0.000	0.000	0.063	0.027
Core Equipment Mass	0.076	0.036	0.102	0.108
Mining Systems Complexity	0.000	-0.002	0.038	0.011
Mission Length	0.001	0.001	0.079	0.031
Operational Efficiency	0.000	-0.001	-0.037	0.038
Payload Delivery Cost	0.000	0.000	0.094	0.016
Reprocess Complexity	0.000	0.003	-0.002	-0.007
Support Equipment Mass	0.001	-0.001	0.072	0.155
Technological Readiness	-0.091	0.034	0.408	0.365

Appendix 3

Bootstrapping (SmartPLS)

Path coefficients	Original sample (O)		Sample mean (M)		Standard deviation		T statistics		P values	
	BW	S	BW	S	BW	S	BW	S	BW	S
Aggregate Cost Driver -> Project Cost Proxy	0.516	0.322	0.514	0.328	0.11	0.146	4.675	2.212	0	0.014
Complexity -> Aggregate Cost Driver	-0.193	0.137	-0.22	0.132	0.121	0.138	1.6	0.991	0.055	0.161
Efficiency -> Aggregate Cost Driver	-0.086	-0.128	-0.103	-0.157	0.146	0.144	0.586	0.89	0.279	0.187
Indirect factors -> Aggregate Cost Driver	0.424	0.371	0.424	0.355	0.143	0.171	2.975	2.165	0.002	0.015
Time -> Aggregate Cost Driver	0.221	0.256	0.201	0.285	0.161	0.122	1.374	2.104	0.085	0.018
Efficiency x Time -> Aggregate Cost Driver	0.193	0.269	0.148	0.231	0.147	0.117	1.314	2.305	0.095	0.011

Outer weights	Original sample (O)		Sample mean (M)		Standard deviation		T statistics		P values	
	BW	S	BW	S	BW	S	BW	S	BW	S
Battery Lifetime -> Time	0.585	0.817	0.528	0.793	0.331	0.18	1.768	4.538	0.039	0
Conversion Eficiency -> Eficiency	0.775	0.727	0.597	0.678	0.509	0.233	1.523	3.117	0.064	0.001
Core Equipment Mass -> Aggregate Cost Drivers	0.507	0.732	0.529	0.716	0.194	0.16	2.611	4.589	0.005	0
Mining System Complexity <- Complexity	0.879	0.92	0.873	0.913	0.137	0.047	6.4	19.74	0	0
Mission Length -> Time	0.65	0.863	0.628	0.815	0.282	0.158	2.305	5.454	0.011	0
Operational Eficiency -> Eficiency	0.424	0.954	0.37	0.889	0.528	0.182	0.803	5.248	0.211	0
Payload Delivery Cost -> Indirect factors	0.446	0.509	0.421	0.485	0.266	0.235	1.678	2.167	0.047	0.015
Reprocess Complexity <- Complexity	0.225	0.807	0.18	0.793	0.27	0.127	0.834	6.365	0.202	0
Support Equipment Mass -> Indirect factors	0.774	0.958	0.749	0.936	0.21	0.074	3.689	12.885	0	0
Technological Readiness -> Aggregate Cost Driver	0.701	0.892	0.663	0.863	0.17	0.109	4.127	8.156	0	0

Total effect	Original sample (O)		Sample mean (M)		Standard deviation		T statistics		P values	
	BW	S	BW	S	BW	S	BW	S	BW	S
Aggregate Cost Driver -> Project Cost Proxy	0.516	0.322	0.514	0.328	0.11	0.146	4.675	2.212	0	0.014
Complexity -> Aggregate Cost Driver	-0.193	0.137	-0.22	0.132	0.121	0.138	1.6	0.991	0.055	0.161
Complexity -> Project Cost Proxy	-0.1	0.044	-0.114	0.051	0.068	0.057	1.462	0.778	0.072	0.218
Efficiency -> Aggregate Cost Driver	-0.086	-0.128	-0.103	-0.157	0.146	0.144	0.586	0.89	0.279	0.187
Efficiency -> Project Cost Proxy	-0.044	-0.041	-0.051	-0.054	0.078	0.058	0.569	0.71	0.285	0.239
Indirect factors -> Aggregate Cost Driver	0.424	0.371	0.424	0.355	0.143	0.171	2.975	2.165	0.002	0.015
Indirect factors -> Project Cost Proxy	0.219	0.12	0.221	0.115	0.095	0.077	2.297	1.555	0.011	0.06
Time -> Aggregate Cost Driver	0.221	0.256	0.201	0.285	0.161	0.122	1.374	2.104	0.085	0.018
Time -> Project Cost Proxy	0.114	0.083	0.097	0.087	0.081	0.052	1.412	1.593	0.079	0.056
Efficiency x Time -> Aggregate Cost Driver	0.193	0.269	0.148	0.231	0.147	0.117	1.314	2.305	0.095	0.011
Efficiency x Time -> Project Cost Proxy	0.099	0.087	0.078	0.074	0.082	0.052	1.216	1.662	0.112	0.049

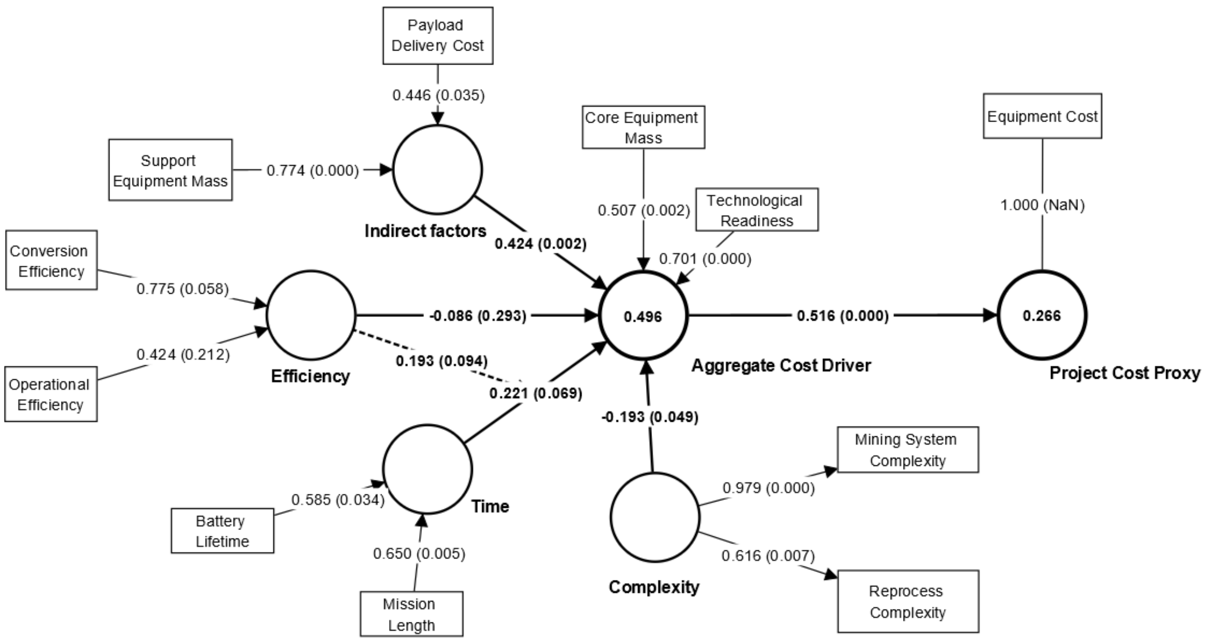
IPMA Importance reference values (SmartPLS)

Sublimation	Project Cost Proxy
Battery Lifetime	0.046
Conversion Efficiency	-0.014
Core Equipment Mass	0.155
Mining System Complexity	0.03
Mission Length	0.052
Operational Efficiency	-0.032
Payload Delivery Cost	0.035
Reprocess Complexity	0.02
Support Equipment Mass	0.106
Technological Readiness	0.234

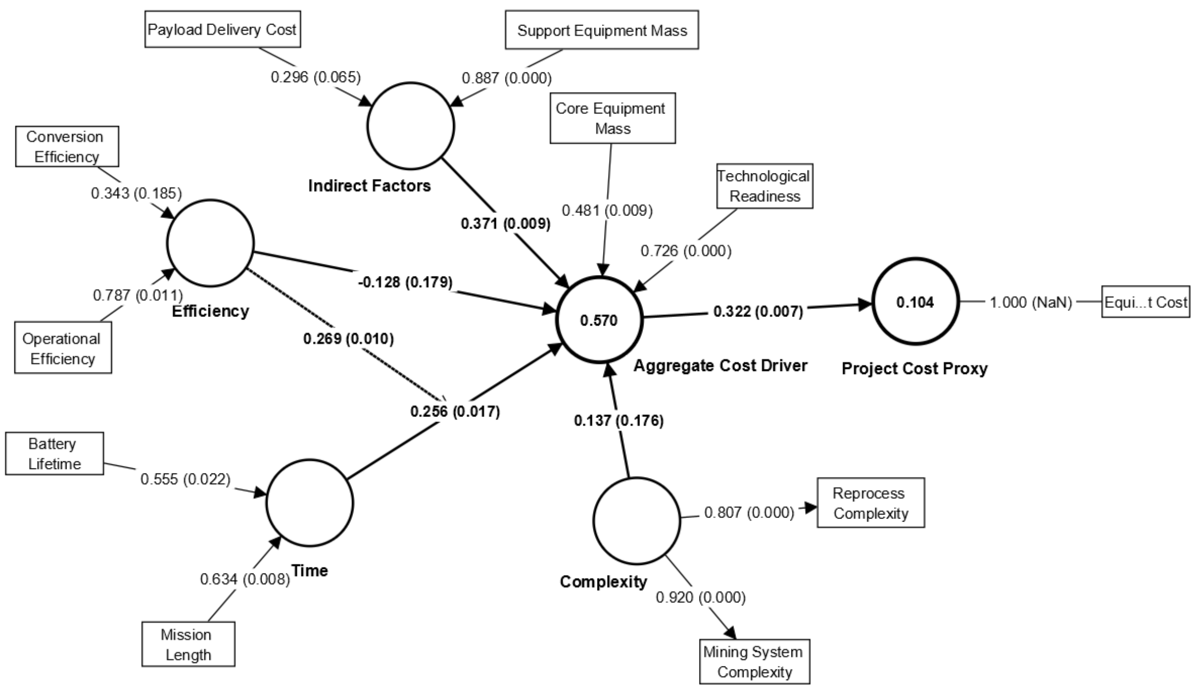
Appendix 4

Path coefficients and p values (SmartPLS)

Bucket wheel



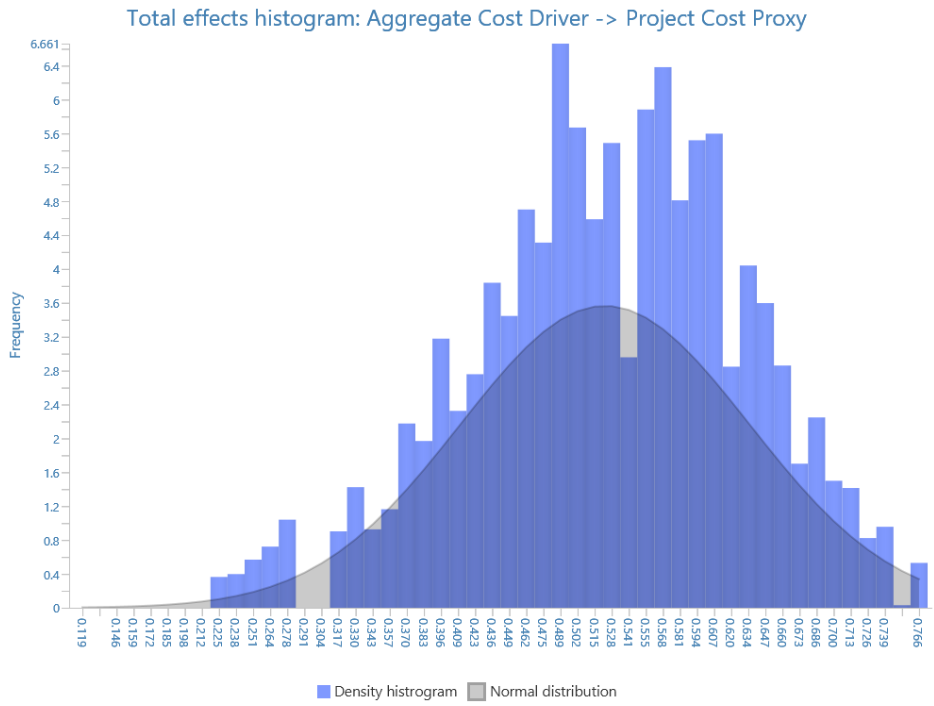
Sublimation



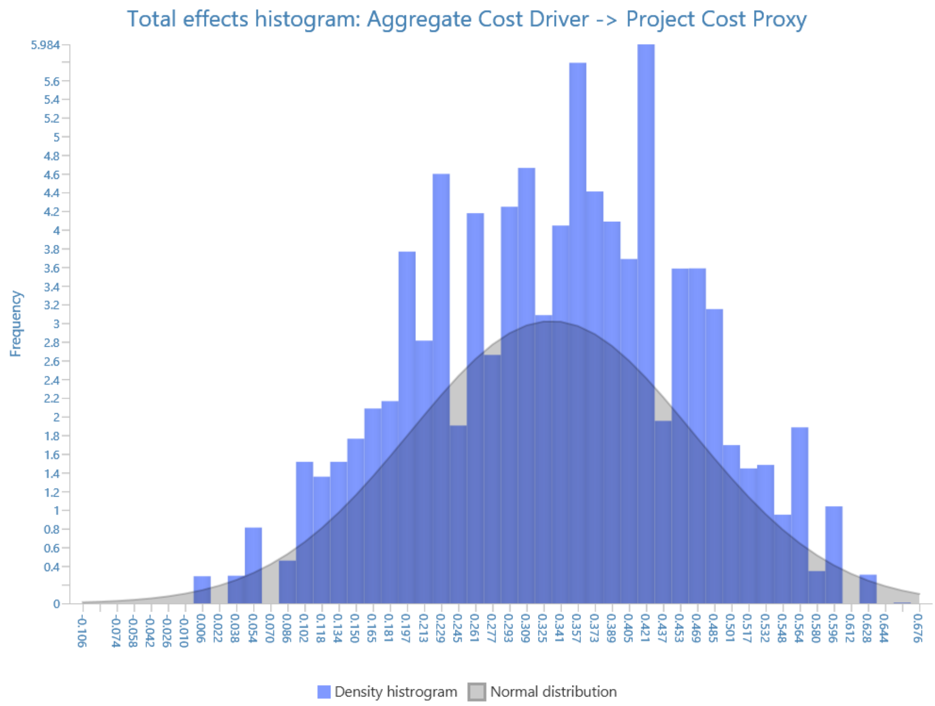
Appendix 5

Total effects histogram (SmartPLS)

Bucket wheel



Sublimation



Appendix 6

Predictions (SmartPLS)

Bucket Wheel

LV prediction summary - PLS-SEM prediction error (descriptives)										
	Mean	**Median**	**Min**	**Max**	**SD**	**kurtosis**	**Skewness**	**Obs**	**test st.**	**p value**
Aggregate Cost Driver	0.027	0.061	-3.449	2.145	0.894	2.02	-0.767	500	0.431	0
Project Cost Proxy	0.014	0.044	-2.876	2.066	1.028	0.047	-0.378	500	0.263	0.001

LV prediction summary - PLS-SEM predictions (descriptives)										
	Mean	**Median**	**Min**	**Max**	**SD**	**kurtosis**	**Skewness**	**Obs**	**test st.**	**p value**
Aggregate Cost Driver	-0.024	-0.012	-1.935	1.967	0.743	-0.432	0.25	500	0.923	0
Project Cost Proxy	-0.014	-0.007	-1.016	1.04	0.382	-0.361	0.307	500	0.921	0

Sublimation

LV prediction summary - PLS-SEM prediction error (descriptives)										
	Mean	**Median**	**Min**	**Max**	**SD**	**kurtosis**	**Skewness**	**Obs**	**test st.**	**p value**
Aggregate Cost Driver	0.058	0.015	-1.978	2.367	0.83	0.044	0.16	500	0.161	0.017
Project Cost Proxy	0.022	0.027	-2.079	1.942	0.982	-0.847	-0.051	500	0.253	0.001

LV prediction summary - PLS-SEM predictions (descriptives)										
	Mean	**Median**	**Min**	**Max**	**SD**	**kurtosis**	**Skewness**	**Obs**	**test st.**	**p value**
Aggregate Cost Driver	-0.065	0.096	-1.728	1.363	0.763	-0.923	-0.332	500	1.035	0
Project Cost Proxy	-0.024	0.03	-0.713	0.557	0.255	-0.628	-0.4	500	0.937	0

Appendix 7

Prediction Error histogram (SmartPLS)

Bucket Wheel on the left-side, sublimation on the right