# *Exploring the Determinants of Digital Transformation for Sustainable Business Model Innovation: A Study in the Architecture, Engineering, and Construction (AEC) Industry*


TONG, SHUI,YUK

# Durham University

## Exploring the Determinants of Digital Transformation for Sustainable Business Model Innovation: A Study in the Architecture, Engineering, and Construction (AEC) Industry

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**Shui-Yuk TONG**
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**Supervisor**
**Prof. Spyros Angelopoulos**

*I confirm that this piece of work is the result of my own work. Materials from work of others have been acknowledged, and quotations and paraphrases suitably indicated.*

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# ABSTRACT

The Architecture, Engineering, and Construction (AEC) industry is undergoing a significant transformation driven by the convergence of digital technologies and sustainability imperatives. However, many AEC firms face challenges in aligning their digital transformation initiatives with sustainable business model (SBM) innovation. This study investigates the key organisational and technological determinants that enable such alignment, with a particular focus on the Hong Kong AEC sector. Drawing on the Triple Bottom Line (TBL) framework and integrating the constructs of Entrepreneurial Orientation (EO), Sustainability Orientation (SO), and Digital Orientation (DO), the study proposes a multidimensional conceptual model. Data were collected from 158 professionals through a survey and analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The results reveal that TBL-aligned digital traits significantly influence SBM innovation both directly and indirectly through EO and SO. Furthermore, DO was found to moderate the relationship between SO and SBM, highlighting the importance of digital maturity as a strategic enabler. The study introduces the 3P2SBMI framework, which conceptualises *purpose* (SO), *people* (EO), and *platform* (DO) as foundational enablers of SBM innovation. A TBL Digital Traits – Organisational Capability Matrix is developed to help firms assess their strategic positioning and transformation readiness. The findings contribute to theory by linking sustainability and digital transformation through a unified model, and offer practical insights for AEC firms, industry leaders, and policymakers. By highlighting how digital capabilities and organisational orientations interact to drive sustainability-oriented innovation, the insights of this study provide a strategic roadmap for advancing digital-sustainability transitions in complex project-based industries.

**Keywords:** *Digital Transformation, Sustainable Business Model Innovation, Triple Bottom Line, AEC Industry, Entrepreneurial Orientation, Sustainability Orientation, Digital Orientation.*

# LIST OF ABBREVIATIONS

| Abbreviation | Full Term/Definition |
|---|---|
| AEC | Architecture, Engineering, and Construction |
| AI | Artificial Intelligence |
| AR/VR | Augmented and Virtual Reality |
| AR | Augmented Reality |
| AVE | Average Variance Extracted |
| BDA | Big Data Analytics |
| BC | Blockchain |
| BIM | Building Information Modelling |
| BMC | Business Model Canvas |
| BMI | Business Model Innovation |
| BREEAM | Building Research Establishment Environmental Assessment Method |
| CB-SEM | Covariance-Based Structural Equation Modelling |
| CC | Cloud Computing |
| CMB | Common Method Bias |
| CR | Composite Reliability |
| CFA | Confirmatory Factor Analysis |
| CITC | Corrected Item-total Correlation |
| DO | Digital Orientation |
| DT | Digital Transformation |
| DTs | Digital Twins |
| EO | Entrepreneurial Orientation |
| ESG | Environmental, Social and Governance |
| EFA | Exploratory Factor Analysis |
| GIS | Geographic Information Systems |
| HTMT | Heterotrait-Monotrait Ratio |
| HOC | Higher-order Construct |
| HKCA | Hong Kong Construction Association |
| HKBIM | Hong Kong Registered BIM Managers |
| HKIA | Hong Kong Institute of Architects |
| IoT | Internet of Things |
| IPD | Integrated Project Delivery |
| KMO | Kaiser-Meyer-Olkin Measure of Sampling Adequacy |
| LCA | Lifecycle Assessment |
| LEED | Leadership in Energy and Environmental Design |

| Abbreviation | Full Term/Definition |
| --- | --- |
| ML | Machine Learning |
| MKC | Market Knowledge Competence |
| MICOM | Measurement Invariance of Composite Models |
| MGA | Multigroup Analysis |
| NPD | New Product Development |
| OC | Organisational Capability |
| PLS-SEM | Partial Least Squares Structural Equation Modelling |
| PER | Personal Networks |
| SEM | Structural Equation Modelling |
| SBM | Sustainable Business Model |
| SO | Sustainability Orientation |
| SDG | Sustainable Development Goals |
| TBL | Triple Bottom Line |
| VIF | Variance Inflation Factor |
| VR | Virtual Reality |

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# INTRODUCTION

The Architecture, Engineering, and Construction (AEC) industry in Hong Kong has typically been one of the least digitally advanced business sectors. The McKinsey's Global Institute Industry Digitisation Index identifies the construction sector as the second lowest in adopting digital technologies, especially in places like China (McKinsey & Company, 2017). However, firms increasingly recognise that digital technologies could improve productivity, sustainability, and competitiveness within this industry. More recent industry reports highlight that a growing number of stakeholders in Hong Kong’s AEC sector begins to view digital transformation (DT) as a strategic priority. This shift is driven by rising demands for efficiency, increasing costs, and greater pressure to meet sustainability goals. Key to this change is using technologies like Building Information Modelling (BIM), which the Hong Kong government mandated in 2017 (HKSAR, 2017) for all public works over HK$30 million. This mandate has accelerated BIM adoption in both public as well as private projects. Beyond BIM, the emergence of Integrated Project Delivery (IPD), Augmented Reality (AR), Artificial Intelligence (AI), and the Internet of Things (IoT) enable greater connectivity and teamwork across construction. While such technologies enable real-time decision-making, better resource distribution, and improved results, many firms struggle to adopt them due to weak digital plans, cultural inertia, and skill shortages.

## 1.1 Digital Transformation in AEC Industry

The AEC industry in Hong Kong is in a pressing stage of transformation, driven by the need for efficiency, productivity, and competitiveness improvements. This reshaping is consistent with the more general pattern of DT occurring globally. It is not only a technological shift but also a recasting of organisational logic and capability. Recent studies have enhanced the understanding of DT beyond mere technology adoption. According to Angelopoulos *et al.* (2023) DT represents a fundamental change in operational logic, enabled by a reversal of agency—from human actors to digital ones. This implies that digital technologies are no longer mere supportive tools; they are decision-makers. Under this lens, DT is more effectively perceived as a recursive, emergent process through which firms iteratively change their structure, roles, and capabilities in response to new technologies, affordances, and stakeholder demands.

Consistent with this understanding, Warner and Wäger (2019) conceptualise DT as a continuous strategic renewal process driven by digital technologies to reconfigure the business model, collaboration, and culture of a firm. This view strengthens the call for firms, particularly in complex project-based markets such as AEC, to initiate DT endeavours as an end-to-end strategic commitment rather than a one-off project.

In the Hong Kong AEC industry, DT goes beyond the implementation of new tools or the automation of manual processes. It calls for a shift away from siloed, linear workflows to more integrated, collaborative, and data-informed ways of doing business. Given that projects in this industry are often highly complex, have tight deadlines, and involve integrated stakeholders, the benefits of digital technology in this context come from real-time communication, interdisciplinary collaboration, and predictive project management.

An overarching understanding of the adoption of digital technologies in the Hong Kong AEC industry is to heighten stakeholder engagement and project delivery. Digital tools are increasing transparency, reducing delays, and helping connect the value chain, leading to more efficient, durable, and client-centred project outcomes. Moreover, with increasingly demanding clients and sustainability as one of the most important prerequisites, digital technologies enable firms to better understand and respond to user demands, environmental conditions, and lifecycle performance.

Furthermore, such technologies must be meaningfully included in decision-making processes (Struijk *et al.*, 2023). This also involves rethinking governance, accountability, and skillsets. DT is not an ‘outcome’ to be "achieved"—it is not a linear matter of eventually ‘arriving.’ Instead, it is an ongoing process of alignment and adjustment, a mutual co-evolution of digital systems and human participants (Angelopoulos *et al.*, 2023; Struijk *et al.*, 2023; Vial, 2019). AEC firms need to question their skills, values, and practices to position themselves at the forefront of an ever more competitive environment.

To conclude, DT in Hong Kong's AEC industry is a journey that is strategic, dynamic, and sociotechnical, not a static destination. However, it has the potential to serve as a driver of value and perhaps even sector-level transformation and sustainability, if it is addressed at an enterprise level, where people, processes, platforms, and cultural change meld to sustain productivity.

## 1.2 Digital Transformation and Sustainability

A major factor driving the DT of Hong Kong's AEC industry is the need to enhance sustainability and reduce environmental impact. DT plays a vital role in this process, enabling firms to adopt more sustainable practices and reduce their carbon footprint. According to Hong Kong's Climate Action Plan 2050 (HKSAR, 2021), the region strives to achieve carbon neutrality by 2050. However, the building and construction industry remains a significant source of carbon emissions. One important technology that promotes sustainable development is BIM in the AEC sector. Through BIM, architects, engineers and contractors can produce digital prototypes of structural or infrastructure projects to simulate and investigate the implementation of the project, detect possible errors and improve the design and construction workflow.

Moreover, BIM can be integrated with AI and big data analytics (BDA) to enhance construction site safety and security. By analysing vast amounts of real-time data from sensors, cameras, and wearable devices, AI algorithms can predict potential hazards, monitor compliance with safety protocols, and alert managers to unsafe behaviours, thereby reducing accidents and improving operational oversight. A study by the National Building Information Modelling Standard of the United States (NBIMS-US) showed that the application of BIM can accelerate project delivery by up to 73% and reduce the weather impact of projects by up to 28% (NBIMS-US, 2015). This is because BIM enables AEC firms to identify and resolve potential issues before they escalate into major problems, reducing costly rework and minimising waste during construction.

By incorporating digital technologies, AEC firms can significantly improve sustainability. As the world works to combat climate change and resource depletion, leveraging such technologies can enable more sustainable practices throughout the lifecycle of a building project. One of the most impactful technologies is BIM, which allows for a comprehensive digital depiction of a building. This technology allows architects and engineers to closely review energy consumption, material utilisation, and waste generation before construction begins. By visualising the entire project in a virtual environment using AR and virtual reality (VR) technology, teams can identify inefficiencies and improve designs for greater energy efficiency and sustainability. This proactive strategy reduces environmental impact and lowers long-term costs. The IoT also plays a key role in sustainability by monitoring building operations in real time. Sensors can track energy consumption, water usage, and indoor air quality, providing valuable data to develop smart resource management plans. For example, smart building systems can automatically calibrate lighting and heating based on occupancy, reducing energy waste.

Overall, the convergence of DT and sustainability presents a unique opportunity for the AEC industry to reimagine its role in addressing environmental challenges. By embedding digital technologies into sustainability strategies, firms can achieve greater operational efficiency, reduce ecological impact, and contribute meaningfully to Hong Kong's broader climate and development goals.

## 1.3 Misconceptions About Digital Technology Adoption

There are some common misconceptions about the role of digital technologies in business transformation and sustainability. One widespread belief is that DT is just about bringing in new technologies into existing business processes. However, this view oversimplifies the concept and fails to acknowledge that DT requires more than just technology adoption. A study by McKinsey Global Institute emphasises that "digital transformation is not just about technology; it's about changing how a company operates, interacts with stakeholders, and creates values" (Lamarre *et al.*, 2023). This shows the need to understand digital change more deeply, beyond merely developing new tools.

Another common misconception is that DT is a one-time investment, rather than an ongoing journey. This misunderstanding can lead to frustration, as DT requires sustained effort and investment over time through many small steps. It is not something that can be accomplished through a single project.

Additionally, many wrongly view the adoption of digital technologies as the end goal of DT, rather than a means to achieve broader organisational objectives. While digital technologies are key enablers of change, their real purpose lies in creating innovative business models, improving customer experiences, and increasing efficiency - all enabled by using digital technologies effectively.

When it comes to sustainability, there is also a common misunderstanding about the role of digital technologies. While many see it as a key driver of sustainable practices, this is not always true. While digital technologies can support sustainability, their effective use requires a nuanced understanding of the complexities involved in DT. By thoughtfully applying these technologies and recognising their strategic implications, AEC firms can better position themselves to contribute to a more sustainable future.

## 1.4 Determinants of Digital Transformation

Examining the factors that drive DT for sustainability and business model innovation (BMI) within Hong Kong's AEC industry is vital for tackling the urgent issues of urbanisation and environmental sustainability. As the industry faces mounting pressure to adopt eco-friendly practices, it becomes increasingly important to understand the factors that fuel DT (World Green Building Council, 2019).

Technological factors are key players in this landscape. The perceived advantages of digital technologies, such as enhanced efficiency and cost reduction, serve as strong motivators for firms to embrace innovation (Rogers *et al.*, 2014). In the AEC sector, tools such as BIM and AI/ML hold significant potential to greatly improve project outcomes and sustainability initiatives (Eastman, 2011). However, the integration of these technologies with existing systems is crucial for their adoption (Na *et al.*, 2023). Firms are more inclined to adopt digital technologies that seamlessly fit into their current processes, helping to minimise the complexity and time involved in workflow (Chen and Tang, 2019).

Moreover, the rapid pace of technological advancement has created a skills gap among the workforce (Siddiqui *et al.*, 2023). Many professionals lack the training needed to effectively use digital tools, which can slow the adoption process (Keung *et al.*, 2023). Additionally, the high initial costs associated with implementing digital technologies can pose a significant barrier, particularly for smaller firms (Eastman, 2011).

Organisational factors are equally critical in propelling DT within the AEC industry. Strong leadership and a commitment from management are crucial for driving DT initiatives forward (World Green Building Council, 2019). Firms that prioritise DT and allocate resources wisely tend to see greater success in their efforts (Bhattacharya and Momaya, 2021). The skills and expertise of the workforce play a vital role in achieving successful DT (Na *et al.*, 2023). Investing in training and development ensures that employees are well-equipped to leverage new tools effectively, which can lead to improved productivity (Chen and Tang, 2019). Moreover, fostering an organisational culture that encourages experimentation and innovation creates an environment conducive to DT (Siddiqui *et al.*, 2023). However, believing that technology alone can solve the long-standing challenges faced by the AEC industry misses the point about the importance of organisational culture and collaboration. Truly successful DT requires a shift in mindset among stakeholders, emphasising continuous learning, adaptability, and collaboration (Siddiqui *et al.*, 2023). Many firms struggle to create this culture, resulting in fragmented implementations that fail to harness the full potential of advanced digital technologies.

Environmental factors, including customer expectations and government support, also play a significant role in shaping the landscape of DT (World Green Building Council, 2019). The growing demand for sustainable practices from clients and stakeholders pushes firms to adopt digital solutions. Understanding customer preferences can guide organisations in their DT efforts (Eastman, 2011). Additionally, supportive policies and incentives from the Hong Kong government can facilitate this transformation within the AEC sector (Bureau, 2018). Regulations that promote sustainability and provide funding for innovative projects encourage firms to invest in digital technologies (World Green Building Council, 2019). Furthermore, the need to adapt to environmental uncertainties, such as climate change and resource scarcity, drives firms to innovate. DT equips firms with the necessary tools to navigate these challenges effectively.

The strategy factor refers to the strategic orientation of a firm, which influences how decisions are made and how resources are allocated to support innovation, sustainability, and long-term competitiveness. The entrepreneurial ethos of a firm indicates its propensity to be innovative, take calculated risks, and act proactively in the face of change (Lumpkin and Dess, 1996). It also includes the level of integration of sustainability in strategic planning as well as day-to-day operations, known as sustainability culture and practice (Claudy *et al.*, 2016). Firms with well-defined strategic direction are better able to ensure DT is in line with wider business objectives such as environmental and operational improvement. The digital preparedness of a firm, as well as its strategic intentionality to embrace cutting-edge technologies, can also impact the success of DT efforts across the board.

## 1.5 Challenges in the Digital-Sustainability Transition

DT in Hong Kong's AEC industry presents several challenges, especially when it comes to achieving sustainability goals. While the advantages of digital technologies, such as enhanced efficiency, reduced cost improved environmental footprint are well acknowledged, several obstacles stand in the way of their effective implementation.

One of the most significant hurdles is the resistance to change among employees (Struijk *et al.*, 2023). Many employees (Struijk *et al.*, 2023) are accustomed to traditional ways of working and might feel hesitant to embrace new technologies. This reluctance can often stem from a lack of awareness about the benefits of DT or fears about job security due to automation. To shift this mindset, firms need to invest in comprehensive training and foster a culture that values innovation and continuous improvement.

Concurrently, the AEC sector in Hong Kong is highly fragmented, involving a diverse range of stakeholders including but not limited to architects, engineers, contractors, and subcontractors, but also the Government, each working with their own systems and standards. This fragmentation makes collaboration and data sharing more complex, both of which are crucial for successful DT. Without a unified approach to technology adoption, projects can suffer from inefficiencies and miscommunication, ultimately hindering efforts towards sustainability.

Furthermore, the rapid pace of technological advancement has created a notable skills gap in the AEC workforce. Many professionals lack the necessary training to effectively utilise tools like BIM. They also lack knowledge of the applications of AI, digital twins (DTs), and the IoT. This shortage of skilled workers can slow down the adoption of such technologies and limit their positive impact on sustainability goals. Bridging this gap requires investment in education and training programs to ensure the workforce is equipped for a digital future.

Implementing digital technologies requires significant upfront investment, which can be a barrier for many firms, particularly smaller companies operating on tight budgets. Although the Hong Kong Government has support funding for the industry, the costs associated with software, hardware, training, and IT support can deter organisations from pursuing DT, even when the long-term benefits are clear. This issue is further complicated by the low-profit margins commonly found in the AEC industry, making it challenging for firms to justify such investments and expenditures.

Another major challenge is the lack of standardised data formats and communication protocols within the AEC industry. This absence of common standards can lead to inefficiencies and misalignment among stakeholders. When integrating various digital technologies becomes difficult, the potential for collaboration and data sharing is limited. Establishing industry-wide standards is essential for facilitating smooth communication and maximising the benefits of DT.

Finally, while in 2017 the Hong Kong SAR Government mandated the use of BIM for all public projects over HK$30 million (HKSAR, 2017), this requirement only applies to the design phase and not the entire construction value chain. To comply with the regulation, many firms have subcontracted 3D modelling services, which have driven up project costs, especially for small and medium enterprises. This limited application of BIM has not catalysed holistic digital transformation across the industry.

## 1.6 Research Objectives and Contributions

The primary aim of this study is to explore and conceptualise the key factors that influence DT in the AEC industry, with a particular focus on how these factors may enable the development of sustainable and innovative business models. The study is guided by the following four objectives:

1. To identify and evaluate technological determinants—such as BIM, AI, IoT, and AR/VR—that have the potential to facilitate or hinder DT in the AEC sector, particularly in the context of sustainability challenges.
2. To examine organisational-level factors (e.g., leadership commitment, organisational culture, and workforce capabilities) that may influence the readiness and implementation of DT initiatives in AEC firms.
3. To investigate broader strategic factors—including innovation posture, sustainability culture and practice, and digital readiness—that may shape how DT is aligned with long-term sustainability and competitiveness goals.
4. To propose a conceptual framework that integrates these key determinants and outlines potential pathways through which DT may contribute to sustainable BMI within the AEC industry.

Based on the above objectives, the central research question guiding this study is:

*What are the key organisational and technological determinants of DT that enable sustainable BMI in the AEC industry?*

This question encapsulates the study's intent to uncover the drivers and enablers of DT, offering insights into how firms can evolve their business models to meet the demands of a more sustainable and digitally integrated future.

In doing so, this study contributes to the theoretical discourse at the intersection of DT, sustainability, and organisational strategy in several ways:

- It extends existing DT literature by incorporating sustainability considerations—such as environmental and social value creation—into models of technological adoption in the AEC industry.
- It proposes a multidimensional conceptual framework that integrates technological, organisational, and strategic drivers of DT as enablers of BMI.
- It enriches the understanding of how organisational context influences the translation of digital capabilities into sustainable outcomes, thereby contributing to the broader literature on change management and innovation in project-based industries.

From a practical perspective, this research offers insights and tools for AEC practitioners, industry leaders, and policymakers:

- It identifies key internal and external factors that AEC firms should consider when planning and implementing DT strategies aligned with sustainability goals.
- It anticipates providing a roadmap or framework that can assist firms in assessing their readiness for DT and identifying critical areas for capability development.
- It informs policy discussions by highlighting potential barriers and enablers of sector-wide DT, in the context of regulatory standards and sustainability mandates.

These theoretical and practical contributions establish the conceptual foundation of the study. Their development and validation are addressed throughout the subsequent chapters and further elaborated in the Discussion Chapter, where key empirical findings are synthesised and integrated into strategic models and frameworks. In doing so, the study bridges the conceptual groundwork presented in this Chapter with the evidence-based insights derived from data analysis.

## 1.7 Structure of Thesis

Following this introduction, the next chapter provides a thorough review of the literature, with an emphasis on DT in relation to sustainable BMI. Additionally, it delves into organisational practices that intersect with entrepreneurship and sustainability. The aim of this chapter is to pinpoint research gaps that merit exploration, while also outlining the theoretical framework and hypotheses that guide this study. The Methodology Chapter details the methodology, covering aspects such as construct development, measurement design, data collection, and analytical techniques. The Analysis and Results Chapter presents the results, showcasing measurement validity, evaluating the structural model, and discussing findings from the multigroup analysis. Finally, the Discussion Chapter delves into the key findings, offering a detailed discussion of their theoretical and practical implications. It introduces the 3P2SBMI Framework and wraps up with a reflection on the study's limitations and recommendations relating to avenues for future research.

# LITERATURE REVIEW

DT serves as a key enabler for novel business model designs within the AEC industry to cope with increasing requests for sustainable improvements. Firms in this industry have started relying on digital technologies to completely reinvent their operational models. In recent years, the convergence of DT, and greening, have significantly transformed the global business environment and led to the creation of new competitive opportunities for firms around the world. The performance of such initiatives is highly dependent upon efficient organisational systems and mechanisms, especially the inclusion of sustainability factors in basic operational philosophies. Entrepreneurial culture, seen as a key factor in these processes (Javalgi and Todd, 2011) presents a challenge for the success of construction projects (Li *et al.*, 2017). This review dissects the complex interlinkages between the DT, BMI, sustainability principles, and entrepreneurial mindset, and thus offers an in-depth conception of the state of the art in the field.

If the AEC industry is to succeed in BMI, it must understand the drivers of DT. These determinants have not yet been empirically explored, and this contribution investigates their role for innovation by shedding light into specific challenges and opportunities of the industry. The results seek to contribute to the body of knowledge by providing practical suggestions and recommendations for AEC firms to successfully capitalise on digital technologies and drive their sustainability efforts.

A narrative approach was adopted for the presentation of the literature review, as it enables a more comprehensive exploration of the issue and incorporates a range of views and the findings of different studies. This approach provides flexibility in synthesising evidence, able to adjust focus as new knowledge becomes evident, particularly around new and emergent themes and issues. Narrative reviews can successfully reconcile the literature, highlight gaps in the available literature, and suggest topics for future research, particularly on the processes and the context of DT for sustainable innovation success.

They also make it possible to contextualise the findings in larger theoretical frameworks, digital technologies, other knowledge areas, sustainability theories, and BMI frameworks. Additionally, narrative reviews render results in an understandable style for those stakeholders concerned with the consequences of digital technologies for the sustainability of businesses. In general, a narrative review allows a full understanding of the nexus of digital technologies and sustainable BMI.

A systematic review method was used to search the literature, this includes the search in academic databases such as Scopus, Web of Science, Google Scholar, and ScienceDirect for specific keywords as presented in Table 2.1. The inclusion criteria focused on the peer-reviewed journal articles in which the relationship between DT and BMI, with respect to the sustainability aspect in the AEC sector, from 1990 to 2023. More than 500 papers were initially found and more than 100 were used to identify essential themes. Cross-referencing with other relevant papers and articles was conducted throughout the literature review and study period to ensure a comprehensive understanding of the topic. This approach helped validate findings, identify gaps, and incorporate diverse perspectives into the analysis.

Table 2.1 – Domains and Key Words Searching

| **Domain** | **Key Words** |
|---|---|
| Digital Transformation | “Digital transformation”<br>“Digital transformation” and “Built industry” or “AEC industry” or “Construction”<br>“Digital vision”<br>“Digital orientation”<br>“Digital strategy”<br>“Digital leadership”<br>“Digitalisation” |
| AEC Digital Technology | “Building information modelling” or “Building information management” or “BIM”<br>“Geographic information systems” or “GIS”<br>“Artificial Intelligent” and “Built industry” or “AEC industry” or “Construction”<br>“Digital twin” and Built industry” or “AEC industry” or “Construction”<br>“Blockchain” and Built industry” or “AEC industry” or “construction”<br>“Cloud computing” and Built industry” or “AEC industry” or “Construction”<br>“3D printing” and Built industry” or “AEC industry” or “Construction”<br>“Machine learning” and Built industry” or “AEC industry” or “Construction”<br>“AR / VR” and “Built industry” or “AEC industry” or “Construction”<br>“Big Data Analytic” and “Built industry” or “AEC industry” or “Construction”<br>“IoT” and “Built industry” or “AEC industry” or “Construction” |
| Sustainability | “ESG”<br>“Triple bottom line”<br>“Sustainable Development Goals” or “SDG”<br>“ESG” and “Built industry” or “AEC industry” or “Construction”<br>“Sustainability” and “Built industry” or “AEC industry” or “Construction”<br>“Sustainability” and “Digital transformation” |
| Business Model | “Business model”<br>“Business model innovation”<br>“Business model canvas”<br>“Sustainable business model” or “Sustainable business model innovation”<br>“Business model” and “Built industry” or “AEC industry” or “Construction” |
| Corporate culture | “Corporate entrepreneurship”<br>“Corporate entrepreneurship” and “Digital transformation”<br>“Entrepreneurial orientation” and “Digital transformation”<br>“Entrepreneurial orientation” and “Business model” |

## 2.1 Digital Transformation

### 2.1.1 Concept and Strategic Foundations

DT is defined as the fundamental and systemic reorganisation of business models, processes, and activities through digitalisation (Mergel *et al.*, 2019). It includes embracing all sorts of digital technologies, such as data analytics, cloud, and AI (Manzoor *et al.*, 2021). The process of transformation is assumed to follow a phased approach: digitisation (shifting analogue data into digital form), digitalisation (applying digital technology to existing processes) and digital transformation (a fundamental change to the business logic and value creation) (Verhoef *et al.*, 2021). These phases depict a mounting degree of organisational transformation which is needed to fully exploit digital technologies.

Angelopoulos *et al.* (2023) present a more subtle perspective of DT as a "fundamental change in operational logic through the reversal of agency from human to digital actors". In this context, DT is not just about adopting digital technologies but about transferring decision rights to them and thereby changing the way firms act, govern and create value. This view emphasises the fact that DT is recursive and becomes a moving target, with humans and digital agents co-adapting to each other. Similarly, Van Zeebroeck *et al.* (2023), suggest that DT enables firms to create new business models, products, services, and improves operational flexibility, and competitive advantage. AlNuaimi *et al.* (2022) highlight that becoming digitally transformed is not just about introducing digital technologies, but also about fostering an attitude and mindset, including experimentation, risk response, and leadership agility. When digital technologies are embedded across a firm it is necessary to re-examine organisational structures, customer engagement approaches, and internal capabilities that drive sustainable value.

### 2.1.2 Drivers and Enablers of Digital Transformation

The forces behind DT are complex, unique to different contexts. Externally, firms face technological forces, customer expectations, competitive forces, and policy and regulatory influences (Nadkarni and Prügl, 2020). Internally, there is an inherent need for constant innovation, operational efficiency and change in business models to stay relevant (Ghosh *et al.*, 2022). The COVID-19 pandemic subsequently upended this, and deepening adoption of digital technologies as remote operations, electronic commerce, and digital service delivery became the new norm for most businesses (Priyono *et al.*, 2020).

One of the key factors which catalyse DT is a clear digital vision, which is a future looking statement identifying the role of digital technologies (Mishra *et al.*, 2023). A powerful digital vision not just informs strategic choices but galvanises internal and external parties around a cohesive transformation narrative. According to AlNuaimi *et al.* (2022), this vision must be tightly linked to the organisation's top-level strategy and yet be pliable enough to be adapted to developing technologies and changing markets.

To realise DT, firms need to develop a digital strategy that is holistic (Struijk *et al.*, 2023). Westerman *et al.* (2014) and Gurbaxani and Dunkle (2019) stress the importance of understanding specific digital capabilities, evaluating the digital context and promoting a culture, which facilitates change and innovation. This investment is not just in technology, but also in talent and in firms where people are coming together and learning from each other. DT is facilitated by leadership and successful digital leaders also need to be agile, have vision, and be open to experimentation and risk (Fernandez-Vidal *et al.*, 2022). They are also balancing short-term performance targets with long-term investments in capability change.

Importantly, Angelopoulos *et al.* (2023), for instance, argue that a precondition for transformation is the capacity of a firm to absorb evolving agency dynamics — in which digital technologies progressively automate actions. This calls for new governance, ethics and digital accountability leadership competencies. In parallel, Struijk *et al.* (2023), suggest information quality management as being an under-investigated yet crucial enabler for successful DT. Their research indicates that when firms establish a strategy to manage the access, accuracy and relevance of data, business transformation becomes more grounded in real operational scenarios and needs from stakeholders.

Combined, these insights highlight that DT is driven not only by external pressures or digital tools, but also by internal capabilities, strategic clarity, adaptive leadership, and high-quality information ecosystems that can support evolving digital agency.

### 2.1.3 Adoption and Challenges in the AEC Sector

DT in the AEC industry is still in its infancy compared to industries such as manufacturing (Adekunle *et al.*, 2021). BIM is increasingly prevalent in AEC, which increases construction efficiency and cooperation among involved parties (Bryde *et al.*, 2013). Yet, the use of BIM in business is unevenly distributed and varies across firms, in particular, Small and Medium-sized Enterprises (SMEs) (Chan *et al.*, 2019). Several studies highlight the significance of ISO 19650 (ISO, 2018) for AEC DT. This standard is fundamental for digitisation within the AEC sector by promoting integration and collaboration between project participants (Davidson *et al.*, 2022). It supports the idea of transition from analogue to digital practices to establish a common operational level to facilitate cooperation (Godager *et al.*, 2022), and assists in governing digitally created data and establishing data-driven cultures (Matthei and Klemt-Albert, 2023).

The increasing rate of technology developments enables organisations to leverage different technologies to keep ahead of the competition (Abioye *et al.*, 2021; Baghalzadeh Shishehgarkhaneh *et al.*, 2022). Start-ups for construction technologies are disrupting the traditional ways of working and introducing new software-based technologies to enhance efficiency and sustainability in construction processes (Sacks *et al.*, 2020). The globalisation of business compels firms to expand their operations and include customers and suppliers, mainly through digital technologies (Halin *et al.*, 2020).

Obstacles and hindrances for the AEC industry in DT are the lack of willingness to change, a shortage of qualified labour, and disconnected supply chains (Zhou *et al.*, 2019). Mitigating these challenges requires collaboration, training, and a holistic perspective (Ozorhon and Karahan, 2017). Supportive policy environments for digital literacy and a culture of innovation should also be considered (Lijauco *et al.*, 2020). The transition from project-driven to data-driven, with an emphasis on digital skills, open standards, and collaboration is critical (Karji *et al.*, 2022). A further challenge is the diversity and fragmentation in the AEC sector (Lavikka *et al.*, 2018), thereby demanding standardisation and open standards such as Industry Foundation Classes (IFC) in BIM, to enhance interoperability and collaboration (Thein, 2011). Having appropriate staff with the right skill is also important and firms need to be able to attract and retain talented employees with the needed digital competencies for their DT endeavours (Mandičák *et al.*, 2020).

### 2.1.4 The Role of Digital Collaboration

DT is very much about collaboration, bringing digital technologies into firms. Digital collaboration promotes innovation by giving employees the tools and resources they need to work together across teams, departments, and geographies. Firms with a progressive digital collaboration culture are more likely to introduce new products and services (Orellana, 2017). Open innovation based on collaborations with external actors is in a position of co-creating new products and services (Levine and Prietula, 2014). Digital collaboration enhances decision-making by offering real-time data and insights. Construction platforms such as Autodesk Bim360, Trimble Connect, and Bentley Projectwise support real-time collaboration allowing faster and better cross-functional decision-making, increasing decision quality (Merschbrock and Munkvold, 2015). DC also accelerates organisational agility, which means that organisations can respond swiftly to customer requirements and changing markets (Gless *et al.*, 2018).

### 2.1.5 Collaboration Tools, Benefits, and Barriers

In the AEC sector, collaboration is necessary for project success. BIM solutions facilitate cooperation, communication, efficiency, error minimisation, and project quality (Oh *et al.*, 2015). Collaboration in design work improves the quality of designs and reduces errors (Forcael *et al.*, 2020). Cyber tools such as VR and AR enhance cooperation (Wen and Gheisari, 2020). Collaboration and project outcomes are also improved under the framework of Integrated Project Delivery (IPD) (Kelly, 2012; Kent and Becerik-Gerber, 2010; Liu *et al.*, 2021).

## 2.2 Sustainability in AEC Industry

Sustainability has become a major concern in the AEC industry because of its significant environmental and social effects. The building sector accounts for 38% of energy-related carbon dioxide emissions worldwide and requires vast amounts of materials and water (UNEP, 2023). These environmental issues as well as growing regulatory requirements and changing social expectations have brought sustainability to the forefront AEC conversation. Notwithstanding these increased levels of understanding, the fragmented nature of the AEC industry, which effectively comprises a consortium of parties including architects, engineers, contractors, and clients presents challenges to both coherent and uniform sustainability practices (Zuo and Zillante, 2005). Mismatched goals and a lack of communication invariably lead to waste and lost opportunities to integrate sustainable strategies. This has prompted calls for collaborative delivery mechanisms, such as IPD to enhance early building stakeholders' engagements and share in the sustainable vision (Miller and Lessard, 2001).

### 2.2.1 AEC Sustainable Practices and Tools

Various tools and techniques have been developed to support the transition to sustainability in AEC. BIM is one of them. BIM offers multi-dimensional modelling with anticipated identification of sustainable opportunities, optimise resource consumption, and minimise construction waste (Eastman, 2011). Its incorporation in the design and construction process contributes to the capacity of project teams to achieve environmental goals and to achieve better lifecycle performance.

Simultaneously, green building certifications, such as LEED (Leadership in Energy and Environmental Design) and BREEAM (Building Research Establishment Environmental Assessment Method) offer a structured approach to implementing and benchmarking sustainable practices (Kibert, 2016). These tools focus on energy efficiency, indoor environmental quality, and material sustainability which consequently impact building performance and occupant health (Hwang and Tan, 2012).

Lifecycle Assessment (LCA) has also been growing in popularity as an approach for assessing environmental impacts of buildings throughout their entire life cycle—from the extraction of raw material to ultimate disposal (Finnveden *et al.*, 2009). In the preliminary design stage, LCA methods enable better-informed decisions about materials, energy systems, and means of construction, leading to potential long-term sustainable benefits (Azhar *et al.*, 2011).

### 2.2.2 Barriers and Facilitators to Sustainability Implementation

Even though tools and frameworks exist, the development and implementation of sustainable practices in AEC is still poor. Critical challenges include low levels of professionals' knowledge and training, high upfront costs, client demand constraints (Khan *et al.*, 2014; Ofori, 2000). Furthermore, the lack of common metrics to enable and measure environmental and other social performance is still curtailing the integration into core corporate policies and practices. On the demand side, policy and regulation have played a growing role. Incentive policy tools, such as a tax credit for green buildings and obligatory energy standards for building energy consumption, have been observed to promote the popularisation and application of sustainable building (Mao *et al.*, 2015). Education and training programms serve also to stimulate the creation of a skilled workforce for sustainability.

### 2.2.3 Sustainability Assessment in Comparative Perspective

Due to the multidimensional characteristics of sustainability, several theoretical approaches have been developed to help apply sustainability principles in the built environment. A comparative review across the four main paradigms (Environmental, Social, and Governance (ESG), Circular Economy, Doughnut Economics, and the TBL) as shown in Table 2.2, considering the strategic and operational scopes, sheds light on varying degrees of relevance.

Table 2.2 – Comparison of Major Sustainability Frameworks

| Framework / Theory | Primary Focus | Level of Application | Key Strengths | Limitations | Reference |
|---|---|---|---|---|---|
| **ESG (Environmental, Social, Governance)** | Investment, risk and performance | External (investment, reporting, compliance) | Widely used by investors; standardised metrics | Compliance-driven; limited internal innovation focus | Eccles *et al.* (2012) |
| **Circular Economy** | Resource efficiency; waste reduction | Operational and systemic | Emphasises lifecycle thinking and closed-loop systems | Focused on material flows; less emphasis on social factors | Geissdoerfer *et al.* (2017) |
| **Doughnut Economics** | Sustainable development within planetary boundaries | Macro (policy, economics) | Integrates social equity and ecological ceilings | Abstract; hard to apply at firm or project level | Raworth (2017) |
| **Triple Bottom Line (TBL)** | People, Planet, Profit value creation | Organisational (strategic and operational) | Balanced, integrative; adaptable across sectors | Lacks standardised metrics for implementation | Elkington (1997) |

#### 2.2.3.1 Environmental, Social and Governance (ESG)

ESG has established itself as a framework for corporate sustainability reporting, especially in the finance and investment industries. It assesses corporate action from 3 perspectives: E (e.g., emissions, energy use), S (e.g., labour practices, diversity), and G (e.g., leadership, transparency). Investors utilise ESG metrics in order to evaluate risks and long-term value creation (Eccles *et al.*, 2012). ESG offers a framework for evaluating sustainability performance, but it tends to be outward-facing and rules-based, valuing reporting and transparency more than strategic change and making it less suitable for informing internal innovation processes.

#### 2.2.3.2 Circular Economy

The circular economy model is based on a continuous loop system, which aims to “reset environmental balance” by reusing/recycling/regenerating and/or reducing waste and reducing the pollution production when materials and resources are extracted, processed, and disposed (Geissdoerfer *et al.*, 2017). Its concepts have been adopted by industries of manufacturing, packaging, and construction, where material efficiency and lifecycle thinking are necessary. However, it underestimates social value creation, the style of governance, or the differences in the strategic attitude of the companies towards sustainability. Thus, it is an appropriate process model but lacks a broader strategic view.

#### 2.2.3.3 Doughnut Economics

Introduced by Raworth (2017), Doughnut Economics presents a model that envisions the fulfilment of human needs to ensure social equality and realisation is achieved within ecological limits. The "inner ring" stands for social foundation (e.g., education, equity, health), whereas the "outer ring" refers to ecological ceilings (e.g., climate change, biodiversity loss). The area between the rings—the “safe and just space for humanity” — is where we ought to locate sustainable development. The model is popular in public policy and urban planning, and although macro-level in nature, it is far less applicable to how strategies and innovation processes are performed at the firm level.

#### *2.2.3.4 Triple Bottom Line (TBL)*

The TBL concept, launched by Elkington (1997), provides an integrated perspective on sustainability by focusing not only on profit but also on three equally important facets: people (social value), planet (environmental preservation), and profit (economic viability). TBL has been frequently used as an orientation framework in studies of sustainable business models (Bocken *et al.*, 2014), innovation and digital transformation (George *et al.*, 2021). Its equal footing architecture enables scientists and practitioners to investigate combinations of trade-offs, synergies, and capacity building between environmental, social, and economic dimensions.

### 2.2.4 TBL as Strategic Framework

The lens of the TBL of economic (profit), environmental (planet), and social (people) performance is used to illustrate a strategic focus on sustainable value creation within the AEC sector (Elkington, 1997). It pushes companies to go beyond compliance and integrate sustainability into their businesses. In construction, TBL embraces energy-conscious design, the use of sustainable materials, and social equity (Bocken *et al.*, 2014). TBL adoption may improve business operations, risk mitigation, and stakeholder confidence and create a competitive edge in a sustainability-focused market (Epstein and Wisner, 2001; Porter and Kramer, 2006). It also serves the global frameworks agenda like the UN SDGs (Lubin and Esty, 2010). However, implementation is yet to be fully accomplished, with difficulties measuring non-financial results and overcoming well-entrenched profit-centered cultures still being evident (Bansal and DesJardine, 2014; Dyllick and Hockerts, 2002). A successful adoption should include leadership support, employee involvement, and incorporate sustainability into long-term strategic objectives.

## 2.3 Business Model Innovation

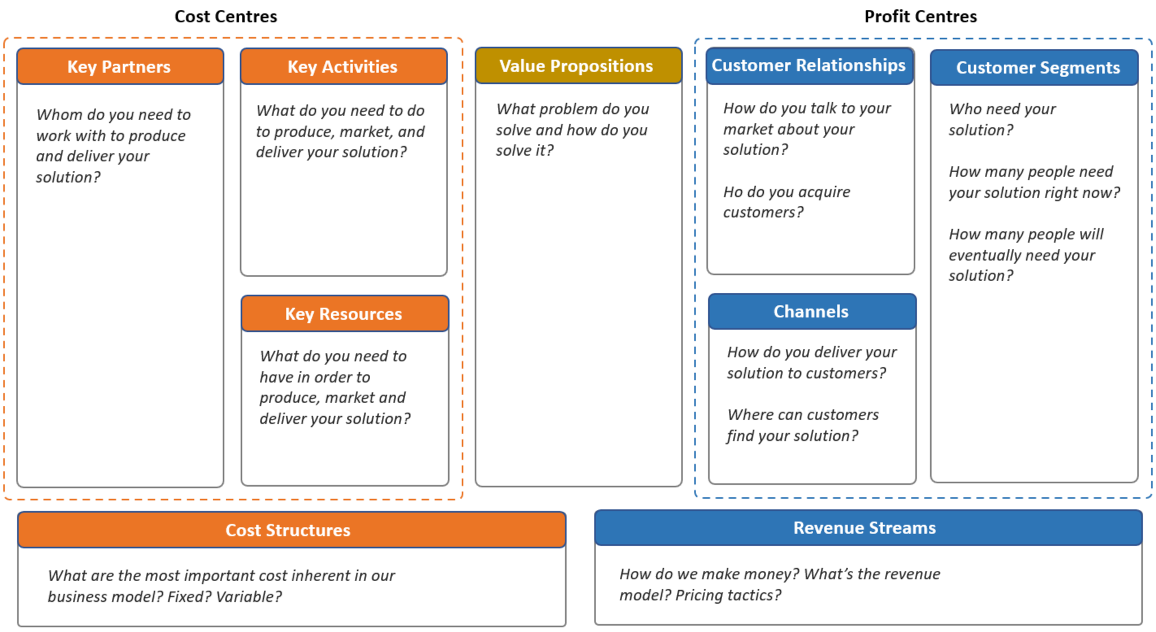
The AEC industry encourages collaboration among architects, engineers, contractors, subcontractors, and material suppliers. The conventional model of separating the design and construction phases (Design-Bid-Build, or DBB) in construction projects may result in disputes and wasted resources. In contrast, flat fee contracting models such as Construction Management at Risk (CMAR), Design-Build (DB), and IPD (Kelly, 2012) have become increasingly common to encourage risk sharing and collaboration, and to improve project results. These delivery mechanisms provide a background to more general discussions around BMI and sustainability in the industry.

It must first be established that the intrinsic concept of BMI should be defined first and is not to be confused with other established concepts, such as innovation, strategy, or business model. BMI defines the recreation, reconfiguring, and realigning of the architecture of actors and activities in and across the business value creation chain, i.e., that of the shaping, reinitiating, or redirecting of the architecture of how actors understand, meet, and collaborate to create, deliver, and capture value. Zott and Amit (2010) describe a business model as a “logical cohesive description of the way in which firms do business” and more recently Bocken *et al.* (2015) explain BMI as the creation of a business model that provides a fundamentally new value proposition or operational logic as compared to existing industry standards. According to Chesbrough and Rosenbloom (2002) the necessity to connect products, services, channels, and markets in new ways, to ensure sustainable flow of revenue is a critical task. This is representative of an increase in demand not just for product or service innovation, but rather for the transformational design of business architecture, considering technological, competitive, and environmental change.

### 2.3.1 The Business Model Canvas as a Catalyst of Innovation

Osterwalder and Pigneur (2010) conception of the Business Model Canvas (BMC) was developed as a strategic device consisting of nine interdependent building blocks: Customer Segments, Value Proposition, Channels, Customer Relationships, Revenue Streams, Key Resources, Key Activities, Key Partnerships, and Cost Structure (Figure 2.1). The BMC helps organisations to visualise, analyse, and understand their business model and has shown to offer benefits in recognising opportunities for innovation and sustainability (Bocken *et al.*, 2015).

Figure 2.1 – Business Model Canvas




The BMC has been useful in supporting organisations to create more sustainable business models (Chesbrough and Rosenbloom, 2002) by identifying value creation and cost reduction possibilities. The BMC has also benefited startups in recognising and giving priority to the key elements of the model at business level and to communicate these ideas with the company's stakeholders (Havemo, 2018). Despite its dominance, the BMC may be seen as problematic because it may be seen as problematic because it oversimplifies the intricacies of business models, provides little guidance for implementation and execution (Teece, 2000), and it does not reflect the dynamic and iterative nature of BMI (Zott *et al.*, 2011).

There is a strong association between BMI and BMC. BMI requires the invention of new business models for creating profits and revenue and redesigning the whole industry or market (Zott and Amit, 2010). It needs modification of the major components of the BMC. Effective BMI relies on a balance between such internal and external factors as strategic vision, market analysis, technology innovation, customer pull and organisational resources. It typically includes using digital technologies to create new value and transform operations and customer experience. Researchers have identified factors that are critical for successful BMI (Osterwalder and Pigneur, 2010; Teece, 2000) Each building block of the BMC can be influenced by digital technologies within the AEC industry as represented in Table 2.3.

Table 2.3 – Impacts of Digital Technologies on BMC's Components

| BMC Block | Impact From Digital Technologies |
|---|---|
| **Customer Systems** | Digital tools help AEC companies know their customers better, such as to leverage BDA and AI to identify the customers' needs and desires, and to provide customised solutions. |
| **Value Proposition** | AEC companies can employ virtual and augmented reality to provide immersive experiences for clients, or BIM to design and build more efficient and sustainable structures. |
| **Channels** | AEC firms leverage digital tools to explore innovative customer engagement, using social media and online platforms to showcase work and connect with clients. |
| **Customer Relationships** | AEC firms use online platforms and project software to enhance communication, collaboration, and real-time updates with clients throughout the project lifecycle. |
| **Revenue Streams** | AEC companies can offer consulting focused on aiding companies in their DT journey or develop software products and solutions tailored to the industry or sector. |
| **Key Resources** | Key resources of AEC firms are affected by digital technologies. For example, companies must invest in new technologies and digital infrastructure to compete. |
| **Key Activities** | Digital technologies are impacting on the key activities of AEC firms. AEC companies need to acquire new skills and capabilities in BDA, AL and digital design and construction. |
| **Key Partnerships** | Digital technologies enable new AEC partnerships, fostering innovation and end-to-end services through collaboration with tech firms. |
| **Cost Structure** | Digital tech changes AEC cost structures, requiring investment in new tools but boosting efficiency and productivity for long-term savings. |

### 2.3.2 Critical Assessment for BMI Measurement Concepts

#### *2.3.2.1 Spieth and Schneider (2016)*

Spieth and Schneider (2016) fill the ongoing gap in BMI research by operationalising and validating a formative measurement of BMI. They base their model on three key elements: value proposition, value structure, and revenue model novelty. These elements are based on the authors' lens on the business model as not just an operational or descriptive tool, rather as an innovating system made up of separate albeit interrelated domains that can be empirically examined. The study is particularly pertinent because previous efforts at organising and evaluating BMI have been mostly typological rather than quantitative or lacked the necessary quantitative criteria to make comparative and causal inferences.

When using a formative approach, every single dimension is said to contribute to the overall construct of innovativeness in a non-reciprocal way − i.e., changes in one dimension (e.g., revenue model) are not automatically mirrored by changes in another dimension (e.g., value architecture).

One important limitation acknowledged by the authors is the lack of integration with sustainability-oriented innovation metrics. It is based only on the physical and metabolic aspects of BMI and does not include social and environmental components, restricting the model's use in the context of sustainable business practices. They propose also to include these dimensions in the model in the future so that it contributes more to the understanding of contemporary strategic challenges.

#### *2.3.2.2 Clauss (2017)*

In contrast, Clauss (2017) develops a reflective measurement scale for BMI, aiming to conceptualise BMI as a latent variable and empirically categorise it through the observable novel combinations within the business model components of the firm. Drawing on the business model canvas (Osterwalder and Pigneur, 2010) and similar streams of literature, Clauss (2017) defines BMIs as purposeful changes in the way a firm creates, delivers, and captures value. These shifts are represented in three sub-constructs: value creation innovation, value proposition innovation, and value capture innovation.

This reflective frame also enables a useful diagnosis for researchers and practitioners alike – BMI can be modelled as an independent, dependent, or mediating construct in wider strategic configurations. Clauss, however, does not examine sector-specific nuances or moderating factors of such a relationship between the factors, which limits the contextual richness of her scale. Moreover, the cross-sectional nature does not reflect the potential dynamics and feedback loops of the BMI that develop with time following market and technological changes.

#### *2.3.2.3 Comparative Insights*

Despite the significant contribution that both studies make to the operationalisation of BMI, they differ in conceptual orientation, measurement philosophy, statistical focus and theoretical fit with AEC industry (see Table 2.4).

Table 2.4 – Comparative Analysis of Business Model Innovation

| Aspect | Spieth and Schneider (2016) | Clauss (2017) |
|---|---|---|
| **Measurement Approach** | Formative (indicators form the construct) | Reflective (construct causes indicators) |
| **Business Model Domains** | Value offering, value architecture, revenue model | Value creation, value proposition, value capture |
| **Methodology** | PLS-SEM with expert surveys; suitable for modular constructs | EFA/CFA with two independent samples; focused on unidimensional structure |
| **Performance Validation** | Moderately tested relationships with innovation and strategy outcomes | Empirical linkage to firm performance (financial and innovation metrics) |
| **Key Limitations** | F-F modelling requires large sample; lack of ESG | Lacks industry-specific focus and does not capture temporal dynamics |
| **Theoretical Fit with AEC** | Strong alignment with modular, project-based AEC innovation logic | Better suited for general business contexts; less tailored to AEC complexity |
| **Model Flexibility** | Allows domain-specific analysis and structural decomposition | Treats BMI as a single latent variable, limiting diagnostic insights |
| **Adaptability to Small Samples** | R-R structure for valid use in small-sample exploratory study | Original structure not ideal for small-sample exploratory studies |
| **Relevance to Research Aims** | Enables targeted assessment of innovation across BMI components. | Less aligned with objective of analysing component-level innovation |

Neither of these models consider the sustainability nor digital transformation aspects that play an increasingly important role in current business model redesign. Spieth and Schneider (2016) explicitly refer to this as a limitation and also discuss directions for future research, whereas Clauss (2017) is still looking into the performance effects, both economic and innovation. The addition of TBL or SBM innovation perspectives would improve the applicability of both frameworks in a research context going forward.

### 2.3.3 Primary Drivers and Enablers for SBM

SBM Innovation in the AEC operates at the confluence of environmental, social, and organisational drivers compelling firms to reconsider the way they create, deliver, and capture value. One of the main reasons behind this fact is the environmental effect of construction activities which leads to very high $CO_2$ emissions at a global level, very large energy consumption, and massive material waste. This has been stimulating attention for carbon-neutral buildings, green infrastructure, and a circular economy (Bocken *et al.*, 2014). Environmental regulation and client demand are increasingly focused on these objectives, adding pressure and opportunity for the AEC sectors to be innovators.

Economic sustainability has, in the meantime, been joined by social sustainability. Topics such as responsible labour and community engagement or city-making are now the fundamentals that nobody disputes, and which investors and the public expect to be addressed, particularly in public and urban projects. Tools such as the GRI Standards (GRI, 2023) and ISSB Standards (IFRS, 2023) offer recommendations to incorporate social aspects in business models.

From an organisational perspective, digital technology and data analysis enable companies to measure and optimise sustainability targets. Therefore, SBM is not solely pressured externally but is also empowered internally by the capabilities and leadership commitment.

### 2.3.4 Status and Challenges in Realising SBM

Although SBM innovation has many advantages, its practice in the AEC industry encounters several difficulties originating from the conservatism of industry culture, the inertia of enterprises, and the complexity of its structure. Numerous organisations are bound to outdated IT infrastructure, a risk-averse business culture, and misaligned reward systems which tend to favour short-term cost minimisation rather than long-term value creation (Bocken *et al.*, 2014). Financial and regulatory doubts compound the problems so that investing in sustainability may seem risky or not essential.

To find out how AEC practices can overcome these obstacles, they need to develop four critical organisational competencies. Management of change is also critical, facilitating firms' ability to negotiate the behavioural and structural shifts necessary to engage in SBM innovation (Opoku *et al.*, 2015). Train the workforce broadly rather than in a single function area, to ensure that employees comprehend and support sustainability objectives.

Strategic foresight is also essential. Companies which express long-term sustainability goals accompanied by performance measures of these goals are more likely to embed sustainability principles in ongoing decision-making (Engert *et al.*, 2016). It also allows firms to be open to new business models, characterised as a willingness "to experiment and take calculated risks" (Covin and Lumpkin, 2011). Both cross-sector collaboration and knowledge-sharing platforms can help to narrow the gap between AEC firms and those with expertise in sustainability. In the end, SBM innovation will succeed not only because of outside forces but through internal flexibility and strategic foresight.

### 2.3.5 TBL as a Lens for SBM in the Digital Era

The TBL stands as an appropriate lens to design and assess Sustainable BMI by AEC (Elkington, 1997). In this digital age, TBL provides an organised methodology to weigh and find harmony between nascent due date from competing impulses for sustainability.

Digital transformation enablers such as BIM, IoT, and AI facilitate the practice of SBM innovation according to the TBL philosophy.

For example, environmental performance that is supported by BIM is energy modelling and lifecycle analysis, whereas social outcomes are monitored via IoT devices for worker safety and indoor air quality (George *et al.*, 2021). They also maximise cost structures and operational efficiencies, which leads to economic sustainability. By utilising TBL, companies are able to consider the wider impacts of their business models beyond the financial bottom line by creating shared value for stakeholders. It encourages transparent reporting and alignment with global standards UN SDGs (United Nations, 2015).

Crucially, TBL encourages companies to treat sustainability as an opportunity for innovation and differentiation instead of just another box to be ticked for compliance. This change of mindset is essential for the future of the AEC in a sustainability-driven world.

## 2.4 Emergent Digital Technologies for AEC Industry

Several studies have proposed classification frameworks for digital technologies in the AEC industry, such as Manzoor *et al.* (2021) and Dou *et al.* (2023) including BIM, Cloud Computing (CC) Geographic Information Systems (GIS), AI, AR, VR, DT, Big Data Analytic (BDA), Blockchain (BC), Sensing and Monitoring Technologies (IoT), and Robotics and Automation.

### 2.4.1 Emergent Digital Technologies

#### *2.4.1.1 Building Information Modelling (BIM)*

BIM is a digital process that has revolutionised the AEC industry (Bryde *et al.*, 2013). BIM utilises 3D computer modelling tools to virtually simulate the graphical, physical, and functional aspects of a building (Succar, 2009). Since the model has the knowledge of the building's components, systems, and space (Arayici, 2008), BIM supports better decision making as it allows project participants to design, evaluate design alternatives, understand impacts, and detect problems earlier.

It enhances accuracy and eliminates rework / errors by detecting conflicts between design elements (Chan *et al.*, 2019). BIM also supports scheduling and building construction coordination in real time, with both resources (Mandičák *et al.*, 2020). Each modelling element carries graphical and non-graphical information such as manufacturer information and costs. Documentation updates automatically with changes. Models themselves are open standards-based and, therefore, can be shared / integrated between platforms, allowing team collaboration, such as openBIM (buildingSMART, 2013).

Embedded data also automates quantity take-offs and clash detection between objects (Chahrour *et al.*, 2021), which helps in construction coordination and error reduction. Useful BIM is data related. There are obstacles in benefit realisation where data are incomplete or inaccurate (Mandičák *et al.*, 2020). Coordination and cooperation among participants are very important to enhance benefits (Oh *et al.*, 2015).

BIM is designed to cover the information throughout the lifetime of a project with the aim to facilitate single-source facilities management (Eastman, 2011). In short, BIM has changed the way we work in an AEC space by making us more efficient and providing better decision making, accuracy, collaboration, and lifecycle data management.

#### *2.4.1.2 Cloud Computing (CC)*

CC has emerged as a promising technology that has potential to change the way projects are planned, designed, implemented, and operated. A CDE specific for cloud computing could enhance communication and collaboration between the different stakeholders in a project, minimising errors and time delays due to miscommunications and wrong information (Bello *et al.*, 2021). Internet-based tools and cloud-hosted centralised project information stores make it possible to collaborate and to connect to up-to-date data from mobile devices.

CC enables resources to be available on the network and to be accessed with standard mechanisms, which provide for design and construction participants transparent access from wherever they are in the world (Wang *et al.*, 2020). It reduces capital cost and saves time, as well as reduce capital-intensive IT resources and infrastructure expenses, which are shared between user organisations.

#### *2.4.1.3 Geographic Information Systems (GIS)*

GIS as a collection of hardware and software that allows capturing, storing, managing and processing spatial data. These tasks include location factors, consideration of alternative designs and evaluation of impacts. By using several layers of spatial data such as land use and land cover, topography, soil and infrastructure, GIS helps to analyse site suitability for proposed project. It also enables various stakeholders to collaborate, making it a platform for shared decision-making and information sharing (Zhu *et al.*, 2018).

Gu and London (2010) point out that GIS generates a range of outputs such as from maps, spatial queries and 3D project models useful for generating a clear picture of the dense urban circumstances. When connected to BIM, GIS provides greater decision support system for AEC professionals. The integration permits 3D models to be overlaid on site maps, enabling users to perform environmental and energy simulations, and ultimately achieve better accuracy, and efficiency in project planning and implementation.

#### *2.4.1.4 Artificial Intelligent (AI)*

AI includes capabilities to apply design model checking, predictive maintenance, quality control, safety monitoring, and optimisation of building performance and energy efficiencies. By enabling routine work to be streamlined and automated, AEC professionals could concentrate on more challenging and creative issues in their profession (Pan and Zhang, 2021; Pan and Zhang, 2022). AI is naturally predisposed to learning from large data sets and identifying complex patterns.

The learning ability enables AI to handle various applications, such as semantic segmentation of building components from images / scans, structural condition assessment using drones, and predictive analytics for building management with IoT sensor data (Plageras *et al.*, 2018). AI also promotes teamwork through chatbots and VR/AR interfaces. For example, AI chatbots and virtual assistants can answer user questions automatically, cutting down response times. AI-based simulations also enable collaboration and decision-making from a distance (Ivanova *et al.*, 2023)

#### *2.4.1.5 Augmented and Virtual Reality (AR/VR)*

As AR/VR offers immersive experience, designers can visualise and traverse through three-dimensional designs. The early analysis of design and fabrication-related problems by AR/VR may prevent project overruns of cost and schedule (Schiavi *et al.*, 2022; Yan *et al.*, 2011). During design and construction phases, AR applications can overlay digital information such as schematics, specifications, and notes, for example, directly on a user's view of a physical space (Azuma, 1997).

One of the key features of AR/VR is their ability to imitate actual or theoretical spaces and material presences through interactive 3D digital models. This ability in simulation enables the engineering / design collaborative domain clash detections, safety planning, and spatial coordination. It also facilitates training, and skills transfer through interactive simulations and mixed reality serious games (Davila Delgado *et al.*, 2020; Li *et al.*, 2018).

With AR/VR, stakeholders can have an immersive experience beyond traditional media of more complex designs and environments. This increases the understanding of end-users and allows them for easy interaction with digital models. By leveraging sensors, AR interfaces also support the delivery of location-based and context-aware information, such as remote assistance and facilities management (Sabzevar *et al.*, 2023).

#### 2.4.1.6 *Digital Twins (DTs)*

DTs can support collaborative iterative design processes through enabling architects, engineers, and contractors to virtually experiment with various design alternatives and construction sequences, providing a real-time test and measure environment to assist in identifying and solving issues at an early stage of the DTs. This early warning provides a cost-effective and proactive decision support during a project or an asset's lifecycle (Salem and Dragomir, 2022; Zhang *et al.*, 2021).

A distinguishing characteristic of DTs is that they can generate digital representations of physical assets, infrastructure systems, or built environments along their life cycle. These models are kept synchronised to the physical twin through integration with IoT sensors and reporting systems (Ozturk, 2021).

DTs could provide any time; any place virtual visits is highly important. Coupled with AR/VR technologies, they facilitate remote collaboration, virtual commissioning, spatially aware asset management, and seamless skills transfer between field and office teams (Opoku *et al.*, 2021).

#### 2.4.1.7 *Big Data Analytic (BDA)*

BDA is capable of improving project delivery by offering real-time information about the pace of construction, revealing possible bottlenecks, and aligning resources as planned (Ahmed *et al.*, 2017).

One of the main applications of BDA is predictive maintenance. BDA understands patterns and trends from heterogenous project data including equipment logs, IoT sensors, and drone images. With predictive modelling, companies can predict when equipment is going to break which means better schedules for upkeep and less of the dreaded ‘unplanned downtime…’ This evidence-based strategy enhances asset reliability and facilitates more effective life cycle cost management (Cheng *et al.*, 2020). Consequently, BDA paradigm changes maintenance approach from a reactive one into a proactive one, improving project performance and extending asset life.

BDA also facilitates scheduling optimisation through enabling real-time monitoring of production. By combining project documents, sensors, and administrative systems, stakeholders can see, track, and reallocating resource as needed. Methods such as process mining and simulation support the anticipation of delays and the improvement of decision-making along the project lifecycle (Bilal *et al.*, 2016). This increases accuracy in planning, productivity monitoring and reaction to on-site conditions.

#### *2.4.1.8 Blockchain (BC)*

BC gives strong potential as a collaboration tool in AEC industry, especially in large projects with numerous contractual parties involved. Also decentralised storage sharing and validation of BIM data can be achieved via BC, overcoming the problem of data silos and improving the trust in shared information (Li *et al.*, 2020; Mahmudnia *et al.*, 2022). Its public ledger provides transparent access to information about construction materials, equipment status, payments, and design documents, increasing accountability and veracity of data among project stakeholders.

BC can also integration with sensors, IoT, and AI, which allow for predictive maintenance by monitoring equipment usage in real time, machinery remote monitoring, and compliance monitoring through the automatic interpretation of measurement data. This synchronisation allows data informed decision making and supports a more cost-efficient operation through the anticipation of issues and the awareness of situations that could develop into serious problems, leading to safer, more reliable project execution (Mahmudnia *et al.*, 2022).

#### *2.4.1.9 Sensing and monitoring technologies (IoT)*

Sensing and monitoring technologies, also refer to IoT, are employed in a broad range in the AEC sector including building performance monitoring, predictive maintenance and energy management. IoT can also use to detect temperature, humidity, and air quality inside buildings, and HVAC systems can be adjusted in real-time (Sarkar *et al.*, 2020; Tang *et al.*, 2019).

One major benefit of IoT in the built environment is its capability to gather real-time operational data from sensors, drones, wearables and other networked devices. This stream of data has been used in different monitoring and analysis applications throughout the AEC lifecycle. When combined with the cutting-edge analytics like AI, data from the IoT features predictive capabilities such as fault detection, structure health monitoring, user behaviour analysis, and prediction of energy consumption (Baghalzadeh Shishehgarkhaneh *et al.*, 2022).

IoT systems can also actuate the physical environment, fulfilling automated reactions based on sensed conditions. The ability to do this allows for more intelligently-controlled operation – for things like adaptive lighting, self-managing facilities, and the "growing" of scaffold systems. Sensing coupled with control via IoT enables safer, greener, smarter construction and building operations (Plageras *et al.*, 2018).

#### *2.4.1.10 3D Printing*

3D printing has facilitated the fabrication of complex architectural geometries, components, and facade elements which are difficult to fabricate with other existing technologies (El-Sayegh *et al.*, 2020). It resulted in an enhanced degree of design freedom as compared to traditional approaches. This enables building elements that are flexible, performative, and visually attractive.

Projects such as Apis Cor and WinSun have demonstrated the creation of 3D printed houses over the course of mere hours. The coupling of robots and 3D printers demonstrates a positive transformation of these two technologies in the building industry (Xu *et al.*, 2022).

3D printing facilitates the iterative design process and prototyping of complex designs. Combined with sensors and built-in computational capabilities, it enables hybridisation in design, manufacturing, and construction (Singh *et al.*, 2021).

### 2.4.2 Strategic Alignment of DT with TBL Goals

Triple Bottom Line framework (Elkington, 1997), argues that organisations should simultaneously pursue economic, environmental, and social responsibilities. In AEC industry, this entails balancing financial performance, ecological responsibility, and social well-being across all phases of the project lifecycle—from early design to operation and decommissioning (Opoku and Fortune, 2011; Zuo and Zhao, 2014).

To systematically evaluate the sustainability contributions of digital technologies, relevant organisational and sustainability theories were aligned with each TBL dimension. Theories were selected based on their ability to explain the specific value created: for economic impacts, value-based theories such as the Knowledge-Based View, Dynamic Capabilities, and Lean Principles were applied; for social impacts, theories including the Relational View, Human Capital Theory, and High Reliability Theory were used to address aspects of collaboration and safety; and for environmental impacts, sustainability-focused frameworks such as Eco-Efficiency, Industrial Ecology, and Cradle-to-Cradle informed the interpretation of ecological outcomes. As shown in Tables 2.5–2.7, these interrelated factors highlight the strategic role of digital innovation in advancing holistic sustainability within the built environment.

#### *2.4.2.1 Economic Impacts*

*Economic Impacts* (Table 2.5): Cloud computing reduces costs through shared infrastructure (Wang *et al.*, 2022), while BIM minimises rework and improves accuracy (Bryde *et al.*, 2013).

Table 2.5 – Profit (Economic Impact)

| Tech | Key Benefit | Theory | Supporting Evidence |
|---|---|---|---|
| BIM | Reduces design rework/costs | Knowledge-Based View | Bryde *et al.* (2013), Chan *et al.* (2019) |
| Cloud | Shared infrastructure savings | Dynamic Capabilities | Zhang *et al.* (2020) |
| Big Data | Optimises schedules | Lean Principles | Bilal *et al.* (2016), Ahmed *et al.* (2017) |
| Blockchain | Supply chain transparency | Dynamic Capabilities | Li *et al.* (2020), Mahmudnia *et al.* (2022) |
| 3D Printing | Cuts material waste | Lean Principles | El-Sayegh *et al.* (2020), (Xu *et al.*, 2022) |

#### *2.4.2.2 Social Advantage*

*Social Advantages* (Table 2.6): AR/VR enhances safety training (Li *et al.*, 2018), and digital twins facilitate remote collaboration (Opoku *et al.*, 2021)

Table 2.6 – People (Social Impact)

| Tech | Key Benefit | Theory | Supporting Evidence |
|---|---|---|---|
| BIM | Stakeholder collaboration | Relational View | Oh *et al.* (2015) |
| Cloud | Centralised team repositories | Relational View | Bello *et al.* (2021) |
| AI/VR | Safety training | High Reliability Theory | Li *et al.* (2018) |
| GIS | Shared spatial decisions | Relational View | Zhu *et al.* (2018) |
| DT | Remote collaboration | Human Capital Theory | Opoku *et al.* (2021) |

#### *2.4.2.3 Environmental Benefits*

*Environmental Benefits* (Table 2.7): BIM-GIS integration enables energy and carbon simulations (Gu and London, 2010), and IoT sensors optimise building operations (Tang *et al.*, 2019)

Table 2.7 – Planet (Environmental Impact)

| Tech | Key Benefit | Theory | Supporting Evidence |
|---|---|---|---|
| BIM+GIS | Energy simulations | Eco-Efficiency | Gu and London (2010) |
| Big Data | Predictive maintenance | Industrial Ecology | Cheng *et al.* (2020) |
| IoT Sensors | Real-time energy monitoring | Industrial Ecology | Tang *et al.* (2019), Sarkar et al. (2020) |
| 3D Printing | Localised manufacturing | Cradle-to-Cradle | Singh *et al.* (2021) |
| DT | Asset lifecycle extension | Cradle-to-Cradle | Ozturk (2021) |

When strategically implemented, these technologies will support BMI and data-driven decision-making that are advancing:

- Financial performance via lean operations as well as dynamic capabilities
- Environmental stewardship through eco-efficiency and cradle-to-cradle design principles
- Social equity via enhanced collaboration and human capital development

This alignment fosters innovation pathways where economic incentives support both planetary sustainability and community interests. The empirical analysis, focused on these relationships, is presented in the coming sections, which explores these connections through their theoretical foundations, linking digital transformation to TBL as an anchoring principle.

### 2.4.3 Challenges in Adoption and Future Trends

Digital technologies adoption in the AEC industry is somehow encountering various barriers. The full implementation of BIM also demands substantial investments of time, financial resources, and workflow modifications, which make it difficult to be adopted by smaller local practices and smaller projects (Zhou *et al.*, 2019). The success of BIM depends on accurate and current data, importation of incomplete or inaccurate data based data impeding the benefits (Zhang *et al.*, 2020). Coordination and collaboration between the project involved parties are also important to achieve the benefits of BIM (Oh *et al.*, 2015). Topics like cloud-computing to AR/VR and big data analytics, have numerous other issues to deal along with, like data security, privacy and standardisation (Emaminejad *et al.*, 2021; Mahamadu *et al.*, 2013; Mantha *et al.*, 2021).

Prospectively, their destiny will be to grow together even more. With the integration of BIM and AR/VR, visualisation will also be enhanced (Schiavi *et al.*, 2022) and AI with improved decision support tools (Zhang *et al.*, 2022) will facilitate collaborative, interactive design support via simulations such as digital twins (Zhang *et al.*, 2021). The BIM and B process links BIM with blockchain to facilitate collaboration (Li *et al.*, 2020). There is a tremendous promise for safer, more productive, less wasteful and more sustainable construction with advancements in sensors, robotics and 3D printing (Tang *et al.*, 2019; Xu *et al.*, 2022). In the end, its increased use, through expanded awareness and integration of it into emerging technology, that will help achieve the full benefits of these technologies.

## 2.5 Key Determinants of Successful Initiatives

The initiatives of DT, BMI, and sustainability development are becoming increasingly challenging. Successful enablers include organisational leadership, innovation culture, human capital, and vision and strategy. In the AEC sector, DT involves recasting of processes, capabilities, and models to extract the value of digital technologies. BMI consists in introducing modifications in the organisation's business model or in designing new models for the purpose of generating and capturing additional value, with particular emphasis on sustainability-based opportunities. Sustainable development aims to protect the natural and human resources we depend on for a high quality of life (e.g., carbon neutral and circular economy practices; Bocken *et al.* (2014) and human rights (GRI, 2023).

Several studies have sought to identify the elements that determine the outcome of efforts in these domains. Firm-level entrepreneurial traits have been correlated with digital transformation and innovation. Firms that have attributes of innovativeness, proactiveness, and risk-taking behaviours are more inclined to grab new opportunities and experiment with business models (Ciampi *et al.*, 2021).

Equally significant are organisational culture and a well-defined strategic orientation. In the context of sustainability innovation, high-level management subscribers for sustainable policies promote employees' intrinsic motivation toward green ideas (Kim et al., 2017; Lozano, 2015). Clear visions for long-term sustainability direct cross-disciplinary decisions (Bocken *et al.*, 2014).

Leadership and communication of the desired objectives are equally vital for digital transformation. Previous studies have shown that the lack of support from company top management is a typical barrier (Porfírio *et al.*, 2021). Clear digital visions and adoption roadmaps enhance the allocation of resources and consumption of change (Hess *et al.*, 2016).

### 2.5.1 Entrepreneurial Orientation

Entrepreneurial Orientation (EO) has often been noted as both influential and important to the growth and flourishing of businesses. EO includes the firm's innovation strategy, risk-taking strategy, proactive strategy, autonomy strategy, competitive aggressiveness strategy, and focus on opportunities strategy. Companies with high levels of EO consistently outperform those with low levels. Such as, being proved that EO has an underlying positive impact on growth and monetary performance of new ventures (Hmieleski and Corbett, 2006) and EO has a correlation with the survival and growth of small firms (Wiklund and Shepherd, 2003). The concept of EO was first defined by (Miller, 2011) as a propensity to engage in higher-risk activities related to the development of new products or services and entry into new markets. Covin and Slevin (1989) developed a conceptualisation of EO and suggested that it is based on 3 dimensions: innovation, risk-taking, and proactiveness. The dimensions of EO were further broadened, making autonomy and competitiveness as the additional dimensions. (Covin and Slevin, 1991) originally conceptualised EO as a unidimensional construct including innovativeness, risk-taking, and proactiveness. With subsequent research has extended this dimensionality and linked EO to the firm's performance (Hmieleski and Corbett, 2006; Wiklund and Shepherd, 2003).

#### *2.5.1.1 Five Dimensions of EO*

Lumpkin and Dess (1996) proposes that EO consists of five dimensions - risk-taking, proactiveness, innovativeness, autonomy, and competitive aggressiveness - possess a strong impact on digital transformation. EO nurtures an experiment-friendly, innovative, and adaptive culture, which helps in an organisation's smooth adoption of digital technologies and for innovating business model (Vrontis *et al.*, 2022).

- Innovativeness, as a key dimension of EO, also contributes to digital transformation positively. Evidence also shows that firms with a high degree of innovativeness have improved performance (Hughes and Morgan, 2007; Zahra and Covin, 1995). These are the companies that are most likely to use digital technologies which have had the biggest effect on disruptive innovation (Kraus *et al.*, 2023). They also use digital technology to service their customers more efficiently and may adopt specific technologies such as BDA (Ciampi *et al.*, 2021).

- Risk-taking, also helps digital transformation importantly. Companies that are willing to take risks are more inclined to carry out digital initiatives, and risk-taking is positively related to digital transformation (Hervé *et al.*, 2021). The transition to digital technologies entails investment risks, and a tolerance for risk-taking helps organisations meet those challenges.

- Proactiveness, as a dimension of EO is important in the digital age. Firms who are proactive rather than reactive are expected to engage in digital technology adoption to secure competitive advantage (Lumpkin and Dess, 1996; Wiklund and Shepherd, 2003). They understand the critical need for digital adoption to remain competitive and have the foresight to embrace digital solutions.
- Autonomy (the extent of influence in decision-making) is related to better performance (Hmieleski and Corbett, 2006; Wiklund and Shepherd, 2003). In the digital age, companies must have the autonomy to be more agile to respond swiftly to market changes and to be able to take on digital technologies.
- Competitive aggressiveness, firms that are more competitive also perform at a high level (Covin and Slevin, 1989). Competitive aggressiveness verifiably could also be correlated with the survival and growth of small enterprises (Wiklund and Shepherd, 2003). Firms must compete to survive and continue to evolve to meet customer needs in the digital age.

Two important concepts that have been highly emphasised in literature and supported by empirical findings are EO and BMI. Several studies have shown a positive association between EO and BMI. For example, Hult *et al.* (2004) indicated that organisations high on EO are more likely to be involved in BMI (i.e., new product/service introduction, new geographical market entry, new technology adoption). Consistent with the present research, Wiklund and Shepherd (2003) reported that high EO firms were more likely to engage in business model experimentation which is a key initiator that leads to BMI goals ultimately.

#### *2.5.1.2 Correlate EO and BMI*

EO and BMI are positively correlated because a higher level of EO plays a major role for firms to take risks and try new things. This risk propensity and willingness to experiment are potential drivers for BMI which allow firms to search for new avenues and develop new innovative business models. High-risk-taking propensity firms were also more likely to utilise innovation (Covin and Slevin, 1991). Moreover, EO and BMI both share to a similar extent strong entrepreneurial attitudes. Firms with high EO are also likely to be highly entrepreneurial - the entrepreneurial organ of the company that is focused on value creation and value capturing (Covin and Slevin, 1989). The same applies to BMI, as it calls for a strong entrepreneurial attitude, given that it "is about how firms create, deliver, and capture value" (Foss and Saebi, 2017) – it is about developing new business models as well as implementing them.

EO plays an important role in facilitating the process of BMI (Ciampi *et al.*, 2021). High EO firms are expected to have business proactivity, they tend to be proactive and to discover new opportunities for BMI. Furthermore, firms with high EO are believed to be more opportunistic and can capitalise on their strategic thinking that is important for the launching and execution of new business models. They also found high-EO firms to engage more in BMI that includes strategies for repositioning and reconfiguration of resources.

Overall, high EO and high collaboration may reinforce each other as the evolution and exploitation of entrepreneurial capabilities will help firms develop and utilise their entrepreneurial assets, while the EO uncovers and enables taking action at new collaboration opportunities (Todeva and Knoke, 2005). Highly EO and collaborative firms are expected to be more innovative, flexible, and competitive in this digital time. Regarding BMI, since high EO firms are less averse to making decisions in uncertain environments and are more innovative than other firms, they are more likely to be engaged in BMI activities. Also, EO can promote BMI by supplying resources and the process of strategic thinking for firms. Hence, firms that are attempting to motivate BMI should add EO as an important component of their strategy, based on the complementarity between EO and collaboration.

### 2.5.2 Sustainability Orientation

Sustainability orientation (SO) as a behavioural dimension refers to the level of commitment and the mindset of firms with the idea to pursue environmental, social and economic goals in shaping visions, strategies, and operations of organisations (Claudy *et al.*, 2016). It influences organisational culture and behaviour to enable an ongoing advancement towards sustainability-oriented performance. Embedded in a strong value system around sustainability, orientation is both expected to drive innovation with the focus on people and planet beyond profits (Jin *et al.*, 2019) well as to help establish a long-term vision also ensuring the well-being of future generations (Hockerts, 2015).

#### *2.5.2.1 Drivers, Enablers and Strategic Implications*

SO indicates an organisation's dedication toward incorporating environmental, social, and economic objectives into its strategy and operations. Leadership buy-in is a key driver. Top management and CEO policymakers actively pursue and support sustainability initiatives and provide strategic guidance and resource allocation to weave these values into the organisation's culture (Eccles *et al.*, 2012). Their engagement generates a sense of urgency and contributes to turning such ethical aspirations into concrete policies and innovation.

Eccles *et al.* (2012) also highlight that employee involvement is a significant driver of sustainability initiatives. Staff who internalise sustainability values work collaboratively toward green goals. Involvement in decision-making, knowledge sharing, and acknowledgment of environmentally friendly actions are identified as key sources of intrinsic motivation. However, a common challenge is the gap between the vision at the top and daily practices on the ground, underscoring the importance of role models and cross-level coordination (Lozano, 2007). This coordination facilitates the co-creation of innovative and cost-effective solutions by interdisciplinary teams. Furthermore, the formalisation of guiding principles, strategic roadmaps, and measurable indicators—such as carbon reduction targets and compliance with ISO14001 (ISO, 2015) enables the measurement and assessment of environmental performance.

A robust SO enables businesses to de-risk and comply with regulatory demands and evolving stakeholder requirements. It builds trust, corporate brand reputation, and bridges organisations with the global sustainability agendas such as the UN SDGs (United Nations, 2015). This is also reinforced by cultural factors, such as common sustainability values, time-oriented thinking, and representative governance (Hockerts, 2015).

SO provides a competitive advantage, theoretically speaking. According to the resource-based view theory, sustainability will lead to the creation of distinctive firm capabilities, for example, eco-innovation and green supply chains (Cantele and Zardini, 2018). Stakeholder theory posits that engagement with the interests of stakeholders leads to trust and results in access to resources, innovation, and cooperation (Freeman *et al.*, 2010).

#### *2.5.5.2 Strategic Dimensions of Sustainability Orientation*

Claudy *et al.* (2016) investigate SO as well as Market Knowledge Competence (MKC) in determining the New Product Development (NPD) success. SO is interpreted as a strategic resource, underlying the firm's commitment to the environment and society as well as deeply rooted in corporate values and innovation practice. The authors conceptualise SO as a second-order reflexive construct consisting of two major dimensions: Sustainability Culture and Sustainable Practices. The former represents the internal values and beliefs for sustainability; the latter incorporates the management cases of those values during the business processes and product development. This configuration makes it possible to evaluate the SO as organisational attitude and practice.

Importantly, Claudy *et al.* (2016) claim that SO in itself does not guarantee the success of NPD. Instead, its value depends on the company's capacity to integrate sustainability with market requirements, pointing out MKC as an essential mediator.

Organisations must not only embrace sustainability; they also must have market foresight to translate these values into meaningful innovations.

The study extends existing literature by reframing SO as a strategic resource rather than a merely normative position. Firms with sustainability integrated into their DNA—especially at the top management team level—are expected to be significantly more prone to embrace radical innovation (RI) and long-term value creation. This is in line with other findings that emphasise the role of leadership and organisation culture for sustainability (Eccles *et al.*, 2012).

In a similar vein, Sung and Park (2018) unravel the nexus of SO and EO. Their study upends the common notion that there's a trade-off between sustainability and entrepreneurship. Rather, they indicate that SO and EO are positively related with each other, with sustainability-oriented firms being more innovative, proactive, risk-taking, and international customers. They also define SO as a multidimensional consideration: ethical responsibility, environmental concern, and stakeholder inclusion. This perspective is consistent with SO as a proactive, value-oriented orientation (Claudy *et al.*, 2016). They contend that SO is synonymous with opportunity recognition and innovation, allowing companies to address social and environmental issues while also remaining competitive.

### 2.5.3 Digital Orientation

Digital orientation (DO) is the overall philosophy, priorities, and strategic stance of an organisation with regard to the adoption and incorporation of digital technologies into its operations, value propositions, and customer experiences (Westerman et al., 2014). A digital-centric company considers cloud, mobile, analytics, automation, and the Internet of Things (IoT) as strategic building blocks to enable digital transformation and secure future success. DO is contingent upon two complementary elements: digital vision and digital strategy (Hess *et al.*, 2016).

Digital Vision is the company's permanent understanding of how digital technologies will change their business model, competition, and client target. It provides a detailed analysis of digital innovation to transform current operations and create value for the future. A clear digital vision drives shared cognition among leadership and employees and guides the organisation in its digital transformation (Hess *et al.*, 2016; Westerman *et al.*, 2014).

Digital strategy, however, turns this vision into concrete initiatives, investments, and organisational shifts. What it does, however, is articulate the precise means by which digital will be utilised to fuel innovation, effectiveness, and engage customers. Vision gives us the "why" and "what." Strategy gives us the "how" and "when."

Empirical studies show that digital impact increases a company's capability to innovate in business models, which involves reconfiguring means of value creation, delivery, and capture in the face of digital disruption (Yoo *et al.*, 2010). In fields such as AEC, the digitisation process has been associated with the generation of new revenue flows from data-driven services, integrated project delivery platforms, predictive asset management models, etc. (Abioye *et al.*, 2021). Successful DO compelling new vision and strategy is a fundamental driver of sustained digital transformation and competitive revitalisation.

## 2.6 Research Gaps

The AEC industry is experiencing a major shift as companies implement sustainability into their business practices. This transition prompts examination of the most important drivers of sustainable BMI. However, there are still important research gaps considering digital transformation and sustainability. Five gaps provide further areas for research (see Table 2.8), specifically the role of emerging technologies in sustainable innovation, the functions of digital strategy, corporate entrepreneurship, and sustainability practices, as well as those of architect versus site construction teams in digital transformation. An exploration of these gaps would be needed to provide directions for future research and improve industry practices in the AEC industry.

Table 2.8 – Literature Gap Summary

| Gap No. | Research Gap | What the Literature Addresses | What Is Missing / Underexplored | How This Study Responds |
|---|---|---|---|---|
| **1** | Role of emerging technologies in Sustainable BMI in AEC | Focus on individual technologies' efficiency and environmental benefits | Lack of integrated understanding of how digital technologies enable SBM aligned with TBL | Develops framework linking TBL-aligned digital traits to SBM in AEC |
| **2** | Interplay between digital strategy, corporate entrepreneurship, and sustainability practices | Elements studied independently in AEC or business strategy literature | Limited empirical research on their interdependence in driving SBM | Investigates joint effects of DO, EO, and SO on SBM |
| **3** | Differences between architects and construction teams in DT and SBM | General AEC-level digital adoption studies | Insufficient comparative analysis of roles and practices between architects and site teams | Proposes differentiated analysis of digital maturity and innovation behaviour across roles |
| **4** | Integration of SO with EO and DO to drive SBM | SO and EO studied separately; limited integration | Lack of empirical models examining interaction among these orientations in innovative outcomes | Develops a conceptual framework linking SO, EO, and DO with SBM |
| **5** | Lack of a comprehensive framework for TBL-aligned DT in AEC | Existing fragmented models (e.g. BMC, TBL, RBV) | No unified model capturing systemic links between digital traits, orientations, and sustainability outcomes | Proposes Figure 2.2 – Research Framework integrating TBL, DO, EO, SO, and SBM |

There is a clear research gap at the intersection of emerging technologies and sustainable BMI in the AEC sector. While there is an increasing amount of literature explaining how innovative technologies shape the greening of the built environment, only a small number of studies focus on how these technologies in particular lead to the development of innovative sustainable business models. Moreover, current studies lack considerations of the strategic implementation of these technologies within sustainability-oriented business models. Empirical investigations into how these technologies' particular characteristics – related to technological potentiality – contribute to innovation towards sustainability are scarce.

The challenges that the AEC sector faces as a complex and dynamic industry interacting with both stakeholders' interests and regulatory imperatives support the need for more insight into how emerging technologies can be deployed in the quest for sustainability. This is a void that highlights a call for specific research to explore the characteristics of these technologies and how they might engage business models in an evolution towards sustainability. Closing this gap might offer lessons to practitioners and policymakers interested in introducing innovative solutions in the AEC industry.

Another important gap is the roles of a company's digital strategy, corporate entrepreneurship, as well as sustainability practices for driving sustainable business model innovativeness. Although there is an increasing amount of research on these factors separately, there is little research on their interdependence and their holistic impact on promoting sustainable innovation in business model development. Being digital is critical when it comes to using technology to increase operational effectiveness and customer interaction, but its role in advancing sustainability in construction is less well understood. Corporate entrepreneurship also fosters creativity and flexibility; the linkage between corporate entrepreneurship with digital strategies and sustainable practices to create sustainable business models needs to be empirically explored. Furthermore, sustainable practices are acknowledged increasingly as necessary for long-term survival, their impact in relation to digital initiatives and entrepreneurial activeness is often underestimated.

By examining how these three elements interact, we may gain valuable insight into forging comprehensive growth strategies that are designed to move the needle on innovation while also being in sync with sustainable ideals. Filling this gap in the literature is imperative for organisations seeking to operate effectively in the increasingly complex world of business. The knowledge obtained may be used by practitioners and policymakers to meaningfully combine digital strategies, entrepreneurial undertakings, and sustainability efforts in a manner that facilitates the design of durable and innovative business models.

A research gap exists on the difference between the practices of architects and site construction as regards their DT and sustainable BMI in AEC. There is considerable material available on DT and the transformation benefits for the AEC domain; however, little attention has been paid to articulating the specific roles and working methods of architects and construction teams within this context. Most architects work in designing and planning, using digital applications to assist with creativity and sustainability. Themed as practical, however, onsite construction (in construction teams) increasingly employs both digital tools for project management, resource distribution, and site efficiency. These disconnects in practice raise the question about how each group embeds DT in their practices and whether these embed impact the development of sustainable BMI.

Although there is an initial interest in measuring SO and EO separately, there is still little knowledge regarding how SO combines with EO and DO to influence innovation in sustainable business models. Claudy *et al.* (2016) and Sung and Park (2018) have primed this work by considering SO as a strategic resource and value-based mindset, though little is known about how these orientations combine empirically to shape innovation outcomes. As sustainability challenges are becoming more complex, there is a need to explore how strategic orientations reinforce or contradict each other when pursuing SBM innovation, especially in dynamic, project-based industries such as AEC.

Finally, TBL-aligned businesses use DT for achieving their TBL goals which results in some specific requirements that are not addressed in any DT framework for aligning itself with the TBL goals of the organisation. There seems to be a clear absence of a holistic conceptual framework that incorporates TBL principles and DT, entrepreneurial culture, and SO in the AEC industry. Current models tend to centre on disconnected issues like BMI or digital maturity without grasping the systemic links between digital characteristics, strategic stances and sustainability results. There is a need for a model to map TBL-aligned digital traits to strategic drivers such as EO, DO and SO to inform theoretical inquiry and practical applications. An offering of this type could enable organisations to discern key levers of potential regarding innovation in complex project environments.

## 2.7 Hypotheses

The proposed five research gaps provide a perspective on the determinants of DT toward sustainable BMI for the AEC industry. Closing the aforementioned gaps can potentially enrich a comprehensive framework on the interplay between DT, sustainability, business culture and practices, and BMI.

### 2.7.1 Digital Features Foster Sustainability Business Model Innovation

Emergent technologies have unique characteristics that companies need to leverage to reconfigure their business models. These attributes can be contrasted with the TBL concept—with its pillars: Profit, Planet, and People. Firms adopting TBL-based tools are more likely to develop innovative and sustainable business models, benefiting AEC companies that support social and environmental goals. This approach provides true end-to-end value and serves as a valid response to today's business challenges.

*H1: TBL positively affects SBM Innovation*

### 2.7.2 Emergent Technologies and Organisational Capability

Organisational Capability (OC) refers to the synergy between EO and SO, highlighting their mutual influence in driving a firm's success (Sung and Park, 2018). EO enables organisations to proactively identify opportunities, while SO ensures these actions align with sustainable practices that address environmental and social challenges. Together, they form a dynamic capability that not only fosters entrepreneurial intentions and profit generation but also supports long-term competitive advantage and firm survival.

TBL-oriented digital technology adoption has a strong impact on SO by encouraging organisations to adopt a holistic mindset that considers economic, environmental, and social factors. These technologies enable the capture and analysis of large quantities of sustainability data, which, in turn, facilitates decision-making and progress monitoring. Technologies such as BC and BDA can further increase transparency in supply chains and sustainability reporting, thereby enhancing accountabilities for all parties involved in the supply chain.

Additionally, it becomes more convenient for designers to incorporate TBL-aligned characteristics into new projects. Such tools also facilitate a new level of stakeholder participation, enabling more consistent communication and involvement in sustainability projects. Furthermore, advancements such as 3D printing and sustainable design software inform the creation of green, innovative products and services. Organisations that align their digital strategies with TBL principles can nurture a strong culture of sustainability with long-term advantages for the organisation and its stakeholders.

*H2: TBL has a positive and direct impact on SO.*

Characteristics of digital technology can have a substantial impact on EO by enabling innovation and agility. BIM, digital twins, data analytics, AI, 3D printing, etc., all enable quick experimentation, allowing companies to innovate new products and services quickly, making them more responsive to market demand. This agility promotes a spirit of entrepreneurship, wherein companies can respond rapidly to changes in the market that present new opportunities. Furthermore, the availability of real-time information allows leaders to make informed decisions, reducing the level of uncertainty and supporting risk-taking behaviour. Digital technologies also enable enhanced collaboration and networking, facilitating knowledge sharing and co-creation.

In addition, tools that facilitate direct engagement between clients and tenants, like BIM and AR/VR, provide clearer insights into project status and performance, leading to greener buildings. Lastly, digital technologies streamline resources and maximise allocation, enabling businesses to concentrate efforts on entrepreneurial strategic endeavours. All these conditions contribute to creating a strong EO in organisations.

*H3: TBL has a positive and direct impact on EO.*

### 2.7.3 Corporate Focus and Sustainable Business Model Innovation

Organisations oriented towards sustainability (SO) are committed to sustainability practices and long-term value creation, motivating them to reconfigure their business models to improve environmental, social, and economic performance. TBL-enabling characteristics provide a lens through which decision-making may be realised, and sustainable TBL factors may be included in BMI. Moreover, SO creates a culture of innovation that promotes experimenting with new ideas aligned with sustainability targets. It also enhances stakeholder engagement, as companies become more attuned to sustainability-related expectations, encouraging BMI. Furthermore, SO results in a greater allocation of resources toward sustainable efforts, which, in turn, supports BMI. SO not only directly affects SBM but also plays a role in the relationship between TBL-compatible characteristics and effective BMI, leading to long-term success for the company.

*H4: SO mediates the positive effect of TBL on SBM Innovation*

Businesses are capable of innovating, developing, and creating value for society. EO comprises elements such as satisfying consumers, innovating, and pursuing proactive interests, all of which are crucial to sustain and catalyse eco-social business models. Firms with high EO are more likely to adopt traits that align with the TBL, as they understand the significance of profit, planet, and people in the strategies they follow. Furthermore, EO promotes a climate of experimentation and agility that allows firms to rapidly make strategic shifts in response to market changes and stakeholder demands for sustainability. This flexibility is important for embedding TBL principles into business processes and developing creative practices to improve sustainability performance. EO also enhances resource allocation by motivating organisations to consider investing in sustainable activities, thus reinforcing the relevance of TBL characteristics within SBM.

In addition, firms with a high level of EO are often more engaged with stakeholders, so cooperation with them can become a source of innovative contributions that can be applied to resolve sustainability problems. This kind of stakeholder engagement also heightens the mediating effect of EO, as it assists firms in configuring their business models to support the TBL. Ultimately, such EO not only has a direct effect on SBM innovation but also acts as a mediator in the relationship between the TBL BMI, leading to long-term success and sustainability.

*H5: EO mediates the positive effect of TBL on SBM Innovation*

Innovativeness, risk-taking, and proactiveness are part of the EO needed to create SBM. However, it is strengthened by a positive SO that, in turn, leverages sustainability into the strategy and aligns entrepreneurial initiatives with environmental and social objectives. EO pushes innovation, and SO ensures these innovations are compatible with the three dimensions: Profit, People, and Planet.

SO also promotes stakeholder participation and collaboration necessary for successful SBM, as it considers different points of view in the innovations. It serves as the linkage between EO and SBM, converting entrepreneurial momentum into sustainable activities. This alignment allows companies to invest in innovations that are powerful and well-received. Lastly, EO fosters innovation, and SO directs it toward sustainable actions, enhancing the relationship between EO and SBM and contributing to long-term value creation.

*H6: The relationship between EO and SBM Innovation will be mediated by SO.*

### 2.7.4 The Role of Digital Orientation

DO represents the digital vision, strategy, and practices within an enterprise that lead to DT. Furthermore, it enhances the capability of organisations to implement TBL characteristics (Muñoz-Pascual *et al.*, 2019), such as efficiency, innovation, quality, and others, more efficiently and effectively through digital means across the value system at economic, social, and ecological levels. Additionally, DO strengthens the effect of SO on SBM by enabling more data-based decision-making, allowing firms to detect new opportunities for improvement and continuously monitor sustainability developments. By moderating the relationship between EO and SBM, DO provides the strategic intent and technological expertise required for experimentation and rapid innovation, enabling firms to respond to market changes with agility. It also facilitates engagement among involved parties, ensuring that new ideas meet their requirements. Ultimately, DO fosters an informed decision-making culture, aligning TBL principles with sustainability and entrepreneurial efforts to advance SBM, thereby achieving more impactful and sustainable outcomes.

*H7: DO positively affect SBM Innovation.*

*H7a: DO moderates the relationship between TBL and SBM Innovation.*

*H7b: DO moderates the relationship between EO and SO.*

*H7c: DO moderates the relationship between SO and SBM Innovation.*

## 2.8 Concluding Remark

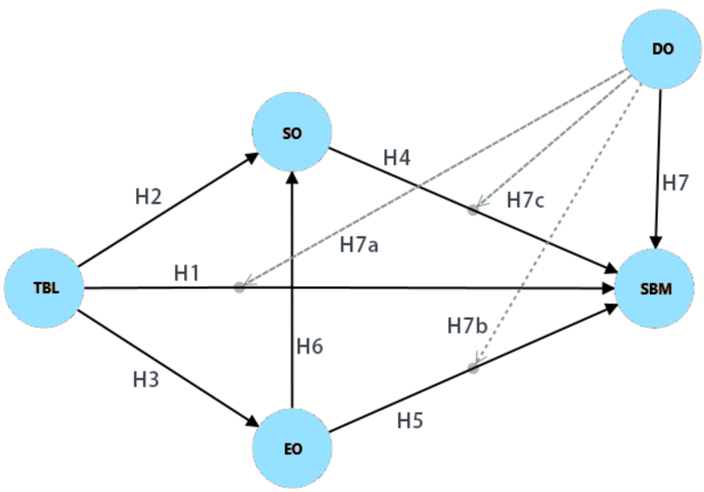
This Chapter has offered an integrative review of the extant literature in the context of DT, SO, EO, and BMI in the AEC sector. It emphasises the growing convergence of digital technologies and sustainability imperatives and how their strategic integration transforms business models and triggers long-term value creation.

The Chapter also highlights the factors (including digital vision, digital strategy, and new technologies) that are the biggest catalysts driving changes in the way businesses operate across various layers of an organisation. It raises the issues of EO and SO as organisational and strategic drivers that support a proactive, innovative, and responsible approach to value creation. Analytical perspectives employed to analyse how companies create, deliver, and capture value while satisfying environmental and social objectives include instruments like the BMC and the TBL.

Despite increased attention from both academics and practitioners, the literature provides only a fragmented understanding of how these factors interrelate in a systematic fashion. To fill this gap, we suggest, in this chapter, a holistic research framework that consolidates TBL, EO, DO, SO, and SBM. The model outlines the direct and indirect stages in the linkages between technology, strategy, and sustainability and their impact on innovation outcomes.

The research framework, shown in Figure 2.2, illustrates the theoretical links between focal constructs and lays the groundwork for the empirical research presented in later chapters. The framework contributes to theory development in the areas of DT, sustainable innovation, and strategic entrepreneurship, while also offering practical implications for AEC firms aiming to succeed in an environment of dynamic change and sustainability.

Figure 2.2 – Research Framework



# METHODOLOGY

This Chapter describes the methodology used to empirically model the relationships between TBL and SBM for the AEC industry. It also analyses the mediating effects of SO and EO, as well as the moderating effect of DO. The research design is grounded in the theories and research gaps identified in the Literature Review chapter, especially the lack of exploration of how emerging digital technologies, converged with TBL principles, shape sustainability innovation strategies in digitally transforming firms.

## 3.1 Research Design

This study adopts a positivist, quantitative research design to test the hypothesised relationships among DT, corporate orientation, and sustainable BMI in the AEC sector. The design is guided by a deductive approach (Zimbardo, 1973), translating theoretical constructs into observable variables for empirical testing (Bell *et al.*, 2022). Data were collected using a single-administration, cross-sectional survey design, which allows for efficient data capture from a broad and heterogeneous group of industry professionals at a single point in time. It is important to note that while this design is effective for identifying significant associations, its cross-sectional nature means that the hypothesised causal pathways are tested for statistical plausibility rather than definitive causal proof.

The research model (see Figure 2.2) contextualises and investigates the direct effects of TBL and SBM innovation, along with moderation and mediation effects. DO also moderates the relationships between TBL and SBM, EO and SBM, and SO and SBM. These relationships were proposed in Section 2.7 following the gaps revealed in Section 2.6.

The survey instrument was designed to align closely with the operational definitions of the constructs, as detailed in Section 3.3. A methodology was employed to facilitate standardised responses among a heterogeneous group of AEC practitioners. Data analysis was conducted by means of Partial Least Squares Structural Equation Modelling (PLS-SEM), an appropriate variance-based technique for complex models, including hierarchical constructs and small to medium samples (Hair *et al.*, 2023). Preliminary analyses were performed with SPSS, and structural modelling was conducted with SmartPLS 4.0.

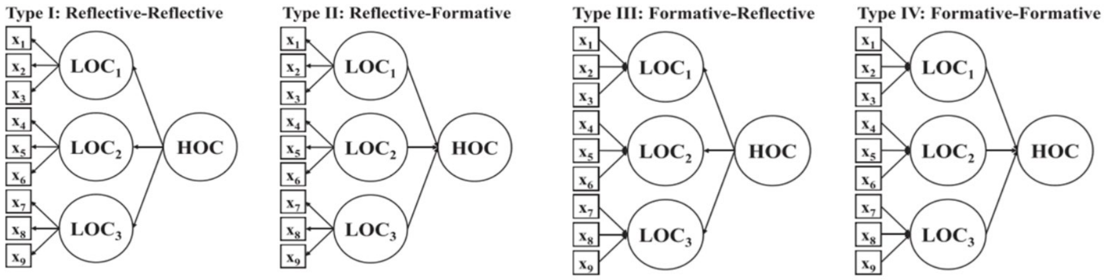
## 3.2 Construct Development and Operationalisation

The establishment of valid and reliable measurement constructs is the foundation of quantitative research and reflects the ability to translate consistent theoretical constructs into observable empirical constructs (Hinkin, 1998). In this research it is investigated not only the direct effect of TBL principles on SBM, but also it investigates how the SO and EO mediate this relationship and how this process is influenced by the DO. Every construct in question was systematically called out by way of well-considered operationalisations that balance theoretical grounding and strong empirical validation approaches.

### 3.2.1 Higher-Order Construct Structures

This study uses a stringent process to illustrate the hierarchical nature of theoretical constructs, combining higher-order models with a structured methodology for a multidimensional framework. Higher-order constructs (HOCs) of structural equation modelling (SEM) provide a powerful technique to account for multidimensionality in data. Figure 3.1 classifies four types of HOC: they describe the relationships between the first-order dimensions and the second-order HOC, as well as between the indicators and their corresponding dimensions. These have been used to guide the operationalisation of HOCs. This approach avoids the over-determination of the relative location of the placodes and provides an effective representation of complex relationships while keeping them theoretically consistent.

Figure 3.1 – Higher-Order Construct Classification




*a) Reflective-Reflective (Type I):*

- Reflective first-order dimensions (indicators reflect dimensions) combine into a reflective higher-order construct (dimensions reflect the HOC).
- Used when first-order dimensions are interchangeable indicators of the higher-order construct (Jarvis *et al.*, 2003).

*b) Reflective-Formative (Type II):*

- Formative first-order dimensions (indicators define dimensions) combine to form a reflective higher-order construct (dimensions reflect the HOC).
- Suitable when first-order dimensions are distinct yet collectively represent the higher-order construct (Diamantopoulos and Winklhofer, 2001).

*c) Formative-Reflective (Type III):*

- Reflective first-order dimensions combine into a formative higher-order construct.
- Applied when first-order dimensions are independent building blocks of the HOC (MacKenzie *et al.*, 2005).

*d) Formative-Formative (Type IV):*

- Both indicators and dimensions function as composite indices in formative relationships.
- Used when neither dimensions nor indicators are interchangeable (Coltman (Coltman *et al.*, 2008).

HOCs provide an efficient way of modelling the abstract concepts where the hierarchy can be maintained on the indicators for the super concept (Becker *et al.*, 2012). This method sounds complex in its construction while keeping the theoretic richness of what it is constructed with. The HOC categories in the study are based on the theoretical concepts described in Chapter Literature Review. For example, TBL is conceptualised as a formative construct formed by three relatively independent dimensions—Profit, People, and Planet—and each of these driven by digital traits that are theoretically sound (see Section 2.4.2 and Tables 2.5–2.7). The HOC structure of each construct and the HOC relationship types used in this study are summarised in Table 3.1.

Table 3.1 – Higher-Order Construct Used

| Type | FO → HO Relationship | Construct Used |
|---|---|---|
| Reflective-Reflective | FO: Reflective → HO: Reflective | EO, SO, DO, SBM |
| Reflective-Formative | FO: Formative → HO: Reflective | TBL |
| Formative-Reflective | FO: Reflective → HO: Formative | Not Applicable |
| Formative-Formative | FO: Formative → HO: Formative | Not Applicable |

### 3.2.2 Construct Operationalisation

*3.2.2.1 Triple-Bottom Line (TBL)*

The TBL is a reflective-formative second-order construct with three formative first-order dimensions (Profit, People, Planet), each of which is measured by three reflective digital features (refer to Section 2.4.2). This model demonstrates digital technology applications for sustainable performance in AEC companies. Its theoretical roots are anchored within the TBL framework of (Elkington, 1997); however, it is also underpinned by knowledge-based, lean, and ecological theories (Bryde *et al.*, 2013; Kibert, 2016). TBL involves three primary-order dimensions consisting of Profit, People, and Planet that constitute the economic, social, and environmental pillars of sustainability. These dimensions are distinct in concept (e.g., social performance is not environmental performance), but they collectively define the construct. Any of the dimensions neglected would change them in a categorical manner (Bocken *et al.*, 2014). Whereas the first-order factors are formative (cause) effect, the second-order TBL concept is a reflective, representing the firm's overall alignment with sustainability.

#### *3.2.2.2 Sustainable Business Model Innovation*

SBM Innovation is modelled from Spieth and Schneider (2016) (refer to Section 2.3.2). Although the initial model was a formative–formative, the reflective-reflective specification is preferred between constructs for reasons of theoretical consistency and methodological consistency as in the case of small-sample and exploratory research. Formative–formative models are adequate when integrating different, non-substitutable dimensions into a higher-order construct, but the sample size needs to be large to obtain model stability and reliable in PLS-SEM (Hair *et al.*, 2021). Due to the exploratory nature of this study and the relatively small sample size, this approach is prone to risks such as estimation bias and model identification problems. On the contrary, the reflective–reflective specification considers SBM innovation as an unobserved variable manifested to its manifest sub-dimensions—value proposition, value network, and revenue logic—that have a common factor (or shared influence).

Such approach is theoretically justifiable and analytically feasible with smaller samples given the availability of Confirmatory Factor Analysis (CFA) and robust latent variable modelling (Kline, 2023). Consistent with Jarvis *et al.* (2003), choice of construct specification ought to be contingent upon the research context and the limitations of data. Therefore, the reflective–reflective model is a theoretically justified and a parsimonious alternative that is appropriate to the purpose of this study.

*3.2.2.3 Entrepreneurial Orientation (EO)*

EO is operationalised as a reflective–reflective second-order construct, capturing a firm's entrepreneurial posture through three core dimensions: Innovativeness, Risk-Taking, and Proactiveness (Covin and Slevin, 1989; Hughes and Morgan, 2007). These dimensions are conceptually distinct but empirically correlated, justifying a higher-order reflective model. Innovativeness reflects a firm's tendency to support creativity and experimentation. Risk-taking captures the willingness to commit resources to uncertain ventures, while proactiveness reflects forward-looking, opportunity-seeking behaviour. Together, they represent the organisational mindset that enables firms to explore, experiment with, and adopt new business models, particularly those aligned with sustainability objectives (see Section 2.5.1).

*3.2.2.4 Sustainability Orientation (SO)*

SO is designed as a reflective–reflective higher-order construct, based on the framework developed by Claudy *et al.* (2016). It comprises two interrelated subdimensions: Sustainability Culture and Sustainable Practices. Sustainability Culture reflects the internalised values, beliefs, and long-term commitment to environmental and social responsibility. Sustainable Practices refer to the operationalisation of these values through actual business activities and processes. The model assumes that a strong sustainability culture drives the implementation of sustainable practices. This structure captures both the attitudinal and behavioural components of organisational sustainability and reflects a firm's capacity to integrate sustainability into strategic and operational decision-making (refer to Section 2.5.2).

*3.2.2.5 Digital Orientation (DO)*

DO is conceptualised as a reflective–reflective construct, drawing from the DT literature (Hess *et al.*, 2016) and grounded in Dynamic Capabilities and Paradox Theory (Nambisan *et al.*, 2019; Verhoef *et al.*, 2021; Westerman *et al.*, 2014). It includes two key subdimensions: Digital Vision and Digital Strategy. Digital Vision refers to a forward-looking, organisation-wide understanding of the role of digital technologies in reshaping the business model. Digital Strategy translates that vision into actionable investments, priorities, and initiatives. Together, these dimensions reflect the strategic intent and readiness to leverage digital technologies. DO also functions as a moderator, influencing how digital traits and orientations impact sustainable BMI (refer to Section 2.5.3).

## 3.3 Measurement Scale Development

The development of robust measurement scales is critical for ensuring the validity and reliability of empirical findings in structural equation modelling (Hair *et al.*, 2019). This section details the systematic process of operationalising the study's key constructs, distinguishing between: (1) newly developed instruments for emerging theoretical domains (TBL, DO), and (2) modified establishing scales that were adapted for the digital and sustainability context (EO, SO, SBM). All scales underwent rigorous validation procedures including expert reviews, and psychometric evaluation to ensure they meet established standards for construct measurement (Netemeyer *et al.*, 2003). The development approach carefully balanced theoretical fidelity with practical measurement considerations, contextualising existing scales where appropriate while creating novel measures for constructs lacking prior instrumentation.

### 3.3.1 Triple Bottom Line (TBL) Measurement Scale

Within the overarching research framework, the TBL construct stands as a multidimensional antecedent impacting the SO, the EO, and the SBM within the broader research stream. As a construct of interest, the specific operationalisation of the TBL construct will need both theoretical richness and empirical detail, especially in the AEC industry. Unlike SO, EO, and SBM—whose measurement scales are adapted from existing literature, the TBL construct was newly developed to the specific, sustainability-aligned effects of digital technologies in AEC context.

*3.3.1.1 Construct Conceptualisation*

The TBL construct is considered more than just a sustainability performance result, but also as a strategic capability that represents the way digital technologies create economic (Profit), social (People), and environmental (Planet) value. The construction of an empirically supported and soundly based TBL measurement scale is therefore key to evaluate the degree of sustainability embedded in DT strategies inside AEC companies. Building on Elkington (1997) framework, the TBL construct in this study is defined as the degree to which digital technologies in AEC projects produce measurable impacts across three interrelated dimensions:

- *Profit*: Economic performance enhancements such as cost reductions, resource utilisation efficiency, and material waste minimisation.
- *People*: Social performance improvements, including stakeholder collaboration, safety outcomes, and workforce development.
- *Planet*: Environmental performance advancements such as energy efficiency, responsible resource consumption, and lifecycle sustainability.

This conceptualisation aligns with contemporary literature that positions TBL as a dynamic organisational ability shaped by technological innovation and transformation processes (Klewitz and Hansen, 2014; Schaltegger *et al.*, 2016).

*3.3.1.2 Methodological Approach to Scale Development*

The TBL measurement scale was developed using a deductive, theory-informed approach, following established best practices in construct development (Churchill Jr, 1979; MacKenzie *et al.*, 2011). The development process consisted of four key stages:

*a) Extensive Literature Review*

A systematic literature review was conducted to identify how emerging digital technologies, such as BIM, AI/ML, IoT, DTs, and 3D printing, contribute to sustainability outcomes in AEC. (refer to Section 2.4).

*b) Item Generation*

Initially, fifteen candidate items were generated—five for each TBL dimension—through thematic coding of the literature (refer to Section 2.4.2). These items encapsulated a spectrum of digital traits linked to sustainability outcomes. Following iterative refinement, the items were distilled into three representative indicators per dimension, resulting in a final nine-item scale.

*c) Theoretical Anchoring*

Each item was mapped to a relevant theoretical framework to ensure conceptual clarity and measurement validity. Theories applied include the Knowledge-Based View, Dynamic Capabilities Theory, Lean Principles, Relational View, High Reliability Theory, Human Capital Theory, Eco-Efficiency, Industrial Ecology, and Cradle-to-Cradle Design. This multi-theoretical foundation enhances the explanatory power of the scale and ensures alignment with sustainability and innovation scholarship (refer to Table 2.5 – 2.7).

*d) Contextualisation to AEC*

For industry relevance and content validity, each measurement item was contextualised to the digital practices and sustainability challenges that are particular to the AEC sector. Technologies were chosen applicable to AEC practices, and item wording was modified to reflect language used in the sector, as well as operational imperatives. Emphasis was placed on question development in order to avoid leading and suggestive wording, and thereby to minimise response bias and increase the objective nature of reports. This increases the face validity and interpretability of the measure for respondents who work in a variety of roles within the AEC industry.

### *3.3.1.3 Scale Specification*

The TBL measurement model uses a reflective-formative structure: nine reflective first-order items (7-point Likert scale) form three formative second-order dimensions (Profit, People, Planet). As shown in Tables 3.2-3.4, each reflective item captures specific manifestations (1='Not at All', 7='To a Great Extent'), while the composite dimensions formatively combine these indicators. This approach recognises reflective measurement at the item level and formative aggregation at the dimension level.

Table 3.2 – TBL Digital Traits (TBL-DT) Measurement – Profit

| Item Code | Description | Theoretical Anchor | Key Technology Examples |
|---|---|---|---|
| TBL-Profit1 | *Design Process Change:* The extent to which BIM and AI technologies modify design accuracy and reduce rework frequency | Knowledge-Based View | BIM, AI |
| TBL-Profit2 | *Resource Allocation Effects:* The degree to which BIM and BDA transform resource utilisation efficiency | Dynamic Capabilities | BDA, CC |
| TBL-Profit3 | *Production Waste Patterns:* How significantly 3D printing technology alters material waste levels in manufacturing processes | Lean Principles | 3D Printing |

Table 3.3 – TBL Digital Traits (TBL-DT) Measurement – People

| Item Code | Description | Theoretical Anchor | Key Technology Examples |
|---|---|---|---|
| TBL-People1 | *Stakeholder Coordination:* The extent to which digital platforms improve collaboration among project stakeholders | Relational View | CC, Digital Platforms |
| TBL-People2 | *Safety Performance:* How VR/AR and ML technologies impact safety incident rates and hazard identification | High Reliability Theory | VR/AR, ML |
| TBL-People3 | *Workforce Capability:* The extent to which digital skills development programs enhance employee competencies | Human Capital Theory | Training Platforms |

Table 3.4 – TBL Digital Traits (TBL-DT) Measurement – Planet

| Item Code | Description | Theoretical Anchor | Key Technology Examples |
|---|---|---|---|
| TBL-Planet1 | Design Environmental Effects: How energy simulation tools influence the environmental footprint of project designs | Eco-Efficiency | BIM-GIS Integration |
| TBL-Planet2 | Resource Consumption Changes: The extent to which BIM, IoT sensors, and digital twins impact energy and material usage | Industrial Ecology | IoT, Sensors |
| TBL-Planet3 | Asset Lifecycle Alteration: How digital asset management systems influence the operational lifespan of building components | Cradle-to-Cradle | DTs |

### 3.3.2 Digital Orientation (DO) Measurement Scale

DO is the strategic stance and preparedness of an organisation for DT, which is the integrated application of digital technologies to transform business models, operational processes, and value delivery systems, as well as to develop digital capabilities across the business and its ecosystem of customers and partners (Mergel *et al.*, 2019). Informed by Verhoef *et al.* (2021) triphasic model—digitisation, digitalisation, and DT—it is particularly relevant in the AEC industry as its levels of digital maturity are heterogeneous (Adekunle *et al.*, 2021).

To overcome the lack of studies of the DO, it is considered a reflective-reflective second order construction and formed by two dimensions: Digital Vision and Digital Strategy (Hess *et al.*, 2016). These dimensions are consistent with theoretical frameworks related to the topic, such as Dynamic Capabilities Theory, Institutional Theory, and Paradox Theory, providing micro- and macro-level explanatory strength.

#### *3.3.2.1 Dimensions of Digital Orientation*

*a) Digital Vision:* It reflects an organisation's ability to formulate and communicate a coherent, long-term digital roadmap. In AEC, this dimension addresses key challenges such as project fragmentation and multi-stakeholder complexity by:

- Aligning digital objectives across project life cycles and teams
- Establishing a common language for digital goals
- Guiding investment in future-ready technologies and standards

*This aligns with (Table 3.5):*

- Dynamic Capabilities Theory: Enables opportunity sensing (Teece, 2018)
- Institutional Theory: Supports standardisation (DiMaggio and Powell, 1983)
- Paradox Theory: Balances long-term innovation with short-term delivery (Smith and Lewis, 2011).

*b) Digital Strategy:* It operationalises the vision through tangible investments, processes, and capabilities. Within AEC contexts, it enables:

- Institutionalisation of collaborative digital workflows
- Investment in digital talent and training
- Pilot testing and scaling of emerging technologies (e.g., AI, IoT, DTs)

*Theoretical foundations include (Table 3.5):*

- Dynamic Capabilities: Resource orchestration for digital adoption
- Institutional Theory: Compliance with industry standards (e.g., ISO 19650)
- Paradox Theory: Managing experimentation alongside execution

Table 3.5 – Theoretical Foundations of Digital Orientation Dimensions

| Theory | Vision Role | Strategy Role | AEC Manifestation |
|---|---|---|---|
| Dynamic Capabilities | Opportunity sensing | Talent/resource allocation | Cross-project BIM deployment |
| Institutional Theory | Standard setting | Best practice adoption | ISO 19650 implementation |
| Paradox Theory | Long-term investment | Short-term execution | DTs pilot scaling |

*3.3.2.2 Measurement Framework*

The DO measurement scale was constructed through tightly controlled theory-to-item mapping to establish construct validity and contextual accuracy in the AEC environment. Each concept item is grounded in thought and an illustration of the unique nature of DO in this industry.

- *Dimensional Synergy:* The dimension scales vision (vision–strategy) and strategy (strategy–vision) distinguish between strategic direction and tactical execution, thus offering a more detailed examination of digital maturity trajectories within an AEC firm context (Table 3.5).
- *Sector Specific Focus:* Outcomes are specifically targeted to tackle AEC sectoral challenges including project fragmentation, planning regulation complexity, and digital skills gaps (Figure 3.2).
- *Theoretical Rigor:* This scale combines the micro and macro theoretical levels, increasing its theoretical vigour in empirical modelling and hypothesis testing (Table 3.6).

Figure 3.2 – Theory-to-Item Mapping

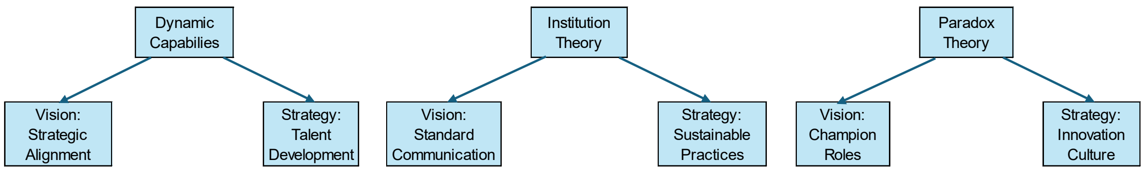



Table 3.6 – DO Measurement Scale Specification

| Dimension | Item Code | Theoretical Anchor | AEC Contextualisation |
|---|---|---|---|
| **Digital Vision** | DO-Vision1 | Strategic fit (Westerman *et al.*, 2014) | BIM roadmap alignment |
| | DO-Vision2 | Isomorphism (DiMaggio and Powell, 1983) | ISO 19650 communication |
| | DO-Vision3 | Paradox resolution (Smith and Lewis, 2011) | Digital champion roles |
| **Digital Strategy** | DO-Strat1 | NRBV pollution prevention (Hart, 1995) | Energy-efficient BIM |
| | DO-Strat2 | Capability reconfiguration (Teece, 2018) | IoT skills development |
| | DO-Strat3 | Exploration ambidexterity (O'Reilly III and Tushman, 2013) | DTs pilots |

#### 3.3.2.3 Measurement Scale

Building from Dynamic Capabilities, Institutional Theory, and Paradox Theory, we created each measurement item to represent specific dimensions of strategic intent (Digital Vision) and implementation capability (Digital Strategy). The item wording was slightly amended to better correspond to AEC terminology, digital workflows, and organisation structures to ensure a fit for context. To further reduce the response bias and to improve the face validity, leading or suggestive questions were also minimised.

The sub-dimension Digital Vision was assessed with a scale of 7-point Likert scale (1=Strongly Disagree to 7=Strongly Agree) and scales the degree to which an organisation's digital roadmap is clearly formalised and communicated. Instead, the Digital Strategy utilised a 7-point frequency/effectiveness scale (1=Not at All to 7=To a Great Extent) that gauged the extent to which digital is implemented through practices such as talent development and sustainable workflows. The resulting items are shown in Table 3.7.

Table 3.7 – DO Measurement Scale

| Dimension | Item Code | Item Wording |
|---|---|---|
| **Digital Vision** | DO-Vision1 | Strategic alignment - Our company digital transformation roadmap aligns with long-term business strategy |
| | DO-Vision2 | Stakeholder communication - Our company digital goals are clearly communicated to all project partners |
| | DO-Vision3 | Leadership - Our company has dedicated digital champions to drive digital initiatives |
| **Digital Strategy** | DO-Strat1 | Sustainable practices - We enforce green digital standards (e.g., cloud-based BIM collaboration) |
| | DO-Strat2 | Talent development - We invest in continuous upskilling for emerging AEC technologies |
| | DO-Strat3 | Innovation culture - We cultivate innovation and transformation culture |

### 3.3.3 Sustainable Business Model (SBM) Measurement Scale

The SBM measurement scales was transferred from Spieth and Schneider (2016) BMI model by using sustainability transition theory (Geissdoerfer *et al.*, 2017) and the Triple Bottom Line approach (Elkington, 1997). This adaptation grounds sustainability indicators but maintains the original three domain structure (Table 3.8). With four guiding principles in place – the explicit integration of environmental and social value creation, industry-specific operationalisation for AEC contexts, original construct boundaries, and 7-point Likert scales for comparability – the measurement scales capture these adaptations in actionable scale items. These scales also measure the trade-off between theoretical robustness and practical applicability to sustainable practices in AEC sector (Table 3.9).

Table 3.8 – Sustainable Business Model Adaptations

| Domain | Original Indicator | Modified Indicator | Adaptation Level |
|---|---|---|---|
| **Value Offering** | Target customers changed | Target sustainability-focused clients | Contextual |
| | Product/service changed | Redesign to reduce environmental/social impacts | Substantial |
| | Market positioning changed | Reposition as sustainable solutions provider | Moderate |
| **Value Architecture** | Core competences changed | Develop sustainability innovation expertise | Substantial |
| | Internal operations changed | Optimise operations for sustainability gains | Enhanced |
| | Partner roles changed | Establish green technology partnerships | Substantial |
| | Distribution changed | Implement sustainable procurement criteria | Added |
| **Revenue Model** | Revenue mechanisms changed | Diversify revenue through sustainable offerings | Contextual |
| | Cost mechanisms changed | Adopt resource-efficient cost structures | Enhanced |

Table 3.9 – SBM Measurement Scale

| Dimension | Item Code | Item Wording |
|---|---|---|
| **Value Offering** | SBM-Valueoff1 | Our customer base prioritises sustainability-focused projects |
| | SBM-Valueoff2 | We have transformed offerings to reduce environmental/social impacts |
| | SBM-Valueoff3 | We are recognised as a sustainable solutions leader |
| **Value Architecture** | SBM-ValueArch1 | We have developed specialised sustainability innovation capabilities |
| | SBM-ValueArch2 | We continuously optimise operations for sustainability performance |
| | SBM-ValueArch3 | We co-develop solutions through green technology partnerships |
| | SBM-ValueArch4 | We mandate sustainability certification for suppliers |
| **Revenue Model** | SBM-Revenue1 | We generate significant revenue from sustainable offerings |
| | SBM-Revenue2 | Our cost structures emphasise long-term resource efficiency |

### 3.3.4 Entrepreneurial Orientation (EO) Measurement Scale

This analysis uses an integrated EO measure combining Miller (1983) and Covin and Slevin (1989) three-dimensional structure with Hughes and Morgan (2007) psychometric refinements (Table 3.10). This hybrid model was employed for two important reasons. First, the original three-part structure (innovativeness, proactiveness, risk-taking) more accurately measures sustainability and digital oriented entrepreneurship by focusing on sustainable product innovation processes, organisational responsiveness to sustainability opportunities, and risk appraisal towards sustainability investments, while omitting less pertinent dimensions such as market aggressiveness and autonomy from Hughes and Morgan's deviated model. Second, Hughes and Morgan's items offer better measurement properties in digital sustainability contexts, primarily due to: i) innovativeness items focusing on technology deployment ("We actively introduce improvements and innovations in our business"), ii) proactiveness items reflecting digital-enabled opportunity identification ("We always try to take the initiative in every situation"), and iii) a revised risk-taking version to accommodate modern market insecurities.

Table 3.10 – EO Scale Adaptation Rationale

| Dimension | Original Conceptualisation (Covin and Slevin 1989) | Adapted Measurement (Hughes and Morgan 2007) | Sustainability Relevance |
|---|---|---|---|
| **Innovativeness** | Product/service leadership focus | Market-driven innovation emphasis | Digital sustainable product R&D |
| **Proactiveness** | First-mover competitive advantage | Opportunity identification capability | Early adoption of green tech |
| **Risk-taking** | Large project investment willingness | Strategic boldness in decision-making | Sustainable investment gambles |

The final measurement instrument comprises nine items across three dimensions, measured on a 7-point Likert scale (1 = Strongly Disagree to 7 = Strongly Agree) are shown in Table 3.11. This measurement approach preserves the original EO nomological network while enhancing relevance for sustainability research contexts, as recommended by recent methodological reviews (Vrontis *et al.*, 2022). The modifications were reviewed and approved by three entrepreneurship scholars to ensure theoretical consistency.

Table 3.11 – EO Measurement Scale

| Dimension | Item Code | Item |
|---|---|---|
| **Risk-taking** | EO-Risk1 | The term “risk taker” is considered a positive attribute for people in our business |
| | EO-Risk2 | People in our business are encouraged to take calculated risks with new ideas |
| | EO-Risk3 | Our business emphasises both exploration and experimentation for opportunities |
| **Innovativeness** | EO-Inno1 | We actively introduce improvements and innovations in our business |
| | EO-Inno2 | Our business is creative in its methods of operation |
| | EO-Inno3 | Our business seeks out new ways to do things |
| **Proactiveness** | EO-Pro1 | We always try to take the initiative in every situation (e.g., against competitors, in projects when working with others) |
| | EO-Pro2 | Our business is creative in its methods of achieving sustainability goals |
| | EO-Pro3 | We seek out new ways to integrate sustainability into our operations |

### 3.3.5 Sustainability Orientation (SO) Measurement Scale

The SO construct was adapted from Claudy *et al.* (2016) original scales, with four key modifications to enhance measurement precision and contextual relevance for project-level sustainability assessment in the AEC industry: i) conversion from importance ratings to 7-point Likert-type agreement scales for improved parametric analysis (Spector, 1992), ii) generalisation from product-specific to project-level applications, iii) addition of operational specificity to practice items (e.g., explicit energy tracking metrics), and iv) alignment of terminology with contemporary sustainability discourse. The revised instrument maintains the original two-dimensional structure (Sustainability Culture and Sustainable Practices) while optimising its applicability to AEC contexts (Table 3.12).

Table 3.12 – SO Scale Adaptation Rationale

| Dimension | Original Formulation | Key Modifications | Theoretical Justification |
|---|---|---|---|
| **Culture** | Importance ratings | Agreement scale | Better captures normative institutionalisation (Hahn et al., 2015) |
| | Product focus | Project-level focus | Fits AEC industry context |
| **Practices** | Product development | Operational projects | Increases generalisability |
| | Generic items | Specific metrics | Enhances measurement precision |

The final set of SO measurement items is shown in Table 3.13. This measurement approach maintains conceptual alignment with Claudy *et al.* (2016) original construct while improving its applicability to project-based organisational contexts. The modifications follow established scale adaptation protocols (Hinkin, 1998) and contemporary sustainability measurement standards (Baumgartner and Rauter, 2017).

Table 3.13 – SO Measurement Scale

| Dimension | Item Code | Item |
|---|---|---|
| **Culture** | SO-Culture1 | We consider environmental sustainability important |
| | SO-Culture2 | We consider social sustainability important |
| | SO-Culture3 | We consider sustainability criteria important for new projects |
| | SO-Culture4 | We consider measuring new projects' progress on sustainability important |
| | SO-Culture5 | We value sustainability-type criteria as important for the future |
| **Practices** | SO-Practices1 | We consider energy consumption and/or carbon emissions in our project work |
| | SO-Practices2 | We include sustainability in our project budget |
| | SO-Practices3 | We select suppliers and partners based on sustainability criteria |
| | SO-Practices4 | We use the triple bottom line (environmental, social, and financial factors) for project planning |

### 3.3.6 Validation Approach for Measurement Scales

Given the single-administration design, formal psychometric testing, comprising reliability analysis (e.g., Cronbach's α), convergent and discriminant validity, and confirmatory / exploratory factor analysis (CFA/EFA) is conducted using the primary dataset (reported in Chapter Analysis and Results). This approach is justified by several methodological safeguards:

- *Theoretical alignment:* All items were derived from theoretically grounded constructs defined in Sections 3.2 and 3.3.
- *Adoption of precedent scales:* Wherever possible, items were adapted from validated instruments in the existing literature.
- *Expert validation:* Two domain experts—a Director of a BIM solutions provider and a CEO of a BIM consultancy—reviewed the full instrument. Their feedback confirmed the clarity of wording, appropriateness of scale types, alignment with AEC terminology, and the logical flow of questions.

While expert pretesting addressed face and content validity, formal statistical validation was deferred to the empirical analysis stage. There, the following steps were undertaken:

- Assessment of internal consistency reliability using Cronbach's α and composite reliability (CR)
- Evaluation of convergent validity via average variance extracted (AVE) and standardised loadings
- Verification of discriminant validity using cross-loadings and the Fornell-Larcker criterion
- Model fit testing through CFA to confirm one-dimensionality of the constructs

Preliminary results, presented in Chapter Analysis and Results, indicate satisfactory reliability and validity across all constructs, thereby supporting the robustness of the measurement model prior to structural model estimation. This approach meets the standards of methodological rigor required for PLS-SEM–based hypothesis testing.

## 3.4 Sampling Design and Data Collection

### 3.4.1 Sampling Design and Rationale

Sampling methodology is a key aspect of research design. It shapes who constitutes the participants from a target group. There are two general types of sampling used: probability and non-probability (Singleton Jr *et al.*, 1988).

With probability sampling techniques (e.g., simple random sampling, stratified random sampling), all members of the population have an equal and known chance of being selected. This methodology enables generalisation of research while reducing selection bias. Nonetheless, its application necessitates a well-defined population frame and is resource-intensive, which is often not feasible in practical research circumstances.

Non-probability sampling techniques, on the other hand, lack known probabilities of the members of a population being included, which can lead to sampling error and affect result generalisability (Singleton Jr *et al.*, 1988). Some warn that this can lead to the overrepresentation of certain subgroups and underrepresentation of others, which could bias findings. However, non-probability sampling is still widespread in social and business research and is what we can expect under the following conditions:

- Exploratory Research Objectives: When the study focuses on identifying emerging patterns rather than testing established hypotheses.
- Resource Limitations: When constraints of time, funding, or population accessibility preclude probability sampling.
- Specialised Populations: When studying geographically dispersed or difficult-to-identify professional groups.
- Practical Considerations: When research efficiency outweighs strict statistical representativeness requirements.

Given this study's exploratory nature, the challenges in establishing a complete population frame, and practical constraints regarding time and access, a non-probability sampling strategy was implemented. This decision aligns with established research practices in the AEC sector, where professional networks and institutional directories commonly serve as recruitment channels.

### 3.4.2 Data Collection

To maintain methodological rigor while addressing practical constraints, the study employed a multi-faceted recruitment approach combining institutional resources and personal networks:

1. Hong Kong Institute of Architects (HKIA): The survey was distributed to 182 members through the institute's official email directory, capturing perspectives from licensed architects, urban designers, and sustainability consultants.

2. Hong Kong Construction Association (HKCA): A total of 306 surveys were distributed to HKCA members, representing contractors, project managers, and civil engineers across the AEC sector's operational tiers.
3. Hong Kong Construction Industry Council BIM Managers (HKBIM): Surveys were sent to 352 registered BIM managers, targeting professionals with specialised expertise in digital construction technologies.
4. Personal Networks (PER): An additional 75 surveys were distributed through professional contacts and referrals, accessing practitioners outside formal institutional memberships.

### 3.4.3 Control Variables and Respondent Characteristics

Apart from the main variables addressed in this study, several variables were included in the survey to control for organisational and respondent-level factors that may be correlated with perceptions of DT and SBM innovation. The addition of these variables enables segmentation analysis, robustness checks, and further explanation of the specific context of the results related to DT in the AEC sector.

The four control variables included are as follows:

- C1. Nature of Company: Participants selected the primary focus of their organisation: (1) Design and Planning (e.g., architectural design, engineering, urban planning, landscape architecture), or (2) Construction and Project Management (e.g., general contracting, subcontracting, construction management, building inspection). This variable distinguishes between different segments of the AEC industry, which may face unique DT challenges and adoption patterns.
- C2. Company Size: Respondents indicated the size of their organisation by selecting one of four brackets: (1) 1–20 employees, (2) 21–100, (3) 101–200, or

(4) Over 200. Organisational size is commonly associated with digital capability, resource availability, and transformation readiness.

- C3. Respondent Role: Participants identified their most relevant role within the organisation from the following options: (1) CEO/COO/Managing Director, (2) Architect, (3) BIM Manager/Engineer/Consultant, or (4) Others. This variable helps assess role-based variation in strategic orientation and perception of DT.
- C4. Perceived Digital Capability for Sustainability: This item measured the organisation's self-reported ability to apply digital technologies towards sustainability throughout the project lifecycle. Responses were captured on a five-point Likert scale ranging from (1) Very poor ability to (5) Exceptional ability.

These control variables were later used during the data analysis phase to explore whether organisational characteristics moderated or influenced the relationships among the main constructs in the hypothesised model and to assess the generalisability of the findings across different firm types and respondent groups. The complete survey questionnaire is provided in Appendix A.

#### 3.4.4 Ethical Considerations

The research was carried out in accordance with general research ethical recommendations. Prior to the survey, the rights of respondents were explained to all participants, stating that their participation was voluntary and that they had the right to refuse to participate or withdraw at any time during the survey. Data privacy was particularly emphasised, and all data were anonymised and saved on cloud servers with password protection. These measures ensured that no entity or person could be traced when summarising results. In addition, the participants were not asked to provide any personal identification, such as their name, email address, or contact number.

### 3.4.5 Survey Deployment and Administration

The research conducted the online survey using Google Forms, which was preferred due to its easy accessibility, low cost, and privacy for respondents. The surveying toolkit included an extensive cover letter explaining the study's intentions, the average time required to complete the survey, and QR codes and hyperlinks for easy access on multiple devices. Distribution modalities included institutional email blasts to members' lists, postal mail for participants for whom an email address of record was not available, and a fill-in-the-blank referral form for personal networks on the instant messaging platform WhatsApp. The distribution statistics and response rates for these four recruitment channels are summarised in Table 3.14.

Table 3.14 – Questionnaire Response

| | **Sample Size** | **Response** | | **Valid** | | **Remark** |
|---|---|---|---|---|---|---|
| | | **N** | **Rate** | **N** | **Rate** | |
| **HKIA** | 182 | 37 | 20.33% | 36 | 19.78% | |
| **HKCA** | 306 | 30 | 9.80% | 27 | 8.82% | |
| **HKBIM** | 352 | 44 | 12.50% | 44 | 12.50% | 13 responses with personal follow-up |
| **PER** | 75 | 52 | 69.33% | 51 | 68.00% | 29 responses with personal follow-up |
| | 915 | 163 | 17.81% | 158 | 17.20% | |

## 3.5 Data Analysis Method

To test the proposed conceptual framework, which contains several latent constructs across hierarchical levels and intricate mediation and moderation paths, PLS-SEM is adopted. PLS-SEM, a variance-based structural modelling approach, is increasingly used in information systems, strategic management, and innovation studies because of its potential for construct development and predictive modelling (Hair Jr *et al.*, 2014; Sarstedt *et al.*, 2014). It is particularly relevant for exploratory studies, where the emphasis is on developing and generating theory, rather than testing an extant theory.

### 3.5.1 Justification for PLS-SEM

The rationale for using PLS-SEM is supported by the theoretical maturity and exploratory nature of the current model, which is a generally accepted criterion for choosing between covariance-based and component-based approaches to SEM. PLS-SEM is suitable for a range of methodological and analytical needs included in the present study. First, it is flexible and can estimate complex models with several constructs, higher-order factors, formative and reflective indicators, and interaction effects. Second, PLS-SEM is insensitive to data that does not follow a multivariate normal distribution, which is typical in behavioural research and organisational studies involving Likert-scale survey data. Third, it is suitable for moderate-to-small sample sizes, which is particularly advantageous for specialised populations like AEC professionals.

In contrast, Covariance-Based SEM (CB-SEM) was deemed less suitable for this study for several key reasons. Primarily, CB-SEM is a confirmatory method that focuses on testing how well a theoretical model fits the data, which contrasts with the predictive and theory-building orientation of this research. Furthermore, CB-SEM imposes stricter assumptions regarding data, including multivariate normality and the need for larger sample sizes (typically >200) to ensure robust estimations. The non-normal distribution of the Likert-scale data and the modest sample size (N=158) in this study would challenge these requirements. Additionally, the inclusion of a formative construct (TBL) is handled more naturally and parsimoniously within the PLS-SEM algorithm, whereas its specification in CB-SEM can be more complex. Therefore, the flexibility of PLS-SEM in handling complex predictive models with less stringent data assumptions made it the superior choice for achieving the research objectives.

The model proposed in this study comprises second-order constructs, formative dimensions, and moderating/mediating paths. These characteristics justify the use of PLS-SEM as the analytic tool, rather than covariance-based SEM, which would require larger sample sizes and more rigorous assumptions. Thus, the statistical software used to estimate and validate the model will be SmartPLS 4.0. It is the most popular software for PLS-SEM and allows users to easily develop, assess, and test PLS-SEM models, run bootstrap procedures, assess the significance of loadings, and perform multi-group analysis.

### 3.5.2 Sample Size Considerations

While PLS-SEM can accommodate relatively small sample sizes, determining the appropriate number of observations is critical to ensure sufficient statistical power and model reliability. Two complementary approaches were used to establish the minimum sample size for this study:

#### *3.5.2.1 The 10-Times Rule*

According to this heuristic, the sample size should be at least ten times the number of maximum structural paths pointing to any endogenous construct or the number of indicators in the most complex measurement model (Hair *et al.*, 2022; Peng and Lai, 2012). For the structural model depicted in Figure 2.2, the most complex construct has five incoming paths, resulting in a minimum sample size requirement of 50.

#### *3.5.2.2 Statistical Power Analysis*

To enhance methodological rigor, a formal power analysis was conducted using Cohen (2013) guidelines for multiple regression. This analysis considers:

- A desired statistical power of 80%,
- A significance level (α) of 0.05,
- A medium effect size ($R^2 = 0.25$), and
- The maximum number of predictors for any endogenous construct.

Based on these parameters, a minimum of 48 observations is required to detect a statistically significant relationship. Table 3.15 provides a summary of required sample sizes under varying model complexities and $R^2$ values.

Table 3.15 – Sample Size in PLS-SEM for Statistical Power of 80%

| Maximum Number of Arrows Pointing at a Construct (Number of Independent Variables) | Significance Level | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 10% | | | | 5% | | | | 1% | | | |
| | Minimum $R^2$ | | | | Minimum $R^2$ | | | | Minimum $R^2$ | | | |
| | 0.10 | 0.25 | 0.50 | 0.75 | 0.10 | 0.25 | 0.50 | 0.75 | 0.10 | 0.25 | 0.50 | 0.75 |
| 2 | 72 | 26 | 11 | 7 | 90 | 33 | 14 | 8 | 130 | 47 | 10 | 10 |
| 3 | 83 | 30 | 13 | 8 | 103 | 37 | 16 | 9 | 145 | 53 | 22 | 12 |
| 4 | 92 | 34 | 15 | 9 | 113 | 41 | 18 | 11 | 158 | 58 | 24 | 14 |
| 5 | 99 | 37 | 17 | 10 | 122 | 45 | 20 | 12 | 169 | 62 | 26 | 15 |
| 6 | 106 | 40 | 18 | 12 | 130 | 48 | 21 | 13 | 179 | 66 | 28 | 16 |
| 7 | 112 | 42 | 20 | 13 | 137 | 51 | 23 | 14 | 188 | 69 | 30 | 18 |
| 8 | 118 | 45 | 21 | 14 | 144 | 54 | 24 | 15 | 196 | 73 | 32 | 19 |
| 9 | 124 | 47 | 22 | 15 | 150 | 56 | 26 | 16 | 204 | 76 | 34 | 20 |
| 10 | 129 | 49 | 24 | 16 | 156 | 59 | 27 | 18 | 212 | 79 | 35 | 21 |

### 3.5.3 Sample Adequacy and Analytical Robustness

The resulting sample size for analysis is 158, which fulfils the 10-times rule and Cohen's power criteria (analysis requirements for estimating model parameters and detecting medium to large effects, respectively). Furthermore, this sample size complies with the bootstrapping operations in SmartPLS 4.0 for the respective path, indirect, and moderator effects investigations. The model comprises reflective and formative constructs, as well as second-order dimensions. SmartPLS 4.0 is suitable for non-normally distributed data and complex models, confirming the reliability of the measurement model, convergent and discriminant validity, and the path relationships.

PLS-SEM and SmartPLS 4.0 contribute to the heuristic and statistical confirmation of sample size to ensure methodological stringency. The analytical framework supports the study's aim of establishing a sound theoretical and empirical framework for digital and sustainability-driven transformation in the AEC industry. Together, these characteristics justify the use of PLS-SEM as both theoretically appropriate and methodologically robust for this study.

## 3.6 Integration of Constructs into the Hypothesised Model

In the proposed theoretical structure (see Figure 2.2), the TBL is considered the main exogenous construct, affecting both SO and EO, which have, in turn, a positive effect on SBM. It mirrors the core assertion of the thesis that digital solutions, with an economic, social, and environmental footing can generate AEC strategic orientations and innovation outputs. Three major pathways are proposed:

(a) *Direct Relationship:* TBL directly impacts SBM. The sustainability features enabled by digital tools directly generate positive outcomes for SBM.

(b) *Mediation Role:* TBL to have indirect effects on SBM via both SO and EO. Also, SO might serve as a mediator in the association between EO and SBM, establishing a stepwise mediation process, which connects sustainability and entrepreneurship to BMI.

(c) *Moderation of DO:* The mechanism is also shown that the effect of TBL on SBM and intermediary processes is contingent on the strength of DO. It points to the conditional nature of digital maturity in promoting or hindering the transformative impact of sustainability-oriented digital technologies on innovation impact.

Collectively, these pathways highlight the strategic alignment of TBL with the DT and innovation logic that forms the basis of the AEC industry’s shift towards sustainable business models.

## 3.7. Study Design Limitations

### 3.7.1 Limitations Acknowledged

This research methodology provides valuable insights into DT but has notable limitations. The study's focus on Hong Kong and a small sample size limits the generalisability of findings to other regions or the broader AEC industry. Additionally, the non-probability sampling approach restricts statistical generalisation beyond the participating firms.

Methodologically, the cross-sectional design identifies potential relationships but cannot confirm their causal direction or temporal stability, which is significant given the complexity of the constructs. This exploratory framework aims to describe associations rather than establish definitive causal mechanisms.

Measurement limitations also arise from the single-administration survey design, requiring psychometric validation within the primary dataset (see Section 3.3.6). While expert pretesting ensured face validity, reliance on perceptual measures instead of objective performance data represents another constraint. These limitations highlight areas for caution and further research in applying the findings.

### 3.7.2 Possible Factors of Mitigation

These limitations were somewhat offset by several factors. The strong theoretical underpinning of the constructs, elaborated in Sections 3.2 and 3.3, created a solid base for the research. The content validity of the study was strengthened by the adaptation of items from existing scales, as well as by expert review. In addition, the methodology chapter provides a clear presentation of all methods used, so that the reader can make sound interpretations given the limitations identified here.

## 3.8 Concluding Remark

This chapter presented an overview of the methodology employed to examine the influence of TBL principles on SBM in the AEC sector. Grounded in a rigorous theoretical foundation, the methodology was designed to ensure construct validity, contextual relevance, and analytical robustness. A cross-sectional survey design, combined with PLS-SEM, was selected to accommodate the complexity and multidimensionality of the proposed model. The chapter covered construct development, measurement scale development, sampling strategy, data collection procedures, and analytical rationale, as well as the validation approach. Particular attention was given to the development of novel constructs (TBL and DO), which were operationalised through theory-driven item generation and expert validation. The use of both heuristic and statistical techniques to establish the minimum sample size further enhanced methodological rigor. Acknowledged limitations, such as the cross-sectional design and non-probability sampling, were mitigated through expert review, transparent reporting, and a clearly defined analytical strategy. Collectively, the methodological approach laid out in this chapter provides a sound foundation for the empirical analyses presented in the next chapter.

# ANALYSIS AND RESULTS

The objective of this Chapter is to present the analyses and results obtained from the quantitative data, providing insights into the relationships between the variables studied. Building on Methodology Chapter, this Chapter systematically presents the findings across five sections, employing quantitative techniques and data analysis using SmartPLS 4.0.

## 4.1 Preliminary Analyses

This Section presents the preliminary analyses conducted using SPSS 26 in preparation for data analysis with SmartPLS 4.0. The primary goal is to establish a foundational understanding of the dataset through various statistical techniques. It starts with frequency analysis to summarise the distribution of key variables, offering insights into the characteristics of the sample population. Next, reliability analysis is performed to evaluate the consistency of the measurement scales. Additionally, Exploratory Factor Analysis (EFA) is utilised to validate underlying relationships among the variables and assess construct validity, ensuring that the measurements accurately reflect the intended constructs. Together, these preliminary analyses lay the groundwork for more advanced modelling and analysis in the subsequent sections of this Chapter.

### 4.1.1 Frequency Analysis

In this study, a total of 902 questionnaires were distributed through various channels, resulting in 158 valid responses and a response rate of 17.52%. This response rate reflects the level of engagement among the targeted participants and serves as a basis for interpreting the subsequent analyses. A frequency analysis table is presented in Table 4.1. In terms of company nature, over 50% of respondents are from "design and planning" sectors, including architectural design, engineering, urban planning, and landscape architecture. Additionally, 33.50% represent construction and project management roles, such as general contracting, subcontracting, construction management, project management, and building inspection. Regarding company size, 53.16% of respondents reported a workforce of "21 to 100 people," while only 2.53% indicated having "more than 200 people".

Table 4.1 – Frequency Analysis

| **Items** | **Categories** | **N** | **Percent (%)** | **Cumulative Percent (%)** |
|---|---|---|---|---|
| **Company Nature** | Design and Planning (Architectural Design, Engineering, Urban Planning, Landscape Architecture) | 95 | 60.13 | 60.13 |
| | Construction and Project Management (General Contracting, Subcontracting, Construction Management, Project Management, Building Inspection) | 63 | 39.87 | 100.00 |
| **Company Size** | 1 to 20 | 42 | 26.58 | 26.58 |
| | 21 to 100 | 84 | 53.16 | 79.75 |
| | 101 to 200 | 28 | 17.72 | 97.47 |
| | Over 200 | 4 | 2.53 | 100.00 |
| **Role / Position** | CEO/COO/MD | 14 | 8.86 | 8.86 |
| | Architect | 53 | 33.54 | 42.41 |
| | BIM Manager/Engineering/Consultant | 79 | 50.00 | 92.41 |
| | Others | 12 | 7.59 | 100.00 |
| **Ability to use Digital Technologies for Sustainability Applications** | Very poor | 14 | 8.86 | 8.86 |
| | Poor | 26 | 16.46 | 25.32 |
| | Moderate | 70 | 44.30 | 69.62 |
| | Strong | 29 | 18.35 | 87.97 |
| | Exceptional | 19 | 12.03 | 100.00 |
| **Total** | | 158 | 100.00 | 100.00 |

In terms of job positions, 50.00% identified as "BIM manager / engineer / consultant," followed by 33.54% who were "architects." Fourteen respondents held CEO/COO/MD roles, accounting for 8.86% of the sample. The high proportion of BIM professionals reflects the digital maturity focus of the sample. Finally, when assessing their ability to utilise digital technology for sustainable development applications, 44.30% rated their ability as "strong," while 18.35% indicated a "medium" ability.

### 4.1.2 Reliability Analysis

Reliability refers to the stability and consistency of results measured by a scale. Higher reliability indicates smaller measurement errors. To assess the internal consistency of the survey measurement items, this study employs the Cronbach's alpha coefficient method. This involves evaluating both the total scale and its subscales. The analysis includes the "corrected item-total correlation (CITC)" and "Cronbach's alpha if item deleted" to refine the measurement items. The Cronbach's alpha value ranges from 0 to 1, with values closer to 1 indicating higher internal consistency and greater reliability. The minimum acceptable Cronbach's alpha for the total scale is 0.7, while for subscales, it is 0.6. The CITC value reflects how well an individual item correlates with the total score of other items; larger values indicate better internal consistency. During the pre-survey, items with a CITC greater than 0.4 are typically retained. The "Cronbach's alpha if item deleted" indicates the change in reliability when an item is removed. If this value exceeds the original Cronbach's alpha, it may suggest that deleting the item could enhance the overall reliability of the scale, making it essential to pay close attention to this metric during analysis.

The reliability results of the survey variables and items are presented in Table 4.2. The overall reliability of the survey reached 0.937, which is above the acceptable threshold of 0.9. Additionally, the reliability for each variable exceeds 0.8, indicating a high level of stability in the data. This suggests that the scale used in this study demonstrates excellent reliability. Furthermore, the CITC values for all indicators are higher than 0.4, and the "Cronbach's alpha if item deleted" values do not exceed the corresponding variable reliability values. As a result, all indicators can be retained for further analysis.

Table 4.2 – Reliability Statistics (Cronbach Alpha)

| Variables / Items | Items | Corrected Item-Total Correlation (CITC) | Cronbach's Alpha if Item Deleted | Cronbach α | Variables Cronbach α | Total Cronbach α |
|---|---|---|---|---|---|---|
| **TBL: TBL-aligned Digital Traits** | | | | | | |
| | TBL-Profit1 | 0.781 | 0.847 | | | |
| TBL-Profit | TBL-Profit2 | 0.796 | 0.834 | 0.890 | | |
| | TBL-Profit3 | 0.778 | 0.850 | | | |
| | TBL-People1 | 0.775 | 0.834 | | | |
| TBL-People | TBL-People2 | 0.799 | 0.810 | 0.883 | 0.903 | |
| | TBL-People3 | 0.747 | 0.858 | | | |
| | TBL-Planet1 | 0.802 | 0.900 | | | |
| TBL-Planet | TBL-Planet2 | 0.834 | 0.874 | 0.915 | | |
| | TBL-Planet3 | 0.852 | 0.860 | | | |
| **EO: Entrepreneurial Orientation** | | | | | | |
| | EO-Inno1 | 0.770 | 0.807 | | | |
| EO-Inno | EO-Inno2 | 0.750 | 0.825 | 0.873 | | |
| | EO-Inno3 | 0.746 | 0.829 | | | |
| | EO-Pro1 | 0.807 | 0.849 | | | |
| EO-Pro | EO-Pro2 | 0.774 | 0.876 | 0.898 | 0.877 | |
| | EO-Pro3 | 0.818 | 0.838 | | | |
| | EO-Risk1 | 0.738 | 0.784 | | | |
| EO-Risk | EO-Risk2 | 0.716 | 0.805 | 0.854 | | |
| | EO-Risk3 | 0.723 | 0.798 | | | |
| **SO: Sustainability Orientation** | | | | | | |
| | SO-Culture1 | 0.807 | 0.913 | | | |
| | SO-Culture2 | 0.809 | 0.913 | | | |
| SO-Culture | SO-Culture3 | 0.810 | 0.913 | 0.929 | | 0.937 |
| | SO-Culture4 | 0.811 | 0.913 | | | |
| | SO-Culture5 | 0.825 | 0.910 | | 0.928 | |
| | SO-Practices1 | 0.816 | 0.906 | | | |
| SO-Practices | SO-Practices2 | 0.836 | 0.899 | 0.925 | | |
| | SO-Practices3 | 0.821 | 0.904 | | | |
| | SO-Practices4 | 0.833 | 0.900 | | | |
| **DO: Digital Orientation** | | | | | | |
| | DO-Vision1 | 0.788 | 0.853 | | | |
| DO-Vision | DO-Vision2 | 0.805 | 0.838 | 0.894 | | |
| | DO-Vision3 | 0.784 | 0.856 | | 0.899 | |
| | DO-Strat1 | 0.815 | 0.846 | | | |
| DO-Strat | DO-Strat2 | 0.794 | 0.864 | 0.900 | | |
| | DO-Strat3 | 0.797 | 0.861 | | | |
| **SBM: Sustainable Business Model** | | | | | | |
| | SBM-ValueArch1 | 0.741 | 0.818 | | | |
| SBM-ValueArch | SBM-ValueArch2 | 0.710 | 0.831 | 0.866 | | |
| | SBM-ValueArch3 | 0.697 | 0.836 | | | |
| | SBM-ValueArch4 | 0.715 | 0.829 | | 0.875 | |
| | SBM-Valueoff1 | 0.676 | 0.779 | | | |
| SBM-Valueoff | SBM-Valueoff2 | 0.695 | 0.763 | 0.831 | | |
| | SBM-Valueoff3 | 0.703 | 0.755 | | | |
| SBM-Revenue | SBM-Revenue1 | 0.667 | - | 0.800 | | |
| | SBM-Revenue2 | 0.667 | - | | | |

### 4.1.3 Exploratory Factor Analysis

EFA is a powerful statistical technique that identifies underlying relationships among observed variables, revealing latent structures that may not be immediately apparent. By reducing dimensionality, EFA simplifies complex datasets, enhancing the clarity of data interpretation (Fabrigar *et al.*, 1999). Although EFA is often utilised in questionnaire design to identify item clusters and develop reliable scales (DeVellis and Thorpe, 2021), it is also valuable for testing construct validity in existing questionnaires.

In this study, EFA uses to analyse the structure of the constructs measurement scales and assess their validity. Construct validity refers to the extent to which theoretical concepts can be accurately measured (DeVellis and Thorpe, 2021). The analysis was based on the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) value and Bartlett's sphericity test results, which determine the suitability of the items for factor analysis. A KMO value below 0.5 indicates unsuitability, while values above 0.7 suggest that the items have sufficient commonality for factor analysis. Additionally, a significant Bartlett's test ($p < 0.05$) confirms the appropriateness of the analysis. In social science research, a cumulative explained variance of over 60% indicates reliable extracted factors, while over 50% suggests acceptable results. This paper conducts the factor analysis based on the standard of cumulative variance explanation exceeding 50%.

Table 4.3 – KMO and Bartlett's Test

| **Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO)** | | 0.841 |
|---|---|---|
| **Bartlett's Test of Sphericity** | Approx. Chi-Square | 5187.073 |
| | df | 861 |
| | Sig. | 0.000 |

All items after the reliability analysis were subjected to exploratory factor analysis, with the results presented in Table 4.3. The KMO value is 0.841, indicating that factor analysis is appropriate. Additionally, the significance probability of the Bartlett's sphericity test is 0.000, which is below the 0.01 threshold. These results demonstrate a strong correlation among the data, confirming that factor analysis can be conducted effectively. Moreover, the results show that all communalities were over 0.5.

In the EFA conducted for this study, the principal component analysis method and varimax rotation were employed, with coefficients having absolute values below 0.5 eliminated. The extraction utilised a fixed number of factors set to 13. This approach was chosen to ensure that all variables contributed meaningfully to the analysis, as each variable demonstrated loadings exceeding 0.5 on their respective components. This indicates a satisfactory level of correlation between the items and the factors, providing a solid foundation for subsequent analyses (Field, 2024).

The total variance explained reached 82.418%, exceeding the minimum threshold of 50%. This indicates that the extracted factors contain a relatively sufficient amount of information and that each item effectively explains its corresponding factor, demonstrating good validity (DeVellis and Thorpe, 2021). Notably, the rotation converged in 8 iterations, suggesting that the algorithm efficiently found a stable solution (Fabrigar *et al.*, 1999). The total variance explained and the rotated component matrix for each variable and item are presented in Tables 4.4 and 4.5, respectively.

Table 4.4 – Total Variance Explained

| Component | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | | Rotation Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|---|---|---|
| | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 12.451 | 29.644 | 29.644 | 12.451 | 29.644 | 29.644 | 4.233 | 10.079 | 10.079 |
| 2 | 4.410 | 10.501 | 40.145 | 4.410 | 10.501 | 40.145 | 3.206 | 7.634 | 17.712 |
| 3 | 3.134 | 7.461 | 47.607 | 3.134 | 7.461 | 47.607 | 2.869 | 6.832 | 24.545 |
| 4 | 2.651 | 6.311 | 53.918 | 2.651 | 6.311 | 53.918 | 2.673 | 6.365 | 30.909 |
| 5 | 2.033 | 4.841 | 58.758 | 2.033 | 4.841 | 58.758 | 2.669 | 6.354 | 37.263 |
| 6 | 1.784 | 4.247 | 63.005 | 1.784 | 4.247 | 63.005 | 2.608 | 6.209 | 43.472 |
| 7 | 1.511 | 3.597 | 66.602 | 1.511 | 3.597 | 66.602 | 2.552 | 6.076 | 49.548 |
| 8 | 1.406 | 3.348 | 69.950 | 1.406 | 3.348 | 69.950 | 2.551 | 6.074 | 55.622 |
| 9 | 1.246 | 2.967 | 72.917 | 1.246 | 2.967 | 72.917 | 2.495 | 5.940 | 61.562 |
| 10 | 1.200 | 2.857 | 75.774 | 1.200 | 2.857 | 75.774 | 2.492 | 5.933 | 67.494 |
| 11 | 0.985 | 2.345 | 78.118 | 0.985 | 2.345 | 78.118 | 2.328 | 5.542 | 73.037 |
| 12 | 0.960 | 2.286 | 80.404 | 0.960 | 2.286 | 80.404 | 2.303 | 5.484 | 78.520 |
| 13 | 0.846 | 2.014 | 82.418 | 0.846 | 2.014 | 82.418 | 1.637 | 3.898 | 82.418 |
| 14 | 0.599 | 1.426 | 83.844 | | | | | | |
| 15 | 0.549 | 1.308 | 85.152 | | | | | | |
| 16 | 0.508 | 1.209 | 86.361 | | | | | | |
| 17 | 0.481 | 1.144 | 87.505 | | | | | | |
| 18 | 0.402 | 0.956 | 88.462 | | | | | | |
| 19 | 0.398 | 0.949 | 89.410 | | | | | | |
| 20 | 0.356 | 0.847 | 90.257 | | | | | | |
| 21 | 0.340 | 0.811 | 91.068 | | | | | | |
| 22 | 0.325 | 0.775 | 91.842 | | | | | | |
| 23 | 0.303 | 0.720 | 92.563 | | | | | | |
| 24 | 0.293 | 0.699 | 93.261 | | | | | | |
| 25 | 0.273 | 0.650 | 93.911 | | | | | | |
| 26 | 0.242 | 0.575 | 94.486 | | | | | | |
| 27 | 0.232 | 0.552 | 95.039 | | | | | | |
| 28 | 0.218 | 0.519 | 95.558 | | | | | | |
| 29 | 0.201 | 0.478 | 96.036 | | | | | | |
| 30 | 0.191 | 0.455 | 96.491 | | | | | | |
| 31 | 0.187 | 0.446 | 96.937 | | | | | | |
| 32 | 0.171 | 0.408 | 97.345 | | | | | | |
| 33 | 0.161 | 0.384 | 97.729 | | | | | | |
| 34 | 0.155 | 0.370 | 98.099 | | | | | | |
| 35 | 0.136 | 0.323 | 98.422 | | | | | | |
| 36 | 0.130 | 0.309 | 98.731 | | | | | | |
| 37 | 0.121 | 0.289 | 99.020 | | | | | | |
| 38 | 0.105 | 0.249 | 99.269 | | | | | | |
| 39 | 0.095 | 0.226 | 99.495 | | | | | | |
| 40 | 0.080 | 0.190 | 99.685 | | | | | | |
| 41 | 0.072 | 0.172 | 99.857 | | | | | | |
| 42 | 0.060 | 0.143 | 100.000 | | | | | | |

Table 4.5 – Rotated Component Matrix

| | Component | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **11** | **12** | **13** |
| SBM-Valueoff1 | | | | | | | | | | | 0.822 | | |
| SBM-Valueoff2 | | | | | | | | | | | 0.774 | | |
| SBM-Valueoff3 | | | | | | | | | | | 0.750 | | |
| SBM-ValueArch1 | | | 0.753 | | | | | | | | | | |
| SBM-ValueArch2 | | | 0.734 | | | | | | | | | | |
| SBM-ValueArch3 | | | 0.709 | | | | | | | | | | |
| SBM-ValueArch4 | | | 0.722 | | | | | | | | | | |
| SBM-Revenue1 | | | | | | | | | | | | | 0.749 |
| SBM-Revenue2 | | | | | | | | | | | | | 0.803 |
| TBL-Profit1 | | | | | | | | 0.829 | | | | | |
| TBL-Profit2 | | | | | | | | 0.801 | | | | | |
| TBL-Profit3 | | | | | | | | 0.814 | | | | | |
| TBL-People1 | | | | | | | 0.841 | | | | | | |
| TBL-People2 | | | | | | | 0.811 | | | | | | |
| TBL-People3 | | | | | | | 0.761 | | | | | | |
| TBL-Planet1 | | | | | | | | | | 0.776 | | | |
| TBL-Planet2 | | | | | | | | | | 0.796 | | | |
| TBL-Planet3 | | | | | | | | | | 0.844 | | | |
| EO-Inno1 | | | | | | | | | | | | 0.704 | |
| EO-Inno2 | | | | | | | | | | | | 0.860 | |
| EO-Inno3 | | | | | | | | | | | | 0.759 | |
| EO-Pro1 | | | | | 0.864 | | | | | | | | |
| EO-Pro2 | | | | | 0.876 | | | | | | | | |
| EO-Pro3 | | | | | 0.856 | | | | | | | | |
| EO-Risk1 | | | | | | 0.833 | | | | | | | |
| EO-Risk2 | | | | | | 0.815 | | | | | | | |
| EO-Risk3 | | | | | | 0.817 | | | | | | | |
| SO-Culture1 | 0.809 | | | | | | | | | | | | |
| SO-Culture2 | 0.840 | | | | | | | | | | | | |
| SO-Culture3 | 0.816 | | | | | | | | | | | | |
| SO-Culture4 | 0.845 | | | | | | | | | | | | |
| SO-Culture5 | 0.779 | | | | | | | | | | | | |
| SO-Practices1 | | 0.801 | | | | | | | | | | | |
| SO-Practices2 | | 0.808 | | | | | | | | | | | |
| SO-Practices3 | | 0.825 | | | | | | | | | | | |
| SO-Practices4 | | 0.768 | | | | | | | | | | | |
| DO-Vision1 | | | | 0.856 | | | | | | | | | |
| DO-Vision2 | | | | 0.867 | | | | | | | | | |
| DO-Vision3 | | | | 0.836 | | | | | | | | | |
| DO-Strat1 | | | | | | | | | 0.859 | | | | |
| DO-Strat2 | | | | | | | | | 0.784 | | | | |
| DO-Strat3 | | | | | | | | | 0.862 | | | | |

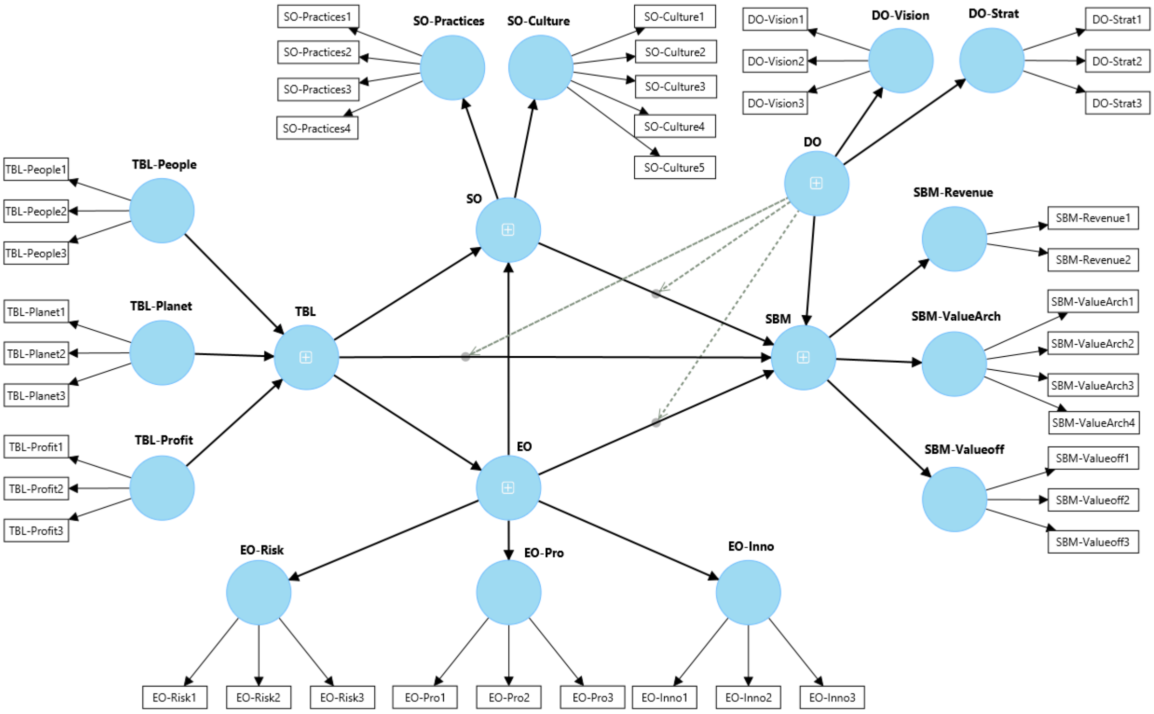
## 4.2 Measurement Model Assessment

Following the preliminary analysis, the focus shifts to the utilising SmartPLS 4.0 for model assessment. The PLS-SEM results evaluation includes two stages – first stage examines measurement model, and second stage examines the structural model (Sarstedt *et al.*, 2014). This measurement model assessment stage is critical for evaluating the relationships among constructs and ensuring that the model accurately reflects the theoretical framework. In this study, all constructs are categorised as higher-order constructs, with one being a reflective-formative construct and the others classified as reflective-reflective constructs.

The reflective-formative construct will be analysed to assess how its dimensions contribute to the overall construct, while the reflective-reflective constructs will be examined for their reliability and validity. This analysis will provide insights into the measurement properties of the constructs and establish a solid foundation for subsequent structural model testing. Utilising SmartPLS 4.0 allows for effective assessment of both measurement and structural relationships, enhancing the robustness of the findings.

The first step involves developing higher-order constructs in the model, which specify the relationships between reflective and formative indicators for the reflective-formative construct, as well as the reflective-reflective constructs, using SmartPLS 4.0. Indicators are assigned to each construct, ensuring that reflective constructs have suitable reflective indicators and that the formative construct includes its corresponding dimensions. A two-layer higher-order model is illustrated in Figure 4.1.

Figure 4.1 – Two Layers Higher-order Model




### 4.2.1 Reliability and Validity

The initial path model estimation assessed the relationships among constructs and identified any errors or warnings in the model setup. Reliability analysis was conducted on reflective constructs, examining Cronbach's alpha and composite reliability (CR), with all values exceeding 0.7, as confirmed in the preliminary analysis.

Validity analysis focused on convergent validity by evaluating the average variance extracted (AVE), which should be greater than 0.5. Convergent validity indicates the degree of aggregation of latent variables corresponding to each observed variable and is measured through factor loading, CR, and AVE. Factor loadings should ideally exceed 0.7, though values between 0.60 and 0.70 are considered acceptable in exploratory research, while those between 0.70 and 0.95 are viewed as satisfactory to good (Hair *et al.*, 2022). CR should also exceed 0.70, and AVE should be above 0.50.

Using SmartPLS 4.0, the analysis showed that the factor loading for all items was greater than 0.6, indicating strong explanatory power. CR for all dimensions ranged from 0.76 to 0.89, demonstrating internal consistency among items within each dimension. The minimum AVE value was 0.51, confirming convergent validity for all constructs (Hair *et al.*, 2022).

In conclusion, the measurement model exhibits both reliability and validity, establishing a solid foundation for further analysis. The results are summarised in Table 4.6.

Table 4.6 – Convergent Validity

| | **Cronbach's alpha** | **Composite reliability (rho_a)** | **Composite reliability (rho_c)** | **Average variance extracted (AVE)** |
|---|---|---|---|---|
| **DO** | 0.899 | 0.900 | 0.923 | 0.665 |
| **DO-Strat** | 0.900 | 0.901 | 0.937 | 0.833 |
| **DO-Vision** | 0.894 | 0.894 | 0.934 | 0.826 |
| **EO** | 0.876 | 0.880 | 0.901 | 0.504 |
| **EO-Inno** | 0.873 | 0.878 | 0.922 | 0.797 |
| **EO-Pro** | 0.899 | 0.904 | 0.937 | 0.831 |
| **EO-Risk** | 0.854 | 0.854 | 0.911 | 0.774 |
| **SBM** | 0.876 | 0.878 | 0.901 | 0.503 |
| **SBM-Revenue** | 0.800 | 0.800 | 0.909 | 0.834 |
| **SBM-ValueArch** | 0.866 | 0.866 | 0.909 | 0.713 |
| **SBM-Valueoff** | 0.832 | 0.836 | 0.899 | 0.748 |
| **SO** | 0.929 | 0.930 | 0.940 | 0.637 |
| **SO-Culture** | 0.929 | 0.930 | 0.946 | 0.779 |
| **SO-Practices** | 0.925 | 0.926 | 0.947 | 0.817 |
| **TBL** | 0.904 | 0.905 | 0.921 | 0.566 |
| **TBL-People** | 0.884 | 0.884 | 0.928 | 0.811 |
| **TBL-Planet** | 0.916 | 0.916 | 0.947 | 0.856 |
| **TBL-Profit** | 0.890 | 0.892 | 0.932 | 0.820 |

### 4.2.2 Discriminant Validity

Discriminant validity is the degree to which a latent variable is distinguished from other latent variables. This study uses the methods to detect discriminant validity including Heterotrait-Monotrait Ratio (HTMT) (Henseler *et al.*, 2015), Fornell-Larcker Criterion (Fornell and Larcker, 1981), and cross loadings and. At this stage, the analysis only conducts the first order reflective model.

#### *4.2.2.1 Heterotrait-Monotrait Ratio*

The HTMT is a metric used to evaluate discriminant validity in structural equation modelling, particularly in PLS-SEM. It compares average correlations between indicators of different constructs to those of the same construct. An HTMT value close to 1 may indicate insufficient discriminant validity. Common thresholds for HTMT are 0.85; values exceeding these suggest potential issues. Table 4.7 presents the HTMT matrix for this study, with the highest recorded value at 0.686, indicating that all constructs are sufficiently distinct. This outcome suggests adequate discriminant validity among the constructs investigated, reinforcing the validity of the measurement model and instilling confidence in the distinctiveness of the constructs used in this study.

Table 4.7 – Heterotrait-Monotrait Ratio Matrix

| | DO-Strat | DO-Vision | EO-Inno | EO-Pro | EO-Risk | SBM-Revenue | SBM-ValueArch | SBM-Valueoff | SO-Culture | SO-Practices | TBL-People | TBL-Planet | TBL-Profit |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **DO-Strat** | | | | | | | | | | | | | |
| **DO-Vision** | 0.673 | | | | | | | | | | | | |
| **EO-Inno** | 0.169 | 0.075 | | | | | | | | | | | |
| **EO-Pro** | 0.193 | 0.108 | 0.532 | | | | | | | | | | |
| **EO-Risk** | 0.086 | 0.058 | 0.590 | 0.391 | | | | | | | | | |
| **SBM-Revenue** | 0.191 | 0.213 | 0.374 | 0.168 | 0.317 | | | | | | | | |
| **SBM-ValueArch** | 0.358 | 0.349 | 0.438 | 0.313 | 0.400 | 0.687 | | | | | | | |
| **SBM-Valueoff** | 0.225 | 0.200 | 0.416 | 0.26 | 0.186 | 0.539 | 0.529 | | | | | | |
| **SO-Culture** | 0.113 | 0.078 | 0.364 | 0.251 | 0.272 | 0.426 | 0.478 | 0.440 | | | | | |
| **SO-Practices** | 0.072 | 0.092 | 0.354 | 0.281 | 0.261 | 0.406 | 0.381 | 0.509 | 0.643 | | | | |
| **TBL-People** | 0.249 | 0.118 | 0.304 | 0.247 | 0.333 | 0.392 | 0.499 | 0.309 | 0.384 | 0.419 | | | |
| **TBL-Planet** | 0.247 | 0.180 | 0.360 | 0.285 | 0.416 | 0.390 | 0.553 | 0.363 | 0.361 | 0.368 | 0.653 | | |
| **TBL-Profit** | 0.213 | 0.113 | 0.388 | 0.285 | 0.329 | 0.428 | 0.470 | 0.303 | 0.411 | 0.483 | 0.528 | 0.562 | |

#### *4.2.2.2 Fornell-Larcker Criterion*

The Fornell-Larcker criterion was applied to assess discriminant validity among the constructs in this study. According to this criterion, the square root of the AVE for each construct must be greater than the correlations between that construct and any other construct. The results presented in Table 4.8 indicate that the square root of the AVE for each construct exceeds the correlations with other constructs, confirming adequate discriminant validity. This outcome supports the validity of the measurement model and ensures that the constructs utilised in this study are sufficiently distinct.

Table 4.8 – Fornell-Larcker Criterion

| | DO-Strat | DO-Vision | EO-Inno | EO-Pro | EO-Risk | SBM-Revenue | SBM-ValueArch | SBM-Valueoff | SO-Culture | SO-Practices | TBL-People | TBL-Planet | TBL-Profit |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **DO-Strat** | 0.913 | | | | | | | | | | | | |
| **DO-Vision** | 0.605 | 0.909 | | | | | | | | | | | |
| **EO-Inno** | 0.149 | 0.05 | 0.893 | | | | | | | | | | |
| **EO-Pro** | 0.173 | 0.096 | 0.476 | 0.912 | | | | | | | | | |
| **EO-Risk** | 0.072 | 0.043 | 0.515 | 0.345 | 0.88 | | | | | | | | |
| **SBM-Revenue** | 0.163 | 0.179 | 0.312 | 0.143 | 0.262 | 0.913 | | | | | | | |
| **SBM-ValueArch** | 0.316 | 0.307 | 0.38 | 0.277 | 0.344 | 0.572 | 0.845 | | | | | | |
| **SBM-Valueoff** | 0.199 | 0.177 | 0.354 | 0.229 | 0.156 | 0.443 | 0.451 | 0.865 | | | | | |
| **SO-Culture** | 0.101 | 0.034 | 0.331 | 0.232 | 0.244 | 0.367 | 0.429 | 0.389 | 0.882 | | | | |
| **SO-Practices** | 0.014 | -0.053 | 0.321 | 0.259 | 0.234 | 0.351 | 0.343 | 0.447 | 0.598 | 0.904 | | | |
| **TBL-People** | 0.221 | 0.102 | 0.266 | 0.221 | 0.29 | 0.33 | 0.437 | 0.269 | 0.35 | 0.38 | 0.901 | | |
| **TBL-Planet** | 0.225 | 0.164 | 0.323 | 0.261 | 0.369 | 0.334 | 0.492 | 0.316 | 0.332 | 0.339 | 0.588 | 0.925 | |
| **TBL-Profit** | 0.192 | 0.101 | 0.345 | 0.258 | 0.287 | 0.361 | 0.413 | 0.26 | 0.374 | 0.439 | 0.469 | 0.509 | 0.906 |

#### *4.2.2.3 Cross Loadings Analysis*

Cross loadings evaluate the contribution of each item to its corresponding latent variable, requiring that the loading of each item on its latent variable exceeds its loadings on all other dimensions. The Fornell-Larcker criterion employs the square root of the AVE for this assessment. According to the standards set by Fornell and Larcker, the correlation coefficient between each construct should be less than the square root of the AVE, as illustrated in the Table 4.9. The bolded values represent the loadings of each item on its latent variable, confirming that each dimension's items load more strongly on their respective latent variables than on any others, thereby satisfying the cross-loading requirements.

Table 4.9 – Cross Loadings

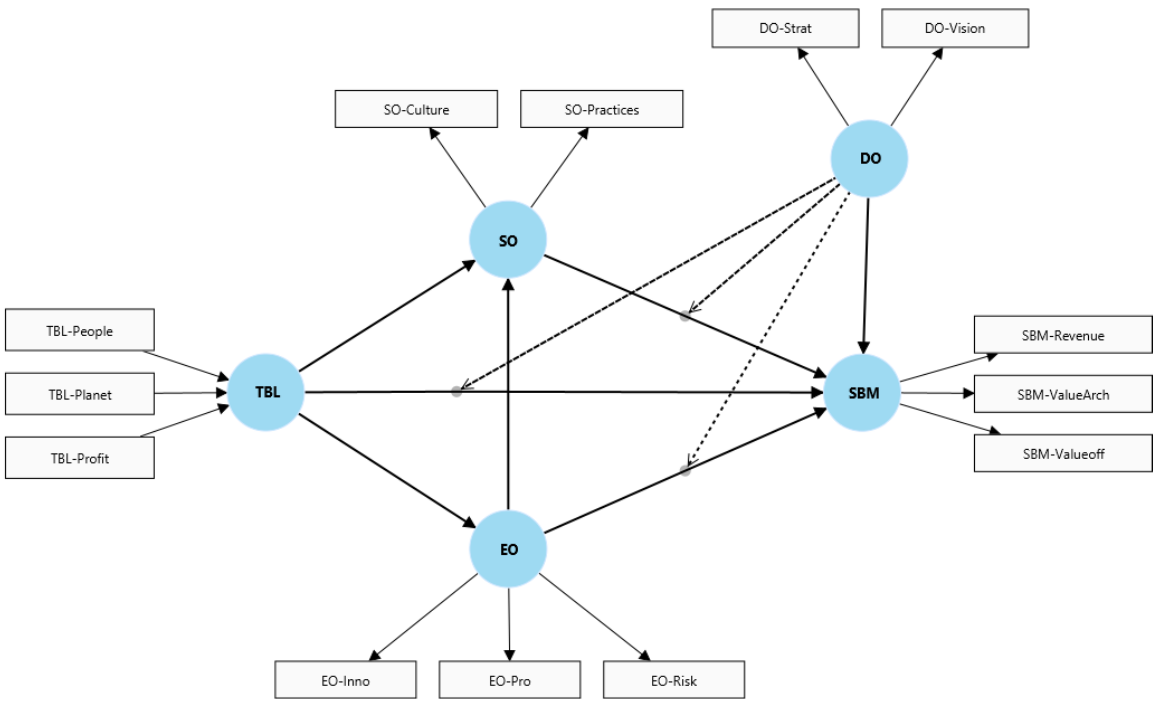
| | DO-Strat | DO-Vision | EO-Inno | EO-Pro | EO-Risk | SBM-Revenue | SBM-ValueArch | SBM-Valueoff | SO-Culture | SO-Practices | TBL-People | TBL-Planet | TBL-Profit |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **DO-Strat1** | **0.918** | 0.529 | 0.108 | 0.137 | 0.017 | 0.102 | 0.262 | 0.147 | 0.147 | 0.049 | 0.229 | 0.213 | 0.201 |
| **DO-Strat2** | **0.913** | 0.614 | 0.214 | 0.218 | 0.095 | 0.178 | 0.297 | 0.229 | 0.065 | -0.002 | 0.143 | 0.218 | 0.208 |
| **DO-Strat3** | **0.907** | 0.509 | 0.081 | 0.115 | 0.084 | 0.164 | 0.306 | 0.167 | 0.066 | -0.009 | 0.238 | 0.184 | 0.115 |
| **DO-Vision1** | 0.56 | **0.907** | 0.016 | 0.1 | 0.003 | 0.054 | 0.246 | 0.118 | -0.019 | -0.106 | 0.069 | 0.145 | 0.087 |
| **DO-Vision2** | 0.543 | **0.915** | 0.088 | 0.092 | 0.032 | 0.17 | 0.262 | 0.18 | 0.034 | -0.069 | 0.025 | 0.097 | 0.072 |
| **DO-Vision3** | 0.546 | **0.904** | 0.032 | 0.069 | 0.084 | 0.266 | 0.331 | 0.184 | 0.076 | 0.032 | 0.185 | 0.204 | 0.117 |
| **EO-Inno1** | 0.08 | -0.003 | **0.908** | 0.44 | 0.566 | 0.265 | 0.356 | 0.278 | 0.338 | 0.328 | 0.183 | 0.259 | 0.309 |
| **EO-Inno2** | 0.175 | 0.099 | **0.88** | 0.369 | 0.356 | 0.284 | 0.338 | 0.331 | 0.241 | 0.237 | 0.265 | 0.251 | 0.241 |
| **EO-Inno3** | 0.151 | 0.046 | **0.89** | 0.459 | 0.442 | 0.287 | 0.325 | 0.344 | 0.301 | 0.289 | 0.27 | 0.353 | 0.366 |
| **EO-Pro1** | 0.117 | 0.032 | 0.429 | **0.919** | 0.359 | 0.095 | 0.245 | 0.188 | 0.223 | 0.274 | 0.179 | 0.221 | 0.26 |
| **EO-Pro2** | 0.202 | 0.114 | 0.374 | **0.89** | 0.251 | 0.128 | 0.212 | 0.184 | 0.163 | 0.162 | 0.199 | 0.196 | 0.152 |
| **EO-Pro3** | 0.16 | 0.119 | 0.49 | **0.926** | 0.327 | 0.167 | 0.296 | 0.252 | 0.242 | 0.265 | 0.226 | 0.291 | 0.285 |
| **EO-Risk1** | 0.03 | 0.017 | 0.418 | 0.342 | **0.886** | 0.169 | 0.324 | 0.173 | 0.225 | 0.184 | 0.292 | 0.383 | 0.226 |
| **EO-Risk2** | 0.076 | 0.055 | 0.461 | 0.269 | **0.872** | 0.231 | 0.262 | 0.09 | 0.187 | 0.172 | 0.206 | 0.273 | 0.252 |
| **EO-Risk3** | 0.084 | 0.042 | 0.481 | 0.299 | **0.881** | 0.291 | 0.321 | 0.149 | 0.231 | 0.26 | 0.267 | 0.316 | 0.279 |
| **SBM-Revenue1** | 0.154 | 0.161 | 0.287 | 0.107 | 0.242 | **0.912** | 0.547 | 0.354 | 0.386 | 0.323 | 0.352 | 0.322 | 0.314 |
| **SBM-Revenue2** | 0.143 | 0.167 | 0.282 | 0.153 | 0.237 | **0.914** | 0.498 | 0.454 | 0.285 | 0.318 | 0.251 | 0.287 | 0.346 |
| **SBM-ValueArch1** | 0.293 | 0.283 | 0.363 | 0.358 | 0.295 | 0.445 | **0.858** | 0.364 | 0.381 | 0.271 | 0.309 | 0.405 | 0.343 |
| **SBM-ValueArch2** | 0.295 | 0.272 | 0.268 | 0.164 | 0.196 | 0.464 | **0.842** | 0.414 | 0.394 | 0.323 | 0.36 | 0.448 | 0.356 |
| **SBM-ValueArch3** | 0.239 | 0.214 | 0.401 | 0.229 | 0.329 | 0.514 | **0.832** | 0.358 | 0.388 | 0.312 | 0.353 | 0.347 | 0.338 |
| **SBM-ValueArch4** | 0.241 | 0.269 | 0.255 | 0.189 | 0.343 | 0.508 | **0.846** | 0.388 | 0.29 | 0.254 | 0.451 | 0.461 | 0.359 |
| **SBM-Valueoff1** | 0.106 | 0.055 | 0.275 | 0.123 | 0.166 | 0.312 | 0.343 | **0.845** | 0.304 | 0.398 | 0.161 | 0.295 | 0.234 |
| **SBM-Valueoff2** | 0.227 | 0.21 | 0.314 | 0.232 | 0.169 | 0.39 | 0.436 | **0.874** | 0.337 | 0.368 | 0.298 | 0.305 | 0.197 |
| **SBM-Valueoff3** | 0.177 | 0.182 | 0.327 | 0.232 | 0.074 | 0.441 | 0.387 | **0.876** | 0.366 | 0.396 | 0.23 | 0.222 | 0.247 |
| **SO-Culture1** | 0.105 | 0.127 | 0.283 | 0.178 | 0.179 | 0.36 | 0.43 | 0.378 | **0.878** | 0.521 | 0.28 | 0.338 | 0.367 |
| **SO-Culture2** | 0.025 | -0.022 | 0.254 | 0.261 | 0.209 | 0.283 | 0.355 | 0.267 | **0.878** | 0.497 | 0.324 | 0.266 | 0.332 |
| **SO-Culture3** | 0.085 | 0.063 | 0.296 | 0.183 | 0.195 | 0.341 | 0.374 | 0.351 | **0.881** | 0.516 | 0.297 | 0.283 | 0.323 |
| **SO-Culture4** | 0.113 | 0.018 | 0.296 | 0.181 | 0.22 | 0.291 | 0.312 | 0.329 | **0.88** | 0.498 | 0.307 | 0.298 | 0.283 |
| **SO-Culture5** | 0.116 | -0.033 | 0.331 | 0.22 | 0.268 | 0.342 | 0.421 | 0.388 | **0.894** | 0.603 | 0.334 | 0.282 | 0.346 |
| **SO-Practices1** | -0.095 | -0.112 | 0.277 | 0.279 | 0.177 | 0.21 | 0.242 | 0.329 | 0.53 | **0.897** | 0.369 | 0.299 | 0.368 |
| **SO-Practices2** | 0.029 | -0.01 | 0.286 | 0.239 | 0.193 | 0.371 | 0.315 | 0.438 | 0.527 | **0.909** | 0.308 | 0.31 | 0.434 |
| **SO-Practices3** | 0.024 | -0.066 | 0.307 | 0.203 | 0.201 | 0.262 | 0.25 | 0.389 | 0.516 | **0.899** | 0.297 | 0.286 | 0.343 |
| **SO-Practices4** | 0.088 | -0.006 | 0.291 | 0.217 | 0.273 | 0.421 | 0.427 | 0.456 | 0.588 | **0.91** | 0.397 | 0.329 | 0.438 |
| **TBL-People1** | 0.188 | 0.151 | 0.159 | 0.167 | 0.241 | 0.255 | 0.395 | 0.229 | 0.238 | 0.307 | **0.899** | 0.519 | 0.391 |
| **TBL-People2** | 0.211 | 0.076 | 0.265 | 0.204 | 0.261 | 0.328 | 0.392 | 0.317 | 0.318 | 0.342 | **0.914** | 0.528 | 0.425 |
| **TBL-People3** | 0.198 | 0.051 | 0.29 | 0.225 | 0.28 | 0.308 | 0.393 | 0.18 | 0.385 | 0.377 | **0.89** | 0.541 | 0.451 |
| **TBL-Planet1** | 0.12 | 0.088 | 0.365 | 0.271 | 0.307 | 0.288 | 0.492 | 0.325 | 0.334 | 0.37 | 0.539 | **0.911** | 0.462 |
| **TBL-Planet2** | 0.252 | 0.19 | 0.295 | 0.275 | 0.35 | 0.31 | 0.446 | 0.285 | 0.284 | 0.312 | 0.562 | **0.93** | 0.505 |
| **TBL-Planet3** | 0.251 | 0.175 | 0.235 | 0.177 | 0.365 | 0.327 | 0.429 | 0.267 | 0.305 | 0.259 | 0.53 | **0.935** | 0.442 |
| **TBL-Profit1** | 0.166 | 0.053 | 0.285 | 0.282 | 0.241 | 0.341 | 0.361 | 0.233 | 0.351 | 0.391 | 0.425 | 0.428 | **0.902** |
| **TBL-Profit2** | 0.203 | 0.095 | 0.312 | 0.216 | 0.251 | 0.327 | 0.39 | 0.245 | 0.36 | 0.399 | 0.447 | 0.499 | **0.915** |
| **TBL-Profit3** | 0.151 | 0.126 | 0.34 | 0.206 | 0.289 | 0.314 | 0.371 | 0.229 | 0.305 | 0.403 | 0.403 | 0.453 | **0.9** |

The analysis of the HTMT and the Fornell-Larcker criterion confirms the discriminant validity of the constructs in this study. Furthermore, the cross-loading analysis indicates that each item loads more strongly on its corresponding latent variable than on others. These findings collectively affirm the reliability and distinctiveness of the constructs employed in this study.

### 4.2.3 Assessment of Higher-order Model

To assess the higher-order model, a new higher-order measurement model must be constructed. The first step is to generate latent variable scores by running the PLS-SEM algorithm on the initial model using SmartPLS 4.0 (see Figure 4.1). This process yields estimated values for the constructs based on the observed data. Once the latent variable scores are obtained, the next step is to export this data file, which includes scores for each of the first-order constructs. These scores will then be used as indicators for the new higher-order model. In SmartPLS, create a new project and add a higher-order construct, incorporating the latent variable scores as items, as shown in Figure 4.2.

Figure 4.2 – Higher-order Model



*4.2.3.1 Correlation Analysis*

Correlation analysis was performed to investigate the relationships between TBL and SBM, EO, SO, and DO. The Pearson correlation coefficient was used to assess the strength of these correlations. The results indicate that all relationships between SBM and TBL, EO, SO, and DO are statistically significant. The correlation coefficients are as follows: 0.545 for SBM and TBL, 0.437 for SBM and EO, 0.536 for SBM and SO, and 0.322 for SBM and DO. Each of these values is greater than 0, signifying a positive correlation between SBM and TBL, EO, SO, and DO. The results of the analysis are presented in Table 4.10.

Table 4.10 – Pearson Correlation Analysis

| | **Mean** | **St. Deviation** | **SBM** | **TBL** | **EO** | **SO** | **DO** |
|---|---|---|---|---|---|---|---|
| **SBM** | 4.274 | 1.141 | 1 | | | | |
| **TBL** | 5.163 | 1.137 | 0.545** | 1 | | | |
| **EO** | 4.473 | 1.216 | 0.437** | 0.444** | 1 | | |
| **SO** | 5.232 | 1.144 | 0.536** | 0.499** | 0.379** | 1 | |
| **DO** | 4.621 | 1.434 | 0.322** | 0.225** | 0.138 | 0.035 | 1 |

* $p$<0.05 ** $p$<0.01

*4.2.3.2 HOC Reflective Model Reliability and Validity*

By running the PLS-SEM algorithm with a factor weighting scheme for the reflective variables, all outer loadings, Cronbach's alpha, CR, and AVE exceeded their respective thresholds. Specifically, the outer loadings should be greater than 0.70, Cronbach's alpha should be above 0.70, CR should also exceed 0.70, and AVE should be greater than 0.50. These results indicate that the model demonstrates strong reliability and validity. The results are shown in Table 4.11.

Table 4.11 – Reliability and Validity of HOC

| Variables | Factor | Outer Loadings | Cronbach's alpha | Composite reliability (rho_a) | Composite reliability (rho_c) | Average variance extracted (AVE) |
|---|---|---|---|---|---|---|
| **DO** | DO-Strat | 0.898 | 0.754 | 0.754 | 0.890 | 0.803 |
| | DO-Vision | 0.893 | | | | |
| **EO** | EO-Inno | 0.868 | 0.707 | 0.731 | 0.836 | 0.631 |
| | EO-Pro | 0.727 | | | | |
| | EO-Risk | 0.781 | | | | |
| **SBM** | SBM-Revenue | 0.813 | 0.741 | 0.760 | 0.852 | 0.659 |
| | SBM-ValueArch | 0.862 | | | | |
| | SBM-Valueoff | 0.756 | | | | |
| **SO** | SO-Culture | 0.892 | 0.749 | 0.749 | 0.888 | 0.799 |
| | SO-Practices | 0.896 | | | | |

*4.2.3.3 HOC Reflective Model Discriminant Validity*

The HTMT and the Fornell-Larcker criterion are used to assess the discriminant validity of the HOC measurement model. The HTMT matrix in Table 4.12 shows all values are below 0.85, with the highest at 0.731, confirming the distinctiveness of the constructs. Additionally, the Fornell-Larcker criterion results in Table 4.13 indicate that the square root of the AVE for each construct exceeds the correlations with other constructs, further confirming adequate discriminant validity. These findings collectively support the validity of the HOC measurement model and ensure sufficient distinctiveness among the constructs.

Table 4.12 – HOC Heterotrait-Monotrait Ratio Matrix

| | DO | EO | SBM | SO | DO x TBL | DO x SO | DO x EO |
|---|---|---|---|---|---|---|---|
| **DO** | | | | | | | |
| **EO** | 0.187 | | | | | | |
| **SBM** | 0.411 | 0.586 | | | | | |
| **SO** | 0.084 | 0.523 | 0.717 | | | | |
| **DO x TBL** | 0.240 | 0.202 | 0.149 | 0.115 | | | |
| **DO x SO** | 0.221 | 0.177 | 0.027 | 0.043 | 0.696 | | |
| **DO x EO** | 0.172 | 0.211 | 0.153 | 0.166 | 0.731 | 0.583 | |

Table 4.13 – HOC Fornell-Larcker Criterion

| | DO | EO | SBM | SO |
|---|---|---|---|---|
| **DO** | 0.896 | | | |
| **EO** | 0.134 | 0.794 | | |
| **SBM** | 0.317 | 0.438 | 0.812 | |
| **SO** | 0.030 | 0.385 | 0.532 | 0.894 |

*4.2.3.4 Higher-order Formative Construct Assessment*

The assessment of formative constructs involves evaluating outer weights, VIF, and p-values to ensure the reliability and validity of the indicators used in the model. The assessment metrics for the TBL formative construct are listed in Table 4.14.

Table 4.14 – Assessment Metrics for the TBL Formative Construct

| Items | Outer Weight | VIF | p-value |
|---|---|---|---|
| **TBL-People** | 0.316 | 1.626 | 0.014 |
| **TBL-Planet** | 0.404 | 1.710 | 0.002 |
| **TBL-Profit** | 0.490 | 1.435 | 0.000 |

The outer weights of the formative items serve as indicators of their contribution to the higher-order construct. The outer weights for TBL-People, TBL-Planet, and TBL-Profit are 0.316, 0.404, and 0.490, respectively. According to Jarvis *et al.* (2003), outer weights in formative models should be interpreted as the influence each indicator has on the construct. Weights above 0.20 are typically deemed significant (Chin, 1998). TBL-Profit, with the highest weight of 0.490, is the most influential indicator, reinforcing its critical role in the construct's formation. TBL-Planet and TBL-People also contribute significantly but to a lesser extent.

The VIF values for the indicators—1.626 for TBL-People, 1.71 for TBL-Planet, and 1.435 for TBL-Profit—indicate low multicollinearity among the items. As a rule of thumb, VIF values below 5 are acceptable, with values below 3 considered excellent (Hair *et al.*, 2022). The observed VIF values confirm that the indicators are sufficiently independent, allowing for accurate assessments of their respective contributions to the HOC. Low multicollinearity is essential for formative constructs as it ensures that the indicators measure distinct aspects of the construct without overlap (Bagozzi and Heatherton, 1994).

The statistical significance of the indicators is confirmed through their p-values, which are 0.014 for TBL-People, 0.002 for TBL-Planet, and 0.000 for TBL-Profit. All p-values are below the critical threshold of 0.05, indicating that each indicator significantly contributes to the higher-order construct. According to Hair *et al.* (2023), statistically significant p-values validate the relevance of the indicators in capturing the essence of the construct. TBL-Profit, with a p-value of 0.000, demonstrates an exceptionally strong significance, suggesting it is crucial for the construct's formation.

The assessment of outer weights, VIF, and p-values collectively supports the validity and reliability of the formative constructs in this study. The positive outer weights indicate significant contributions, while acceptable VIF values confirm low multicollinearity among the indicators. Furthermore, statistically significant p-values reinforce the relevance of the indicators in defining the HOC. These findings align with established literature, affirming that the indicators effectively encapsulate the intended dimensions of TBL-aligned Digital Traits. The rigorous assessment of these metrics enhances the overall robustness of the formative model, contributing to the reliability of the research outcomes.

## 4.3 Structural Model Evaluation

Having successfully completed the measurement model assessment with favourable results; this Section focuses on the structural model assessment of the HOC model. The structural model is essential as it delineates the relationships between constructs and clarifies the theoretical framework guiding the research. Evaluating the structural model aims to confirm the hypothesised paths and their significance, providing insights into how the constructs interact.

This assessment will involve analysing the VIF values to check for multicollinearity among the constructs, ensuring the reliability of the path coefficient estimates. Additionally, $R^2$ values will be examined to evaluate the model's explanatory power, and $Q^2$ values will be calculated to assess predictive relevance, indicating how well the constructs can forecast outcomes. Path coefficients will also be analysed to determine the strength and direction of the relationships among the constructs. Furthermore, potential mediating and moderating effects will be explored to gain a deeper understanding of the dynamics within the model. Ultimately, the structural model assessment will validate the proposed relationships and enhance understanding of their implications in the context of sustainable BMI and DT.

### 4.3.1 Collinearity

Collinearity is assessed using the VIF values. The outer VIF values for the indicators range from 1.316 to 1.710, while the inner VIF matrix for the constructs is presented in Table 4.15. The results indicate that the tolerance values are well below the VIF threshold of 3.00 for the predictor constructs, which is considered excellent (Hair *et al.*, 2022), and there is no indication of strong common method bias (CMB).

Table 4.15 – Inner Model VIF Matrix

| | **DO** | **EO** | **SBM** | **SO** | **TBL** |
|---|---|---|---|---|---|
| **DO** | | | 1.109 | | |
| **EO** | | | 1.334 | 1.253 | |
| **SBM** | | | | | |
| **SO** | | | 1.431 | | |
| **TBL** | | 1.000 | 1.571 | 1.253 | |
| **DO x TBL** | | | 2.847 | | |
| **DO x SO** | | | 2.015 | | |
| **DO x EO** | | | 2.236 | | |

### 4.3.2 Predictive Relevance, Effect Size and Model Fit

This Section will determine the $R^2$ (coefficient of determination), which measures the proportion of variance in the dependent variable explained by the independent variables, indicating the model's explanatory power. Furthermore, $Q^2$ (predictive relevance) assesses how well the model can predict outcomes, with values greater than zero suggesting that the model has predictive capability (Geisser, 1975; Stone, 1974). Additionally, $f^2$ (effect size) will be examined to evaluate the strength of the relationships between constructs, providing insights into the importance of each predictor in the model (Cohen, 2013). Together, these metrics offer a comprehensive understanding of the model's performance and its ability to explain and predict outcomes.

#### *4.3.2.1 $R^2$ Assessment*

$R^2$, or the coefficient of determination, indicates the proportion of variance in the dependent variable that is predictable from the independent variables. High $R^2$ values generally signify a better model fit and greater explanatory power (Hair *et al.*, 2023).

The $R^2$ values for the endogenous latent variables—EO, SBM, and SO—provide insights into the model's explanatory power and fit. The $R^2$ and $R^2$ adjusted values are shown in Table 4.16.

Table 4.16 – $R^2$ and $R^2$ Adjusted Values

| | **R-square** | **R-square adjusted** |
|---|---|---|
| **EO** | 0.202 | 0.197 |
| **SBM** | 0.475 | 0.450 |
| **SO** | 0.285 | 0.276 |

With an $R^2$ of 0.205 for EO, approximately 20.5% of the variance in EO is explained by the model. Although this is below the common threshold of 0.33 for moderate explanatory power (Chin, 1998), it still exceeds the minimum threshold of 0.19, suggesting a degree of influence from the predictors. This finding aligns with Covin and Slevin (1989), indicating that EO can be influenced by various contextual factors.

With an $R^2$ of 0.475 for SBM, about 47.5% of the variance in SBM demonstrates moderate to strong explanatory power. This suggests that nearly half of the variance in SBM can be accounted for by the independent variables in the model, reflecting the significance of these predictors in shaping sustainable business practices (Bocken *et al.*, 2014).

With an $R^2$ of 0.285 for SO, approximately 28.5% of the variance in SO is explained by the model. While it exceeds the threshold of 0.19 for weak explanatory power (Hair *et al.*, 2023), it remains below the moderate threshold of 0.33. This indicates a fair degree of influence, but, similar to EO, it suggests that additional factors may be needed for a more comprehensive understanding of sustainability outcomes (Elkington, 1997).

The $R^2$ assessment reveals a mixed performance across the constructs. SBM stands out with strong explanatory power, indicating that the predictors effectively capture the dynamics of sustainable business practices. In contrast, EO and SO exhibit weaker explanatory capabilities.

The overall Goodness-of-Fit (GOF), calculated as the mean of AVE multiplied by the mean of $R^2$ and then squared, results in a value of 0.516, which exceeds the threshold of 0.36. This indicates that the model fits well when considering all constructs collectively, despite individual $R^2$ values being lower. This suggests that the model can still provide valuable insights into the relationships among the constructs, reinforcing the importance of sustainable practices in business innovation and strategy (Porter, 2011).

#### *4.3.2.2 $Q^2$ Assessment*

In addition to evaluating the $R^2$ value, Stone-Geisser's $Q^2$ is used as an indicator of the path model's predictive relevance (Geisser, 1975; Stone, 1974). A $Q^2$ value greater than zero for a specific endogenous latent variable indicates that the PLS-SEM path model has predictive relevance for that construct (Hair *et al.*, 2023). The $Q^2$ value of latent variables in the PLS-SEM path model is obtained through the blindfolding procedure. Blindfolding is a sample reuse technique that systematically deletes data points to provide estimates of their original values.

For this procedure, an omission distance D is required. Literature recommends a value for the omission distance between 5 and 12 (Hair *et al.*, 2023). An omission distance of seven (D=7) means that every fifth data point of a latent variable's indicators will be eliminated in a single blindfolding round. As the blindfolding procedure necessitates the omission and prediction of every data point of the indicators used in the measurement model of the selected latent variable, an omission distance of D=7 results in seven blindfolding rounds. Consequently, the number of blindfolding rounds always equals the omission distance.

During the first blindfolding round, the procedure starts with first data point and omits every D-th data point of a latent variable's indicators. Then, the procedure estimates the SmartPLS path model by using the remaining data points. The omitted data represent missing values and are treated accordingly (e.g., by mean value replacement or pairwise deletion). The PLS-SEM results are then used to predict the omitted data points. The difference between the omitted data points and the predicted ones are the prediction error. The sum of squared prediction errors is used to calculate the $Q^2$ value. Blindfolding is an iterative process. In the second blindfolding round, the algorithm starts with the second data point, omits every D-th data point and continues as described before. After D blindfolding rounds, every data point has been omitted and predicted.

It is recommended that the omission distance values D should be between 5 and 12 (Hair *et al.*, 2023). Table 4.17 presents the $Q^2$ for each endogenous latent variable using an omission distance of 7 (D=7). $Q^2$ represents the predictive relevance of the variables, with larger values indicating stronger predictive relevance. A $Q^2$ value of 1 signifies that the model is fully predicted, while a $Q^2$ of 0 indicates no difference from replacing it with the average. A $Q^2$ value less than 0 suggests that the model has no predictive relevance, whereas a $Q^2$ greater than 0 indicates that the model possesses some level of predictiveness. The path test of the model is conducted using PLS-SEM. The $Q^2$ values for each variable are shown in the table above, and since all $Q^2$ values are greater than zero, the model meets the requirements for further analysis.

Table 4.17 – $Q^2$ Sheet

| | SSO | SSE | $Q^2$ (=1-SSE/SSO) |
|---|---|---|---|
| **DO** | 316.000 | 316.000 | |
| **EO** | 474.000 | 420.785 | 0.112 |
| **SBM** | 474.000 | 337.719 | 0.288 |
| **SO** | 316.000 | 250.570 | 0.207 |
| **TBL** | 474.000 | 474.000 | |

#### *4.3.2.3 Effect Size*

Accessing the $f^2$ effect size in SEM helps to understand the strength of the relationships between constructs. The $f^2$ value indicates how much variance in the dependent variable is explained by an independent variable when controlling for other variables. Table 4.18 shows the $f^2$ matrix. The analysis highlights the significant role of TBL in enhancing EO, as indicated by a strong $f^2$ value (0.253). Both SO and TBL are critical drivers of sustainable business innovation, demonstrated by moderate $f^2$ values. However, the small effect sizes for the relationships between EO and SBM, as well as TBL and SBM, suggest limited practical impact, indicating the need for further exploration of additional influencing factors. Lastly, the negligible interaction effects involving DO imply that it may not be a key driver in improving the effectiveness of TBL, EO, or SO.

Table 4.18 – f-Square Matrix

| | EO | SBM | SO |
|---|---|---|---|
| **DO** | | 0.098 | |
| **EO** | | 0.045 | 0.044 |
| **SBM** | | | |
| **SO** | | 0.142 | |
| **TBL** | 0.253 | 0.073 | 0.192 |
| **DO x TBL** | | 0.008 | |
| **DO x SO** | | 0.030 | |
| **DO x EO** | | 0.000 | |

#### *4.3.2.4 Model Fit*

The model fit statistics provide insights into how well the estimated model aligns with the saturated model, which represents a perfect fit. The value matrix is presented in Table 4.19, illustrating key metrics that evaluate the model's performance.

Table 4.19 – Model Fit

| | Saturated model | Estimated model |
|---|---|---|
| **SRMR** | 0.068 | 0.070 |
| **d_ULS** | 0.424 | 0.451 |
| **d_G** | 0.216 | 0.219 |
| **Chi-square** | 215.375 | 218.094 |
| **NFI** | 0.696 | 0.692 |

- SRMR (Standardised Root Mean Square Residual) values below 0.08 are generally considered acceptable (Hu and Bentler, 1999). Both values indicate that the fit is reasonable.
- d_ULS (Squared Euclidean Distance) indicates that lower values represent a better fit. The estimated model shows a slight increase in d_ULS, suggesting a somewhat poorer fit compared to the saturated model (Henseler *et al.*, 2015).

- d_G (Geodesic Distance) has lower values that indicate better model fit. The values are very close, indicating that the estimated model does not deviate significantly from the saturated model (Sarstedt *et al.*, 2021).
- Chi-square values that are higher indicate worse fit; however, the chi-square value alone is not sufficient for model evaluation. It is essential to assess it in conjunction with degrees of freedom and the associated p-value (Kline, 2023).
- NFI (Normed Fit Index) values closer to 1 indicate better fit, with values above 0.90 generally considered acceptable (Bentler and Bonett, 1980). Both values are below this threshold, suggesting that improvements are needed for better model fit.

In summary, while the fit statistics suggest that the estimated model is reasonably close to the saturated model, the slight increases in SRMR, d_ULS, and chi-square values indicate a marginally poorer fit. The NFI values suggest that the overall model fit could be improved. However, the model is still considered acceptable.

### 4.3.3 Significance and Relevance of Path Coefficients

Assessing the significance and relevance of the structural model relationships was conducted using SmartPLS 4.0, which estimates the structural model relationships (the path coefficients) to illustrate the connections between the constructs. Significance was determined through bootstrapping.

PLS-SEM does not assume that the data is normally distributed, which means that parametric significance tests (e.g., those used in regression analyses) cannot be applied to test the significance of coefficients such as outer weights, outer loadings, and path coefficients. Instead, PLS-SEM relies on a nonparametric bootstrap procedure (Davison and Hinkley, 1997; Efron and Tibshirani, 1986) to assess the significance of the estimated path coefficients.

In the bootstrapping process, subsamples are created by randomly drawing observations from the original dataset (with replacement). These subsamples are then used to estimate the PLS path model. This process is repeated until a large number of random subsamples, typically around 5,000, have been generated.

The parameter estimates (e.g., outer weights, outer loadings, and path coefficients) derived from these subsamples are used to calculate standard errors for the estimates. With this information, t-values are computed to evaluate the significance of each estimate. Table 4.20 presents the results of the path coefficients and structural relationships. Overall, these results indicate strong positive relationships among the constructs in the model.

Table 4.20 – Path Coefficients

| | **Original sample (O)** | **Sample mean (M)** | **Standard deviation (STDEV)** | **T statistics (\|O/STDEV\|)** | **P values** |
|---|---|---|---|---|---|
| **DO -> SBM** | 0.239 | 0.238 | 0.064 | 3.730 | 0.000 |
| **EO -> SBM** | 0.178 | 0.179 | 0.063 | 2.824 | 0.002 |
| **EO -> SO** | 0.198 | 0.196 | 0.081 | 2.441 | 0.007 |
| **SO -> SBM** | 0.328 | 0.322 | 0.070 | 4.656 | 0.000 |
| **TBL -> EO** | 0.450 | 0.455 | 0.084 | 5.364 | 0.000 |
| **TBL -> SBM** | 0.245 | 0.250 | 0.079 | 3.106 | 0.001 |
| **TBL -> SO** | 0.415 | 0.418 | 0.074 | 5.607 | 0.000 |

- DO has a statistically significant positive effect on SBM, with a standardised regression coefficient of $\beta$=0.239 and a significance test result of $p$<0.001, supporting this relationship.

- EO has a statistically significant positive effect on SBM, with a standardised regression coefficient of $\beta$=0.178 and a significance test result of $p$<0.010, supporting this relationship.

- EO also has a statistically significant positive effect on SO, with a standardised regression coefficient of $\beta$=0.198 and a significance test result of $p$<0.050, which supports this path.

- SO has a statistically significant positive effect on SBM, with a standardised regression coefficient of $\beta$=0.328 and a significance test result of $p$<0.001, supporting this relationship.
- TBL has a statistically significant positive effect on EO, with a standardised regression coefficient of $\beta$=0.450 and a significance test result of $p$<0.001, supporting this path.
- TBL has a statistically significant positive effect on SBM, with a standardised regression coefficient of $\beta$=0.245 and a significance test result of $p$<0.010, reinforcing this relationship.
- TBL has a statistically significant positive effect on SO, with a standardised regression coefficient of $\beta$=0.415 and a significance test result of $p$<0.001, supporting this path.

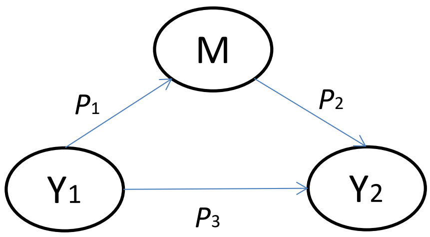
### 4.3.4 Mediation and Moderation Effects

This Section examines the mediating roles of individual EO and SO in the relationship between TBL and SBM. It also investigates the moderating role of DO in the pathways from EO and SO to SBM. Analysing mediation and moderation effects is crucial for understanding the dynamics among TBL, EO, SO, DO, and SBM. Mediation refers to how an independent variable influences a dependent variable through a mediator, clarifying the mechanism of action (Baron and Kenny, 1986). In contrast, moderation examines how the strength or direction of a relationship changes based on a moderator variable (Hayes, 2017). Together, these analyses offer valuable insights into the interactions among different variables in this study and contribute to a more comprehensive understanding of behavioural phenomena.

*4.3.4.1 Mediation Effect Analysis*

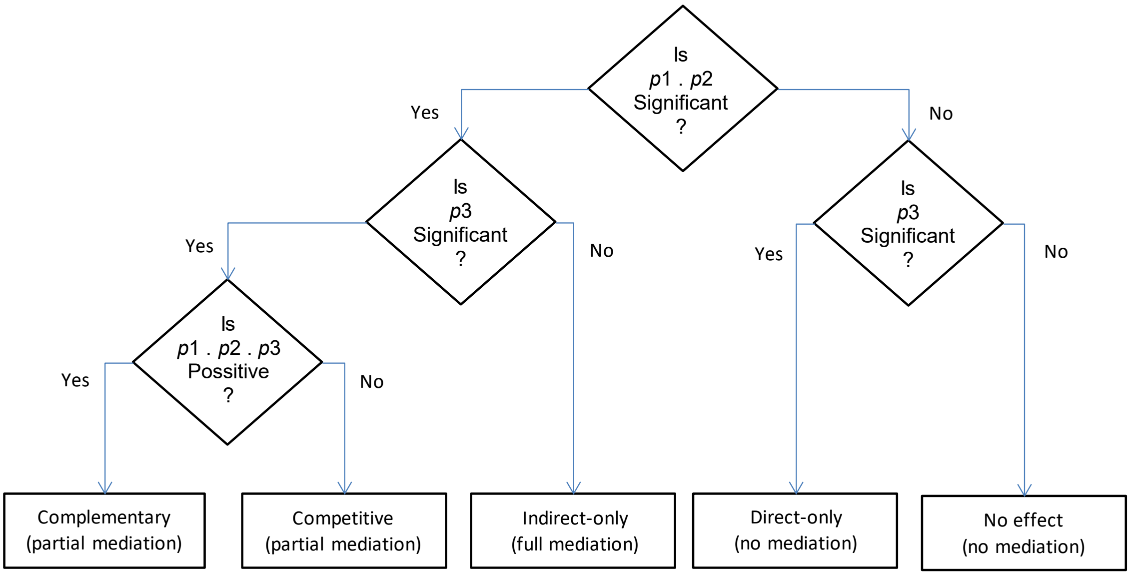
Mediation occurs when a third variable, known as the mediator, intervenes between two related constructs. Specifically, a change in the exogenous construct leads to a change in the mediator variable, which subsequently results in a change in the endogenous construct within the PLS-SEM path model. Thus, the mediator variable influences the nature of the relationship between the two constructs, as illustrated in Figure 4.3.

Figure 4.3 – General Mediation Model




Analysing the strength of the mediator variable's relationships with other constructs is crucial for understanding the mechanisms underlying the cause-effect relationship between an exogenous construct and an endogenous construct. While the analysis can focus on a single mediator variable, the path model can also incorporate multiple mediators simultaneously. To analyse a mediator model, Zhao *et al.* (2010) propose a framework, illustrated in Figure 4.4, which Hair *et al.* (2022) recommend for PLS-SEM. This framework categorises relationships into two types of non-mediation: "direct-only non-mediation," where the direct effect is significant, but the indirect effect is not, and "no-effect non-mediation," where neither effect is significant. For mediation, "complementary mediation" occurs when both effects are significant and point in the same direction, while "competitive mediation" has both effects significant but in opposite directions. "Indirect-only mediation" is characterised by a significant indirect effect with no significant direct effect, indicating full mediation.

Figure 4.4 – Mediation Analysis Procedure




In the research framework depicted in Figure 2.2, the TBL exogenous construct influences both the mediator variables EO and SO, which subsequently affect the endogenous construct SBM. Specifically, this model illustrates the relationships between TBL and EO, TBL and SO, as well as TBL, EO, and SO together impacting SBM. This indicates how TBL affects both EO and SO, leading to changes in SBM.

In line with the methodological approach outlined in Section 3.1, it is crucial to interpret these proposed mediating pathways as statistical associations rather than proven causal chains. A significant mediation effect in this cross-sectional context indicates that the relationship between the independent and dependent variable is significantly accounted for by the presence of the mediator, providing support for the hypothesised theoretical sequence.

The analysis calculated the effect size for each mediating effect in the model, with the results summarised in Table 4.21. The significance test revealed that EO influences SBM through SO with a p-value of less than 0.050, indicating that SO acts as a mediator in the relationship between EO and SBM. Additionally, TBL affects SBM through EO, also with a significance level of $p<0.050$, confirming EO's mediating role in this relationship.

Furthermore, the significance test for TBL's influence on SBM through both EO and SO yielded a p-value of less than 0.05, indicating that both EO and SO serve as mediators in this process. Finally, TBL's influence on SBM through SO alone was significant at $p<0.001$, reinforcing SO's role as a mediator in the relationship with TBL. As indicated in Figures 4.3 and 4.4, all paths P1, P2, and P3 are positive and significant, suggesting that the mediation effects are considered complementary (Hair *et al.*, 2023).

Table 4.21 – Specific Indirect Effects

| | **Original sample (O)** | **Sample mean (M)** | **Standard deviation (STDEV)** | **T statistics (\|O/STDEV\|)** | **P values** |
|---|---|---|---|---|---|
| **TBL -> EO -> SO -> SBM** | 0.029 | 0.029 | 0.015 | 1.979 | 0.024 |
| **TBL -> SO -> SBM** | 0.136 | 0.134 | 0.037 | 3.644 | 0.000 |
| **TBL -> EO -> SBM** | 0.080 | 0.082 | 0.034 | 2.322 | 0.010 |
| **TBL -> EO -> SO** | 0.089 | 0.089 | 0.04 | 2.207 | 0.014 |
| **EO -> SO -> SBM** | 0.065 | 0.063 | 0.03 | 2.193 | 0.014 |

#### *4.3.4.2 Moderating Effect Analysis*

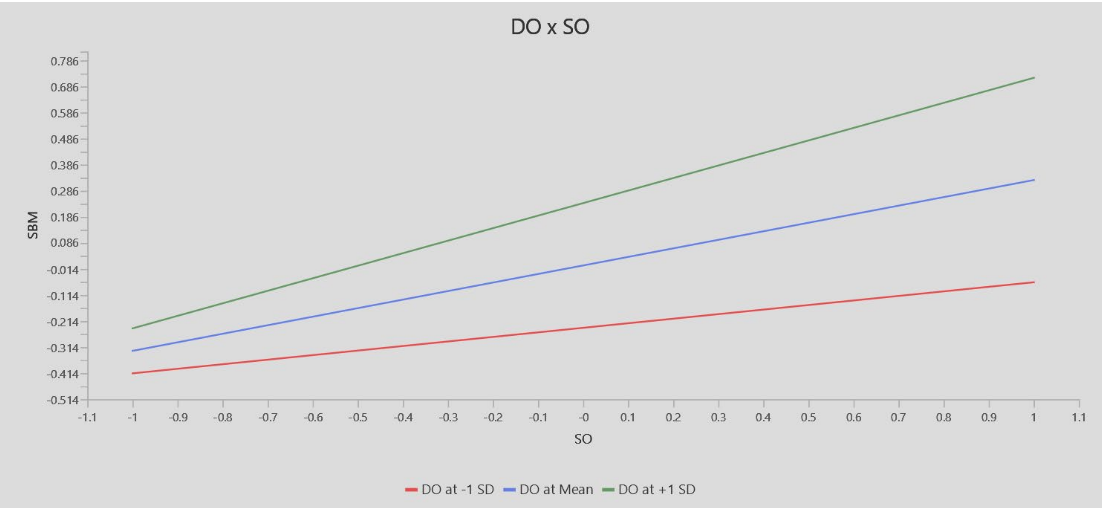
The moderation effect analysis investigates how DO serves as a moderator in the relationships between TBL and SBM, EO and SBM, and SO and SBM. This analysis identifies the conditions under which TBL, EO, and SO exert varying impacts on SBM. The results of the moderating path coefficients are presented in Table 4.22, highlighting how the strength or direction of these relationships changes based on the presence of the moderator DO (Hayes, 2017).

Table 4.22 – Path Coefficients of Moderating

| | **Original sample (O)** | **Sample mean (M)** | **Standard deviation (STDEV)** | **T statistics (\|O/STDEV\|)** | **P values** |
|---|---|---|---|---|---|
| **DO x TBL -> SBM** | -0.091 | -0.088 | 0.088 | 1.035 | 0.150 |
| **DO x EO -> SBM** | 0.002 | -0.004 | 0.07 | 0.026 | 0.490 |
| **DO x SO -> SBM** | 0.153 | 0.153 | 0.078 | 1.969 | 0.024 |

The standardised regression coefficient for the interaction term between DO and TBL on SBM is $\beta$ = −0.091, showing no significant regression effect, as evidenced by a significance test result of $p$=0.150 (greater than 0.050). Similarly, the standardised regression coefficient for the interaction term between DO and EO on SBM is $\beta$=0.002, also indicating no significant regression effect, with a significance test result of $p$=0.490 (greater than 0.050), which does not support this path either. In contrast, the standardised regression coefficient for the interaction term between DO and SO on SBM is $\beta$=0.153 indicating a significant positive regression effect, with a significance test result of $p$=0.024 (less than 0.050), supporting this path. This suggests that DO plays a significant positive moderating role in the relationship between SO and SBM, as illustrated in the simple slope graph in Figure 4.5.

Figure 4.5 – DO x SO Simple Slope Analysis




As illustrated in Figure 4.5, the red line represents the relationship between SO and SBM when the mean of DO is low, the blue line corresponds to the mean level of DO, and the green line reflects the situation when DO is high. As DO increases from low to high, the angle between the lines and the horizontal axis rises, indicating a steeper slope. This suggests that the positive relationship between SO and SBM strengthens with increasing levels of DO, demonstrating that the moderating variable enhances the positive association between SO and SBM from a weak to a strong effect.

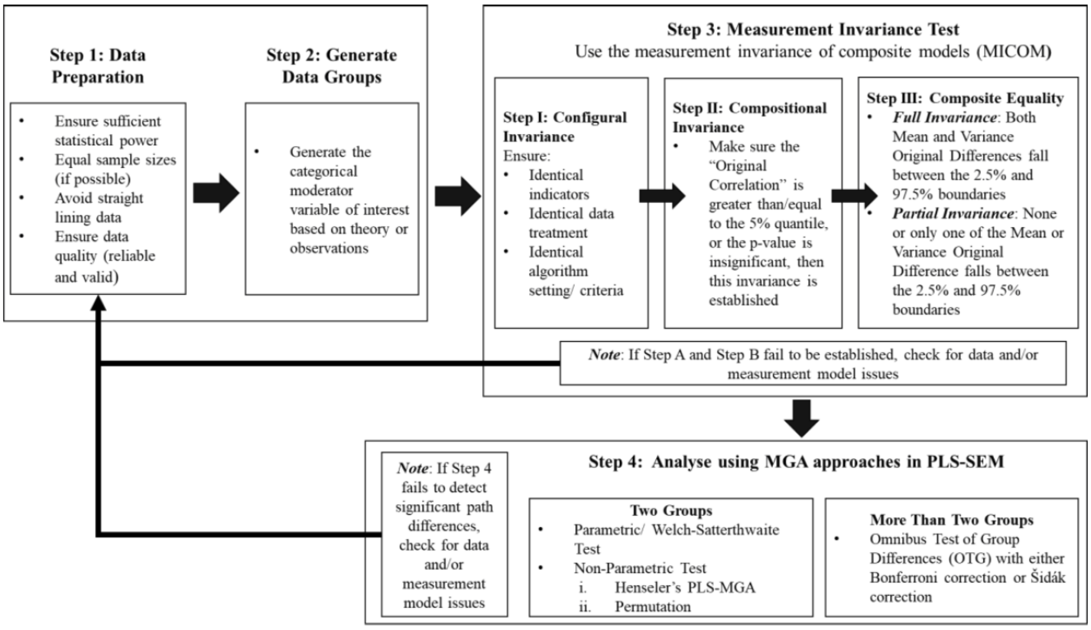
The structural model assessment evaluates the relationships among constructs, confirming their validity through techniques like bootstrapping. Significant paths between TBL, EO, SO, and SBM are revealed. The mediating analysis shows that EO and SO enhance the impact of TBL on SBM, clarifying the mechanisms involved. Additionally, the moderating analysis examines the role of DO, demonstrating that while DO strengthens the connection between SO and SBM, it does not significantly affect the relationships between TBL and SBM or EO and SBM. Together, these analyses offer a comprehensive understanding of the dynamics in sustainable BMI.

## 4.4 Multigroup Analysis

In the AEC industry, the effective use of digital technology is vital for driving transformation and enhancing value creation. This Section presents a multigroup analysis (MGA) conducted using SmartPLS 4.0 to examine the differences between two distinct groups: Design and Planning (Design), and Construction and Project Management (Construction).

The primary objective of this analysis is to test the hypothesis that the Design and Planning group utilises digital technology more extensively than the Construction and Project Management group. This hypothesis is based on the premise that the Design group operates at the forefront of the AEC value chain, uniquely positioning them to create value and influence subsequent stages of the project lifecycle. Additionally, this analysis will explore the roles of various determinants that contribute to achieving DT within these groups. The guidelines for running MGA in PLS-SEM is illustrated in Figure 4.6 (Cheah *et al.*, 2020).

Figure 4.6 – Guidelines for Running MGA in PLS-SEM




### 4.4.1 Data Preparation by Generating Data Groups

This Section addresses data preparation and the generation of data groups for MGA. In SmartPLS, creating data groups is a simple and efficient process that facilitates the segmentation of responses. For this study, we will generate separate data groups for Design and Construction, ensuring each group is adequately prepared for further analysis.

It is essential to first ascertain that the number of observations in each group meets the minimum sample size requirements necessary to ensure statistical power. The most widely used method for estimating minimum sample size in PLS-SEM is the "10-fold rule" approach (Hair *et al.*, 2022; Peng and Lai, 2012). For the model depicted in Figure 4.2, applying the 10-fold rule results in a minimum sample size of 30.

Hair *et al.* (2022) contend that the 10-fold rule serves as a rough guideline for determining minimum sample size. In PLS-SEM, it is vital to evaluate sample size in the context of the model and its data characteristics, which should be informed by power analyses focusing on the section of the model with the highest number of predictors. They also suggest following a rule established by Cohen (2013) that incorporates statistical power analysis for multiple regression models and outer loading values. Table 4.23 outlines the minimum sample size requirements to detect $R^2$ values of 0.1, 0.25, 0.5, and 0.75 in endogenous constructs within the structural model. This table considers significance levels of 1%, 5%, and 10%, with a statistical power of 80% across varying levels of PLS-SEM model complexity. For models with a maximum of three independent variables, only 45 samples are necessary to achieve 80% statistical power for an $R^2$ value of at least 0.25 at a 5% significance level. In some cases, 37 samples may also suffice.

Table 4.23 – Sample Size in PLS-SEM for Statistical Power of 80%

| Maximum Number of Arrows Pointing at a Construct (Number of Independent Variables) | Significance Level | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 10% | | | | 5% | | | | 1% | | | |
| | Minimum $R^2$ | | | | Minimum $R^2$ | | | | Minimum $R^2$ | | | |
| | 0.10 | 0.25 | 0.50 | 0.75 | 0.10 | 0.25 | 0.50 | 0.75 | 0.10 | 0.25 | 0.50 | 0.75 |
| 2 | 72 | 26 | 11 | 7 | 90 | 33 | 14 | 8 | 130 | 47 | 10 | 10 |
| 3 | 83 | 30 | 13 | 8 | 103 | 37 | 16 | 9 | 145 | 53 | 22 | 12 |
| 4 | 92 | 34 | 15 | 9 | 113 | 41 | 18 | 11 | 158 | 58 | 24 | 14 |
| 5 | 99 | 37 | 17 | 10 | 122 | 45 | 20 | 12 | 169 | 62 | 26 | 15 |
| 6 | 106 | 40 | 18 | 12 | 130 | 48 | 21 | 13 | 179 | 66 | 28 | 16 |
| 7 | 112 | 42 | 20 | 13 | 137 | 51 | 23 | 14 | 188 | 69 | 30 | 18 |
| 8 | 118 | 45 | 21 | 14 | 144 | 54 | 24 | 15 | 196 | 73 | 32 | 19 |
| 9 | 124 | 47 | 22 | 15 | 150 | 56 | 26 | 16 | 204 | 76 | 34 | 20 |
| 10 | 129 | 49 | 24 | 16 | 156 | 59 | 27 | 18 | 212 | 79 | 35 | 21 |

In this study, the total number of responses is 158, with 95 from Design and Planning and 63 from Construction and Project Management. Both groups exceed the necessary thresholds of 30 and 37, ensuring adequate statistical power for subsequent analyses. Additionally, the dataset does not present any issues with missing values, reliability, or validity.

### 4.4.2 Multigroup Model Assessment

#### *4.4.2.1 Reliability and Convergent Validity*

The assessment of the measurement model adheres to the criteria outlined in Section 4.2.3 for both reflective and formative constructs. Table 4.24 presents the evaluation of reliability and convergent validity for the reflective constructs. As the complete dataset was examined in the previous section, this Section focuses on the assessment of the two groups: Design and Construction.

Table 4.24 – Multigroup Reliability and Convergent Validity

| Variables | Factor | Outer Loadings | Cronbach's alpha | Composite reliability (rho_a) | Composite reliability (rho_c) | Average variance extracted (AVE) |
|---|---|---|---|---|---|---|
| **Complete Data Set** | | | | | | |
| DO | DO-Strat | 0.898 | 0.754 | 0.754 | 0.890 | 0.803 |
| | DO-Vision | 0.893 | | | | |
| EO | EO-Inno | 0.868 | 0.707 | 0.731 | 0.836 | 0.631 |
| | EO-Pro | 0.727 | | | | |
| | EO-Risk | 0.781 | | | | |
| SBM | SBM-Revenue | 0.813 | 0.741 | 0.760 | 0.852 | 0.659 |
| | SBM-ValueArch | 0.862 | | | | |
| | SBM-Valueoff | 0.756 | | | | |
| SO | SO-Culture | 0.892 | 0.749 | 0.749 | 0.888 | 0.799 |
| | SO-Practices | 0.896 | | | | |
| **Design and Planning (Design)** | | | | | | |
| DO | DO-Strat | 0.895 | 0.793 | 0.807 | 0.906 | 0.827 |
| | DO-Vision | 0.925 | | | | |
| EO | EO-Inno | 0.862 | 0.694 | 0.708 | 0.831 | 0.622 |
| | EO-Pro | 0.716 | | | | |
| | EO-Risk | 0.780 | | | | |
| SBM | SBM-Revenue | 0.794 | 0.741 | 0.752 | 0.852 | 0.657 |
| | SBM-ValueArch | 0.841 | | | | |
| | SBM-Valueoff | 0.797 | | | | |
| SO | SO-Culture | 0.920 | 0.808 | 0.809 | 0.912 | 0.839 |
| | SO-Practices | 0.912 | | | | |
| **Construction and Project Management (Construction)** | | | | | | |
| DO | DO-Strat | 0.906 | 0.670 | 0.709 | 0.856 | 0.748 |
| | DO-Vision | 0.823 | | | | |
| EO | EO-Inno | 0.884 | 0.707 | 0.786 | 0.832 | 0.625 |
| | EO-Pro | 0.702 | | | | |
| | EO-Risk | 0.775 | | | | |
| SBM | SBM-Revenue | 0.847 | 0.742 | 0.798 | 0.853 | 0.662 |
| | SBM-ValueArch | 0.901 | | | | |
| | SBM-Valueoff | 0.670 | | | | |
| SO | SO-Culture | 0.922 | 0.566 | 0.567 | 0.822 | 0.697 |
| | SO-Practices | 0.747 | | | | |

For the Design group, all outer loadings, Cronbach's alpha, CR, and AVE exceeded their respective thresholds. Specifically, outer loadings should be greater than 0.70, Cronbach's alpha should be above 0.70, CR should also exceed 0.70, and AVE should be greater than 0.50. These results indicate that the model demonstrates strong reliability and validity.

In contrast, the Construction group has two outer loadings below 0.70, with the lowest being 0.67. Additionally, the Cronbach’s alpha for DO is 0.67, and for SO, it is 0.566, both below the threshold of 0.70. The CR for SO is 0.567 (rho_a), while the overall CR (rho_c) is 0.822, which is considered acceptable. The AVE for all constructs is above the threshold of 0.50.

For outer loadings between 0.40 and 0.70, Hair *et al.* (2022) recommend examining CR and AVE. If the AVE meets the minimum threshold of 0.50, the indicators can be retained. Although Cronbach's Alpha is below the acceptable level, the CR (rho_c) for SO suggests that the construct may still reliably measure the underlying concept.

Given that both constructs are crucial to the study, it is advisable to retain them for analysis while acknowledging their questionable reliability. These limitations have been taken into account when interpreting results related to these constructs.

#### *4.4.2.2 Discriminant Validity*

The assessment method for discriminant validity employed the HTMT. The findings indicate in Table 4.25 show that all values are below the threshold of 0.85, confirming that both groups exhibit discriminant validity.

Table 4.25 – Multigroup Heterotrait-Monotrait Ratio Matrix

| | DO | EO | SBM | SO | DO x TBL | DO x SO | DO x EO |
|---|---|---|---|---|---|---|---|
| **Complete Data Set** | | | | | | | |
| DO | | | | | | | |
| EO | 0.187 | | | | | | |
| SBM | 0.411 | 0.586 | | | | | |
| SO | 0.084 | 0.523 | 0.717 | | | | |
| DO x TBL | 0.240 | 0.202 | 0.149 | 0.115 | | | |
| DO x SO | 0.221 | 0.177 | 0.027 | 0.043 | 0.696 | | |
| DO x EO | 0.172 | 0.211 | 0.153 | 0.166 | 0.731 | 0.583 | |
| **Design and Planning (Design)** | | | | | | | |
| DO | | | | | | | |
| EO | 0.19 | | | | | | |
| SBM | 0.338 | 0.68 | | | | | |
| SO | 0.086 | 0.567 | 0.743 | | | | |
| DO x TBL | 0.243 | 0.172 | 0.152 | 0.073 | | | |
| DO x SO | 0.145 | 0.181 | 0.096 | 0.068 | 0.748 | | |
| DO x EO | 0.175 | 0.079 | 0.08 | 0.036 | 0.771 | 0.604 | |
| **Construction and Project Management (Construction)** | | | | | | | |
| DO | | | | | | | |
| EO | 0.172 | | | | | | |
| SBM | 0.569 | 0.46 | | | | | |
| SO | 0.226 | 0.38 | 0.747 | | | | |
| DO x TBL | 0.249 | 0.379 | 0.254 | 0.349 | | | |
| DO x SO | 0.146 | 0.285 | 0.286 | 0.366 | 0.781 | | |
| DO x EO | 0.227 | 0.333 | 0.072 | 0.151 | 0.471 | 0.513 | |

#### *4.4.2.3 Formative Construct Assessment*

For the formative construct, the assessment metrics for the TBL for both groups and the complete dataset are listed in Table 4.26. The outer weights of the formative items indicate their contribution to the HOC. Typically, outer weights above 0.20 are considered significant (Chin, 1998). However, in the Construction group, the outer weight for TBL-People is 0.141, which falls below this threshold. This indicates that the contribution of TBL-People to the HOC is not considered significant.

Table 4.26 – Multigroup Assessment Metrics for the TBL Formative Construct

| | Complete Data Set | | | Design and Planning (Design) | | | Construction and Project Management (Construction) | | |
|---|---|---|---|---|---|---|---|---|---|
| **Items** | Outer Weight | VIF | p-value | Outer Weight | VIF | p-value | Outer Weight | VIF | p-value |
| **TBL-People** | 0.316 | 1.626 | 0.014 | 0.386 | 1.784 | 0.002 | 0.141 | 1.792 | 0.382 |
| **TBL-Planet** | 0.404 | 1.710 | 0.002 | 0.478 | 1.614 | 0.000 | 0.639 | 2.104 | 0.103 |
| **TBL-Profit** | 0.490 | 1.435 | 0.000 | 0.306 | 1.906 | 0.011 | 0.424 | 1.259 | 0.094 |

The VIF values for both the Design and Construction groups suggest low multicollinearity among the items. Generally, VIF values below 5 are acceptable, with values below 3 deemed excellent (Hair *et al.*, 2022).

In the Design group, all p-values are below the critical threshold of 0.050, indicating that each indicator significantly contributes to the HOC. Conversely, the analysis of the Construction group revealed that the p-values for three key items were not significant. Although the VIF values for these items are acceptable, indicating no multicollinearity concerns, the lack of statistical significance suggests that other factors may be influencing the results. A critical limitation is the sample size of the Construction group (n=63), which reduces the statistical power of the analysis (Cohen, 2013). Consequently, the non-significant findings for this subgroup may be attributable to a Type II error, where a true underlying effect is not detected due to insufficient data.

While the findings highlight non-significant relationships for these items, it is essential to consider the impact of sample size on the results. Additionally, these non-significant results may indicate that the construct does not operate effectively within the Construction group or that external factors may be influencing the outcomes (Bagozzi and Yi, 1988; Hair *et al.*, 2023). Due to the smaller sample size in the Construction group, interpretation of non-significant paths should be made cautiously, as statistical power may be limited.

#### 4.4.2.4 Structural Model Collinearity

The first step involves using the VIF to assess collinearity within the structural model. Table 4.27 displays the inner VIF values for the two groups and the complete dataset. The results indicate that the tolerance values are significantly below the VIF threshold of 5.00, which suggests collinearity among the predictor constructs  Furthermore, most VIF values are below 3.00, indicating an excellent level of collinearity (Hair *et al.*, 2022), and there is no indication of strong CMB.

Table 4.27 – Multigroup Collinearity (VIF)

| | **Complete Data Set** | **Design and Planning (Design)** | **Construction and Project Management (Construction)** |
|---|---|---|---|
| **DO -> SBM** | 1.109 | 1.102 | 1.164 |
| **EO -> SBM** | 1.334 | 1.517 | 1.27 |
| **EO -> SO** | 1.253 | 1.497 | 1.071 |
| **SO -> SBM** | 1.431 | 1.818 | 1.195 |
| **TBL -> EO** | 1.000 | 1.000 | 1.000 |
| **TBL -> SBM** | 1.571 | 2.322 | 1.292 |
| **TBL -> SO** | 1.253 | 1.497 | 1.071 |
| **DO x TBL -> SBM** | 2.847 | 3.734 | 3.033 |
| **DO x SO -> SBM** | 2.015 | 2.304 | 3.146 |
| **DO x EO -> SBM** | 2.236 | 2.526 | 1.466 |

#### 4.4.2.5 R² Assessment

The R² values provide insights into the proportion of variance in each dependent variable that is explained by the independent variables in the model. Table 4.28 shows the R² and adjusted R² values for the Design group, Construction group, and the complete dataset.

Table 4.28 – Multigroup R Square

| | **Complete Data Set** | | **Design and Planning (Design)** | | **Construction and Project Management (Construction)** | |
|---|---|---|---|---|---|---|
| | **R-square** | **R-square adjusted** | **R-square** | **R-square adjusted** | **R-square** | **R-square adjusted** |
| **EO** | 0.202 | 0.197 | 0.332 | 0.325 | 0.066 | 0.051 |
| **SBM** | 0.475 | 0.450 | 0.500 | 0.460 | 0.567 | 0.512 |
| **SO** | 0.285 | 0.276 | 0.438 | 0.426 | 0.084 | 0.054 |

*<u>Design Group:</u>*

- The $R^2$ of EO is 0.332 that means approximately 33.2% of the variance in EO is explained by the independent variables. This indicates a moderate level of explanatory power, suggesting that the model captures some key factors influencing EO. The adjusted $R^2$ is slightly lower, reflecting the number of predictors in the model. It suggests that the model remains relevant after adjusting for the number of variables.
- The $R^2$ of SBM is 0.500 that explains 50% of the variance in SBM, indicating a strong level of explanatory power. This suggests that the independent variables are highly relevant in understanding SBM in the Design group. The adjusted $R^2$ value indicates that the model remains effective after accounting for the number of predictors.
- The $R^2$ of SO is 0.438 that means approximately 43.8% of the variance in SO is explained, indicating a good level of explanatory power. The adjusted $R^2$ confirms the model's effectiveness after accounting for predictors.

*<u>Construction Group:</u>*

- The $R^2$ of EO is 0.066 meaning only 6.6% of the variance in EO is explained, indicating a low level of explanatory power. This suggests that many other factors not included in the model may significantly influence EO in this group. The adjusted $R^2$ further emphasises the limited effectiveness of the model for EO, as it accounts for the number of predictors.
- The $R^2$ of SBM is 0.567 that strong value shows that 56.7% of the variance in SBM is explained, indicating an effective model for this group. The adjusted $R^2$ suggests that the model still explains a substantial amount of variance after adjusting for the number of predictors.
- The $R^2$ of SO is 0.084 that explains only 8.4% of the variance in SO, indicating a

low level of explanatory power. This suggests that many other factors may significantly influence SO in this group. The adjusted $R^2$ further emphasises the limited effectiveness of the model for SO.

The Design group exhibits strong explanatory power for SBM and SO, while EO shows moderate effectiveness. In contrast, the Construction group reveals low explanatory power for EO and SO yet demonstrates strong explanatory power for SBM. Although the $R^2$ values for certain constructs, such as EO and SO in the Construction group, are low, this does not exclude the possibility of conducting analysis. MGA path analysis can provide insights into how relationships vary between groups, even if some constructs account for less variance. Additionally, the smaller sample sizes in the Construction group may impact the reliability of the results, especially for constructs with low $R^2$ values.

#### *4.2.4.6 $Q^2$ Assessment*

the $Q^2$ values indicate varying levels of predictive relevance across constructs and groups. Table 4.29 shows the multigroup Q2 assessment values.

*Design Group*

- It shows moderate to strong predictive relevance for EO, SBM, and SO with all values are greater than 0.

*Construction Group*

- The Construction group exhibits negative predictive relevance for EO and SO, indicating the model does not effectively explain their variance. However, SBM shows moderate predictive relevance. Despite the low $Q^2$ values for EO and SO, multigroup path analysis can still reveal insights into how relationships differ between groups. Additionally, smaller sample sizes may affect the reliability of results, particularly for constructs with low $Q^2$ values.

Table 4.29 – Multigroup $Q^2$ Sheet

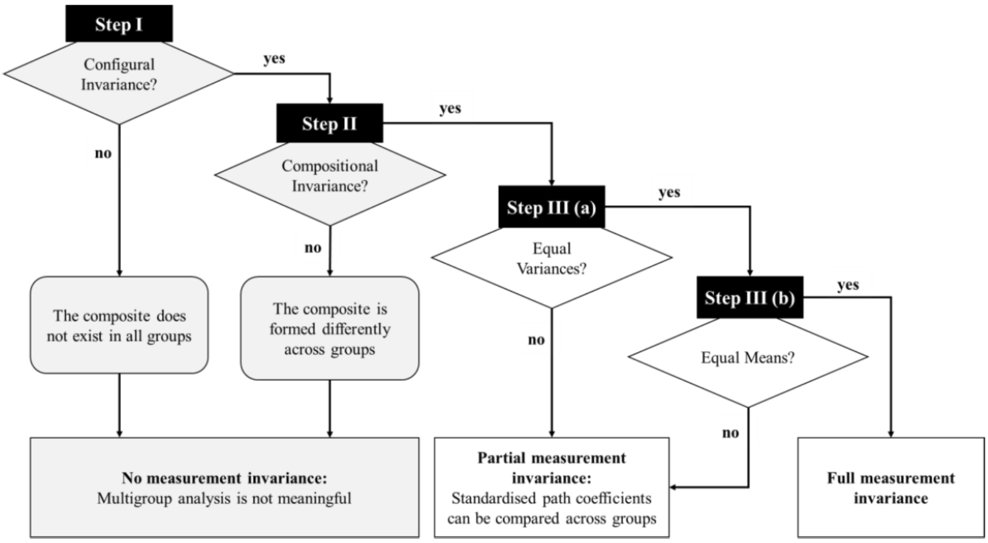
| | Complete | | | Design | | | Construction | | |
|---|---|---|---|---|---|---|---|---|---|
| | **SSO** | **SSE** | **Q²(=1-SSE/SSO)** | **SSO** | **SSE** | **Q² (=1-SSE/SSO)** | **SSO** | **SSE** | **Q² (=1-SSE/SSO)** |
| **DO** | 316 | 316.000 | | 190 | 190.000 | | 126 | 126.000 | |
| **EO** | 474 | 420.785 | 0.112 | 285 | 230.064 | 0.193 | 189 | 189.414 | -0.002 |
| **SBM** | 474 | 337.719 | 0.288 | 285 | 206.910 | 0.274 | 189 | 142.035 | 0.248 |
| **SO** | 316 | 250.570 | 0.207 | 190 | 123.561 | 0.35 | 126 | 128.637 | -0.021 |
| **TBL** | 474 | 474.000 | | 285 | 285.000 | | 189 | 189.000 | |

### 4.4.3 Measurement Invariance Test using MICOM

This step focuses on evaluating measurement invariance in PLS-SEM. Measurement invariance, also known as measurement equivalence, confirms that the measurement models accurately represent the same attribute under varying conditions (Henseler *et al.*, 2015). Variations in path coefficients (β values) between latent variables may arise from different interpretations by respondents, rather than genuine differences in structural relationships. Hult *et al.* (2008) emphasise that failing to establish invariance can result in low statistical power, imprecise estimators, and potentially misleading conclusions. Therefore, assessing measurement invariance is essential prior to conducting MGA, as it ensures that group differences in model estimates are not influenced by distinct meanings attributed to latent variables.

To enhance the validity of results, Henseler *et al.* (2015) introduced the Measurement Invariance of Composite Models (MICOM) procedure, which aligns with the principles of composite modelling in PLS-SEM. The MICOM procedure, illustrated in Figure 4.7, consists of three key steps: (i) assessing configural invariance (Step I), (ii) evaluating compositional invariance (Step II), and (iii) examining the equality of composite mean values and variances across groups (Step III) (see Hair *et al.* (2023) for detailed explanations).

Figure 4.7 – The Measurement Invariance of Composite Models Procedure




If both configural invariance and compositional invariance are confirmed, partial measurement invariance is established, allowing for the comparison of path coefficients using MGA. Full measurement invariance is achieved when composites exhibit equal means and variances across groups, enabling data pooling and potentially increasing statistical power, thus making MGA unnecessary (Henseler *et al.*, 2015). However, if partial measurement invariance is confirmed, the researcher can proceed with MGA.

The MICOM analysis was conducted using the SmartPLS feature. The results are detailed under the Quality Criteria → MICOM section, which includes three tabs: Step 2, Step 3a (Variances), and Step 3b (Means).

Step 2 evaluates the stability of the measurement model across groups by examining original correlations and permutation means. As shown in Table 4.30, all constructs maintain measurement invariance across groups, indicating stable relationships. The high original correlations reflect strong relationships within the groups. Additionally, the permutation p-values, all exceeding 0.05, suggest that there are no significant measurement differences across the groups for any of the constructs. These results confirm measurement invariance, allowing for valid group comparisons. Consequently, the results of Step 2 support only partial measurement invariance.

Table 4.30 – MICOM Step 2 Result

| | Original correlation | Correlation permutation means | 5.00% | Permutation p value |
|---|---|---|---|---|
| **DO** | 0.994 | 0.989 | 0.957 | 0.428 |
| **EO** | 0.996 | 0.992 | 0.975 | 0.599 |
| **SBM** | 0.997 | 0.997 | 0.991 | 0.371 |
| **SO** | 1.000 | 0.997 | 0.99 | 0.721 |
| **TBL** | 0.979 | 0.944 | 0.831 | 0.683 |

Table 4.31 presents the results of Step 3a (Variance), which evaluates whether significant differences exist in the variances of constructs between groups. For DO, the p-value (0.023) indicates a significant variance difference, suggesting that responses regarding DO vary more widely between groups. Likewise, for SO, the p-value (0.017) indicates significant variance differences, meaning perceptions of SO are more variable across groups. Conversely, constructs such as EO, SBM, and TBL do not show significant variance differences, indicating consistency in perceptions across groups for these constructs.

Table 4.31 – MICOM Step 3a (Variance) Results

| | Original difference | Permutation mean difference | 2.50% | 97.50% | Permutation p value |
|---|---|---|---|---|---|
| **DO** | 0.457 | 0.005 | -0.352 | 0.382 | 0.023 |
| **EO** | 0.102 | 0.023 | -0.382 | 0.463 | 0.369 |
| **SBM** | -0.164 | 0.011 | -0.328 | 0.375 | 0.213 |
| **SO** | 0.556 | 0.012 | -0.376 | 0.435 | 0.017 |
| **TBL** | 0.196 | 0.016 | -0.397 | 0.459 | 0.230 |

Step 3b (Means) is presented in Table 4.32. This step assesses whether significant differences exist in the means of the constructs between groups. The results indicate that for EO, the p-value (0.009) reveals a significant means difference, suggesting differing perceptions of EO between the groups. Similarly, for SO, the p-value (0.011) also indicates a significant difference. In contrast, other constructs such as DO, SBM, and TBL show no significant means differences, as their p-values are above 0.050.

Table 4.32 – MICOM Step 3b (Means) Results

| | **Original difference** | **Permutation mean difference** | **2.50%** | **97.50%** | **Permutation p value** |
|---|---|---|---|---|---|
| **DO** | -0.106 | 0.002 | -0.295 | 0.289 | 0.261 |
| **EO** | -0.409 | -0.005 | -0.295 | 0.278 | 0.009 |
| **SBM** | -0.08 | -0.002 | -0.272 | 0.262 | 0.318 |
| **SO** | -0.364 | -0.001 | -0.267 | 0.288 | 0.011 |
| **TBL** | 0.009 | -0.005 | -0.271 | 0.274 | 0.469 |

Given that the results from Step 3 concluded that not all composite means values and variances were equal, only partial measurement invariance is supported. Therefore, it is appropriate to confidently compare standardised path coefficients across the groups through MGA in PLS-SEM.

### 4.4.4 Test of MGA Comparisons

Once partial measurement invariance is established using MICOM, the next step is to assess group differences through MGA in SmartPLS. This analysis allows for the comparison of parameters such as path coefficients, outer weights, and outer loadings between the Design and Planning groups and the Construction and Project Management groups.

SmartPLS offers five different approaches for group comparisons based on bootstrapping (Hair *et al.*, 2023): Henseler's Bootstrap-Based MGA (Henseler *et al.*, 2009); Parametric Test (Keil *et al.*, 2000); Welch-Satterthwaite Test (Welch, 1947); Permutation

Test (Chin and Dibbern, 2009) which can be estimated using the MICOM path coefficient option in SmartPLS; Omnibus Test of Group Differences (OTG) (Sarstedt *et al.*, 2021), suitable for comparing more than two groups.

In this study, the MICOM path coefficient method is utilised, and the results from the permutation multigroup analysis provide insights into the differences in path coefficients between the Design and Construction groups, as shown in Table 4.33.

Table 4.33 – Permutation Multigroup Analysis: Path Coefficients

| | Original (Design) | Original (Construction) | Original difference | Permutation mean difference | 5.00% | 95.00% | Permutation p value |
|---|---|---|---|---|---|---|---|
| **DO -> SBM** | 0.168 | 0.400 | -0.232 | 0.005 | -0.218 | 0.241 | 0.042 |
| **EO -> SBM** | 0.196 | 0.185 | 0.010 | 0.012 | -0.210 | 0.235 | 0.507 |
| **EO -> SO** | 0.064 | 0.242 | -0.178 | 0.006 | -0.291 | 0.298 | 0.159 |
| **SO -> SBM** | 0.293 | 0.424 | -0.131 | 0.005 | -0.245 | 0.258 | 0.191 |
| **TBL -> EO** | 0.576 | 0.258 | 0.319 | -0.006 | -0.280 | 0.298 | 0.041 |
| **TBL -> SBM** | 0.261 | 0.278 | -0.018 | -0.011 | -0.295 | 0.248 | 0.485 |
| **TBL -> SO** | 0.623 | 0.110 | 0.513 | -0.003 | -0.242 | 0.253 | 0.002 |
| **DO x TBL -> SBM** | -0.152 | 0.063 | -0.215 | -0.016 | -0.329 | 0.291 | 0.151 |
| **DO x EO -> SBM** | 0.041 | -0.072 | 0.114 | 0.015 | -0.237 | 0.277 | 0.242 |
| **DO x SO -> SBM** | 0.177 | 0.131 | 0.045 | 0.004 | -0.280 | 0.300 | 0.404 |

- DO → SBM: The path coefficient is significantly higher in the Construction group. The permutation p-value (0.042) indicates a significant difference, suggesting that the impact of DO on SBM is stronger in Construction than in Design.
- EO → SBM: The difference is minimal (0.010) and not statistically significant (p-value = 0.507), indicating that EO has a similar impact on SBM across both groups.
- EO → SO: The significant difference (-0.178) suggests that EO influences SO more strongly in Construction, but the p-value (0.159) indicates this difference is not statistically significant.

- SO → SBM: Although the path coefficient is higher in Construction, the difference (-0.131) is not statistically significant (p-value = 0.191), indicating similar impacts across the groups.
- TBL → EO: The large positive difference (0.319) coupled with a significant p-value (0.041) suggests that the TBL has a stronger influence on EO in the Design group compared to Construction.
- TBL → SBM: The difference is negligible (-0.018) and not statistically significant (p-value = 0.485), indicating similar influences on SBM.
- TBL → SO: The significant difference (0.513) and a very low p-value (0.002) indicate that the TBL has a much stronger effect on SO in the Design group compared to Construction.
- DO x TBL → SBM: The difference (-0.215) is not statistically significant (p-value = 0.151), indicating no strong interaction effect between DO and TBL on SBM.
- DO x EO → SBM: The small difference (0.114) and a p-value of 0.242 suggest no significant interaction between DO and EO on SBM.
- DO x SO → SBM: The negligible difference (0.045) and a p-value of 0.404 indicate no significant interaction effect.

The analysis reveals that there are significant differences in path coefficients primarily for DO to SBM and TBL to SO, indicating that these relationships vary meaningfully between the Design and Construction groups. Other relationships show similar influences across groups, suggesting that while some aspects of digital and sustainability strategies differ between groups, others remain consistent. This insight can inform targeted strategies for leveraging digital technology and sustainability initiatives within each group.

### 4.4.5 Multigroup Path Coefficients

*4.4.5.1 Path Coefficients*

The parameter estimates (e.g., outer weights, outer loadings, and path coefficients) derived from these subsamples are used to calculate standard errors for the estimates for each group. With this information, t-values are computed to evaluate the significance of each estimate. Table 4.34 presents the results of the path coefficients and structural relationships.

Table 4.34 – Multigroup Path Coefficients

| | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics (\|O/STDEV\|) | P values |
|---|---|---|---|---|---|
| **Complete Data Set** | | | | | |
| **DO -> SBM** | 0.239 | 0.238 | 0.064 | 3.73 | 0.000 |
| **EO -> SBM** | 0.178 | 0.179 | 0.063 | 2.824 | 0.002 |
| **EO -> SO** | 0.198 | 0.196 | 0.081 | 2.441 | 0.007 |
| **SO -> SBM** | 0.328 | 0.322 | 0.07 | 4.656 | 0.000 |
| **TBL -> EO** | 0.450 | 0.455 | 0.084 | 5.364 | 0.000 |
| **TBL -> SBM** | 0.245 | 0.250 | 0.079 | 3.106 | 0.001 |
| **TBL -> SO** | 0.415 | 0.418 | 0.074 | 5.607 | 0.000 |
| **Design and Planning (Design)** | | | | | |
| **DO -> SBM** | 0.167 | 0.161 | 0.089 | 1.883 | 0.030 |
| **EO -> SBM** | 0.195 | 0.195 | 0.101 | 1.935 | 0.027 |
| **EO -> SO** | 0.064 | 0.056 | 0.115 | 0.554 | 0.290 |
| **SO -> SBM** | 0.293 | 0.274 | 0.11 | 2.647 | 0.004 |
| **TBL -> EO** | 0.576 | 0.579 | 0.085 | 6.816 | 0.000 |
| **TBL -> SBM** | 0.261 | 0.28 | 0.136 | 1.924 | 0.027 |
| **TBL -> SO** | 0.623 | 0.629 | 0.091 | 6.838 | 0.000 |
| **Construction and Project Management (Construction)** | | | | | |
| **DO -> SBM** | 0.398 | 0.428 | 0.106 | 3.743 | 0.000 |
| **EO -> SBM** | 0.189 | 0.169 | 0.101 | 1.878 | 0.030 |
| **EO -> SO** | 0.242 | 0.24 | 0.188 | 1.287 | 0.099 |
| **SO -> SBM** | 0.422 | 0.432 | 0.099 | 4.285 | 0.000 |
| **TBL -> EO** | 0.258 | 0.289 | 0.184 | 1.403 | 0.080 |
| **TBL -> SBM** | 0.281 | 0.281 | 0.157 | 1.788 | 0.037 |
| **TBL -> SO** | 0.110 | 0.147 | 0.162 | 0.678 | 0.249 |

The analysis reveals distinct path coefficients and significance levels between the Design and Construction groups. In the Design group, most relationships are significant, particularly the strong influence of TBL on both EO and SO. Key significant paths include DO -> SBM, EO -> SBM, and SO -> SBM, demonstrating effective connections among these constructs. In contrast, the Construction group shows significant paths for DO -> SBM, EO -> SBM, and SO -> SBM, while EO -> SO and TBL -> SO are not significant. These findings underscore the varying influences of constructs across the two groups, suggesting that strategies for achieving sustainable BMI differ.

#### *4.4.5.2 Mediation Effects*

The mediator effects of EO and SO influences the nature of the relationship between the TBL and SBM for each group as shown in Table 4.35.

Table 4.35 – Multigroup Specific Indirect Effects

| | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics (\|O/STDEV\|) | P values |
|---|---|---|---|---|---|
| **Complete Data Set** | | | | | |
| **TBL -> EO -> SO -> SBM** | 0.029 | 0.029 | 0.015 | 1.979 | 0.024 |
| **TBL -> SO -> SBM** | 0.136 | 0.134 | 0.037 | 3.644 | 0.000 |
| **TBL -> EO -> SBM** | 0.080 | 0.082 | 0.034 | 2.322 | 0.010 |
| **TBL -> EO -> SO** | 0.089 | 0.089 | 0.04 | 2.207 | 0.014 |
| **EO -> SO -> SBM** | 0.065 | 0.063 | 0.03 | 2.193 | 0.014 |
| **Design and Planning (Design)** | | | | | |
| **TBL -> EO -> SO -> SBM** | 0.029 | 0.029 | 0.015 | 1.979 | 0.024 |
| **TBL -> SO -> SBM** | 0.136 | 0.134 | 0.037 | 3.644 | 0.000 |
| **TBL -> EO -> SBM** | 0.080 | 0.082 | 0.034 | 2.322 | 0.010 |
| **TBL -> EO -> SO** | 0.089 | 0.089 | 0.04 | 2.207 | 0.014 |
| **EO -> SO -> SBM** | 0.065 | 0.063 | 0.03 | 2.193 | 0.014 |
| **Construction and Project Management (Construction)** | | | | | |
| **TBL -> EO -> SO -> SBM** | 0.029 | 0.029 | 0.015 | 1.979 | 0.024 |
| **TBL -> SO -> SBM** | 0.136 | 0.134 | 0.037 | 3.644 | 0.000 |
| **TBL -> EO -> SBM** | 0.080 | 0.082 | 0.034 | 2.322 | 0.010 |
| **TBL -> EO -> SO** | 0.089 | 0.089 | 0.04 | 2.207 | 0.014 |
| **EO -> SO -> SBM** | 0.065 | 0.063 | 0.03 | 2.193 | 0.014 |

In the Design group, significant paths include TBL -> SO -> SBM and TBL -> EO -> SBM, indicating meaningful relationships. However, paths involving TBL -> EO -> SO -> SBM and EO -> SO -> SBM are not significant. In the Construction group, all paths are not significant, suggesting limited predictive power in these relationships. These findings highlight the differing influences of constructs between the two groups, indicating that strategies may need to be adjusted accordingly.

#### *4.4.5.3 Multigroup Moderating Effect Analysis*

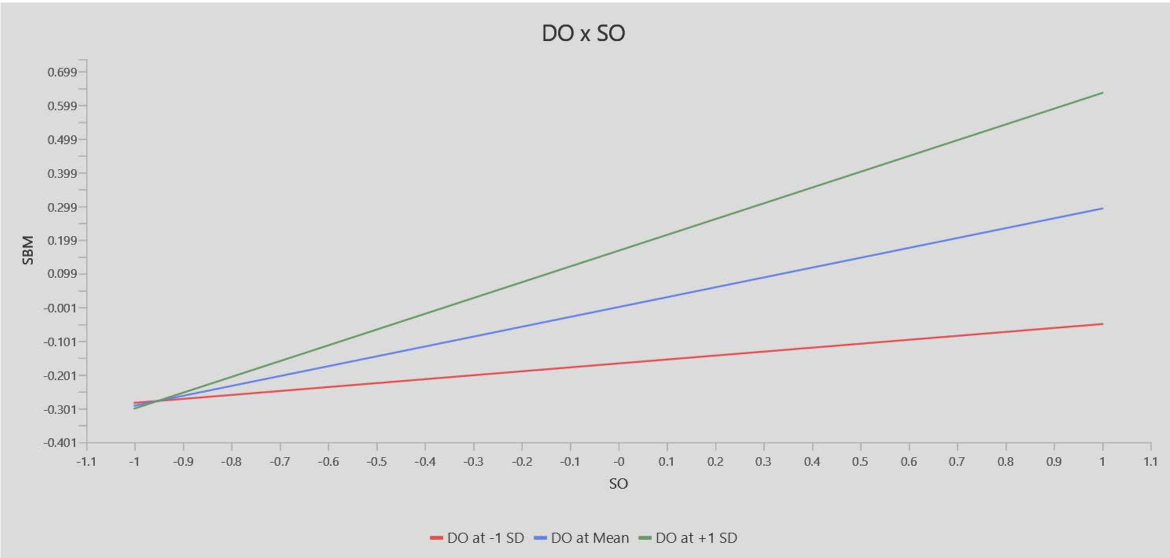
The analysis of the moderating effects for each group is presented in Table 4.36. In the Design group, the interaction between DO and SO shows a marginally significant effect on SBM, while interactions with TBL and EO are not significant. Conversely, all interactions in the Construction group lack significance, indicating limited predictive power. These findings suggest some influence in the Design group, whereas the Construction group reveals no significant interactions, emphasising the need for tailored strategies in each context.

Table 4.36 – Multigroup Path Coefficients of Moderating

| | **Original sample (O)** | **Sample mean (M)** | **Standard deviation (STDEV)** | **T statistics (\|O/STDEV\|)** | **P values** |
|---|---|---|---|---|---|
| **Complete Data Set** | | | | | |
| **DO x TBL -> SBM** | -0.091 | -0.088 | 0.088 | 1.035 | 0.150 |
| **DO x EO -> SBM** | 0.002 | -0.004 | 0.07 | 0.026 | 0.490 |
| **DO x SO -> SBM** | 0.153 | 0.153 | 0.078 | 1.969 | 0.024 |
| **Design and Planning (Design)** | | | | | |
| **DO x TBL -> SBM** | -0.151 | -0.157 | 0.134 | 1.126 | 0.130 |
| **DO x EO -> SBM** | 0.041 | 0.034 | 0.114 | 0.362 | 0.359 |
| **DO x SO -> SBM** | 0.176 | 0.184 | 0.131 | 1.345 | 0.089 |
| **Construction and Project Management (Construction)** | | | | | |
| **DO x TBL -> SBM** | 0.062 | 0.053 | 0.183 | 0.337 | 0.368 |
| **DO x EO -> SBM** | -0.071 | -0.083 | 0.149 | 0.478 | 0.316 |
| **DO x SO -> SBM** | 0.132 | 0.076 | 0.107 | 1.238 | 0.108 |

Notably, the marginally significant interaction between DO and SO in the Design group mirrors the pattern observed in the complete dataset (Figure 4.8). As DO increases from low to high, the angle between the lines and the horizontal axis rises, indicating a steeper slope. This suggests that the positive relationship between SO and SBM strengthens with higher levels of DO, demonstrating that the moderating variable enhances the association between SO and SBM, shifting it from weak to strong.

Figure 4.8 – Design Group DO x SO Simple Slope Analysis




## 4.5 Concluding Remark

The structure of this Chapter consists of two major analytical blocks: base model analysis and multigroup analysis. The first part examines the overall fit of the research model (first-order and higher-order) for the measurement and structural models based on reflective and formative first order constructs. Among other aspects, discriminant validity as well as the collinearity of the model are also confirmed by the analysis.

Among the others, discriminant validity as well as collinearity of model are also confirmed by the analysis. Structural path coefficient analysis provides very strong support for most of the study's hypothesised relationships.

The second part of the second section performs a multigroup analysis comparing the Design and Planning group (Design) to the Construction and Project Management group (Construction). Substantial discrepancies among sustainable BMI appear to be indicated between the two groups, however, the rather small sample size in the Construction group may lead to the biased results. A more detailed discussion will be presented in Discussion Chapter.

Findings from the Structural model reveal that the positive effect of TBL positively influences both EO and SO, which in turn result in SBM Innovation. TBL demonstrates direct effects on SO (0.415) and EO (0.450), and both mediators contribute significantly to SBM (0.136 for SO and 0.080 for EO). The effects of DO are otherwise, except for the interaction of DO x SO also not significantly affecting SBM (0.153). This evidence points to the importance of DO in driving the development of sustainable business practices and provides grounds for future investigation of the moderating role of DO. Summary of hypotheses can be found in Table 4.37.

Table 4.37 – Hypothesis Testing Summary

| **Hypothesis** | **Path** | **Coefficient** | **p-value** | **Result** |
|---|---|---|---|---|
| **H1** | TBL→SBM | 0.245 | 0.001 | Supported |
| **H2** | TBL→SO | 0.415 | 0.000 | Supported |
| **H3** | TBL→EO | 0.450 | 0.000 | Supported |
| **H4** | TBL→SO→SBM | 0.136 | 0.000 | Supported |
| **H5** | TBL→EO→SBM | 0.080 | 0.010 | Supported |
| **H6** | EO→SO→SBM | 0.065 | 0.014 | Supported |
| **H7** | DO→SBM | 0.239 | 0.000 | Supported |
| **H7a** | DO×TBL→SBM | -0.091 | 0.150 | Not Supported |
| **H7b** | DO×EO→SBM | 0.002 | 0.490 | Not Supported |
| **H7c** | DO×SO→SBM | 0.153 | 0.024 | Supported |

The findings from this chapter confirm the theoretical model developed in the Literature Review chapter and lay the groundwork for the practical guidance presented in the Discussion chapter. In general, the results highlight the strategic need to combine digital capabilities with sustainability to promote innovation and long-term competitiveness in the AEC sector.

# DISCUSSION

This Chapter synthesises the key empirical findings from the chapter on Analysis and Results and interprets them within the context of established theoretical and conceptual frameworks. It begins by discussing the core results, focusing on how TBL-aligned digital traits influence SBM innovation in the AEC industry.

## 5.1 Discussion of Key Findings

This study investigated the impact of TBL traits on SBM, with EO and SO as mediating mechanisms, and DO as a moderator. The findings from the structural equation modelling and multigroup analysis provide several important insights.

### 5.1.1 TBL's Influence on SBM (H1)

The results confirm that TBL traits have a significant positive effect on SBM ($\beta = 0.245, p = 0.001$), supporting H1. This supports the proposition that digital technologies such as BIM, IoT, and AI—when aligned with sustainability goals—can drive innovation that creates value across economic, environmental, and social dimensions (Bocken *et al.*, 2014; Elkington, 1997).

### 5.1.2 TBL's Influence on SO and EO (H2, H3)

TBL traits positively influenced SO ($\beta = 0.415, p < 0.001$) and EO ($\beta = 0.450, p < 0.001$), confirming H2 and H3. These results suggest that sustainability-aligned digital tools cultivate a culture of innovation and stakeholder engagement (Claudy *et al.*, 2016), reinforcing the synergy between sustainability and entrepreneurship (Vrontis *et al.*, 2022).

### 5.1.3 Mediation Effects (H4, H5, H6)

The mediation analyses revealed significant indirect relationships, consistent with the proposed theoretical model:

- TBL → SO → SBM ($\beta = 0.136$, $p < 0.001$)
- TBL → EO → SBM ($\beta = 0.080$, $p = 0.010$)
- EO → SO → SBM ($\beta = 0.065$, $p = 0.014$)

These findings support the layered mediation model, suggesting that the influence of TBL-aligned digital traits on SBM is not purely direct. Instead, a significant part of this relationship is statistically accounted for by the firm's internal EO and SO. This indicates that EO and SO are crucial mechanisms through which the value of digital sustainability initiatives is associated with innovative business models.

### 5.1.4 DO Direct and Moderating Effects (H7, H7a–H7c)

DO had a significant direct effect on SBM ($\beta = 0.239$, $p < 0.001$), confirming H7. Among the moderation effects, only the interaction between DO and SO was significant ($\beta = 0.153$, $p = 0.024$), suggesting that digital maturity strengthens the relationship between sustainability culture and innovation (Verhoef *et al.*, 2021).

### 5.1.5 Multigroup Analysis: Design vs. Construction

Multigroup comparisons revealed functional differences in how digital-sustainability strategies manifest:

- TBL's influence on EO and SO was significant for the Design group, but the model lacked explanatory power for these constructs in the Construction group, indicating a fundamental difference in strategic drivers.
- DO had a stronger effect on SBM in the Construction group
- Mediation effects were more pronounced among Design professionals, who focus more on early-stage innovation.

The MGA revealed meaningful differences between design and construction professionals. For the Design group, TBL had a pronounced and significant effect on both EO and SO, aligning with their strategic role in early-phase innovation. Critically, however, the model failed to explain the drivers of EO and SO for the Construction subgroup, showing very low $R^2$ values and negative $Q^2$ values, which indicates a lack of predictive relevance. This suggests that for construction professionals, firm-level strategic orientations may be overshadowed by more immediate, project-specific operational pressures such as budget adherence, scheduling, and site logistics.

In contrast, DO had a greater effect on SBM in the Construction group; this indicates that while broad strategic orientations may be less salient for them, the practical, operational integration of digital tools is directly linked to downstream innovation. Mediation effects were also stronger for Design professionals, suggesting a more integrated link between SO and innovation outcomes in design-led roles. These findings highlight the need for tailored transformation strategies across AEC functions and flag the specific drivers of strategic orientation within construction firms as a critical area for future investigation.

## 5.2 Theoretical Contributions

This study makes several meaningful contributions to the theoretical discourse on DT, sustainability, and BMI, particularly within the context of the AEC industry.

First, this study integrates sustainability principles—captured through the TBL framework—into the DT academic discourse, where previous studies have often separated technological advancement from environmental and social outcomes. By empirically validating that digital traits aligned with TBL significantly influence SBM, this study addresses a well-documented gap in the literature (e.g., Bocken *et al.* (2014), Verhoef *et al.* (2021))

Second, the study introduces a novel conceptual model that synthesises five core constructs—TBL, EO, SO, DO, and SBM—into an integrated, higher-order structural framework. This model enables a holistic understanding of how digital capabilities, organisational values, and strategic orientations coalesce to drive sustainable innovation. It contributes to the literature by operationalising these constructs using a combination of reflective–reflective and reflective–formative measurement models, thus offering a scalable and transferable framework for future empirical research.

Third, by highlighting the mediating roles of EO and SO in translating digital sustainability traits into SBM, this study enriches theories related to innovation diffusion, dynamic capabilities, and organisational transformation. It empirically demonstrates that DT is not only a technological process but also a socio-organisational evolution shaped by leadership, culture, and strategic intent. This aligns with and extends existing frameworks on organisational readiness and change management (e.g., Teece (2018); Claudy *et al.* (2016)).

Fourth, this study provides a sector-specific contribution by tailoring its framework to the unique challenges of the AEC industry. The use of multigroup analysis (Design vs. Construction) reveals that the influence of DO and SO varies significantly across professional domains, thereby adding granularity to the understanding of transformation processes in this complex, fragmented sector.

Fifth, this study contributes to the theoretical knowledge by providing a nuanced understanding of how digital and sustainability strategies play out across different organisational roles in the AEC sector. Contrary to the assumption of homogeneity between design professionals (e.g., architects and engineers) and construction professionals (e.g., site managers and contractors) in earlier studies, the multigroup analysis suggests that the two groups imply different dynamics of DO, sustainability engagement, and innovation outcomes. More specifically, TBL had more pronounced effects on EO and SO for the design group, but DO exerted more impact on SBM

Innovation for the construction group. These results offer new insights to the theories of innovation diffusion and digital maturity by demonstrating that professional role mediates the internalisation of digital capabilities and the leveraging of digital capabilities for sustainable innovation.

This differentiated perspective contributes to role-based organisational change theory and suggests the development of finer-grained frameworks that account for intra-industry differences in digitalisation paths.

## 5.3 Practical Implications

The results of this study provide several practical implications for industrial professional, firm leaders, and policymakers who are interested in deploying / scaling DT initiatives for sustainability in the AEC context.

First, the study confirms that aligning digital technologies with sustainability objectives significantly enhances BMI. AEC firms can use the validated TBL-aligned digital traits—such as BIM-enabled cost reduction, AI-assisted safety improvements, and IoT-driven energy efficiency—as a strategic blueprint for operationalising sustainable transformation.

Second, the strong mediating effects of EO and SO emphasise the critical role of internal culture and leadership in achieving transformation. Firms should cultivate a culture that embraces innovation and sustainability by promoting proactive, risk-tolerant behaviour (EO), embedding sustainability into strategic planning and daily operations (SO), and designating digital champions to lead and support change initiatives (DO). This underscores the importance of leadership training and cultural change programs alongside technology implementation.

Third, the findings suggest that the success of DT is significantly moderated by the organisation's DO, particularly in how it enhances the SO impact on SBM. Firms should invest in:

- Continuous digital upskilling programs
- Cross-functional collaboration platforms
- Role-specific training in technologies like BIM, digital twins, and AI

These initiatives not only enhance technical competence but also build the cultural readiness necessary for a successful and sustainable DT.

Fourth, the study also highlights the influence of external factors such as regulatory standards (e.g., ISO 19650) and client demand for green buildings. AEC firms can use these insights to:

- Align innovation strategies with evolving compliance requirements
- Leverage sustainability as a market differentiator
- Build resilience by anticipating environmental and digital compliance landscapes

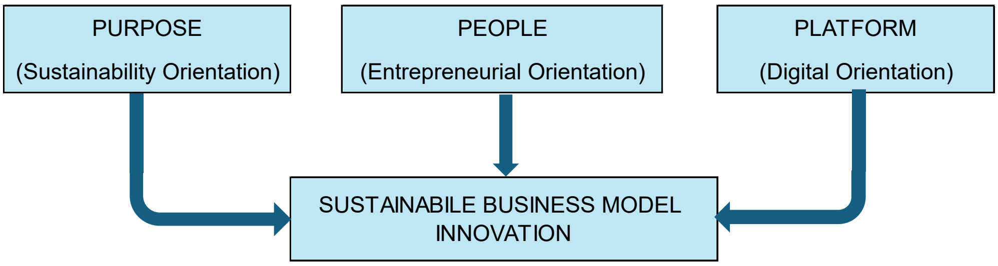
By aligning internal capabilities with external demands, AEC firms can strategically position themselves as leaders in the digital sustainability transition.

Fifth, multigroup analysis shows that design professionals benefit more from TBL-aligned innovation at the strategic and planning level, while construction professionals rely more on executional digital tools. This suggests that transformation strategies should be function-specific, with unique metrics, training, and support systems for different roles within the value chain.

## 5.4 The 3P Model

In response to the increasing demand for integrating sustainability into DT strategies, this study introduces a memorable and actionable strategic model—the 3P Model. Based on the complex empirical findings, the model distils the essential organisational enablers for the successful execution of SBM innovation in the AEC by Schaltegger *et al.* (2016). The 3P model (Figure 5.1) aims to be theoretically rigorous, yet informative, providing a roadmap for how organisations can address the convergence of DT and sustainability.

Figure 5.1 – Visual Representation of the 3P Model




### 5.4.1 Empirical Support

The findings from pervious Chapter, Analysis and Results provide strong empirical support for the 3P model:

- Sustainability Orientation (Purpose) was found to significantly mediate the relationship between TBL and SBM ($\beta = 0.245$, $p < 0.001$), confirming its central role as a value-driven enabler of innovation.

- Entrepreneurial Orientation (People) also significantly influenced SO and SBM, suggesting that a culture of innovation feeds into a sustainability mindset (EO → SO: $\beta = 0.198$, $p < 0.050$; EO → SBM: $\beta = 0.178$, $p < 0.010$), supporting a sequential path from EO to SO to SBM.

- Digital Orientation (Platform) was found to significantly moderate the relationship between SO and SBM ($\beta = 0.328$, $p < 0.001$), reinforcing the role of digital maturity in scaling sustainability-driven innovation efforts.

### 5.4.2 Overview of the 3P Model

The 3P model identifies three critical enablers that drive SBM Innovation:

- Purpose — Represented by SO: Purpose reflects the organisation's long-term commitment to environmental and social value creation. It encompasses the alignment of corporate values, mission, and operations with sustainability principles (Claudy *et al.*, 2016).

- People — Represented by EO: People refer to the internal culture, leadership, and capability to initiate and manage innovation. EO reflects a firm's risk-taking, proactiveness, and innovativeness (Covin and Slevin, 1989).
- Platform — Represented by DO: This model conceptualizes 'Platform' not merely as technological infrastructure, but as the strategic readiness required to make it effective. Therefore, it is represented by DO, which encompasses the vision, commitment, and capability to transform disparate technologies such as BIM, AI, and IoT into a cohesive, value-generating business asset (Khin and Ho, 2019; Van Zeebroeck *et al.*, 2023).

Together, these three enablers form a pathway toward SBM, where Purpose provides direction, People energise and mobilise the organisation, and Platform provides the tools and structure for execution.

These results confirm that organisations with strong sustainability values, entrepreneurial cultures, and digital capabilities are significantly more likely to innovate their business models in alignment with Triple Bottom Line principles. This model reflects a streamlined yet evidence-based pathway, grounded in the outcomes of this study and relevant literature.

### 5.4.3 Strategic Implications

The 3P2SBMI model offers a clear and actionable framework for AEC firms seeking to embed sustainability into DT strategies. The model can be used as a diagnostic tool, strategic roadmap, or communication framework, making it highly adaptable across organisational levels.

- *For executives and managers,* the model provides a lens to assess organisational readiness across three critical dimensions.

- *For change agents and innovation leaders,* it highlights where cultural and strategic shifts are needed to enable SBM.
- *For policymakers and industry bodies,* it offers a foundation for designing capability-building programs aligned with national sustainability goals.

### 5.4.4 Theoretical Contributions

The 3P model contributes to the literature by integrating organisational orientation theories (Covin and Slevin, 1989; Lumpkin and Dess, 1996), SO (Claudy *et al.*, 2016), and dynamic capabilities theory (Teece, 2018) into a practical framework for SBM innovation. It emphasises that technological tools alone do not drive innovation—they must be supported by a shared purpose and empowered people. The 3P model offers a simplified and actionable model that synthesises the essential enablers of SBM innovation in the AEC context. Grounded in empirical evidence and aligned with contemporary theory, provides a valuable guide for organisations seeking to align their DT with sustainability imperatives in a coherent, strategic, and human-centric way.

## 5.5 TBL Digital Traits - Organisational Capability Matrix

To extend the theoretical contribution and practical relevance of this study, a strategic typology through the intersection of two robust dimensions: TBL Digital Traits and Organisational Capabilities which is here conceptualised as the combine strategic presence of SO and EO. This 2x2 matrix (Figure 5.2) serves as both a diagnostic tool and a strategic roadmap for classifying AEC firms based on their readiness to innovate business models in support of TBL outcomes.

Figure 5.2 – Proposed TBL Digital Traits - Organisational Capability Matrix

| | **Low TBL Digital Traits** | **High TBL Digital Traits** |
|---|---|---|
| **High Organisational Capability** | **Sustainability Reformers**<br><br>Strong internal capabilities but lacking digital transformation aligned with TBL principles. integration. | **Sustainable Innovators**<br><br>High TBL-aligned digital traits and strong organisational capabilities. Well-positioned for SBM |
| **Low Organisational Capability** | **Conventional Operators**<br><br>Low on both dimensions. Minimal readiness for sustainability-driven innovation. | **Tech-Efficiency Seekers**<br><br>Digitally mature in TBL terms but lacking the strategy and cultural orientation for sustainability. |

*Construction of the Matrix:*

- TBL Digital Traits (TBL): Aggregated from DT items reflecting environmental, social, and economic sustainability alignment (e.g., smart resource use, carbon reduction, social impact).
- Organisational Capability (OC): Derived by averaging EO and SO scores, capturing a firm's internal culture, strategic orientation, and sustainability practices.

This typology is grounded in the empirical findings reported in Chapter Analysis and Results, where both SO ($\beta = 0.328$, $p < 0.001$) and EO ($\beta = 0.178$, $p < 0.01$) were found to be significant direct predictors of SBM innovation. Their individual contributions suggest that firms require both a clear sustainability culture and a proactive, risk-taking approach to effectively innovate their business models in response to digital and environmental pressures.

### 5.5.1 Quadrant Descriptions

1. *Sustainable Innovators* (High TBL, High OC)

   Firms scoring high on both TBL and OC. These firms demonstrate integrated digital-sustainability strategies and are best positioned for SBM innovation.

2. *Tech-Efficiency Seekers* (High TBL, Low OC)

   Firms with strong digital TBL traits but weak internal sustainability cultures. Likely to adopt green technologies without embedding sustainability in strategy or values.

3. *Sustainability Reformers* (Low TBL, High OC)

   High internal orientation toward sustainability and entrepreneurship, but low TBL digital maturity. These firms may lack the digital infrastructure to realise their ambitions.

4. *Conventional Operators* (Low TBL, Low OC)

   Low on both dimensions. These firms are the least prepared for sustainability transitions and may be vulnerable to future regulatory or market shifts.

### 5.5.2 Strategic Use of the Matrix

*For Practitioners:*

- Self-assessment: Firms can locate themselves in the matrix by evaluating their current digital practices (aligned with TBL) and their strategic posture (OC).
- Roadmap guidance: The matrix can help identify which capability dimension—digital or strategic—needs development to move toward the “Strategic Innovator” position.

*For Researchers:*

- Typological classification: Researchers can segment AEC firms using mean scores or composite indices of TBL digital traits and OC.

- Comparative analysis: This typology can support comparative testing of SBM, innovation performance, or ESG outcomes across strategic firm types.

## 5.6 The 3P2SBMI Framework

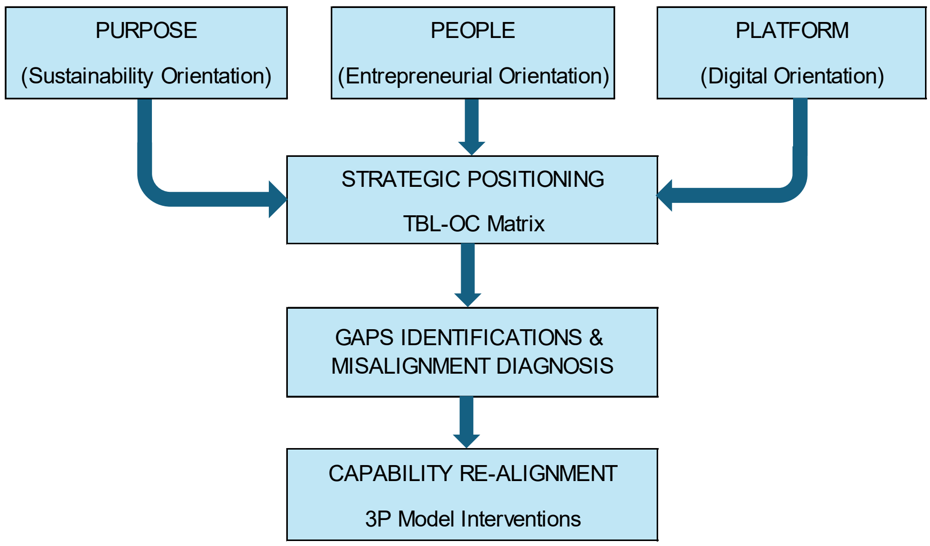
To translate the conceptual and empirical results in a practical roadmap, this section introduces 3P2SBMI Evolutionary Framework (Figure 5,3) as a dynamic four-stage process, which supports AEC firms diagnosing, positioning, and realigning their strategic capabilities for SBM innovation. A model with the recognition that digital and sustainability transformation is neither one-size-fits-all, nor a linear process with a clear starting and end point, but as an interactive process.

DT is widely regarded as a continuous and iterative analysis of endogenous and exogenous contingencies (Angelopoulos *et al.*, 2023), and transformation success hinges on endogenous indicators such as leadership, information quality, disciplined execution, and technology readiness (Struijk *et al.*, 2023). These insights support the underpinning of the 3P model (People, Process, and Platform) on which this study is based for capability assessment and targeted intervention (see Section 5.4). Therefore, the 3P2SBMI framework provides a structured approach through which firms can iteratively develop and align their internal systems to support scalable, sustainability-driven innovation.

### 5.6.1 Four Stages of 3P2SBMI Framework

The 3P2SBMI evolutionary framework consists of 4 stages, which together make a closed-loop learning and improvement cycle customised to the transformation conditions in the AEC industry.

Figure 5.3 – 3P2SBMI Framework




*Stage 1: Internal Capability Assessment via the 3P Model*

The process begins with 3P model for a diagnostic of the firm's people, process and platform (3P) capabilities, evaluated in relation to the firm's strategic orientations — DO, SO, and EO. This step identifies whether the foundational capabilities are in place to support sustainable innovation.

- People: Leadership mindset, cross-functional collaboration, and digital literacy.
- Process: Innovation routines, ESG integration, and strategic agility.
- Platform: Digital infrastructure, data systems, and technology adaptability.

This assessment helps firms uncover capability gaps across the internal enablers that are critical to effective digital and sustainability transformation.

*Stage 2: Strategic Positioning via the TBL - OC Matrix*

In this stage, the firm is positioned on the TBL - OC matrix (see Section 5.5). This step evaluates how well internal capabilities are translating into external sustainability performance, based on:

- The extent to which digital tools and practices are aligned with Triple Bottom Line (TBL) goals.
- The strength of OC operationalised through the combination of SO and EO.

This matrix classifies firms into one of four strategic profiles (e.g., Strategic Innovators, Sustainability Reformers), providing a high-level view of the firm's transformation maturity.

*Stage 3: Gap Identification and Misalignment Diagnosis*

This stage compares the outcomes from Stage 1 and Stage 2 to identify misalignments between internal capabilities and strategic outcomes. This allows firms to diagnose whether performance gaps stem from executional weaknesses, governance fragmentation, or lack of strategic alignment.

For example:

- A firm may have advanced platforms but limited agility in processes or leadership support, undermining its ability to deliver TBL value.
- Conversely, a firm with strong sustainability and entrepreneurial intent may lack the digital infrastructure to scale or operationalise its goals.

This stage is vital for uncovering the root causes of underperformance in transformation efforts.

*Stage 4: Capability Re-alignment through 3P Interventions*

In the final stage, the 3P model is re-applied as a targeted intervention framework to close the gaps identified in Stage 3:

- Purpose: Redesign workflows to embed ESG criteria, improve innovation routines, and enhance coordination.

- People: Strengthen leadership, build digital and sustainability competencies, and foster a transformation-driven culture.
- Platform: Upgrade or integrate digital tools to support data-driven sustainability tracking, lifecycle analysis, and decision-making.

This stage reinforces the continuous and adaptive nature of transformation, enabling firms to cycle back to Stage 1 and begin a new round of strategic capability development.

In conclusion, the 3P2SBMI Framework provides a structured, theory-based, and action-oriented guideline for AEC enterprises endeavouring to develop the digital and sustainability transformation capability. The 3P model is enriched and clarified by its synthesis with a dynamic theory of transformation and strategic positioning and offers both diagnostic and strategic insights. It enables companies to progress from ad hoc or one-off initiatives to a structured and scalable approach to SBM innovation.

### 5.6.2 Implications for Researchers and Policy Makers

*For Researchers:*

- Provides a structured, empirically grounded framework for studying digital and sustainability transformation processes.
- Enables longitudinal and comparative studies across firms, projects, or sectors.
- Offers a basis for quantitative model testing and mixed-method research on SBM innovation and capability alignment.
- Bridges micro-level (organisational) and macro-level (industry/systemic) transformation analysis.

*For Policy Makers:*

- Serves as a diagnostic tool to assess industry readiness for digital sustainability transitions.
- Informs the design of policy interventions targeting human capital, process innovation, and digital infrastructure.

- Supports national or regional strategies related to net-zero, circular economy, and ESG compliance in the AEC industry.
- Can be applied to public-private partnerships and funding programs aimed at capability development.

### 5.6.3 Theoretical Contributions

- Conceptualises DT as a continuous, iterative process aligned with Angelopoulos *et al.* (2023).
- Extends the 3P model (People, Process, Platform) as a practical application of enablers.
- Integrates internal capability assessment with external strategic positioning, bridging the gap between organisational readiness and innovation outcomes.
- Contributes to the SBMI literature by linking strategic orientations (DO, SO, EO) to a staged transformation pathway.
- Provides a scalable, adaptable framework that can inform future research on sustainability-driven DT across industries.

## 5.7 Limitations

While the theoretical contribution and practical implication of this study are valuable and important, there are some limitations of this study. Acknowledging these limitations bolsters the transparency, replicability, and trustworthiness of the research and provides a foundation for developing future research.

### 5.7.1 Methodological Limitations

This study employed a robust quantitative design; however, several methodological limitations may affect the validity, reliability, and generalisability of the findings. These limitations pertain to aspects of research design, sampling strategy, measurement techniques, and statistical procedures.

First, a cross-sectional survey design was used in the study, which was conducted at one time point. Though this is fine for associating variables, it does not allow establishing causality or time-series tracking of organisational transformation. For example, although the findings indicate that EO and SO partially mediate the association between TBL digital traits and SBM innovation, the causal sequence of such relationships cannot be unambiguously established. Longitudinal or panel designs in future studies should focus more on how these dynamics evolve and how the dynamics help sustain each other over time.

Second, the dataset was only sampled from AEC practitioners practicing in the most densely populated urban economy in Hong Kong with its unique governance regime, maturity of technology, and sustainability requirements (e.g. BEAM Plus, ISO 19650). This is valuable context which however may reduce the generalisability of findings to other sites with divergent institutional, economic, or cultural settings. Digital maturity and SO could be very different in other Western developed countries or rural construction markets. Hence, further research is required to replicate this framework in other countries to test its generalisability.

Third, the study adopted convenience (purposeful) sampling, focusing on AEC professionals with mid to senior-level experience, including architects, construction engineers, and predominantly BIM professionals. While this approach enhances relevance and data quality, it may introduce selection bias. Respondents are likely more aware of sustainability and digitalisation issues than average, which could lead to an overestimation of correlations. Moreover, the sample may not sufficiently represent small businesses, subcontractors, or other participants with low digital maturity. Employing a more stratified or random sampling method could improve external validity. Additionally, the use of a single, self-administered questionnaire for all variables at one point in time introduces potential CMB, which can inflate observed correlations and further affect the robustness of the findings.

Fourth, the study is based on self-reported survey data of AEC professionals; thus, it is vulnerable to biases such as social desirability bias or recall bias. Respondents may unintentionally overstate claims about their organisation's level of digital maturity or their adherence to practices of sustainability to match what they perceive as desirable, biasing the findings. Such a subjective perception of performance, instead of objective measuring of performances, restricts the ability of the study to verify relationships between constructs. A future area for consideration could involve triangulation of findings using objective sources (e.g. organisational performance data, case studies) to increase the rigour.

Fifth, although the Kaiser criterion based on eigenvalues greater than 1 suggested the retention of 10 components, this study employed a fixed-factor extraction of 13 components grounded in a strong theoretical framework. The rotated component matrix revealed high factor loadings (primarily above 0.70) with minimal cross-loadings, and each construct demonstrated clear empirical distinctiveness. As such, the decision to retain 13 factors is methodologically defensible (Fabrigar *et al.*, 1999). Nevertheless, such an approach should be also acknowledged as a methodological limitation of this study, and future research with a larger and more diverse sample is recommended to further validate the 13-factor structure and reinforce the model's empirical foundations.

Finally, the study lies in the application of a two-stage approach in the PLS-SEM analysis, whereby latent variable scores were generated from the initial model and subsequently used as indicators to construct higher-order constructs. Although this technique is consistent with established guidelines for handling complex hierarchical models in PLS-SEM (Hair *et al.*, 2022), it may be interpreted as a form of "second factor analysis". As such, this analytic sequence could introduce a degree of conceptual or statistical disconnection between the first-order constructs and their higher-order representations. Future research, therefore, could consider extracting and applying factor scores directly from the initial analysis, provided that this aligns with the theoretical definition and measurement structure of the constructs involved.

### 5.7.2 Conceptual Limitations

Beyond methodological concerns, the study also faces conceptual limitations that relate to theoretical assumptions and model design. These limitations highlight potential issues in construct alignment, model directionality, and the dynamic nature of contextual variables

First, the multigroup analysis revealed a key limitation. The model's relatively weak predictive power for the smaller Construction subgroup creates ambiguity, making it unclear whether this reflects a genuine theoretical misspecification or a statistical artifact due to low power. Future research must therefore use larger samples for this group while also testing alternative models that account for the project-based drivers unique to the construction function.

Second, another potential limitation concerns the conceptual proximity of the independent and dependent constructs, all of which are grounded in the sustainability domain— TBL, SO, and SBM innovation. While these constructs were carefully developed and validated as theoretically and empirically distinct, their thematic alignment may give rise to concerns about potential conceptual circularity. Future research could further validate the construct structure and confirm the directionality of relationships.

Third, the model assumes alignment among the TBL dimensions—Profit, People, and Planet—without explicitly addressing real-world trade-offs. In practice, organizations may implement digital innovations that improve environmental outcomes but come at a financial cost or impact employment. This study does not directly account for such tensions, which could limit the model's practical applicability. Future research could examine how firms manage these trade-offs in different strategic or industry contexts.

Fourth, the framework assumes that all relationships between constructs are unidirectional. Although some constructs were theoretically positioned to minimize concerns about reverse causality, many of these relationships are likely to be reciprocal in practice. For instance, the outcomes of SBM innovation could potentially reshape organizational orientations and TBL traits. These reciprocal dynamics could not be captured within the cross-sectional design. Future research could apply longitudinal or systems thinking approaches to better capture these dynamic, iterative relationships.

Finally, while modelled as a contextual factor, DO may itself evolve as a result of engaging in sustainability-driven digital innovation. This challenges its independence as a moderator and relates to the broader concern that the model assumes one-way causal paths, potentially overlooking dynamic feedback effects. Future research could consider alternative model structures or longitudinal designs to capture these interdependencies.

## 5.8 Directions for Future Research

Based on the present results and the limitations outlined above, several prospects for future research are proposed. These directions aim to enhance theoretical understanding, improve methodological rigor, and strengthen the practical applicability of the 3P2SBMI Framework.

First, future research should adopt longitudinal designs to capture the temporal evolution of digital-sustainability transformation. This would allow scholars to examine how firms move across the quadrants of the TBL-OC Matrix, how the 3P enablers develop over time, and how SBM outcomes evolve in response to internal and external stimuli. Process-based case studies could also uncover the organisational routines, leadership decisions, and learning mechanisms that underpin successful transformation.

Second, while the current study used quantitative methods to validate structural relationships, qualitative research can offer richer insights into the "how" and "why" behind these relationships. For example, in-depth interviews with AEC leaders might reveal how sustainability values are communicated internally or how digital platforms are integrated into everyday workflows. Ethnographic or action research could also be used to track real-time implementation of SBM initiatives in project settings.

Third, replicating the study in other geographical regions (e.g., Europe, Southeast Asia, Middle East) would test the cultural and institutional robustness of the 3P2SBMI framework. Additionally, extending the research to other project-based industries—such as infrastructure, oil and gas, or manufacturing—would determine whether the enablers and typologies hold in different organisational ecosystems. Such comparative research could reveal sector-specific drivers or inhibitors of digital-sustainability integration.

Fourth, must address the ambiguity in the multigroup analysis. The primary goal is to determine if the model's failure for the smaller construction subgroup is a statistical artifact or a substantive finding. This requires a dual approach: first, securing a larger sample of construction professionals to ensure statistical validity, and second, testing alternative models that incorporate the project-level drivers unique to the construction function. This will clarify the model's limitations and help build more accurate theories for the industry.

Fifth, while this study focused on EO and SO as mediators and DO as a moderator, future research could explore alternative or complementary constructs, such as:

- Organisational Agility: The ability to rapidly adapt to digital or environmental changes.
- Leadership Commitment: The role of top management advocacy in driving SBM.
- Collaborative Capabilities: How partnerships across the value chain influence transformation.
- Sustainability Maturity Models: Integrating stage-based models to assess progression.

These variables could deepen the understanding of multi-level influences on SBM and refine the predictive power of the model.

Finally, future work could focus on translating the 3P2SBMI Framework into practical assessment instruments:

- Organisational self-diagnostic surveys
- Benchmarking tools for strategic positioning
- Maturity models for digital-sustainability alignment

Such instruments would be valuable for both research and industry application, particularly if tested across multiple firms and validated statistically.

## 5.9 Conclusion

This study set out to explore the determinants of DT for SBM innovation in the AEC industry. In response to escalating demands for environmental performance, client value, and operational efficiency, the study sought to understand how AEC firms can align digital technologies with sustainability goals to reconfigure their business models. The research was guided by the overarching question: *What are the key organisational and technological determinants of DT that enable sustainable BMI in the AEC industry?*

### 5.9.1 Revisiting the Four Key Objectives

1. To identify and evaluate technological determinants—such as BIM, AI/ML, IoT, and VR/AR—that facilitate or hinder DT in the AEC sector, particularly in relation to sustainability goals.
2. To examine key organisational factors, including leadership commitment, organisational culture, entrepreneurship, and workforce capabilities, that influence the readiness and effectiveness of DT initiatives
3. To investigate the mechanisms through which DT enables SBM Innovation, with a focus on how digital maturity interacts with organisational practices to reshape business operations in the AEC context.

4. To develop and validate a comprehensive conceptual framework that integrates both technological and organisational determinants to guide AEC firms in aligning DT with sustainability-driven innovation strategies.

Through a quantitative research approach, incorporating quantitative data collected from 158 mid- to senior-level professionals in Hong Kong's AEC sector, this research has made meaningful progress in addressing the stated objectives. The findings contribute valuable empirical insights to the academic literature on DT and sustainable BMI, while also offering practical guidance for AEC firms navigating the complexities of technological and sustainability-driven change.

### 5.9.2 Revisiting the Research Gaps

In addition to achieving the research objectives, this research also directly contributed to addressing five specific research gaps identified in Literature Review Chapter. Below review each gap and demonstrate how the findings of this study contribute to closing them.

#### *5.9.2.1 Research Gap 1*

*Role of Emerging Technologies in Sustainable Business Model Innovation*

This research supported that the digital traits of TBL-aligned technology including BIM, IoT and AI/ML and DT contribute to enhancing SBM innovation. Rather than considering that digital tools are simply operational enablers, they can be seen to be driving innovation that is aligned with TBL values, which benefits the environment, society and economy. This contribution recasts emerging technologies as strategic enablers of sustainability-deepening innovation, not in what they do, but in what they are for.

#### *5.9.2.2 Research Gap 2*

*Interplay Between Digital Strategy, Corporate Entrepreneurship, and Sustainability Practices*

The findings offer evidence that DO, EO and SO are not independently active, rather they synergistically combine, interact and affect SBM. Independent roles for EO and SO as mediators of TBL effects were identified and DO emerge both as a direct determinant of SBM and a moderator of the SO → SBM relationship. Such findings contribute toward a resource-based view of transformation, suggesting that digital strategies need to be embedded within an entrepreneurial culture and value of sustainability to fully stimulate innovation.

#### *5.9.2.3 Research Gap 3*

*Differences Between Architects and Construction Teams in DT and SBM*

This study, using multi-group analysis, revealed significant differences between Design and Construction professionals in their road maps to SBM. Designers showed higher mediation through EO and SO, suggesting a larger involvement in strategic and radical innovation. In contrast, Construction professionals exhibited relatively higher reliance on DO for performance outcomes. These findings highlight the importance of tailoring role-specific strategies for DT, addressing a gap in the literature that had hitherto considered AEC sector as one homogeneous category.

#### *5.9.2.4 Research Gap 4*

*Integration of Sustainability Orientation with Entrepreneurial and Digital Orientations*

Although the previous work usually investigated SO and EO separately, this paper provides an integrated model that reveals the relationship between them to facilitate SBM. The findings verify serial mediation of the relationship of TBL attributes via EO and SO and confirm the differences in the strength of the relationships with DO. This integrated view provides an enriched view on how values, capabilities and strategies co-evolve to foster sustainable innovation, pushing forward theoretical debates on orientation interactions in transformation processes.

#### *5.9.2.5 Research Gap 5*

*Lack of a Comprehensive Framework for TBL-Aligned DT*

This paper introduced and empirically tested a holistic model that connects digital traits TBL-oriented with SBM mediated by EO, SO and DO. Through the integration of reflective–formative together with higher-order modelling using PLS SEM, the model is able to express both the structural complexity and strategic interrelations of DT. This integrated framework offers a scalable and transferable approach for future research and practice, directly addressing previous calls for systemic thinking in AEC sustainability transitions. It advances beyond existing fragmented models by offering a cohesive and empirically validated structure.

### 5.9.3 Strategic and Theoretical Contributions

The study introduced a simplified yet robust model—the 3P Pathway to SBM—which identifies three core enablers: Purpose (SO), People (EO), and Platform (DO). This model offers a clear and actionable framework for assessing and enhancing organisational readiness for SBM. Additionally, a 2x2 TBL-OC Readiness Matrix was developed to classify firms based on their strategic alignment and maturity, offering diagnostic and comparative value for both researchers and practitioners.

These models were further integrated into the 3P2SBMI Framework, which connects internal enablers with external strategic positioning. This integrative framework offers a comprehensive roadmap for AEC firms seeking to align DT with sustainability outcomes in a coherent and phased manner.

From a theoretical perspective, the study contributes to the literature on dynamic capabilities, organisational readiness, and sustainability-oriented innovation by demonstrating how digital, entrepreneurial, and sustainability orientations interact to produce transformational outcomes. It also advances sector-specific knowledge by contextualising these dynamics within the project-based and multidisciplinary environment of the AEC industry.

### 5.9.4 Implications for Practice and Policy

The findings offer actionable insights for industry leaders, consultants, and policymakers:

- AEC firms should assess their current orientation across the 3P dimensions and strategically address capability gaps.
- Function-specific transformation strategies should be developed to reflect the differing needs of design and construction roles.
- Policymakers and industry bodies can use the 3P2SBMI framework to design capacity-building initiatives and regulatory incentives that promote digital-sustainability alignment.

### 5.9.5 Reflections on Limitations and Future Research

This study has openly recognised its methodological and conceptual limitations and potential sources of bias, such as selection bias, self-reporting, social desirability, CMB, and the contextual specificity of Hong Kong's AEC sector. While purposeful sampling and a cross-sectional survey have provided valuable insights, these approaches may limit the generalisability and causal interpretation of the results.

To address these concerns, the research implemented several strategies: engaging multiple professional bodies for sampling, ensuring respondent anonymity, using neutral and clearly worded questions, varying scale anchors and formats, and applying EFA and VIF to assess and minimise CMB.

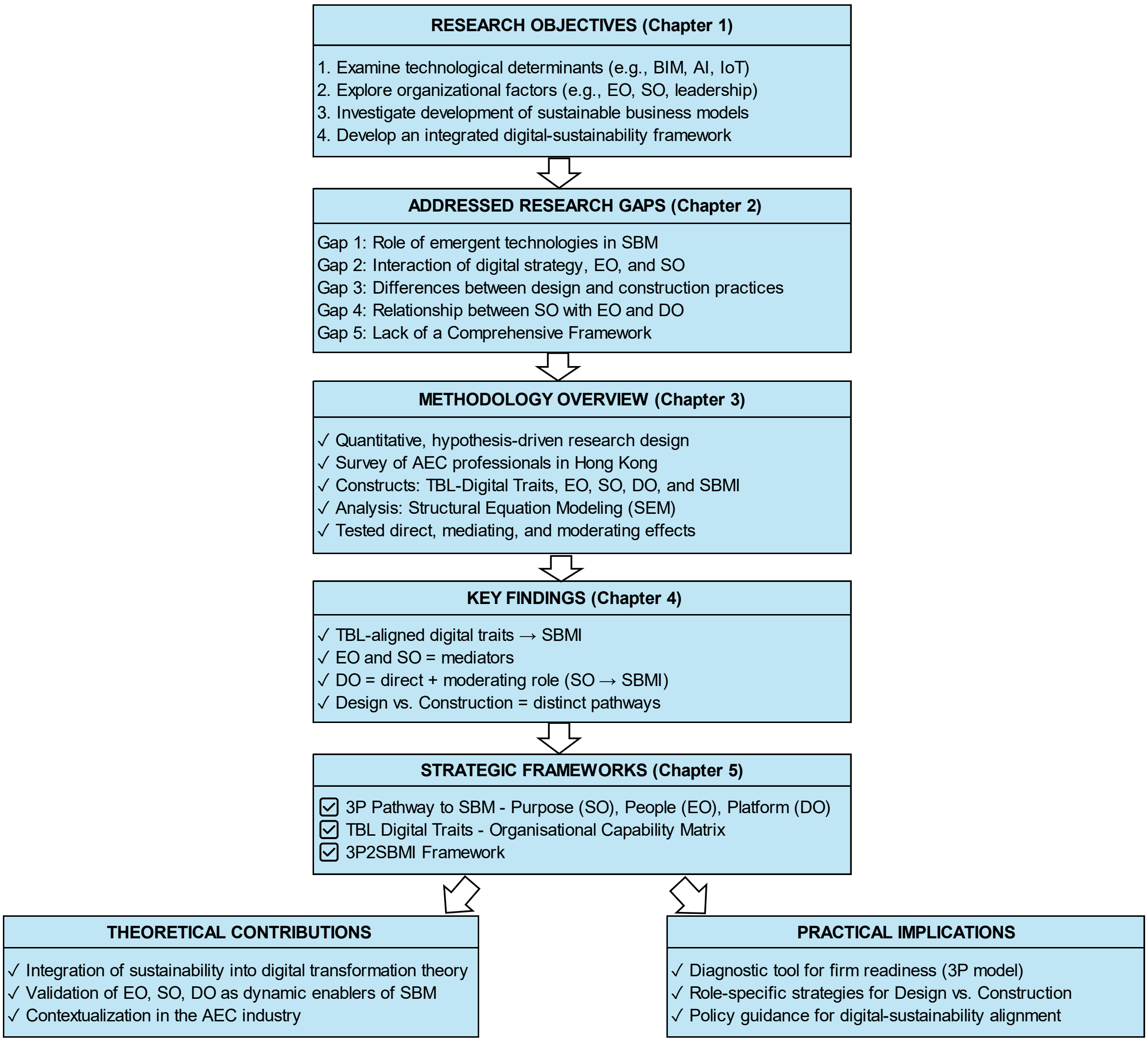
Looking ahead, future research should consider longitudinal or mixed-method designs, integrate objective performance measures, and expand to broader and more diverse samples across different regions and industry segments. By critically reflecting on these limitations and setting out clear directions for future inquiry, this study increases transparency and lays a strong groundwork for further validation and extension of the 3P2SBMI framework in a variety of contexts.

In addition to methodological considerations, this study has also acknowledged several conceptual limitations related to model structure, construct alignment, and theoretical assumptions. These include the possibility of conceptual overlap between sustainability-oriented constructs, the assumption of unidirectional relationships, and the treatment of dynamic constructs like DO as static moderators. Addressing these conceptual concerns, future research should explore reciprocal and feedback effects, refine construct definitions to reduce thematic redundancy, and test alternative model configurations using systems thinking or longitudinal approaches. By doing so, scholars can further strengthen the theoretical robustness and practical relevance of the 3P2SBMI framework across diverse organisational and sectoral contexts.

### 5.9.6 Visual Summary of Conclusions

To consolidate the key research objectives, findings, theoretical contributions, and practical implications, the Figure 5.4 conceptual map provides a visual summary of the study's overall contributions. This figure visually summarises the research objectives, addressed gaps, key findings, strategic models, and the resulting theoretical and practical contributions. It offers a synthesised overview of the study's scope and outcomes while serving as a roadmap for future academic and industry applications.

Figure 5.4 – Conceptual Map of Research Conclusions



### 5.9.7 Closing Reflection

This study set out to explore how DT can enable SBM innovation in the AEC industry. Grounded in the Hong Kong context, it developed and validated a comprehensive framework integrating technological traits (TBL), organisational capabilities (EO and SO), and strategic intent (DO). The findings highlight the critical interplay between these factors in shaping innovation outcomes and offer a clear roadmap for firms navigating digital-sustainability transitions. The study contributes to theory and practice by demonstrating that DT must be more than a technological upgrade—it must be purpose-driven, people-enabled, and strategically integrated. The 3P Model, TBL-OC Matrix and 3P2SBMI Framework provide actionable models for firms to assess, plan, and implement transformation initiatives. As the AEC industry faces increasing pressure to respond to climate change, resource constraints, and digital disruption, this study reinforces the urgency of aligning sustainability and digital strategies. It also underscores the importance of internal capabilities—entrepreneurial mindset, sustainability culture, and digital readiness—as levers for long-term value creation. Ultimately, this study advances the discourse on SBM innovation within project-based industries and offers a timely, evidence-based foundation for future academic inquiry, industry transformation, and policy design. In an era where sustainability is no longer optional and digitalisation is inevitable, the integration of both is not just a strategic advantage—it is a necessity.

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# APPENDIX A – QUESTIONNAIRE

## Organisational Practices for Digital Transformation and Sustainability in the AEC Industry

**You are invited to participate in a confidential academic research study conducted by a Doctor of Business Administration (DBA) candidate at Durham University Business School** (www.durham.ac.uk/business), under academic supervision.

The purpose of this survey is to explore **Organisational Practices for Digital Transformation and Sustainability** in Hong Kong's Architecture, Engineering, and Construction (AEC) sector. There are no right or wrong answers. Please respond honestly based on your knowledge and experience.

**Your participation is voluntary**, and you may withdraw at any time before submitting the survey. Your responses will be treated with the **strictest confidentiality** and will be **anonymised and aggregated** for analysis. No personally identifiable information (e.g., your name, email, or phone number) will be collected, and individual responses will not be reported.

The survey should take approximately **10 to 15 minutes** to complete.

If you have any questions about the research or your rights as a participant, please contact the researcher, **Mr. Tong**, at **s.y.tong@durham.ac.uk** or call **(852) 9388-1383**.

**Thank you for your time and valuable contribution to this study.**

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### Part A - Digital Practices in Your Organisation

This section focuses on how your organisation uses digital technologies to support environmental, social, and financial goals.

1. The extent to which BIM and AI technologies modify design accuracy and reduce rework frequency.
    - To a Great Extent
    - To a Significant Extent
    - To a Considerable Extent
    - To a Moderate Extent
    - To a Small Extent
    - To a Minimal Extent
    - Not at All

2. The degree to which BIM and Big Data analytics transform resource utilisation efficiency.
    - To a Great Extent
    - To a Significant Extent
    - To a Considerable Extent
    - To a Moderate Extent
    - To a Small Extent
    - To a Minimal Extent
    - Not at All

3. How significantly 3D printing technology alters material waste levels in manufacturing processes.
    - To a Great Extent
    - To a Significant Extent
    - To a Considerable Extent
    - To a Moderate Extent
    - To a Small Extent
    - To a Minimal Extent
    - Not at All

4. The extent to which digital platforms improve collaboration among project stakeholders.
    - To a Great Extent
    - To a Significant Extent
    - To a Considerable Extent
    - To a Moderate Extent
    - To a Small Extent
    - To a Minimal Extent
    - Not at All

5. How VR/AR and ML technologies impact safety incident rates and hazard identification.
    - To a Great Extent
    - To a Significant Extent
    - To a Considerable Extent
    - To a Moderate Extent
    - To a Small Extent
    - To a Minimal Extent
    - Not at All

6. The extent to which digital skills development programs enhance employee competencies.
    - To a Great Extent
    - To a Significant Extent
    - To a Considerable Extent
    - To a Moderate Extent
    - To a Small Extent
    - To a Minimal Extent
    - Not at All

7. How energy simulation tools influence the environmental footprint of project designs.
    - To a Great Extent
    - To a Significant Extent
    - To a Considerable Extent
    - To a Moderate Extent
    - To a Small Extent
    - To a Minimal Extent
    - Not at All

8. The extent to which BIM, IoT sensors, and digital twins impact energy and material usage.
    - To a Great Extent
    - To a Significant Extent
    - To a Considerable Extent
    - To a Moderate Extent
    - To a Small Extent
    - To a Minimal Extent
    - Not at All

9. How digital asset management systems influence the operational lifespan of building components?
    - To a Great Extent
    - To a Significant Extent
    - To a Considerable Extent
    - To a Moderate Extent
    - To a Small Extent
    - To a Minimal Extent
    - Not at All

### Part B – Business Model in Your Organisation

Questions in this section explore how your company develops innovative and sustainable ways of doing business.

1. Our customer base prioritises sustainability-focused projects.
    - To a Great Extent
    - To a Significant Extent
    - To a Considerable Extent
    - To a Moderate Extent
    - To a Small Extent
    - To a Minimal Extent
    - Not at All

2. We have transformed offerings to reduce environmental/social impacts.
    - To a Great Extent
    - To a Significant Extent
    - To a Considerable Extent
    - To a Moderate Extent
    - To a Small Extent
    - To a Minimal Extent
    - Not at All

3. We are recognised as a sustainable solutions leader.
    - To a Great Extent
    - To a Significant Extent
    - To a Considerable Extent
    - To a Moderate Extent
    - To a Small Extent
    - To a Minimal Extent
    - Not at All

4. We have developed specialised sustainability innovation capabilities.
    - To a Great Extent
    - To a Significant Extent
    - To a Considerable Extent
    - To a Moderate Extent
    - To a Small Extent
    - To a Minimal Extent
    - Not at All

5. We continuously optimise operations for sustainability performance.
    - To a Great Extent
    - To a Significant Extent
    - To a Considerable Extent
    - To a Moderate Extent
    - To a Small Extent
    - To a Minimal Extent
    - Not at All

6. We co-develop solutions through green technology partnerships.
    - To a Great Extent
    - To a Significant Extent
    - To a Considerable Extent
    - To a Moderate Extent
    - To a Small Extent
    - To a Minimal Extent
    - Not at All

7. We mandate sustainability certification for suppliers.
    - To a Great Extent
    - To a Significant Extent
    - To a Considerable Extent
    - To a Moderate Extent
    - To a Small Extent
    - To a Minimal Extent
    - Not at All

8. We generate significant revenue from sustainable offerings.
    - To a Great Extent
    - To a Significant Extent
    - To a Considerable Extent
    - To a Moderate Extent
    - To a Small Extent
    - To a Minimal Extent
    - Not at All

9. Our cost structures emphasise long-term resource efficiency.
    - To a Great Extent
    - To a Significant Extent
    - To a Considerable Extent
    - To a Moderate Extent
    - To a Small Extent
    - To a Minimal Extent
    - Not at All

### Part C – Entrepreneurial Mindset in Your Company

These questions focus on how your company encourages innovation, takes risks, and identifies new opportunities.

1. We actively introduce improvements and innovations in our business.
    - Strongly Agree
    - Agree
    - Somewhat Agree
    - Neutral
    - Somewhat Disagree
    - Disagree
    - Strongly Disagree

2. Our business is creative in its methods of operation.
    - Strongly Agree
    - Agree
    - Somewhat Agree
    - Neutral
    - Somewhat Disagree
    - Disagree
    - Strongly Disagree

3. Our business seeks out new ways to do things.
    - Strongly Agree
    - Agree
    - Somewhat Agree
    - Neutral
    - Somewhat Disagree
    - Disagree
    - Strongly Disagree

4. We always try to take the initiative in every situation (e.g., against competitors, in projects when working with others?
   - Strongly Agree
   - Agree
   - Somewhat Agree
   - Neutral
   - Somewhat Disagree
   - Disagree
   - Strongly Disagree

5. Our business is creative in its methods of achieving sustainability goals.
   - Strongly Agree
   - Agree
   - Somewhat Agree
   - Neutral
   - Somewhat Disagree
   - Disagree
   - Strongly Disagree

6. We seek out new ways to integrate sustainability into our operations.
   - Strongly Agree
   - Agree
   - Somewhat Agree
   - Neutral
   - Somewhat Disagree
   - Disagree
   - Strongly Disagree

7. The term “risk taker” is considered a positive attribute for people in our business.
   - Strongly Agree
   - Agree
   - Somewhat Agree
   - Neutral
   - Somewhat Disagree
   - Disagree
   - Strongly Disagree

8. People in our business are encouraged to take calculated risks with new ideas.
   - Strongly Agree
   - Agree
   - Somewhat Agree
   - Neutral
   - Somewhat Disagree
   - Disagree
   - Strongly Disagree

9. Our business emphasises both exploration and experimentation for opportunities.
    - Strongly Agree
    - Agree
    - Somewhat Agree
    - Neutral
    - Somewhat Disagree
    - Disagree
    - Strongly Disagree

## Part D – Sustainability Focus in Your Company

This section looks at how committed your company is to sustainability and environmentally responsible practices.

1. We consider environmental sustainability important.
    - Strongly Agree
    - Agree
    - Somewhat Agree
    - Neutral
    - Somewhat Disagree
    - Disagree
    - Strongly Disagree

2. We consider social sustainability important.
    - Strongly Agree
    - Agree
    - Somewhat Agree
    - Neutral
    - Somewhat Disagree
    - Disagree
    - Strongly Disagree

3. We consider sustainability criteria important for new projects.
    - Strongly Agree
    - Agree
    - Somewhat Agree
    - Neutral
    - Somewhat Disagree
    - Disagree
    - Strongly Disagree

4. We consider measuring new projects' progress on sustainability important.
    - Strongly Agree
    - Agree
    - Somewhat Agree
    - Neutral
    - Somewhat Disagree
    - Disagree
    - Strongly Disagree

5. We value sustainability-type criteria as important for the future.
   - Strongly Agree
   - Agree
   - Somewhat Agree
   - Neutral
   - Somewhat Disagree
   - Disagree
   - Strongly Disagree

6. We consider energy consumption and/or carbon emissions in our project work.
   - To a Great Extent
   - To a Significant Extent
   - To a Considerable Extent
   - To a Moderate Extent
   - To a Small Extent
   - To a Minimal Extent
   - Not at All

7. We include sustainability in our project budget.
   - To a Great Extent
   - To a Significant Extent
   - To a Considerable Extent
   - To a Moderate Extent
   - To a Small Extent
   - To a Minimal Extent
   - Not at All

8. We select suppliers and partners based on sustainability criteria.
   - To a Great Extent
   - To a Significant Extent
   - To a Considerable Extent
   - To a Moderate Extent
   - To a Small Extent
   - To a Minimal Extent
   - Not at All

9. We use the triple bottom line (environmental, social, and financial factors) for project planning.
   - To a Great Extent
   - To a Significant Extent
   - To a Considerable Extent
   - To a Moderate Extent
   - To a Small Extent
   - To a Minimal Extent
   - Not at All

**Part E – Digital Vision and Strategy**

This section examines how your company plans and executes the use of digital technologies.

1. Our company digital transformation roadmap aligns with long-term business strategy.
   - Strongly Agree
   - Agree
   - Somewhat Agree
   - Neutral
   - Somewhat Disagree
   - Disagree
   - Strongly Disagree

2. Our company digital goals are clearly communicated to all project partners.
   - Strongly Agree
   - Agree
   - Somewhat Agree
   - Neutral
   - Somewhat Disagree
   - Disagree
   - Strongly Disagree

3. Our company has dedicated digital champions to drive digital initiatives.
   - Strongly Agree
   - Agree
   - Somewhat Agree
   - Neutral
   - Somewhat Disagree
   - Disagree
   - Strongly Disagree

4. We enforce green digital standards (e.g., cloud-based BIM collaboration).
   - To a Great Extent
   - To a Significant Extent
   - To a Considerable Extent
   - To a Moderate Extent
   - To a Small Extent
   - To a Minimal Extent
   - Not at All

5. We invest in continuous upskilling for emerging AEC technologies.
   - To a Great Extent
   - To a Significant Extent
   - To a Considerable Extent
   - To a Moderate Extent
   - To a Small Extent
   - To a Minimal Extent
   - Not at All

6. We cultivate innovation and transformation culture.
    - To a Great Extent
    - To a Significant Extent
    - To a Considerable Extent
    - To a Moderate Extent
    - To a Small Extent
    - To a Minimal Extent
    - Not at All

**Part F – General Information**

This section looks basic information about your company

1. What is the nature of your company's work?
    - Design and Planning (Architectural Design, Engineering, Urban Planning, Landscape Architecture)
    - Construction and Project Management (General Contracting, Subcontracting, Construction Management, Project Management, Building Inspection)

2. What is the size of your company?
    - 1 to 20 employees
    - 21 to 100 employees
    - 101 to 200 employees
    - Over 200 employees

3. What is your role in the company?
    - CEO/COO/Managing Director
    - Architect
    - BIM Manager/Engineer/Consultant
    - Other

4. How would you rate your company's ability to use digital technologies for sustainability throughout the project lifecycle?
    - Very poor ability
    - Poor ability
    - Moderate ability
    - Strong ability
    - Exceptional ability

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**Thank You for Your Participation!**

Thank you for taking the time to complete this survey. If you have any questions, feedback, or would like to learn more about the findings of this research, please feel free to contact:

**Mr. Tong**
Email: s.y.tong@durham.ac.uk
Phone: **(852) 9388-1383**

Your input is greatly appreciated, and we thank you for your support.

# APPENDIX B – SUPPLEMENTARY DATA ANALYSIS FROM SPSS

Table A1 – Convergent Validity (SPSS)

| Factor | Title | Factor Loading | CR | AVE |
|---|---|---|---|---|
| SBM-ValueArch | SBM-ValueArch1 | 0.858 | 0.909 | 0.713 |
| | SBM-ValueArch2 | 0.842 | | |
| | SBM-ValueArch3 | 0.832 | | |
| | SBM-ValueArch4 | 0.846 | | |
| SBM-Valueoff | SBM-Valueoff1 | 0.845 | 0.899 | 0.748 |
| | SBM-Valueoff2 | 0.874 | | |
| | SBM-Valueoff3 | 0.876 | | |
| SBM-Revenue | SBM-Revenue1 | 0.912 | 0.909 | 0.834 |
| | SBM-Revenue2 | 0.914 | | |
| SBM | SBM-ValueArch | 0.887 | 0.901 | 0.503 |
| | SBM-Valueoff | 0.755 | | |
| | SBM-Revenue | 0.776 | | |
| TBL-Profit | TBL-Profit1 | 0.902 | 0.932 | 0.82 |
| | TBL-Profit2 | 0.915 | | |
| | TBL-Profit3 | 0.9 | | |
| TBL-People | TBL-People1 | 0.899 | 0.928 | 0.811 |
| | TBL-People2 | 0.914 | | |
| | TBL-People3 | 0.89 | | |
| TBL-Planet | TBL-Planet1 | 0.911 | 0.947 | 0.856 |
| | TBL-Planet2 | 0.93 | | |
| | TBL-Planet3 | 0.935 | | |
| TBL | TBL-Profit | 0.791 | 0.921 | 0.566 |
| | TBL-People | 0.827 | | |
| | TBL-Planet | 0.858 | | |
| EO-Inno | EO-Inno1 | 0.908 | 0.922 | 0.797 |
| | EO-Inno2 | 0.88 | | |
| | EO-Inno3 | 0.89 | | |
| EO-Pro | EO-Pro1 | 0.919 | 0.937 | 0.831 |
| | EO-Pro2 | 0.89 | | |
| | EO-Pro3 | 0.926 | | |
| EO-Risk | EO-Risk1 | 0.886 | 0.911 | 0.774 |
| | EO-Risk2 | 0.872 | | |
| | EO-Risk3 | 0.881 | | |
| EO | EO-Inno | 0.852 | 0.901 | 0.504 |
| | EO-Pro | 0.757 | | |
| | EO-Risk | 0.771 | | |
| SO-Culture | SO-Culture1 | 0.878 | 0.946 | 0.779 |
| | SO-Culture2 | 0.878 | | |
| | SO-Culture3 | 0.881 | | |
| | SO-Culture4 | 0.88 | | |
| | SO-Culture5 | 0.894 | | |
| SO-Practices | SO-Practices1 | 0.897 | 0.947 | 0.817 |
| | SO-Practices2 | 0.909 | | |
| | SO-Practices3 | 0.899 | | |
| | SO-Practices4 | 0.91 | | |
| SO | SO-Culture | 0.914 | 0.94 | 0.637 |
| | SO-Practices | 0.872 | | |
| DO-Vision | DO-Vision1 | 0.907 | 0.934 | 0.826 |
| | DO-Vision2 | 0.915 | | |
| | DO-Vision3 | 0.904 | | |
| DO-Strat | DO-Strat1 | 0.918 | 0.937 | 0.833 |
| | DO-Strat2 | 0.913 | | |
| | DO-Strat3 | 0.907 | | |
| DO | DO-Vision | 0.895 | 0.923 | 0.665 |
| | DO-Strat | 0.897 | | |