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# Construction Industry Capacity Evaluation: Using Business Intelligence for Data-Driven Insights

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**Abstract**
Access to reliable capacity insights is critical for stakeholders in the construction industry, yet planning often suffers from uncertainties and inconsistent data. The goal of this research is to leverage data-driven business intelligence tools to evaluate and optimise the interplay of supply and demand in the construction industry, addressing capacity challenges while providing actionable insights for informed decision-making and strategic planning. This study adopts a mixed-methods approach, combining bibliometric analysis, a literature review, and a case study of Auckland, New Zealand. Using business intelligence tools, the research examines seasonal trends in project initiations and completions, resource inefficiencies, and contractor dependencies. The findings confirm the prevalence of boom-bust cycles and reliance on external contractors during peak periods. Despite limitations in data standardisation, this study demonstrates the potential of business intelligence tools to improve capacity planning and resource allocation.

**Keywords**
Business Intelligence, Construction Planning, Supply and Demand Analyis

## 1 Introduction

The construction sector has played an essential role in the New Zealand aggregate economy in terms of revenue generation, capital formation, and job creation, all of which contribute to gross domestic product (GDP) and socioeconomic development(M. Ahmad et al., 2019) (Munir Ahmad et al., 2019; Hossain & Nadeem, 2019). Considering the substantial role of the construction sector in economic development, the government must give due attention and focus to the construction sector (Sui Pheng et al., 2019). The Construction industry provides products such as housing, infrastructure, industrial and commercial buildings, repair, and maintenance. The opportunity for business to expand is closely tied to the industry's success and similarly suffers from a lack of infrastructure. Accordingly, natural disaster factors can impact the industry level as a whole or different project, such as disasters, climate change, and demographic changes (Ebi et al., 2021). The construction industry significantly contributes to employment, domestic capital formation, and GDP. When the construction industry

operates at full capacity, the GDP rises. Indeed, limited construction capacity is a major economic issue. In New Zealand, for example, the construction sector continued to benefit from operating in a boom environment, increasing its contribution to GDP by 14.3% for the fiscal year ending in June 2021, following an annual decline of 6% from June 2020 to June 2019. Accordingly, The goal of this research is to leverage data-driven business intelligence tools to evaluate and optimise the interplay of supply and demand in the construction industry, addressing capacity challenges while providing actionable insights for informed decision-making and strategic planning.

## 2 Literature Review

Forecasting capacity in the construction industry is critical in policy formulation and implementation because the construction industry plays an important role in a country's economic development process. Planning or predicting the capacity considers a complex and challenging mission due to numerous factors that can influence both supply and demand (Jiang & Liu, 2011). The supply influences factors such as population growth, changes in national income, fluctuations in interest rates and changes in household expenditure, investment in technology, changes in standards and regulations, and availability of skilled workers and materials. And demand can be directly influenced by technological advancement and changes in consumer behavior, economic condition (Sui Pheng et al., 2019), inflation, unemployment (Musarat et al., 2021), demographical change, tax, regulation, and trade and government policies (Bucea-Manea-Țoniș et al., 2020; Ratnasabapathy et al., 2021). All play significant roles when explaining variations in construction demand. Due to the uncertainty of the factors, forecasting supply and demand at the industry level is challenging (Chang-Richards et al., 2017; Zhao et al., 2022).

Construction in New Zealand follows the same factors, complexity, geographical isolation, and micro-market size (Bull et al., 2021). Construction is a complex dynamic sector that is impacted by a range of factors that can impact the demand for construction projects, the availability of skilled workers and materials and machinery, and the speed of construction processes. This research is essential to address the dynamic factors and can also help stakeholders understand the key drivers of supply and demand and opportunities by using business intelligence techniques.

Capacity prediction can help address over or under capacity issues for the overall construction industry. In an over-capacity situation, construction companies have excess resources, leading to inefficiencies and increased costs (Liu et al., 2022). By predicting overcapacity, companies can take steps to reduce production, such as reducing working hours, temporarily stopping production, or reducing the number of workers. In an under-capacity situation, companies do not have enough resources to meet the demand for their services, leading to delays and decreased productivity. By predicting under-capacity, companies can take steps to increase production capacity, such as hiring additional workers, increasing working hours, or investing in new equipment(Emrath, 2021).

## 3 Methodology

This study employs a mixed-method approach to evaluate the capacity dynamics within the construction industry, particularly focusing on the interplay between supply and demand factors. The methodology integrates bibliometric analysis, a comprehensive literature review, and a case study analysis using business intelligence tools (Jelodar & Yiu, 2012). These steps are detailed as follows:

1. **Bibliometric Analysis and Literature Review**: The bibliometric analysis was conducted using the Scopus database due to its extensive coverage of peer-reviewed literature. The analysis was conducted to identify and synthesise academic literature on capacity forecasting

in the construction industry. The search query included 'Planning OR Prediction AND Construction Industry AND Capacity' in titles and abstracts, covering a time span from 2000 to 2024.. The initial search returned 35 articles, which were screened based on relevance, methodological rigour, and their focus on construction industry capacity. Papers that primarily focused on supply chain logistics, unrelated industries, or lacked empirical analysis were excluded, leaving 18 key studies for in-depth analysis.. These papers were examined to identify key input and output variables relevant to capacity planning in construction planning (Table 1). This review provided the theoretical foundation for the study and informed the identification of critical factors affecting construction capacity.

2. **Case Study: Auckland, New Zealand**: The case study focused on construction capacity in Auckland, utilising a hoistorical dataset for project register from Pacificon, which covers the New Zealand construction industry. The dataset provided valuable insights into construction projects initiated in Auckland; however, it had notable limitations. While project values and timelines were available, granular details such as labour force composition, specific material usage, and subcontractor roles were missing. This limitation affected the ability to analyse resource allocation in detail. Future studies should seek to integrate supplier and workforce data for a more comprehensive capacity assessment. The dataset includes information such as project values, locations, and timelines but lacks granular details on materials, labour, and technology. Projects that commenced in 2022 were analysed, totalling 783 entries. These projects were matched with contractor data to explore capacity trends across supply and demand dimensions. Given the dataset constraints, the study focused on contractor data as a proxy for supply-side capacity. Contractor availability and distribution are key indicators of construction industry health, influencing project completion rates and workforce demand. By analysing local versus external contractor contributions, we gain insights into Auckland's construction sector resilience.
3. **Data Analysis with Business Intelligence Tools**: Business intelligence tools, specifically Power BI, were employed to analyse the dataset and visualise capacity trends. The tools facilitated the integration of supply and demand data to construct a model that provides a comprehensive overview of construction capacity. This model enabled the identification of regional and cross-regional contractor contributions. Data analysis in Power BI was conducted using a combination of DAX (Data Analysis Expressions) functions and built-in analytics features. The primary DAX functions used include:

    - **SUMX** to compute total project values across contractor regions.
    - **CALCULATE** to filter demand trends by contractor type.
    - **FORECAST.ETS** for time-series forecasting of project completions. Additionally, custom visuals were developed using Power BI's R integration to display contractor concentration in different regions.

    Predictive analytics was integrated into the Power BI model using its built-in forecasting tool. The ETS (Exponential Smoothing) model was applied to historical data on project initiations and completions, allowing stakeholders to anticipate peak demand periods. This model identified Q1 and Q4 as critical resource-intensive periods, aligning with seasonal trends observed in past studies.

    In addition, "The Power BI dashboard was designed with interactive elements, including:

    - Drill-through reports that allow users to explore individual project details.
    - Cross-filtering to compare different contractor types and regions.
    - Geospatial mapping to visualise contractor activity across Auckland.

4. **Key Variables and Factors**: The study examined key factors influencing supply (e.g., material availability, labour shortages, technological advancements, and government regulations) and demand (e.g., project locations, supply chain dynamics, and project types). These factors were systematically matched and analysed to understand their impact on capacity trends.

# 4 Results and discussion

The study focused on assessing construction capacity by analysing supply and demand factors using business intelligence tools. This section summarises key findings, supported by visual representations and insights from the dataset used.

## 4.1 Capacity Prediction Insights

The bibliometric analysis and literature review revealed the critical factors influencing capacity prediction in the construction industry. These include materials, labour, technology, regulations (supply-side), and location, contractor availability, and project type (demand-side). Table 1 summarises the key variables and outcomes from existing studies related to capacity prediction in various construction contexts. The papers listed in Table 1 address different aspects of capacity prediction and planning in various fields of construction. The research aims to identify the resources required to meet the demand at the project or organisational level. Several factors affect capacity planning, including material availability, labor resources, technological advancements, economic factors, and contractor capabilities (Sadeghi et al., 2024). The studies mentioned in summary use various approaches to address capacity planning challenges in their respective fields. In addition, disruptive events such as natural disasters can damage construction projects and infrastructure, causing delays, cost overruns, and safety hazards on the supply side. They can also disrupt supply chains and transportation networks, making construction materials and equipment difficult to deliver to job sites (Mirhosseini et al., 2022). On the other hand, natural disasters can alter the demand for construction services. Following a natural disaster, for example, there may be an increased demand for reconstruction and rebuilding services, increasing construction activity. However, this surge in demand may be fleeting, and businesses may suffer as a result. Accordingly, the main factors that can affect capacity as supply and demand in the construction industry are summarised in the next sub-sections. Over time, there has been a shift in capacity forecasting from traditional econometric models towards AI-driven predictive analytics. The latest studies highlight the increasing role of business intelligence tools such as Power BI in construction planning. This study contributes by integrating these trends into a case study of Auckland's construction sector.

### *4.1.1 The main Factors influencing supply:*

**Materials:** the availability of the material is a critical factor for the construction industry and the completion and success of projects. Any disruption of material can directly affect the industry. The shortage of material led to the project having delayed cost overrun and even cancellation of the project (Dvaipayana et al., 2021; Golkhoo & Moselhi, 2019).

**Labor:** labor shortage limits capacity; companies cannot take on more projects when they don't have enough skilled workers. The shortage of labor can impact the overall supply in construction. The skilled shortage can Delayed projects, increased costs, decreased quality, reduced innovation, and limited capacity are some of the ways in which a shortage of skilled labor can impact the industry's resilience (Akomah et al., 2020; Kim et al., 2020).

**Technology:** emerging technologies can have an impact on supply by improving efficiency and enhancing quality, increasing safety (Daniel et al., 2009), and reducing cost (Cole et al., 2019).

**Government Regulation:** new regulations from the government which impact approval or permits can increase cost and delay and can protect the environment and safety, which impacts the supply (Emrath, 2016). Governments can also incentivise the construction industry to increase the supply of certain construction projects by providing tax credits or subsidies (Zhang et al., 2023).

Table 1. Capacity prediction /planning related scholarly papers.

| No. | Reference | Input variables | Output variables |
|---|---|---|---|
| 1 | (Mohapatra et al., 2022) | Performance data (workers' physical), Equipment data | Lifting capacity of workers |
| 2 | (Huang et al., 2022) | Material data, Load data, Geometric data | Resistance of Stainless-Steel Tubes under Compression |
| 3 | (Ngo et al., 2021) | Concrete data, Steel properties data, Geometric data | Ultimate bearing capacity in concrete-filled steel tube |
| 4 | (Opeyemi & Neubert, 2021) | Resource data, Duration of the projects, Cost | Project Performance |
| 5 | (Sikeridis & Devetsikiotis, 2020) | Vehicle demand, Infrastructure capacity, Road network | Capacity planning for charging stations |
| 6 | (Alsanat et al., 2019) | Aluminium grade, Channel size Load type, Thickness | Load transporting Capacity |
| 7 | (Hamzeh et al., 2019) | Resource data, Waste generation Time, Cost | Performance metrics |
| 9 | (Rogelj et al., 2019) | Population aging | Ambient Assisted Living |
| 10 | (Aggarwal & Gupta, 2015) | Capacity utilization, Product demand, Cost, Resources | N/A |
| 11 | (Arashpour et al., 2014) | Production capacity, Availability of Resource, schedule of project , Demand | Workflow stability |
| 12 | (Wang et al., 2014) | Steel production, Consumption, Import/export data, Economic factors | Steel cycle flow |
| 13 | (Pauliuk et al., 2013) | Iron production, Trade, Sector statistics | In-use iron stock |
| 14 | (Macia et al., 2010) | Pipeline material, Design specifications, Loading conditions | Strain-based design |
| 15 | (Chien et al., 2010) | Technology diffusion rate, Product life cycle stage, Market trends, Historical sales data | Demand forecast |
| 16 | (Fung et al., 2004) | Soil conditions, Pile dimensions Materials | piles capacity prediction |
| 17 | (Dawood & Neale, 1993) | Market demand, customer preference, competitor information | Sales forecast |
| 18 | (Cazalet, 1978) | Capacity planning, power demand, supply | N/A |

### *4.1.2 The main Factors influencing demand:*

**Locations:** The location of a construction project can impact its demand. Areas with high population growth and economic development tend to have a higher demand for construction services. Similarly, regions with a strong infrastructure plan or large-scale development projects tend to have a higher demand for construction work (Karra, 2005; Teizer et al., 2013).

**Suppliers/Supply-Chain/Contractors:** The availability and reliability of suppliers and the supply chain can affect the demand for construction work. A reliable and well-established supply chain can help to ensure that materials and resources are available when needed, which can increase demand for construction work (Stiles et al., 2012).

**Type:** Different types of construction projects require different skills and resources. For example, commercial construction projects require more specialised skills and resources than residential projects (Agapiou et al., 1995). As such, the demand for construction services may vary depending on the type of project.

## 4.2 Case study of the New Zealand construction industry

The dataset for Auckland, New Zealand, provided insights into the distribution and trends of construction projects initiated in 2022 and is either completed of on-going to date. The dataset encompassed essential attributes such as project location, total value, start and end dates, and contractor details. Supply-side variables included project monetary values and locations, representing the financial and geographic distribution of construction activities. Demand-side factors, including contractor availability and type (local or external), highlighted the capacity of the industry to meet project requirements. The integration of these datasets facilitated a comprehensive view of Auckland's construction dynamics.

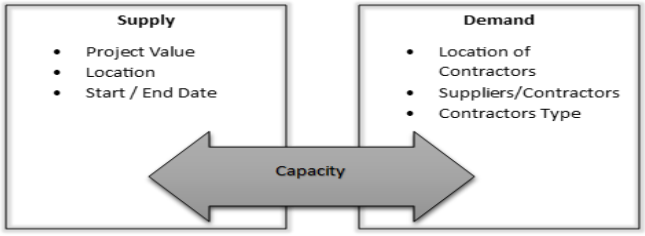



**Figure 1:** Factors available in the Auckland dataset

The dataset did not include detailed information such as materials, labor, and technology, but it did include the project value as the price for all expenses for materials, labor, and technology encountered, as shown in Figure 1. Using project IDs as unique identifiers, supply-side data (e.g., project value and timeline) was linked with demand-side factors (e.g., contractor location and type). The resulting matches demonstrated how effectively projects utilised available contractor resources.

- **Regional Dependencies**: A significant proportion of projects (70%) were completed by Auckland-based contractors, while the remaining 30% relied on contractors from other cities in New Zealand and Australia. This regional dependency indicated a robust local contractor base but also highlighted reliance on external resources for specific projects.
- **Temporal Distribution**: Time-series analysis of project initiation dates revealed peaks in the first and fourth quarters of 2022, suggesting seasonal variations in construction activity. These peaks corresponded to periods of high demand for contractors and resources, potentially straining capacity.

An in-depth examination of contractor data provided insights into the role of local versus external contractors in meeting construction demand.

- **Local Contractors**: The majority of Auckland projects were completed by local contractors, underscoring their central role in the regional construction industry. These contractors

predominantly handled small- to medium-sized projects, reflecting their focus on maintaining consistent capacity across diverse activities.

- **External Contractors**: Projects outsourced to external contractors accounted for approximately 30% of the total value. These contractors typically engaged in high-value or specialised projects, indicating their complementary role in addressing capacity constraints for complex or large-scale developments.

# 5 Power BI Tool Development and Application

The Power BI tool was employed to integrate and visualise data from the Auckland construction industry dataset, focusing on the supply and demand aspects. Before analysis, the dataset underwent an extensive cleaning and preprocessing phase. This involved resolving inconsistencies, handling missing values, and standardising data formats to ensure reliability and compatibility with Power BI environment. New variables were derived to enrich the analysis, such as categorising contractors based on their locations and operational types. The development process involved the following steps:

### *5.1.1 Data Integration*

Once the dataset was prepared, supply-side data (e.g., project values and locations) was integrated with demand-side data (e.g., contractor availability and types). This integration was achieved using unique project identifiers, enabling a comprehensive view of each project's supply and demand characteristics. Power BI's robust data modelling features facilitated the creation of a unified database, establishing relationships between these variables. This integration formed the foundation for subsequent analysis and visualisation, allowing stakeholders to explore interactions between supply and demand factors effectively.

### *5.1.2 Dashboard Development*

The development of interactive dashboards in Power BI was a critical step in this study. These dashboards were designed to highlight key performance indicators (KPIs) such as the number of projects, the distribution of contractors, and the total value of projects. The dashboards featured visual elements such as bar charts, pie charts, and geographical maps to represent data dynamically. Filters and slicers were implemented to provide users with the flexibility to explore specific aspects of the dataset, such as focusing on projects of a particular size or contractor type. The interactive nature of the dashboards allowed stakeholders to engage with the data intuitively and extract customised insights.

### *5.1.3 Trend Analysis and Visualisation*

To capture trends over time, the Power BI tool included time-series visualisations that examined project initiation and completion patterns. Comparative analysis features were also incorporated, enabling an exploration of local versus external contractor contributions to Auckland’s projects. Geographic data was plotted using Power BI’s mapping tools to provide a spatial representation of contractor locations and project distributions. Percentage breakdowns, such as the proportion of projects outsourced to contractors outside Auckland, were visualised to offer additional clarity. As illustrated in Figure 4, around 30% of projects in Auckland are completed by contractors in other locations, and 70% are happened in Auckland by Auckland-based contractors.

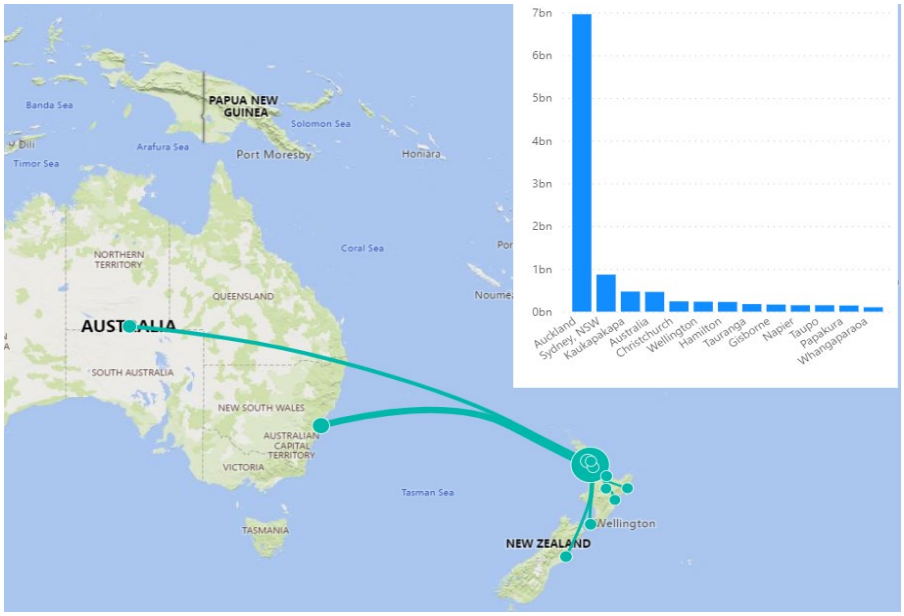



**Figure 3.** The contractors' locations that work on projects in Auckland.

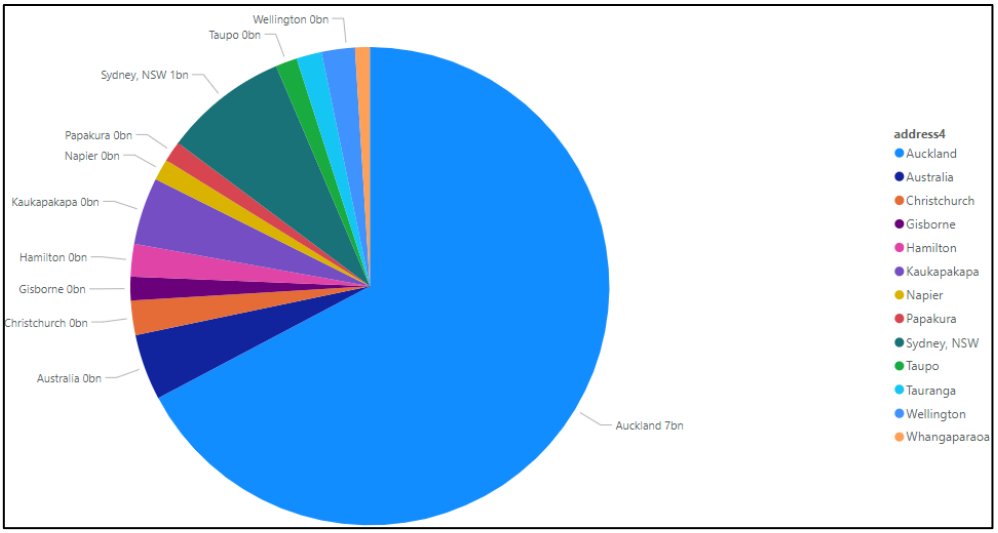



**Figure 4.** Shows the percentage of Auckland projects outsourced or completed by contractors in other locations.

### *5.1.4 Embedded Insights from Analysis*

The Power BI model illuminated critical dynamics of Auckland's construction capacity. For example, geographic visualisations demonstrated that most high-value projects were concentrated in central Auckland, while smaller-scale projects were more evenly distributed across the region. Additionally, the tool highlighted the dominance of a few major contractors in handling the largest projects, raising questions about the resilience and diversity of the local contractor base. The tool highlighted regional dependencies by illustrating the distribution of projects completed by Auckland-based contractors versus those from other cities or countries. Additionally, it provided a basis for forecasting future capacity utilisation patterns, enabling better resource planning and policy development. Furthermore, by correlating project values with completion rates, the analysis identified periods where capacity utilisation peaked, potentially indicating risks of resource shortages. These insights, drawn directly from the Power BI analysis, are pivotal for stakeholders aiming to optimise construction processes and mitigate risks.

# 6 Discussion

The comprehensive analysis of Auckland's construction projects in 2022 provided significant insights into trends in project initiation and completion, contractor contributions, and capacity utilisation. These findings are summarised and integrated into Table 2 for clarity and are further elaborated below.

## 6.1 Analysis of Trends and Dependencies

A key finding of the study was the seasonal variation in project initiations and completions, with peaks observed in the first and fourth quarters of 2022. This pattern is evident in the time-series visualisation (Figure 1), which demonstrates that while project initiation surged during these periods, completion rates lagged behind. This indicates potential resource constraints or inefficiencies, particularly during high-demand months. The study also explored dependencies between local and external contractors. Local contractors contributed to 70% of project completions, primarily handling small to medium-scale projects. However, external contractors were indispensable during peak periods, addressing capacity shortfalls for high-value or complex projects. This interdependence underscores the importance of balancing local capacity development with strategic outsourcing to external contractors.

## 6.2 Contractor Contributions and Project Values

The comparative analysis revealed that local contractors maintained steady contributions across all months, focusing on routine projects. Conversely, external contractors accounted for up to 40% of the total project value during peak months (Figure 2). This highlights their pivotal role in managing specialised or high-value projects. Table 1 further illustrates this division, showing the proportion of contributions in terms of project value and type. Geographic distribution also provided valuable insights. High-value projects were concentrated in central Auckland, typically involving large-scale infrastructure or commercial developments. Suburban areas, however, showed a more even distribution of smaller-scale residential and community projects, reflecting varying contractor specialisations and resource demands.

## 6.3 Capacity Utilisation Patterns

Capacity utilisation analysis revealed over- and under-capacity trends. During peak periods, over-capacity was marked by extended project timelines and reliance on external contractors. During slower periods, under-utilisation of resources suggested opportunities for redistributing workloads or initiating new projects to stabilise demand.

## 6.4 Applications and Future Uses of the Power BI Tool

The Power BI model demonstrated its utility as a decision-support system for construction industry stakeholders. By providing real-time insights into capacity utilisation, the tool enables policymakers, contractors, and clients to anticipate resource bottlenecks and optimise workflows. Future enhancements could significantly extend the tool's capabilities. Integrating machine learning algorithms within Power BI would enable predictive analytics, offering early warnings for potential project delays or resource constraints. Moreover, expanding the dataset to include detailed information on labour availability, material supply chains, and technology usage would refine its analytical depth. Cross-regional implementations could provide comparative insights, fostering best practices across the construction sector. Finally, the development of a mobile-friendly interface for the tool would ensure accessibility, enabling stakeholders to access insights on-the-go.

# 7 Conclusion

This study highlights the complexities of evaluating supply and demand in the construction and infrastructure sectors. Using data-driven business intelligence tools, specifically Power BI, the case study of Auckland, New Zealand, demonstrated how such tools can integrate and visualise multifaceted data to provide actionable insights into capacity dynamics. The findings revealed seasonal patterns, contractor dependencies, and resource allocation trends, offering stakeholders a basis for informed decision-making and strategic planning. However, significant challenges and limitations emerged. The dataset's lack of standardisation, with both structured and unstructured formats, complicated the analysis process. Additionally, incomplete information on critical capacity factors, such as labour availability, equipment utilisation, technological adoption, and project-specific details, constrained the depth of analysis. The absence of robust historical data further limited the development of predictive models, which are essential for long-term sector planning. Despite these limitations, the study underscores the potential of business intelligence tools to address traditional gaps in capacity evaluation. Future work should focus on improving data standardisation and granularity while integrating advanced analytics like machine learning to enhance predictive capabilities. By addressing these challenges, stakeholders can optimise resource allocation, mitigate capacity constraints, and foster a more resilient and efficient construction industry. This study serves as a foundation for advancing data-driven approaches in construction capacity planning.

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