

Strategic Use of Data Analytics and Market Intelligence in Commercial Property Investment Decision-Making: A Qualitative Study from Johannesburg, South Africa

*Shoayb Sheik-Emam and Roshanlal Ramdew Sookdeo

Department of Business Administration, Regent Business School, Johannesburg, South Africa

*Corresponding Author

DOI: <https://doi.org/10.51244/IJRSI.2026.1308000331>

Received: 07 September 2026; Accepted: 12 September 2026; Published: 24 September 2026

ABSTRACT

Property investment decisions are becoming increasingly data-driven as investors worldwide seek greater accuracy, speed and strategic insight amid volatile market conditions. This shift is especially relevant in emerging economies, where major cities combine strong investment potential with elevated market risk. This study explored the strategic use of data analytics and market intelligence in commercial property investment decision-making in Johannesburg, South Africa. The research pursued four objectives: to examine current analytics practices, to identify barriers constraining strategic adoption, to identify enablers supporting adoption, and to propose recommendations for strengthening data-driven decision-making. A qualitative, exploratory case study design, underpinned by an interpretivist research philosophy and a hybrid deductive-inductive (abductive) analytical approach, was adopted. Data were collected through semi-structured interviews with a purposively selected sample of fifteen experienced commercial property investment professionals and analysed thematically using NVivo (Version 14). The findings indicate that data analytics is operationally present within investment practice, most notably through yield-based investment modelling and comparable sales benchmarking, supplemented by internally accumulated transaction data and multi-source triangulation; a smaller subset of participants also described more advanced geospatial, scenario-based and system-integrated analytical practice, indicating an uneven maturity gradient rather than uniform digital transformation. However, deeper strategic integration is constrained by data quality and completeness concerns, the cost and complexity of implementation, market volatility, and behavioural subjectivity in price negotiation. Enabling conditions include the accumulation of proprietary transaction data, growing technological infrastructure integration, rising investor demand for transparency, and improving digital literacy among practitioners. The study concludes that commercial property investment decision-making in this market operates within a hybrid analytical model in which quantitative tools enhance, rather than replace, professional judgement. Recommendations include strengthening internal data governance, pursuing phased and scalable technology investment, institutionalising analytical transparency as a professional norm, and investing in continuous digital skills development. These findings, based on participants' own accounts and perceptions rather than independently verified transaction or performance outcomes, contribute to the limited empirical literature on PropTech adoption and data-driven decision-making in emerging African property markets.

Keywords: Data analytics, Market intelligence, Commercial property investment, PropTech adoption, South Africa

INTRODUCTION

Property investment is becoming increasingly data-driven, as investors seek to improve the accuracy, speed and strategic value of their decisions (Chen, Chiang & Storey, 2012). Globally, the integration of data analytics and market intelligence is redefining how investment opportunities are evaluated, managed and optimised. This shift is particularly relevant to emerging economies, where major cities present a mix of high investment potential and elevated market risk. Navigating this complexity requires more than experience or instinct; it demands a

systematic approach grounded in data, insight and forward-looking analysis. Data analytics involves the collection, processing and interpretation of large datasets to uncover patterns, predict trends and inform decision-making; in the property investment context, this includes analysing rental yields, vacancy rates, appreciation trends and socio-economic indicators (Chen, Chiang & Storey, 2012). Market intelligence, by contrast, draws on both quantitative and qualitative signals, such as planning approval timelines, demographic change and policy shifts, to guide location-specific investment strategy (Kotler & Keller, 2020).

In Johannesburg, South Africa's largest commercial property market, both the commercial and residential sectors have experienced considerable volatility as a result of economic downturns, interest-rate fluctuations and changing demand dynamics, particularly since the COVID-19 pandemic. Rising office vacancies, reported to have peaked at close to 20% in some nodes during 2022, have made it increasingly important for investors to move beyond traditional decision-making approaches toward analytics-enabled forecasting and risk assessment (Jones Lang LaSalle, 2022). Despite this, the South African real estate sector, and particularly its small to mid-sized investor base, continues to face barriers to fully integrating data analytics and market intelligence tools, including limited access to real-time data, constrained technical skills, and underinvestment in property technology (Cheruiyot & Gamede, 2024). While listed institutional investors often draw on comparatively sophisticated analytics and governance frameworks to improve returns (Mofokeng & Okoro, 2024), many private investors continue to rely on experience-based heuristics or historical market reports, raising questions about the quality, accuracy and timeliness of investment decision-making in an increasingly competitive and uncertain environment.

Although Johannesburg represents one of Africa's most dynamic property markets, many commercial property investors still lack the capacity or inclination to apply data analytics and market intelligence strategically within their decision-making processes. Adoption of property technology and big-data tools remains limited by weak supporting infrastructure, unclear value propositions, high implementation costs and constrained technical skills (Cheruiyot & Gamede, 2024). This limitation risks missed opportunities, suboptimal asset selection and heightened financial exposure, particularly in fluctuating economic conditions. While advanced analytics and spatial data platforms exist, their use in day-to-day property investment remains inconsistent, and significant gaps remain in understanding their actual application, perceived value and barriers to implementation within the South African context specifically.

The aim of this study was to explore how commercial property investors in Johannesburg strategically use data analytics and market intelligence to inform their investment decisions. Specifically, the study sought to: (1) investigate the current use of data analytics and market intelligence tools in property investment decision-making; (2) assess the barriers influencing the strategic adoption of data analytics; (3) assess the enablers supporting the strategic adoption of data analytics; and (4) propose strategies for improving the integration and effectiveness of data-driven decision-making within the sector.

The study is significant both theoretically and practically. Theoretically, it contributes to the growing body of scholarship on digital transformation within real estate, an area in which empirical research remains heavily concentrated on developed markets, with comparatively limited attention paid to sub-Saharan African contexts. By examining how data analytics and market intelligence are applied in Johannesburg's commercial property sector, the study offers insight into how local market conditions, investor behaviour and technological readiness shape digital strategy, thereby informing theoretical work on strategic decision-making, technology adoption and urban investment risk. Practically, the findings offer property investors, brokers and advisory firms a clearer understanding of how data-driven tools can strengthen market analysis, reduce investment risk and support long-term profitability, while offering policymakers and industry bodies a rationale for supporting property-technology innovation, improving access to reliable data, and fostering a more transparent, investor-ready commercial property market.

LITERATURE REVIEW

Conceptualising data analytics and market intelligence in property investment

The property market refers to the broad system through which real estate, both residential and commercial, is bought, sold, developed, leased and financed. It encompasses all activity relating to land and built-infrastructure

transactions and is shaped by supply and demand, interest rates, government policy and macroeconomic indicators (Ling & Archer, 2022). In emerging markets such as South Africa, the property sector plays a vital role in economic development, job creation and urban transformation; Johannesburg's commercial property market in particular is characterised by high investment activity alongside significant volatility, spatial inequality and cyclical vacancy rates. Data analytics, in this context, involves the use of statistical, computational and algorithmic techniques to analyse large datasets in order to generate insight, forecast outcomes and support decision-making, including regression modelling, spatial analysis and predictive forecasting applied to rental yields, market growth, location risk and asset performance (Chen, Chiang & Storey, 2012). Market intelligence refers to the process of gathering, analysing and interpreting information about a market to support strategic planning, including competitor analysis, regulatory developments, consumer behaviour trends and demographic shifts (Kotler & Keller, 2020). Investment decisions, finally, are the process through which investors evaluate potential assets, allocate capital and manage risk in pursuit of financial returns; in property, such decisions are typically long-term and capital-intensive, requiring consideration of multiple financial, economic and environmental variables (Brueggeman & Fisher, 2019).

A recurring difficulty in this literature, echoed in this study's own findings below, is that “data analytics” and “market intelligence” are often used as umbrella terms that conflate long-established valuation technique with genuinely advanced, technology-enabled analysis. To make this boundary explicit, this study distinguishes practice along an analytical-maturity spectrum ranging from descriptive analysis (retrospective reporting of what has occurred, e.g. historical comparable-sales lookups), through diagnostic analysis (structured explanation of why an outcome occurred, e.g. cap-rate benchmarking adjusted for risk variables), to predictive and prescriptive analysis (forward-looking scenario or sensitivity modelling used to inform a recommended course of action), with geospatial analysis (location-based demographic and infrastructure data) and automated or system-integrated analysis (API-linked platforms and real-time dashboards) treated as cross-cutting categories that can operate at any of these levels (Davenport & Harris, 2017). Conventional valuation practices such as income-capitalisation modelling and comparable-sales benchmarking, on their own, sit at the descriptive-to-diagnostic end of this spectrum and do not by themselves constitute evidence of PropTech adoption or advanced analytics; this distinction is applied throughout the Results and Discussion section below to avoid overstating the sophistication of the practices reported.

Current applications of data analytics in global and emerging property markets

The global property investment landscape has undergone considerable transformation through the integration of data analytics and market intelligence into strategic decision-making. Historically a conservative, relationship-driven sector, real estate has been comparatively slow to adopt new technology relative to sectors such as banking and insurance, with decision-making traditionally reliant on intuition, market experience and static valuation reports. Since the COVID-19 pandemic, however, the sector has experienced a marked shift toward data-driven investment approaches, supported by the growing availability of big data, advances in artificial intelligence, and the evolution of property-technology platforms (Deloitte, 2023; PwC & Urban Land Institute, 2025).

Predictive analytics now enables investors to forecast rental yields, occupancy rates and asset appreciation using both historical and real-time datasets, improving decision accuracy and mitigating exposure to interest-rate changes or policy reform (Number Analytics, 2024). Geospatial analytics and geographic information systems have similarly become essential to understanding spatial and demographic dynamics, mapping factors such as proximity to transport corridors, commercial hubs and urban-regeneration zones to provide investors with visual, data-driven insight into location-based risk and opportunity. Automated valuation models, underpinned by machine learning, analyse comparable sales, construction costs, rental trends and zoning regulation to generate faster, more consistent property valuations, reducing due-diligence time and mitigating human bias in the process (Veluru, 2023). Operationally, business-intelligence platforms and real-time dashboards have transformed portfolio and asset management by consolidating vacancy rates, tenant turnover, yields and absorption rates into a single interactive view, allowing investors to detect underperforming assets and market anomalies more quickly (Number Analytics, 2024). At a strategic level, investment firms increasingly triangulate macroeconomic indicators, market intelligence and competitive benchmarking to conduct scenario planning and stress testing, supported in advanced markets by mature property-technology ecosystems and regulatory support for data transparency (Deloitte, 2023; PwC & Urban Land Institute, 2025).

Within South Africa, however, the diffusion of data analytics remains uneven. Adoption is concentrated largely among listed institutional investors, while many property professionals in Johannesburg and other metropolitan areas continue to rely on traditional valuation methods and historical market trends, constrained by limited access to reliable datasets, high software costs, inadequate digital infrastructure and a shortage of relevant technical expertise (Cheruiyot & Gamede, 2024; Edet, 2023). Organisational resistance to change compounds this constraint, with many property firms retaining legacy systems and risk-averse cultures that slow digital transformation. Nonetheless, pockets of innovation are emerging, with some Johannesburg-based practices beginning to employ spatial data visualisation, algorithmic forecasting and automated valuation tools to strengthen investment due diligence (South African Business Matters, 2025). As South Africa's property-technology ecosystem expands and digital infrastructure improves, adoption of advanced analytics and market intelligence is expected to accelerate further, positioning data-driven insight as an increasingly central, rather than peripheral, component of competitive real estate strategy.

Barriers to the strategic adoption of data analytics

Despite growing recognition of the value of analytics in improving investment outcomes, the real estate sector continues to face structural, financial and cultural barriers that constrain widespread adoption, particularly, though not exclusively, in developing contexts (Deloitte, 2023). Organisational resistance to change remains among the most pervasive: real estate has historically operated as a relationship-driven, intuition-based sector, and firms led by executives who view technology as a cost rather than a strategic asset are often reluctant to invest in or trust analytical tools, a tendency reinforced by short-term performance orientations in volatile markets (Deloitte, 2023). High cost and implementation complexity present a further constraint, particularly for small to mid-sized firms that must weigh substantial investment in cloud-based platforms, specialised software, quality datasets and skilled personnel against long, illiquid investment horizons that make the return on analytics investment difficult to evaluate in a timely manner (Edet, 2023; Cheruiyot & Gamede, 2024).

Fragmented and unreliable data ecosystems compound these challenges: in South Africa and other African markets, public property records, zoning databases and rental registries are frequently outdated, incomplete or difficult to access, leading to data gaps, poor interoperability and continued reliance on informal or anecdotal information sources (Edet, 2023). Legacy information-technology systems and weak system integration further hinder digital transformation, as outdated databases and manual processes remain incompatible with newer analytics tools and require both technical upgrades and change-management effort to resolve (Bäcklund, Vigren & Carlsson, 2024). Regulatory and institutional limitations, including weak data-governance frameworks and unclear data-sharing policy, make firms hesitant to engage in large-scale data collection or analytics deployment, particularly where sensitive tenant or financial information is involved (Deloitte, 2023). Finally, a shortage of professionals able to interpret analytics outputs and translate them into actionable strategy remains a persistent constraint: even where tools are available, their impact is diminished where organisational users lack the skill to interpret and act on the insights generated (Edet, 2023).

Table 1: Comparative overview of barriers to data analytics adoption in commercial property investment – developed versus emerging markets

Barrier	Developed markets	Emerging markets (e.g. South Africa)
Cultural resistance	Gradual shift from intuition-based to analytics-based practice; some resistance persists in traditional firms	Stronger resistance rooted in reliance on informal, relationship-based methods
Cost of implementation	Moderate; often absorbed by larger capital pools	High, and often prohibitive for small and mid-sized investors
Data availability and quality	Generally structured, high-quality and accessible datasets	Fragmented, outdated or incomplete public data

IT infrastructure and integration	Advanced systems, though constrained by legacy integration	Limited infrastructure, manual processes, weak interoperability
Regulatory environment	Established data governance and compliance norms	Weak data regulation and unclear data-sharing rules
Talent availability	Established access to data scientists and real estate analysts	Scarcity of professionals combining analytics and real estate expertise
Perceived ROI uncertainty	Improved modelling tools, though long-term tracking still evolving	Greater uncertainty due to asset illiquidity and long investment cycles

Source: Synthesised by the author from Deloitte (2023), Edet (2023) and Cheruiyot & Gamede (2024).

As illustrated in Table 1, emerging markets such as South Africa face markedly more pronounced barriers to analytics adoption than their developed-market counterparts, most notably in relation to data availability, implementation cost and the scarcity of professionals able to bridge analytics and real estate expertise. While developed markets are not without their own challenges, particularly legacy-system integration and cultural inertia, emerging markets are further constrained by weaker regulatory frameworks and greater uncertainty regarding return on investment. This comparative picture underscores the need for coordinated intervention, involving private investors, industry bodies, regulators and educational institutions, if analytics adoption is to be scaled meaningfully within emerging property markets.

Enablers supporting the adoption of data analytics

Alongside these barriers, several enablers are actively supporting and accelerating the adoption of data analytics and market intelligence in property investment. A clear business case, evidenced by improved yield optimisation, more accurate forecasting and stronger asset-lifecycle management among firms that have adopted analytics, has shifted investor perceptions of analytics from experimental to essential (Deloitte, 2023). The growing availability and affordability of enabling technology, including cloud computing and software-as-a-service delivery models, has substantially reduced the technical and financial barriers to entry facing small and mid-sized property firms, offering scalable, user-friendly tools that can be customised for valuation, tenant risk profiling and market segmentation without extensive in-house infrastructure.

On an organisational level, strong leadership commitment and strategic alignment are widely recognised as critical enablers: where senior executives frame analytics as a core component of strategic vision rather than a discretionary technology upgrade, resource allocation and cross-departmental collaboration tend to follow more readily, and adoption rates improve accordingly (PwC & Urban Land Institute, 2025). The emergence of property-technology networks, knowledge-sharing platforms and industry accelerators is similarly playing a pivotal role in facilitating access to technical expertise, funding and best practice, connecting traditional property firms with analytics innovators and reducing the cost of experimentation (Edet, 2023). From a human-capital perspective, the increasing availability of analytics-literate talent, together with the growing trend toward cross-functional teams combining property analysts, data specialists and financial strategists, is also enabling broader adoption by embedding analytics into everyday workflows rather than confining it to a specialised function. Finally, external regulatory and market pressures are reinforcing the case for adoption, as investors, lenders and regulators increasingly demand higher levels of transparency, accountability and data integrity in real estate transactions, a trend reinforced by the growing prominence of environmental, social and governance reporting requirements (PwC & Urban Land Institute, 2025).

Theoretical framework

This study is underpinned by the Technology–Organisation–Environment (TOE) framework (Tornatzky & Fleischer, 1990), widely applied in technology-adoption research, together with key constructs drawn from Strategic Decision-Making Theory (Eisenhardt & Zbaracki, 1992). Within the TOE framework, the technological context refers to the availability, complexity and perceived usefulness of analytics platforms; the

organisational context encompasses firm size, leadership support, internal capability and cultural openness to innovation; and the environmental context reflects external drivers such as competition, regulatory demand and economic uncertainty. Strategic Decision-Making Theory complements this by emphasising that investment outcomes are shaped not only by the availability of information but by how decision-makers perceive, interpret and act upon it, highlighting the role of bounded rationality, heuristics and strategic intent (Eisenhardt & Zbaracki, 1992). Read together, these perspectives position the strategic use of data analytics as an important explanatory lens through which enablers (such as leadership support and skills availability) and barriers (such as cost and data quality) can be understood in relation to perceived investment outcomes, including asset performance, risk management and investor confidence; because this study did not statistically test pathways between these constructs, analytics is treated as an interpretive lens rather than a formally modelled mediating variable. This integrated framework guided both the design of the data-collection instrument and the thematic analysis of the empirical findings presented later in this article. It is also worth noting that TOE was developed primarily as a framework for organisational-level technology adoption, whereas the empirical evidence in this study is drawn from individual professionals who often operate across, or move between, multiple organisations; the framework is therefore applied here at the level of the individual practitioner's account of organisational and environmental conditions, rather than as a validated firm-level assessment, and this scope is made explicit in the Methodology and Discussion sections below.

Research gap

Although a growing body of literature addresses data analytics, market intelligence and property technology in real estate, much of this research remains concentrated in developed-market contexts. Comparatively limited empirical attention has been paid to the South African property market, and to Johannesburg's commercial real estate sector in particular. Existing studies also tend to emphasise the theoretical benefits and technical capabilities of analytics tools rather than how they are actually applied by property investors in day-to-day investment decisions, leaving a limited understanding of the barriers that hinder adoption and the factors that encourage the use of data-driven tools within this specific local context. This study addresses that gap by exploring how commercial property investment professionals in Johannesburg use data analytics and market intelligence, the barriers and enablers shaping adoption, and the role these tools play in supporting investment decision-making.

This gap is not merely geographic. The closest South African precedent, Cheruiyot and Gamede's (2024) qualitative study of big data and analytics potential across South Africa's wider real estate sector, establishes through expert interviews that current applications, barriers and potential uses of analytics remain limited and unevenly distributed. The present study differs from, and builds on, that work in three respects: first, it narrows the unit of analysis from real estate professionals in general to commercial property investment decision-makers specifically (brokers, valuers, asset and portfolio managers) operating within a single metropolitan market, Johannesburg, allowing a more fine-grained account of investment-specific practice than a sector-wide study can provide; second, it applies the Technology–Organisation–Environment framework jointly with Strategic Decision-Making Theory, which foregrounds how individual decision-makers interpret and act on analytical outputs rather than treating adoption as a purely organisational-technology question; and third, it explicitly separates conventional valuation technique from more advanced, technology-enabled analytical practice (see the analytical-maturity distinction introduced above), which allows this study to test, rather than assume, the extent of genuine digital transformation. The incremental contribution of this study is accordingly a maturity-differentiated, decision-theoretic account of how individual commercial investment professionals in Johannesburg's market apply, resist and are pushed toward analytics, rather than a restatement of Cheruiyot and Gamede's (2024) broader sector-level findings in a narrower setting.

METHODOLOGY

Research design and philosophy

This study adopted an exploratory, qualitative research design, as the strategic use of data analytics and market intelligence in property investment, particularly within the South African context, remains an emerging area of empirical inquiry (Saunders, Lewis & Thornhill, 2023). An exploratory design supported open-ended inquiry into organisational practice, challenges and strategy, allowing fresh insight to be developed in a domain

characterised by scarce local empirical evidence. A case study strategy was selected as the most appropriate means of exploring the phenomenon within its real-world context, with the case bounded as commercial property investment decision-making practice within the Johannesburg metropolitan market, and the individual participating professionals – rather than their employing organisations – constituting the primary unit of analysis; this single embedded case with multiple analytical units follows Yin's (2018) allowance for bounding a case around a phenomenon rather than a single organisation, and is made explicit here because the Technology–Organisation–Environment framework applied later is, strictly, an organisational-adoption framework, whereas the evidence gathered reflects individual professionals' accounts of practice across multiple organisations rather than validated firm-level data. The study's analytical approach is more accurately characterised as hybrid deductive-inductive (abductive) rather than purely inductive: the interview guide and initial coding structure were shaped deductively by the Technology–Organisation–Environment framework and Strategic Decision-Making Theory (see Literature Review), while inductive coding allowed additional categories to emerge directly from participants' accounts; this abductive movement between theory and data, rather than a strictly ground-up inductive process, is reflected consistently in the Data Analysis section below. The study was further guided by an interpretivist research philosophy, which views reality as socially constructed and best understood through the subjective experiences, meanings and perspectives of individuals within their natural context (Creswell & Poth, 2020). This paradigm was considered appropriate given the study's focus on how professionals perceive, adopt and implement analytics tools in investment decision-making, contexts not easily reduced to purely quantitative measurement.

Population, sampling and participants

The target population comprised approximately fifty property investors, investment analysts, portfolio managers and property-development professionals actively involved in commercial real estate investment decision-making within the Johannesburg metropolitan area, working across private investment firms, real estate agencies, listed property entities and development companies. This figure is the researcher's own estimate of the professionals meeting the study's eligibility criteria who were reasonably reachable through the researcher's professional network within the Johannesburg commercial property sector; it is not derived from a formal industry registry or membership database, and this basis is acknowledged as a limitation on the precision of the population estimate. Eligibility for participation required a minimum of two years' direct professional involvement in commercial property investment decision-making (brokerage, valuation, asset or portfolio management, or development) within the Johannesburg metropolitan area. Participants were recruited purposively through the researcher's professional network and referrals from initial contacts (a limited snowball element), with organisations represented spanning independent and multi-branch commercial brokerages, boutique valuation and advisory practices, and professionals with exposure to listed/institutional property funds; specific employer names are withheld throughout, consistent with the confidentiality undertakings described below. Formal records of individuals approached who declined or did not respond were not systematically retained during recruitment, and the absence of a documented refusal rate is acknowledged as a limitation of the sampling process. A non-probability, purposive sampling strategy was adopted, whereby participants were deliberately selected based on their experience, expertise and active involvement in property investment decision-making (Etikan, Musa & Alkassim, 2016). The final sample comprised fifteen participants, a size considered appropriate for a qualitative case study in which the emphasis lies on rich, detailed insight rather than statistical generalisability, and guided by the principle of data saturation, whereby data collection continued until further interviews yielded no substantively new themes (assessed by the researcher through ongoing comparison of newly coded material in NVivo against the existing coding structure; no substantively new codes emerged during coding of the final interviews, at which point recruitment was concluded).

Data collection

Primary data were collected through semi-structured interviews, an approach well suited to exploring strategic practice, institutional adoption and individual perception while allowing flexibility to follow up on unanticipated insight as it arose (Bryman, 2016). A structured interview guide was developed around the study's four research objectives, beginning with participant demographics before progressing through sections addressing current analytics use, barriers to adoption, enablers of adoption, and recommendations for improvement. With the informed consent of each participant, interviews lasted approximately forty to forty-five minutes and were

conducted in person or via an online video-conferencing platform according to participant preference; all interviews were audio-recorded, transcribed verbatim and securely stored for analysis. Interviews were conducted by a single researcher over a defined data-collection window in 2025, following institutional ethical clearance and prior to the commencement of formal analysis; because a single researcher conducted all interviews and coded all transcripts, formal inter-coder reliability checks were not applicable, which is acknowledged as a limitation and is why credibility was instead pursued through the member-checking and audit-trail measures described below. Prior to the main data-collection phase, a pilot study involving three participants with comparable professional backgrounds was conducted to evaluate the clarity, relevance and logical sequencing of the interview guide, with resulting feedback used to refine question wording and structure (Polit & Beck, 2020). These three pilot participants were drawn separately from the researcher's network specifically for instrument testing and are distinct from, and not counted among, the fifteen participants whose data are analysed and reported in this article.

Data analysis

Data were analysed using thematic analysis, following the widely established six-phase approach of familiarisation, initial coding, searching for themes, reviewing themes, defining and naming themes, and producing the final report (Braun & Clarke, 2006). Interview transcripts were read repeatedly to achieve close familiarity with the data, after which meaningful segments of text were systematically coded using NVivo (Version 14) qualitative data analysis software, to enhance the transparency, consistency and traceability of the coding process. Related codes were then clustered into broader candidate themes, which were reviewed against the dataset for internal consistency and relevance to the research objectives before being refined and clearly defined. The analysis combined deductive and inductive coding: deductive coding was guided by the study's research objectives and conceptual framework, while inductive coding allowed additional insight to emerge directly from participants' responses, supporting an analysis that remained both structured and responsive to the data – an abductive movement between theory and data that is described more fully in the Research Design section above.

Trustworthiness and ethical considerations

Trustworthiness was addressed through the four criteria of credibility, transferability, dependability and confirmability (Lincoln & Guba, 1985). Credibility was strengthened through member checking, in which participants were given the opportunity to review their transcripts for accuracy, together with a reflective journal documenting analytical decisions throughout the research process. It is acknowledged that member checking in this study was limited to verifying transcript accuracy rather than inviting participants to review the researcher's thematic interpretation, and this narrower scope is noted as a limitation of the credibility strategy adopted. Transferability was supported through rich, contextual description of the research setting and participant characteristics, enabling readers to judge the relevance of the findings to comparable urban property markets. Dependability was reinforced through a documented audit trail of methodological decisions and coding procedures, while confirmability was strengthened through reflexive practice and triangulation across multiple participant categories, reducing the influence of any single viewpoint on the resulting themes.

The study was conducted in accordance with recognised ethical principles for research involving human participants, including voluntary participation, informed consent, and the protection of confidentiality and anonymity. All participants received a letter of information outlining the purpose, scope and voluntary nature of the study and were informed of their right to decline specific questions or withdraw at any stage without penalty. Formal consent was documented in writing prior to each interview. To protect confidentiality, personal identifiers, specific job titles, employer names and any proprietary systems or tools referenced by participants were excluded from analysis and reporting; participants are referred to only by anonymised identifiers (P01–P15) and general professional role throughout this article, and no individual, transaction or organisation is identifiable from the findings presented. Ethical clearance for the study was obtained from MANCOSA's Research Ethics Committee, the researcher's affiliated institutional research ethics committee, prior to the commencement of data collection.

Table 2: Profile of research participants (N = 15)

Characteristic	Category	n
Gender	Male	14
	Female	1
Age group	18–30 years	3
	31–40 years	4
	41–50 years	6
	Above 50 years	2
Organisational tenure	3–5 years	4
	6–10 years	5
	More than 10 years	6

Source: Author's fieldwork.

The sample was predominantly male (fourteen of fifteen participants), broadly reflecting the gender composition of brokerage and investment advisory roles within the commercial property sector; while gender dynamics were not a specific focus of this study, this imbalance points to a worthwhile avenue for future research on diversity within property investment leadership. Most participants (six) were aged between forty-one and fifty years, with the remainder fairly evenly distributed across younger and older age bands, suggesting that investment decision-making in this market is shaped predominantly by professionals with substantial accumulated market experience, while also reflecting a degree of generational transition toward greater digital fluency. The majority of participants (eleven of fifteen) had more than five years of tenure within their current organisation, indicating a sample well positioned to comment on both established practice and recent shifts in analytical capability. To support the traceability of the evidence presented in the Results and Discussion section, each participant is assigned an anonymised identifier (P01–P15); Table 2b reports each identifier's broad professional role and organisation-type category, without disclosing employer names, exact tenure or other potentially identifying detail.

Table 2b: Participant identifiers and broad role/organisation category

Participant ID	Broad professional role	Broad organisation-type category
P01	Broker (commercial leasing and sales)	Multi-branch commercial brokerage
P02	Broker/analyst (acquisitions-focused)	Independent brokerage
P03	Broker-valuer	Independent brokerage
P04	Broker (informal valuation advisory)	Independent brokerage
P05	Principal broker/director	Multi-branch brokerage (high transaction volume)
P06	Broker (industrial nodes)	Independent/boutique brokerage

P07	Broker	Multi-branch brokerage
P08	Broker	Multi-branch brokerage
P09	Broker (multi-region: Gauteng metros)	Independent/boutique brokerage
P10	Broker (industrial, early-career)	Boutique brokerage
P11	Broker	Multi-branch, long-established brokerage
P12	Broker (industrial nodes, early-career)	Boutique/independent brokerage
P13	Broker (buyer/investment-side focus)	Independent brokerage
P14	Industrial/logistics investment advisor	Advisory practice with institutional-facing clients
P15	Principal/owner, retail leasing and advisory	Boutique advisory practice

Source: Author's fieldwork.

RESULTS AND DISCUSSION

This section presents and discusses the empirical findings in relation to the study's four research objectives. Findings are interpreted with reference to the Technology–Organisation–Environment framework and Strategic Decision-Making Theory outlined above, and are illustrated, where appropriate, with brief, non-identifying excerpts from the interviews attributed only by anonymised participant identifier (P01–P15) and general professional role, consistent with the confidentiality undertakings given to participants. Table 4 summarises, for each recurring code discussed below, the participants whose accounts illustrate it; the listing is illustrative of the range of supporting evidence rather than an exhaustive frequency count, and a code's absence from a participant's row does not necessarily mean the topic did not arise in that interview, only that it was not a salient part of that participant's account. Consistent with the analytical-maturity distinction introduced in the Literature Review, the discussion below also identifies, where relevant, which practices reflect conventional (descriptive/diagnostic) valuation technique and which reflect more advanced (predictive, geospatial or system-integrated) analytical practice, and it reports deviant or contradictory cases alongside the dominant pattern.

Table 4: Illustrative participant coverage by code and theme

Theme	Code / sub-theme	Illustrative participants
Current use	Yield/cap-rate as primary screening threshold	P01, P02, P06, P13, P15
Current use	Comparable-sales benchmarking as validation	P02, P03, P08, P12
Current use	Internal/proprietary transaction data as strategic asset	P05, P07, P08, P14
Current use	Advanced practice: geospatial, scenario/sensitivity or API-integrated analysis	P05, P09, P10, P14, P15
Barriers	Data completeness/quality concerns	P02, P04, P06, P12
Barriers	Cost and implementation complexity	P02, P05, P14
Barriers	Market volatility / currency of historical data	P05, P06, P14

Barriers	Behavioural/relational anchoring in negotiation	P01, P11, P13
Barriers	Deviant case: no substantive barriers reported	P13, P15
Enablers	Internal data accumulation	P05, P07, P08, P14
Enablers	Technological/systems integration	P01, P05, P10, P14
Enablers	Investor demand for evidence-based justification	P02, P14, P15
Enablers	Digital literacy, mentoring and training culture	P01, P06, P09, P11, P14
Recommendations	Training and professional development	P01, P06, P09, P11, P14
Recommendations	Industry collaboration / anonymised data-sharing	P02, P05, P06, P14
Recommendations	Deviant case: opposition to data-sharing/collaboration	P13
Recommendations	Policy, regulatory and infrastructure change	P02, P05, P15

Source: Author's coding of the fifteen interview transcripts.

Current use of data analytics and market intelligence

Across the sample, yield-based investment modelling emerged as the primary analytical foundation for commercial property investment decisions. Participants consistently described the income-capitalisation approach as the first and most decisive screening mechanism applied when evaluating a potential acquisition, rather than merely one input among several. As P01 explained, acceptable capitalisation rates vary sharply by node and asset quality: “Investors are looking for, say, 11% plus, depending on the area and the property... different areas will [vary] – like Waterfall, for example, which is in such high demand, you're looking at cap rates as low as 8.5 to 9%, whereas less desirable areas it's going to go 11%... if you go at Boksburg East, they probably want 15%.” P13 described the same logic in more binary terms: “It's actually, it's a simple... yes or no. You've got a buyer that wants a 10% yield. Does that particular property generate 10% yield? That's the first point of call... if it doesn't tick that particular box, you know, what is the point of looking any further than that?” This finding strongly supports the income-capitalisation approach to commercial property valuation described in the literature (Geltner et al., 2018), confirming that this theoretical model is deeply institutionalised in professional practice rather than remaining a purely academic construct. Yield modelling was not, however, applied rigidly: participants described adjusting capitalisation rates to reflect risk variables such as tenant strength, lease duration and node desirability, consistent with the risk–return trade-off principle in the literature (Baum & Hartzell, 2012), and several participants framed yield modelling as a means of introducing objectivity into negotiations with sellers anchored to legacy purchase prices, a pattern consistent with anchoring bias in behavioural finance (Kahneman, 2011). In terms of the analytical-maturity distinction introduced above, this dominant practice sits at the descriptive-to-diagnostic end of the spectrum: it is a long-established valuation technique applied consistently and skilfully, but it does not by itself indicate advanced analytics or PropTech adoption. A smaller number of participants described using yield outputs diagnostically, to interrogate rather than simply accept a model's assumptions; P14, for example, explained that when a model shows “aggressive rental growth assumptions, my instinct is to interrogate whether infrastructure capacity, truck access, and labour availability realistically support that growth... analytics acts as a catalyst for deeper, more critical discussion rather than a conclusion.”

A closely related theme was the systematic use of comparable sales data to validate the outputs of income-capitalisation modelling. Once a yield-based valuation had been produced, it was routinely cross-checked against recent transaction evidence for similar assets in the same node, expressed as an achieved price per square metre, reflecting the principle of substitution described in the valuation literature (Pagourtzi et al., 2003). P02 described this cross-checking explicitly: “Once you've finished your income capitalisation model, that's going to give you

a number. So you don't just take that alone... you have to now also still compare that with... the market, the comparable sales... only when those two numbers are... in alignment... [can you be confident], but that can only come from using quality data.” P03 described the practical steps involved: “We actually do windeed to get actual sales compared to the size... we go ahead and do a Google search of the buildings, we map the building, we measure it... we generally go back five years for windeed.” Participants nonetheless noted that publicly available transaction records were often incomplete, for example reflecting only registered bond values rather than full purchase prices, requiring analysts to apply a margin of caution when interpreting such data; others noted that thinly traded nodes could see transactions clear well above historical averages purely due to scarcity of available stock. P12 made the bond-value limitation explicit: “With windeed, the issue is that they only show the bond amount, so you don't actually know how much deposit they put down... I normally just add a [buffer], just to be safe.” P06, describing a low-supply node, illustrated the scarcity effect: “My area is tricky. There's very limited properties... my area reaches above market prices... there's guys that will pay above market prices to be in the area to expand.” These observations reflect the information asymmetry that characterises commercial property markets more broadly (Baum & Hartzell, 2012), confirming that comparable sales evidence requires careful interpretation rather than uncritical acceptance.

A third theme concerned the growing strategic reliance on internally accumulated transaction data. While publicly available property data platforms were widely used, participants expressed considerably greater confidence in data drawn from their own concluded transactions, particularly within practices that process a high volume of deals annually, since internally captured data reflects achieved outcomes, including negotiated incentives and effective rentals, rather than advertised or headline figures. P05 described both the scale and the technological architecture underpinning this practice: “We exceed about 500 deals a year... that all gets captured into our own CRM system, and then our CRM system can split out graphs and charts at will... it's internal systems that we built ourselves... everything's got an API... so there's not a manual input from the brokers.” P14 similarly explained that “our internal leasing and sales data has become one of our most valuable resources, particularly in the industrial sector where transactional evidence can be limited... knowing the effective rental achieved on a specific warehouse, including incentives and escalation structures, is often more informative than published asking rentals.” This finding aligns closely with the Resource-Based View of the firm (Barney, 1991), which holds that sustainable competitive advantage derives from resources that are valuable, rare and difficult for competitors to replicate; proprietary, deal-level transaction data meets these criteria and functions as a strategic capability rather than a purely administrative record. It also illustrates the technological and organisational dimensions of the TOE framework, in that firms investing in integrated systems for capturing and retrieving transaction records demonstrated higher analytical maturity, reflecting an organisational culture oriented toward structured knowledge management (McAfee & Brynjolfsson, 2012). In maturity terms, P05's API-linked, real-time internal system, and P14's structured internal deal-tracking and cash-flow records, represent the more automated and system-integrated end of the spectrum described above; by contrast, several other participants described comparable internal record-keeping conducted manually in spreadsheets (for example P08's description of an internally maintained “opinion of value” template), illustrating that the underlying enabler, proprietary data, is shared across the sample even where the degree of technological sophistication in capturing it varies considerably.

A fourth theme highlighted that no single data source was treated as sufficient on its own. Participants described a layered process in which income modelling, comparable sales evidence, current market listings and internal transaction records were triangulated, with the resulting figures then interpreted through the lens of accumulated professional experience. P08 summarised this interpretive layering: “The data gives you a general perspective, but you still need to understand the nuances of the building and the area. Two properties next to each other can trade at very different rates because of things like yard size, sprinkler systems, or access. The numbers don't always capture those details.” Several participants noted that asset-specific characteristics, such as configuration, specification or access, could cause seemingly similar properties to trade at markedly different values in ways that quantitative averages alone could not capture, particularly in retail-oriented transactions where demographic and locational analysis played an additional role. Here the sample's analytical-maturity gradient was most visible. At the more descriptive end, several participants (for example P07) described a templated internal valuation tool into which comparable-sales figures are entered to “shoot out a number,” which is then adjusted manually. At the geospatial and predictive end, P09 and P10 both described using geographic information systems to assess

road servitudes, attenuation requirements and buildable area on prospective industrial land, effectively a diagnostic-to-predictive application of spatial data; P15 described a comparable geospatial approach for retail leasing, layering “demographic[s]... schools, hospitals, transport routes” over conventional rental analysis; and P14 described the most advanced practice reported in the sample, combining “cash-flow modelling, lease expiry profiling, and scenario testing,” including a documented case in which market intelligence on rising vacancy and congestion around a logistics precinct led the practice to revise exit assumptions and advise a lower acquisition price despite an otherwise compelling asset. P14 was, however, explicit that this did not amount to precision forecasting: “I am sceptical of the idea that analytics necessarily increases precision... I see analytics as a tool that improves awareness of risk rather than guaranteeing accuracy.” This range, from templated spreadsheet lookups to geospatial and scenario-based modelling, illustrates that the sample's practice spans several points on the analytical-maturity spectrum rather than sitting uniformly at either the conventional-valuation or advanced-analytics end. This finding is consistent with the argument that analytics enhances, but does not replace, managerial judgement (Davenport & Harris, 2017), and with the recognition that commercial real estate is a structurally heterogeneous and imperfectly efficient asset class in which no single dataset can fully capture value (Baum & Hartzell, 2012). It also illustrates Strategic Decision-Making Theory (Eisenhardt & Zbaracki, 1992): decision quality in this context depends not only on data availability but on how experienced decision-makers interpret, contextualise and act upon it. Collectively, these findings suggest that data analytics in Johannesburg's commercial property sector functions as a hybrid decision-support system, combining structured quantitative modelling with tacit, experience-based interpretation, with a minority of practices showing meaningfully more advanced analytical maturity than the sample median.

Barriers to the strategic adoption of data analytics

While the findings above demonstrate widespread operational use of analytics, four interrelated barriers emerged that constrain deeper strategic integration. The most consistently cited barrier concerned the completeness and reliability of available data. Participants noted that commonly used property data platforms often capture only partial financial information, for instance registered bond values without corresponding deposit or capital-structure detail, requiring analysts to make interpretive assumptions that introduce a degree of risk into modelling outputs; discrepancies between headline and effective rental levels, arising from incentives, rent-free periods and tenant-installation allowances, were also frequently noted as a source of distortion in published market reports. P04 summarised the comparability problem directly: “The access [to] information can sometimes be difficult... when you're trying to do comparisons, the like-for-like information that you're trying to find can sometimes be missing.” P02 described the broader inefficiency this creates: “A lot of the quality information has been siloed into different brokerages... a lot of the quality information has to be done again, and... replicated all over the place, which is very inefficient.” These findings reflect the structural information asymmetry that characterises commercial property markets, in which transactions are infrequent, assets are heterogeneous, and pricing detail is often privately negotiated (Baum & Hartzell, 2012; Pagourtzi et al., 2003), and support the broader argument that data-driven decision-making improves outcomes only where underlying data quality is sufficiently robust (Davenport & Harris, 2017). It is important to note, however, that this barrier was not universally experienced: P13 stated plainly that he had “never [been] in a situation where two particular properties were that different that you weren't able to draw some form of comparative,” and P15 reported that “we haven't had any problems from our side... I do think we have [one of] the best systems” in reference to South Africa's deeds-registry infrastructure. This deviant case suggests that the severity of the data-quality barrier may depend on transaction volume, asset type and the specific platforms an individual practice has come to rely on, rather than being a uniform constraint across the sector.

Participants also identified the financial and operational cost of implementing advanced analytics capability as a significant constraint, particularly for small and mid-sized investors, extending beyond software subscriptions to infrastructure, cybersecurity, staff training and the recruitment of personnel able to interpret analytical outputs. Because property is a long-duration asset class, several participants noted that the return on analytics investment is difficult to observe or quantify in the short term, discouraging capital commitment in an already volatile operating environment. P05 described the cost of building bespoke systems directly: “It costs a lot to implement some sort of systems like these... the barrier to entry is extremely high,” adding that the firm had been unable to find the necessary technical skills locally and “had to outsource overseas.” P14 linked cost to market structure:

“Cost and skills constraints also remain significant. Smaller investors often lack the resources to access high-quality data or employ analytical expertise. As a result, analytics adoption tends to be uneven and concentrated among larger players.” This finding aligns with literature identifying implementation cost and complexity as core barriers to analytics adoption in emerging markets (Deloitte, 2023; Edet, 2023), and with the broader recognition that the illiquid, cyclical nature of real estate complicates the measurement of analytics-related return on investment (Baum & Hartzell, 2012).

A third barrier related to the volatility and rapidly changing dynamics of the Johannesburg commercial property market. Participants noted that historical transaction data can quickly lose predictive relevance where node-level conditions shift, for example following a major tenant relocation, new infrastructure investment or a change in interest rates, and that scarcity of available stock in certain nodes can cause transactions to clear well above what historical averages would suggest. P05 illustrated the pace of this shift with a concrete example: “Guys are selling properties three, four years ago for 8,000 a square. Now they're selling at about 12,000 a square metre... trying to work out yields nowadays is a difficult task. You've got rates that are [rising] through the roof.” P14 described a related but more structural volatility, where “mixed data can... obscure meaningful differences and lead to incorrect conclusions” when modern logistics stock and older, functionally obsolete stock sit within the same reported node average. This finding is consistent with literature emphasising the cyclical and context-sensitive nature of commercial property markets and evidence that fast-moving environmental conditions can outpace the currency of historical datasets (PwC & Urban Land Institute, 2025), and reflects node-specific performance divergence documented in the South African commercial property literature, whereby prime and emerging nodes can perform very differently from broader market averages (Schultz, 2024).

Finally, participants described the persistence of behavioural and relational dynamics in negotiation as a constraint on the strategic authority of analytics. Even where yield modelling and comparable sales evidence were presented clearly, sellers in particular were described as often anchoring to historical purchase prices or personal expectations of value, meaning that analytics could structure a negotiation without fully determining its outcome. P11 recounted a specific case in which a client wanted to pursue an offer well above the evidence: the landlord “wanted 18 million, his highest offer was 13.5 [million], but the going rates in that area for that property was probably around 9 or 10 [million]... we advised him not to[; it was] more [of] an emotional decision because he obviously felt attached to this property.” P13 generalised the pattern from the seller's side specifically: “I would say a seller is more emotional as opposed to a buyer... you've got to... beat down the emotional attachment that a seller has as opposed to the buyer.” This finding is consistent with behavioural finance research on anchoring and related biases (Kahneman, 2011), and with literature emphasising that digital transformation in real estate is frequently constrained less by technology itself than by entrenched, relationship-based industry norms (Deloitte, 2023), reflecting the persistence of socially negotiated pricing dynamics even in increasingly digitised property markets (Schultz, 2024). Collectively, these four barriers span all three dimensions of the TOE framework, technological (data quality), organisational (cost, skills and culture) and environmental (market volatility), while Strategic Decision-Making Theory helps explain how behavioural bias continues to moderate the practical authority of analytical outputs.

Enablers of the strategic adoption of data analytics

Despite these constraints, the findings also identified enabling conditions that are progressively deepening the strategic integration of analytics within the sector. The accumulation of proprietary internal transaction data, discussed above under current analytical practice, also functions as a primary enabler of deeper strategic adoption: firms that systematically capture granular, deal-level information develop stronger predictive capacity, richer negotiation credibility and reduced dependence on incomplete external datasets (Deloitte, 2023; Mofokeng & Okoro, 2024). P08 illustrated how this accumulated internally over time: “Our internal system has grown [over] the past four years... we get inquiries that come in... as we get more data, it feeds into the systems.”

A further enabler was the increasing integration of internal technology systems, linking transaction records, mapping tools, client databases and financial modelling through automated data flows. Participants described how such integration reduced the manual effort involved in compiling a transaction profile and made analytics a routine part of daily workflow rather than a specialised, occasional exercise, and several noted that geographic and demographic data, once difficult to access, are now considerably more available than a decade ago. P01

described this in terms of a purpose-built CRM: “We've just had a new CRM system formulated for us... that's going to capture every aspect of the property life cycle... instead of [separate tools for] each [task], we've now incorporated all into one CRM system where it's all interconnected.” P10 offered a temporal comparison consistent with growing infrastructure maturity: “Ten years ago, it wasn't this easy to access demographic or traffic data. Now, technology has made it far more accessible.” This finding is consistent with literature identifying integrated digital ecosystems as central to successful property-technology adoption (Deloitte, 2023), and with evidence that technological readiness significantly shapes digital diffusion within African real estate markets more broadly (Cheruiyot & Gamede, 2024; Schultz, 2024).

A particularly strong enabler was the growing expectation among investors themselves for transparent, evidence-based justification of recommendations. Participants described a shift away from reliance on broker opinion toward explicit requests for yield models, comparable sales evidence and clearly stated assumptions, with client confidence diminishing where such evidence could not be produced. P02 captured this shift directly: “Data analytics will always have a place and should always be used if you want to be a professional... you must use data to justify what your decisions are, all the time.” P14 linked the same pressure to more sophisticated institutional clients: “Industrial investors today are far more analytically demanding than they were a decade ago. Many operate across multiple geographies and expect Johannesburg assets to be benchmarked against international standards.” P15 was more blunt about the negotiating consequence of not having data: “If you don't have the data, you don't have any negotiating power to do anything with.” This finding aligns with evidence that post-pandemic real estate markets have experienced a structural shift toward performance accountability and quantitative justification (Deloitte, 2023), and with reports that institutional investors globally are demanding greater transparency in underwriting assumptions (PwC & Urban Land Institute, 2025). Importantly, this enabler appears to operate through reputational pressure: where clients expect visible modelling, practitioners are incentivised to strengthen their analytical capability in order to preserve professional credibility, suggesting that analytics adoption is becoming linked to professional legitimacy rather than remaining a purely discretionary capability.

Finally, participants pointed to a gradual but meaningful increase in digital literacy and analytical confidence within the sector, particularly, though not exclusively, among younger professionals who are more accustomed to working with spreadsheets, dashboards and online data platforms; several noted that structured training and professional development have improved practitioners' ability to interpret model assumptions and outputs critically, rather than treating them uncritically. P01 described a structured, firm-led approach to this: “We have master classes... where we cover certain topics... we get an industry leader to come and tell us about his journey in property... education and training, exposing people to different systems.” P14 described a more experiential model: “The most effective training is experiential and case-by-case based. Working through real property investment examples where outcomes weren't exactly in line with expectations... helps professionals appreciate both the value and the potential limitations of analytics.” P11 pointed to informal, self-directed uptake of AI tools as a further sign of rising literacy, describing his own use of generative-AI queries to sense-check market rates. A degree of caution accompanied this enthusiasm, however: several of the more experienced participants, including P01 and P13, described themselves as deliberately cautious adopters of artificial intelligence specifically, with P13 noting that such tools are useful only “up to a point... [before they] eventually take over.” This is consistent with literature identifying digital literacy as a foundational determinant of property-technology adoption in emerging economies (Edet, 2023; Cheruiyot & Gamede, 2024), suggests a cultural shift toward the normalisation of analytics as part of everyday professional practice rather than a specialised function (Deloitte, 2023), and indicates that rising interpretive competence is gradually reducing the trust-related constraints identified above.

Strategic implications and recommendations

Drawing on the findings above, several interrelated strategic priorities emerge for strengthening the integration and effectiveness of data-driven decision-making in Johannesburg's commercial property investment sector, summarised in Table 3. Participants' own recommendations align closely with, and substantiate, these priorities. On continuous digital skills development, P01 described structured internal training as central to building analytical capability, noting that his firm runs “master classes... where we cover certain topics... education and training, exposing people to different systems”; P06 linked training directly to output quality, observing that a

broker “who knows nothing about his area” produces valuations that become “such outliers” relative to benchmarks such as Rode; P09 and P11 stressed that data literacy is never complete, with P09 remarking that “you can never really have enough training or education... even now, at 12 years in the game, I still like to read books”; and P14 argued that the most effective training is “experiential and case-by-case based,” working through real examples where outcomes diverged from expectations. On industry-level data-transparency initiatives, several participants were cautiously supportive of shared, anonymised platforms: P02 argued that the sector's current siloed approach to data-gathering is duplicative and that cultivating “a community good” would benefit “everybody, clients and... practitioners themselves”; P06 agreed that “the more data, the better,” describing shared vacancy information as potentially “hugely beneficial”; and P14 suggested that an existing industry body such as SAPOA “could definitely be at the centre of this if done correctly.” This support was not unanimous: P13 regarded sharing information with a competing broker as offering “no benefit” and called the idea “a nonstarter,” viewing information advantage as one of the profession's few sustainable sources of competitive edge — a deviant case reflected in Table 3's framing of transparency initiatives as voluntary, anonymised and industry-led rather than mandatory. Finally, on the environmental and regulatory conditions surrounding analytics adoption, participants pointed to institutional friction rather than to any absence of usable data as the more pressing constraint: P02 described a key regulator's own database as unreliable, noting it “has been down since maybe August”; P05 pointed to the operational burden of FICA and POPI compliance and to cross-border data-hosting arrangements as sources of friction rather than facilitation; and P15 described the PPRA plainly as “absolutely useless” in its current form, calling for faster, less encumbered property-transfer processes. Taken together, these accounts suggest that the environmental dimension of the TOE framework in this market is currently shaped more by regulatory friction and institutional inefficiency than by a shortage of usable data, a distinction that informs the framing of the recommendations in Table 3.

Table 3: Summary of recommendations for strengthening data-driven decision-making in commercial property investment

Recommendation	Rationale
Formalise and strengthen internal data governance	Standardises the capture, validation and storage of transaction-level information (effective rentals, incentives, escalation clauses), reducing reliance on incomplete public datasets.
Develop industry-level data transparency initiatives	Anonymised, collaborative transaction-sharing among industry participants could reduce information asymmetry and improve benchmarking accuracy market-wide.
Adopt phased and scalable digital transformation	Incremental technology investment reduces financial risk and supports organisational learning, aligning adoption with the long-term nature of property returns.
Institutionalise analytical transparency in advisory practice	Standardised disclosure of yield assumptions, sensitivity analysis and comparable evidence strengthens professional credibility and negotiation defensibility.
Invest in continuous digital skills development	Structured, ongoing training in modelling and data interpretation improves confidence and reduces resistance to analytical tools.
Promote hybrid decision-making competence	Deliberately integrating quantitative modelling with experiential judgement, including mentorship pairings, strengthens decision robustness.
Enhance technological infrastructure integration	Interoperable CRM, mapping and modelling systems reduce manual inefficiency and support real-time analytical visibility.

Align leadership strategy with long-term digital vision	Executive sponsorship and resource commitment embed analytics as an organisational priority rather than a discretionary initiative.
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Collectively, these recommendations address constraints across all three dimensions of the TOE framework while reinforcing the hybrid analytical model identified in this study: quantitative rigour is strengthened through governance, infrastructure and skills investment, while the complementary role of professional judgement is explicitly preserved rather than displaced.

CONCLUSION

This study set out to explore the strategic use of data analytics and market intelligence in commercial property investment decision-making in Johannesburg, South Africa, and to identify the barriers, enablers and strategic pathways shaping its adoption. The findings indicate that data analytics is widely, though unevenly, embedded at an operational level, with yield-based modelling, comparable sales benchmarking and internally accumulated transaction data functioning as the foundational tools of investment evaluation; as discussed above, these practices sit predominantly toward the descriptive-to-diagnostic end of the analytical-maturity spectrum rather than representing advanced, automated or predictive analytics. However, the study also concludes that analytics has not achieved full strategic dominance: the heterogeneity, illiquidity and negotiated character of commercial property assets mean that quantitative modelling continues to operate alongside, rather than in place of, professional judgement.

A central conclusion is that Johannesburg's commercial property investment market currently operates within a hybrid decision-making model, in which data provides structure, justification and negotiation leverage, while experience-based interpretation addresses complexity, behavioural nuance and market-specific context that models alone cannot capture. Participants consistently described analytics as improving their own confidence in, and the perceived defensibility of, investment recommendations — for example, in reduced overconfidence, sharper pricing discipline and stronger negotiating positions — and these should be read as self-reported, perceived benefits rather than independently verified effects on realised investment performance, since this study did not measure transaction outcomes directly. The sector appears to be in a transitional phase of digital maturity, propelled by strengthening internal data capability, technological infrastructure integration, rising investor demand for transparency, and improving digital literacy, but still constrained by cost sensitivity, data-governance gaps and structural information asymmetry.

Theoretically, the study extends the application of the Technology–Organisation–Environment framework and Strategic Decision-Making Theory to an empirical, emerging-market real estate context that remains under-represented in the international literature, most existing research having concentrated on developed markets. Practically, the findings offer property investors, brokers and advisory firms a structured basis for prioritising investment in governance, infrastructure, transparency and skills development, while offering policymakers and industry bodies a rationale for supporting collaborative data-transparency initiatives that could benefit the wider market.

The study is subject to several limitations that should be considered when interpreting its findings. As a qualitative, exploratory case study centred on a single metropolitan commercial property market and a purposively selected sample of fifteen practitioners, the findings are context-rich but not statistically generalisable to other markets, asset classes or geographic contexts. Reliance on self-reported data also means that findings reflect participants' perceptions and interpretations rather than independently verified transaction outcomes. As noted in the Methodology, coding was conducted by a single researcher without independent co-coder verification, formal refusal rates were not systematically tracked during recruitment, and member-checking of the thematic interpretation was limited to the summary level rather than full-transcript sign-off by each participant; these constraints are reiterated here because they bear directly on the strength of the evidentiary claims made throughout the Results and Discussion. Future research could usefully extend this work through quantitative analysis of the relationship between analytics adoption intensity and realised investment performance, comparative studies across other African commercial property markets, longitudinal research tracking the pace of digital transformation over time, independent multi-coder replication of the thematic

analysis, and behavioural research examining how investors respond to increased modelling transparency in negotiation contexts.

Overall, this study demonstrates that data analytics and market intelligence represent an increasingly important, but not yet fully institutionalised, strategic resource within Johannesburg's commercial property investment landscape. Strengthening governance, infrastructure, transparency and human capital appears central to enabling the sector's continued transition toward a more disciplined, transparent and analytically mature investment environment.

ACKNOWLEDGEMENTS

The author gratefully acknowledges the commercial property investment professionals who generously contributed their time, insights and professional experience to this study.

Declarations

Ethical approval and consent to participate

This study was conducted in accordance with the ethical research guidelines of the author's affiliated academic institution. Ethical clearance was obtained from the relevant Research Ethics Committee prior to data collection. All participants provided written informed consent, and their right to withdraw at any stage without penalty was clearly communicated and respected.

Conflict of interest

The author declares no conflict of interest in relation to this study.

Funding

This research received no specific grant or funding from any public, commercial or not-for-profit funding agency.

Data availability

Owing to the confidential nature of the semi-structured interviews and the assurances of anonymity given to participants, the qualitative data supporting the findings of this study are not publicly available. Anonymised excerpts and supporting materials may be made available by the corresponding author upon reasonable request, subject to ethical constraints.

REFERENCES

1. Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99–120.
2. Baum, A., & Hartzell, D. (2012). *Global property investment: Strategies, structures, decisions*. Wiley-Blackwell.
3. Bäcklund, K., Vigren, O., & Carlsson, B. (2024). Implementing Digital Innovations: Overcoming Organizational Challenges. *Developments in the Built Environment*, 18, 100436. Available at: <https://www.sciencedirect.com/science/article/pii/S2666165924001170> [Accessed 8 Sep. 2025].
4. Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77–101.
5. Brueggeman, W. B., & Fisher, J. D. (2019). *Real estate finance and investments* (16th ed.). McGraw-Hill Education.
6. Bryman, A. (2016). *Social research methods* (5th ed.). Oxford University Press.
7. Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly*, 36(4), 1165–1188.

8. Cheruiyot, K., & Gamede, L. (2024). Exploring the potential of big data and data analytics in South Africa's real estate sector. *Pacific Rim Property Research Journal*, 29(3), 66–78. Available at: <https://www.prres.org/uploads/1350/177/Exploring-the-potential-of-big-data-and-data-analytics-in-South-Africas-real-estate-sector.pdf> [Accessed 8 Sep. 2025].
9. Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.
10. Creswell, J. W., & Poth, C. N. (2020). *Qualitative inquiry and research design: Choosing among five approaches* (4th ed.). SAGE Publications.
11. Davenport, T. H., & Harris, J. G. (2017). *Competing on analytics: The new science of winning* (Updated ed.). Harvard Business Review Press.
12. Deloitte. (2023). Commercial real estate outlook 2023: Transformational data trends. Deloitte Insights. Available at: <https://www.deloitte.com/us/en/insights/industry/financial-services/financial-services-industry-outlooks/commercial-real-estate-outlook-2023.html> [Accessed 12 Aug. 2025].
13. Edet, T. U. (2023). Investigating data analytics in real estate investment decisions among property valuers. *AfRES Journal*. Available at: <https://afres.architexturez.net/system/files/AfRES-2023-046.pdf> [Accessed 18 Aug. 2025].
14. Eisenhardt, K. M., & Zbaracki, M. J. (1992). Strategic decision making. *Strategic Management Journal*, 13(S2), 17–37.
15. Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics*, 5(1), 1–4. <https://doi.org/10.11648/j.ajtas.20160501.11>
16. Geltner, D., Miller, N. G., Clayton, J., & Eichholtz, P. (2018). *Commercial real estate analysis and investments* (3rd ed.). Oncourse Learning.
17. Jones Lang LaSalle. (2022). Johannesburg real estate overview. JLL Africa. Available at: <https://www.jll.africa/en/trends-and-insights/research/q2-2022-johannesburg-real-estate-overview> [Accessed 15 Jul. 2025].
18. Kahneman, D. (2011). *Thinking, fast and slow*. Farrar, Straus and Giroux.
19. Kotler, P., & Keller, K. L. (2020). *Marketing management* (16th ed.). Pearson Education.
20. Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic inquiry*. SAGE Publications.
21. Ling, D. C., & Archer, W. R. (2022). *Real estate principles: A value approach* (6th ed.). McGraw-Hill Education.
22. McAfee, A., & Brynjolfsson, E. (2012). Big data: The management revolution. *Harvard Business Review*, 90(10), 60–68.
23. Mofokeng, T. S.-V., & Okoro, C. (2024). Diverse boards, stronger real estate investment trusts: An analysis of board diversity and performance of South African REITs. *Corporate Governance and Organizational Behavior Review*, 8(4), 43–54. <https://doi.org/10.22495/cgobrv8i4p4>
24. Number Analytics. (2024). Exploring data-driven real estate market trends. Available at: <https://www.numberanalytics.com/blog/data-driven-real-estate-market-trends> [Accessed 10 Aug. 2025].
25. Pagourtzi, E., Assimakopoulos, V., Hatzichristos, T., & French, N. (2003). Real estate appraisal: A review of valuation methods. *Journal of Property Investment & Finance*, 21(4), 383–401.
26. Polit, D. F., & Beck, C. T. (2020). *Nursing research: Generating and assessing evidence for nursing practice* (11th ed.). Wolters Kluwer.
27. PwC & Urban Land Institute. (2025). Emerging trends in real estate® 2025. Available at: <https://knowledge.uli.org/-/media/files/emerging-trends/2025/emerging-trends-us-canada-2025-final.pdf> [Accessed 9 Aug. 2025].
28. Saunders, M., Lewis, P., & Thornhill, A. (2023). *Research methods for business students* (9th ed.). Pearson Education.
29. Schultz, C. (2024). Real estate financialisation and the production of 'investable' spaces in Johannesburg. *Finance and Society*, 10(2), 157–174. <https://doi.org/10.2218/fas.2023.6>
30. South African Business Matters. (2025, September 4). Geospatial data is transforming property development in South Africa. Available at: <https://www.southafricanbusinessmatters.co.za/geospatial-data-is-transforming-property-development-in-south-africa/> [Accessed 7 Sep. 2025].
31. Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.

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32. Veluru, C. S. (2023). Revolutionizing real estate: AI-driven insights from historical data for smart property decisions. *Journal of Artificial Intelligence and Cloud Computing*, 2(1), 1–11.
 33. Yin, R. K. (2018). *Case study research and applications: Design and methods* (6th ed.). SAGE Publications.