Adoption of digital technologies in valuation practice: a survey of valuers' perspectives in New Zealand

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Abstract

Purpose: The adoption of digital technology among valuers globally remains low, limiting the profession's ability to modernise and meet evolving market demands. The aim of this study is to investigate the factors influencing technology adoption among valuers in New Zealand

Design/methodology/approach: Guided by existing literature and established technology acceptance theories, this study developed a survey instrument that was distributed to registered valuers in New Zealand. Responses from 131 participants were analysed using descriptive statistics and logistic regression.

Findings: The results reveal that a significant majority of valuers (60.3%) reported the non-adoption of digital technologies, indicating a substantial gap in the profession. The strongest driver of adoption was the valuers' perception of opportunities, such as improved efficiency, valuation quality, and professional transformation, with each unit increase in opportunity perception associated with a more than fourfold increase in adoption likelihood (AOR = 4.58, p = 0.001). While concerns about accuracy and data protection were common, their influence was weaker when opportunity perception was considered. Mid-career valuers (5–10 years of experience) showed lower adoption rates in unadjusted models, although this effect was not significant after controlling for other factors. Educational attainment showed some association, with master's degree holders more likely to adopt, but this was limited by the sample size.

Practical implications: Efforts to increase adoption should focus on enhancing valuers' understanding of the benefits of digital technologies through targeted communication, peer-led training and case-based demonstrations. Regulatory bodies should support this transition by addressing data protection concerns and promoting clear guidelines.

Originality/value: This study contributes novel insights into the underexplored area of technology adoption in New Zealand's valuation profession. It highlights the primacy of individual opportunity perception over demographic or organisational factors and offers a foundation for future research and policy development.

Keywords: Digital technology, Valuation practice, New Zealand valuers, Technology adoption, Property valuation

Introduction

As property markets become increasingly complex, the demand for accurate and timely valuations has intensified significantly (Scheurwater, 2017). This evolving landscape necessitates the integration of digital technologies as indispensable tools for data gathering, processing, and reporting, enabling valuers to enhance their methodologies (Scheurwater, 2017; Santoro et al., 2018). Vital technologies, such as unmanned aerial vehicles (UAVs), artificial intelligence (AI), automated valuation models (AVMs), and geospatial technologies, such as geographical information systems (GIS), are reshaping the valuation process. Despite their potential, technology acceptance within the property profession remains notably low, often lagging behind other sectors (Scheurwater, 2017; Toole, 1998). This is particularly concerning considering that many corporate clients already leverage digital solutions to streamline their business operations.

Several factors contribute to the slow adoption of technology among valuers, including apprehensions regarding cybersecurity, legal liabilities, and financial implications of data protection (Avci & Erzurumlu, 2023; Toufaily et al., 2021; Lois et al., 2020). The complexity of certain technologies (Ullah et al., 2021; Hoxha & Sadiku, 2019; Ullah & Sepasgozar, 2019; Wei, 2012), acquisition costs (Ullah et al., 2021; Ullah & Sepasgozar, 2019; Hoxha & Sadiku, 2019), and the need for ongoing reskilling to effectively utilise these tools (Kasim et al., 2024; Kasim et al., 2023) further exacerbate these challenges. In today's digital era, businesses cannot afford to disregard opportunities for optimising operational capacity and performance, as this is essential for securing market share and gaining a competitive edge in the increasingly globalised workspace, where larger corporations dominate over smaller firms (Scheurwater, 2017; Lizarzaburu & Del Brio, 2018; Lois et al., 2020).

Property valuers, as statutorily authorised professionals responsible for accurate property value estimations in organised economies, must enhance their valuation methodologies to minimise financial risk exposure and improve the reliability of valuation outcomes, which are vital for strategic decision-making (Scheurwater, 2017; Achu, 2013). Digital technologies can serve as pivotal decision support systems (DSS) that enhance the accuracy and quality of valuation processes (Scheurwater, 2017; Tidwell & Gallimore, 2014). By facilitating better data analysis and reducing cognitive errors (Broekema et al., 2022; Gallimore, 1996), minimising material uncertainty (Kaluthanthri & Hippola, 2023; Toole, 1998), and mitigating external client influences (Levy & Schuck, 1999; Amidu et al., 2008; Crosby et al., 2018; Klamer et al., 2019), digital tools address the critical challenges inherent in traditional valuation practices. The ability of these technologies to reduce inaccuracies and inconsistencies in valuation outcomes, as demonstrated in various studies (Crosby, 2000; Baffour Awuah & Gyamfi-Yeboah, 2017; Bogin & Shui, 2020), reinforces the necessity for valuers to adopt such innovations to elevate valuation quality (Grover, 2016; Abidoye & Chan, 2017).

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Against this backdrop, the importance of quality valuations cannot be overstated; they are crucial for global financial stability and for mitigating the cascading effects of inaccurate assessments on international financial systems (Newell et al., 2010). Furthermore, ensuring high-quality valuations supports the ongoing relevance of the valuation profession in the global market, highlighting the imperative for the profession to embrace technological advancements to tackle valuation discrepancies and meet the demand for rapid assessments (Scheurwater 2017).

The study examines individual, organisational and technological factors influencing digital technology adoption and the role of technology in valuation practice. The subsequent sections will detail the formulation of hypotheses, the research design adopted for the analysis, and the key findings derived from the study.

Literature review and hypotheses development

Technology and valuation

Big data and technological innovations in the global business landscape drive the continuous quest for improvement in operations. These advancements have propelled the evolution of professional practices across various industries. Historically, property valuation practices transitioned from manual typewriters and carbon copies to personal computers and digital word processing systems, ushering in a new era of electronic data management and email communication instead of courier services for communication. Valuation computations have evolved from analogue calculators to spreadsheets and advanced modelling techniques (Kirkwood, 2004; Balfour, 2001).

Currently, property valuation practices are adapting to technological innovations, such as Property Technology (PropTech), which enhance the valuation process (Braesemann & Baum, 2020; Saull et al., 2020; Saiz, 2020; Aihie, 2019). These technological transformations arise from the necessity to streamline valuation practices, especially in light of the significant errors attributed to valuers during various global financial crises (Kasim et al., 2024; Gilbertson & Preston, 2005).

For instance, advanced statistical modelling techniques, including multiple regression analysis (MRA), computer-assisted mass appraisal (CAMA), computer-aided valuations (CAV), automated valuation models (AVMs), and artificial neural networks (ANNs), are highlighted in property literature as innovative approaches to ensure scientific rigour in the valuation process. These approaches significantly enhance the quality assurance functions of property valuations in financially critical decision-making (Abidoye & Chan, 2017; Scheurwater, 2017; Kamarudin & Daud, 2014; Achu, 2013; Mimis et al., 2013; Lenk et al., 1997; McCluskey et al., 1997; Rossini, 1997; Czernkowski, 1990).

The primary goal of adopting these statistical models is to strengthen the valuation process and enhance the overall valuation quality (Tidwell & Gallimore, 2014). The evolution of automation

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in valuation has integrated these technological innovations into traditional valuation practices, providing decision support systems (DSS) for valuers (Tidwell & Gallimore, 2014). Valuers are expected to possess a thorough understanding of property market operations and effectively reflect market conditions in their analyses of property values (French & Gabrielli, 2018).

Therefore, the emergence of digital technologies within both public and private sectors presents governments and regulators with opportunities to enhance operational efficiency and gain social approval (Mdanat et al., 2018; Lois et al., 2020). For example, Tidwell and Gallimore (2014) explored the use of DSS in valuations and noted that integrating technology and innovative techniques can significantly diminish the cognitive biases typically associated with appraisals. This integration is likely to enhance the quality of report writing in terms of visuals and standardisation, while streamlining valuation processes to facilitate quicker turnaround times (Scheurwater, 2017; Kirkwood, 2004; Balfour, 2001).

Thus, while acknowledging the potential unintended consequences of technology, the use of DSS can foster a more positive perception of valuations by improving data accuracy and enhancing client services (Kasim et al., 2025b).

Technology acceptance theories

Various models have been developed to examine technology adoption and its acceptance. A search of popular literature on the "Diffusion of Innovation" theory (Rogers, 2003) yields several key frameworks, including the Technology Acceptance Model (TAM) (Davis, 1989), the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003), and the Technology, Organisation, and Environment (TOE) framework by Tornatzky and Fleischer (1990). According to Rogers (2003), the diffusion of innovation is influenced by individual factors, the characteristics of the innovation itself, communication channels, and variables within the social system.

The UTAUT model specifies that "effort expectancy", "facilitating conditions", and "performance expectancy" significantly affect an individual's acceptance of technology (Venkatesh et al., 2003). "Effort expectancy" refers to the ease of use associated with the technology, while "facilitating conditions" denote an individual's belief regarding the availability of institutional or personal support for technology adoption. "Social influence" encompasses an individual's beliefs, attitudes, and behaviours that can be shaped by leadership, compliance, conformity, or peer pressure. Finally, "performance expectancy" describes the perceived improvements in performance resulting from the use of technology (Venkatesh et al., 2003).

Additional drivers of technology acceptance identified in the UTAUT model include age, gender, experience, and the "voluntariness" of technology usage, which serve as moderating factors (Ayaz & Yanartas, 2020). In the context of property valuation, some literature indicates that older

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professionals often resist adopting new technologies because of a lack of training on emerging innovations and concerns regarding the practicality and cost-effectiveness of these technologies (Balfour, 2001).

It is important to note that studies on technology acceptance within the property profession are limited; when available, they tend to focus disproportionately on the development and testing of valuation models, while providing little insight into the factors influencing the acceptance of emerging technological approaches and their implications for the profession.

Individual factors

In the digital environment, the capacity to invest in and use technology will become a leverage that some firms will exploit to strengthen the analytical and technical skills of their staff and develop specialised competencies for the application of information technologies to drive business operations (Kasim et al., 2024; Kasim et al., 2023; Vasarhelyi & Romero, 2014; Lois et al., 2020; Lee & Xia, 2006). From the valuation perspective, a professional must possess both 'principles' and 'applied' knowledge of property valuation to effectively undertake professional valuations (Kasim et al., 2024; Kasim et al., 2023; Amidu et al., 2019). So, valuers' knowledge requirements in the digital environment will include digital or technology skills (Kasim et al., 2024; Kasim et al., 2023). Amid digitalisation, researchers have reported that property professionals generally lag in the adoption of digital technologies (Scheurwater, 2017; Toole, 1998). The reason for the slow rate of adoption of technology in the property profession remains unclear. Some studies show that age, gender, experience, and willingness to use technology (Talukder, 2014; Meyer, 2011; Venkatesh et al., 2003) moderate professionals' acceptance of technology. The attitude of the ageing workforce towards technology-driven changes is risk aversion in defence of the status quo ante (Olawande Oni, 2013; Meyer, 2011). For instance, Balfour (2001) highlights that there is resistance among older professionals towards the adoption of new technologies. This study tests this hypothesis to establish the correlation between professionals' demographics and the use of new technologies. This study tests this hypothesis to establish the correlation between professionals' demographics and the use of new technologies.

- *H1. The gender of valuers has no effect on the use of digital technology tools in valuation practice.*
- *H2. The age group of valuers has a positive effect on the use of digital technology tools in valuation practices.*
- *H3. The educational qualifications of valuers positively affect the use of digital technology tools in valuation practice.*
- *H4. Years of practice have a positive effect on the use of digital technology tools in valuation practice.*

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Organisational factors

From the firm level, professionals' adoption of new technology is influenced by the capabilities of technology to impact operational processes (Meyer, 2011; Lee & Xia, 2006; Bajwa & Lewis, 2003). Thus, advances in and use of valuation technology help equip valuers with innovative analytics for gathering and analysing data, and formatting valuation reports (Baum et al., 2020; Scheurwater, 2017). However, PropTech adoption in the valuation process raises concerns about how valuers deal with potential issues such as clients' privacy and data security (Avci & Erzurumlu, 2023), valuers' independence, and objectivity when using CAV. Other practical challenges such as fraud associated with technology deployment in business operations increase the risk of professional liabilities which can harm valuers' integrity and the profession's image. This would be detrimental to the core function of valuation which is to serve as a quality assurance process for the finance management of capital assets for prudent corporate finance decision-making (Achu, 2013). Therefore, as data become increasingly digitised, the use of statistical models such as AVMs by valuation firms for the valuation of homogeneous properties and the transition to other real estate asset classes will increase (Shetty et al., 2020; Sipan et al., 2012). Nonetheless, digital cameras, spreadsheets and geographic information systems have enhanced valuation practices by streamlining data collection and analysis, reporting and turnaround times (Kasim et al., 2024; Scheurwater, 2017; Kirkwood, 2004; Balfour, 2001).

Typically, the type and size of an organisation are determinant factors in managing its operations. Studies suggest that company type and size impact technology acceptance (Meyer, 2011; Bajwa & Lewis, 2003; Kelley & Helper, 1999). In the digital era, the requirements for bidding for most government contracts (Balfour, 2001) and other corporate business contracts sometimes spell out some minimum technological expertise that must be met besides the specifications for company type and size (Lee & Xia, 2006; Bajwa & Lewis, 2003). The increasing preference for digitally enabled solutions by public and private clients significantly impacts the nature of professional service procurement and provision (Kiss, 2017; Van Laar et al., 2017). As firms adopt digital technologies, employees must upgrade their skills (Thomas & Lambert, 2019; Kiss, 2017) to effectively use these tools to provide innovative solutions to clients (Cheloti & Mooya 2023; Wilkinson et al., 2018). Organisations' human, financial and technological resources differ from one institution to another. Smaller companies may face challenges of limited expertise and budgets (Meyer, 2011; Bajwa & Lewis, 2003) impacting innovation adoption rate. This highlights the extent to which institutional context shapes innovation acceptance.

Thus, while valuation technologies are important innovations in the valuation field, the skill sets of valuers coupled with the professional standards required or business clients' expectations about the standards of service deliveries could influence the use of technology in valuation (Kasim et al., 2024; Kasim et al., 2025b; Scheurwater, 2017). Nurhajati (2016) highlighted how understanding and adopting cloud computing, for instance, improves business process efficiency. Likewise, Januszkiewicz (2016) claimed that technology can reduce the time and effort required to execute

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a task. This is important for valuers since the amount a firm can make depends on the valuations completed (Balfour, 2001). Meanwhile, technology adoption has inherent barriers like investment costs (Ullah et al., 2021; Abidoye et al., 2021). While perceived usefulness may motivate firms to adopt new technologies, the technology budget may be beyond the capacity of small firms. Disparities in human, financial and technological resources can affect adoption because adoption costs may include training and technical support in addition to initial costs (Abidoye et al., 2021; Ullah et al., 2021). However, training support aligns with perceived ease of use since well-trained users are more likely to find new technologies easy to use and beneficial. Besides, firms with IT infrastructure or staff due to their multidisciplinary nature may view new technologies as highly valuable in enhancing productivity and competitive advantage (Hameed et al., 2012).

The application of technology will improve valuers' operational efficiency, while challenging valuers to upskill to harness the full potential of digital innovations to enhance service delivery (Wilkinson et al., 2018; Peto, 1997). In line with improving business operational efficiency, Al-Gahtani and King (1999) and Clegg et al. (1997) suggest that institutions should create technology acceptance-enabling environments through training tailored for institutional growth and competitiveness. In most cases, employees require management support (Ahuja & Thatcher, 2005) and incentives (Bhattacherjee, 1998) to learn and use technological innovation through on-the-job training programmes (Alipour et al., 2016; Alipour et al., 2009). Thus, the availability of innovative programmes, technical support services, and professional development assistance tends to critically influence technology acceptance and use (Quick & Davies, 1999). While standards are evolving globally, valuers will need to become digital professionals, and training and education will play a critical role in ensuring the smooth transformation of the valuation profession (Ayodele et al., 2020; Oladokun & Gbadegesin, 2017; Brugger & Gehrke, 2018; Poon, 2014), particularly if existing training programmes and valuation standards are deficient in the skills and competencies required for the new information age (Kasim et al., 2024; Kasim et al., 2023). Moreover, technology enables digital records management which is important in firms where different professionals share data that form the basis for decision-making. To establish the significance of organisational factors such as training support, traditional data management practices, company type and size influencing the acceptance of digital technology in valuation practice, the following hypotheses were formulated:

- *H5. The valuation company type has no effect on the use of digital technology tools in the valuation practice.*
- *H6. The size of the valuation company positively affects the use of digital technology tools in valuation practice.*
- *H7. The time-consuming nature of a manual collection of data positively affects the use of digital technology tools in valuation practice.*
- *H8. Technology training positively affects digital technology tools' use in valuation practice.*

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Technological factors

The adoption of technology in property valuation is increasingly shaped by the perceived opportunities and risks associated with innovative tools and methodologies. Recent studies confirm that the integration of technologies, particularly artificial intelligence (AI), is transforming traditional property valuation (Kasim et al., 2025a). Automated Valuation Models (AVMs) that utilise machine learning algorithms are pivotal; they enhance both accuracy and efficiency by minimising human error in estimations and enabling the analysis of voluminous datasets to identify market trends (Abidoye & Chan, 2018; Atilola et al., 2019).

AI techniques, including neural networks and support vector machines, significantly improve the reliability of property valuations, especially in dynamic markets where conventional methods may falter (Kasim et al., 2025b; Abidoye et al., 2021; Jain & Raman, 2021). This technological shift not only accelerates valuation processes but also improves investor confidence through enhanced data analytics that inform valuation decisions (Urban & Maphumulo, 2022). The inclusion of blockchain technology into property transactions has transformative potential by enhancing transaction transparency and security. Blockchain's immutable ledger can streamline transactions and automate processes through smart contracts, mitigating risks of fraud and inconsistency in records (Osmani et al., 2020). However, regulatory uncertainty remains a critical barrier to full integration (Kasim et al., 2025a). Building Information Modelling (BIM) and other spatial data tools are also complementing modern valuation by enabling 3D analysis of environmental and architectural factors. These developments signify a methodological shift that supports more data-driven and context-aware valuations (Yamani, 2021; Kasim et al., 2025a).

Nevertheless, empirical studies highlight challenges in adoption. Professionals express concern over the 'black box' nature of AI models, which obscure valuation rationale and hinder trust among valuers and clients (Kasim et al., 2025b). Further, the diffusion of innovation in property valuation remains slow due to conservative attitudes within the profession and misalignment between technology developers and users (Kasim et al., 2025b). Cybersecurity threats also emerge as key risks in the digital transformation journey, with organisations needing robust data protection systems to guard against breaches and uphold trust (Bian et al., 2024; Kasim et al., 2025a). The integration of blockchain, although promising, is also limited by outdated legal frameworks and institutional inertia (Osmani et al., 2020). Digital transformation is altering professional roles in valuation practices. Automation raises concerns about job displacement, while upskilling becomes imperative. Research reveals a growing demand for supplemental skills in IT, data analysis, and digital communication among valuers to remain competitive. The necessity for coordinated professional development is clear, requiring collaboration among training institutions, regulatory bodies, and valuation firms (Liman et al. 2025; Kasimet al., 2024).

In summary, empirical findings emphasise the interplay between technological opportunity and perceived risk as determinants of technology adoption in property valuation. Higher perceived

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opportunities correlate with adoption intent, while higher perceived risks deter adoption (Kasim et al., 2025a). Based on these insights, this study proposes the following hypotheses:

H9. Perceived opportunities positively influence the adoption of digital technology in valuation practice.

H10. Perceived risk negatively influences the adoption of digital technology in valuation practice.

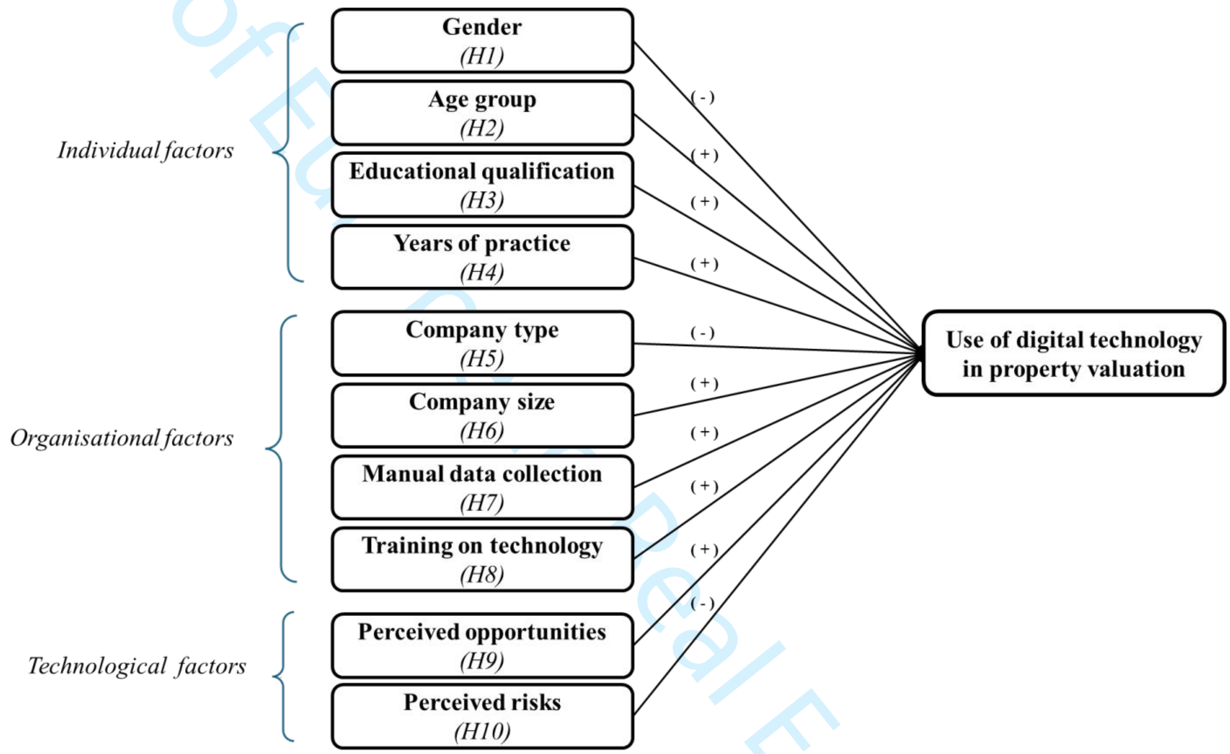

Figure 1: Research model (authors' construct)

Methodology

Data collection

This study used a web survey methodology to collect data from the target population of registered valuers in New Zealand. The web survey was distributed through the Property Institute of New Zealand (PINZ) to ensure that it reached the intended audience.

The survey consisted of the following three parts:

1. Sociodemographic and organisation information that examined variables such repondents' sex, age group, highest educational qualification, years of practice experience, company type (e.g. private valuation practice, multidisciplinary property company (defined as an organisation involved in multiple aspects of property services such as valuation,

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management, development, and investment), government department, other) and company size (small, medium, or large).

2. Use of digital technology in valuation that examined whether respondents had utilised any of a range of emerging technologies in their professional practice. The listed technologies included big data, blockchain, artificial intelligence (AI), automated valuation models (AVMs), smart contracts, image streaming, drones, 3D building information modelling (BIM) visualisation, and virtual reality. Respondents who selected "None of the above" were coded as non-adopters (0), while those who reported using at least one technology were classified as adopters (1).
3. Likert scale questions developed to measure the perceived opportunities (e.g. expediting the valuation process, improving quality, increasing productivity and efficiency, transforming the profession) and perceived risks (e.g. reduced accuracy, insufficient consideration of valuation factors, data protection challenges, and increased vulnerability to cyberattacks) associated with adopting digital technology in valuation.. Responses were recorded on a five-point Likert scale ranging from 1 ("strongly disagree" or "most unlikely") to 5 ("strongly agree" or "most likely").

To ensure content validity and enhance readability, a pilot test interviews was conducted involving feedback from five registered valuers, whose suggestions were incorporated into the finalised survey instrument. The invitation to participate was subsequently emailed to approximately 831 members of the Property Institute of New Zealand, who are also registered valuers at the time of the survey. Over a four-week period, 131 valuers accessed and completed the online survey.

Statistical analysis

Data were analysed using a combination of descriptive and inferential statistical techniques to comprehensively explore the factors influencing technology adoption. Descriptive statistics, including frequencies and percentages, were used to summarise the distribution of categorical variables and to provide an overview of the sample characteristics. The chi-square test was used to assess the associations between categorical variables. In instances where expected cell counts fell below 5, Fisher's exact test was used to maintain statistical validity when the expected cell counts fell below five. These tests were chosen for their robustness in detecting non-random associations between variables, which is critical for understanding the potential links to technology adoption.

Simple and multivariaable logistic regression analyses were conducted to identify the factors affecting technology adoption. . Simple logistic regression was first applied to assess the individual effect of each variable on the likelihood of adopting a technology. This method provided estimates of odds ratios (ORs), enabling the quantification of the strength and direction of associations and facilitating the interpretation of their practical significance. Subsequently, multivariable logistic regression was performed to control for potential confounding factors and evaluate the independent contribution of each variable. This step was essential for isolating the most influential

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factors while accounting for inter-variable relationships. Adjusted odds ratios (AORs) were reported to reflect these refined estimates. In this study, statistical significance was set at $p < 0.05$ for all analyses and data analysis was performed using R.

Results

Descriptive statistics

Use of digital technology in valuation

A total of 131 valuers participated in this survey. Among these respondents, 79 (60.3%) reported not using any of the listed technologies and were categorised as nonadopters. In contrast, 52 (39.7%) indicated the use of at least one technology, classifying them as adopters. The technologies considered for adoption included big data, blockchain, artificial intelligence (AI), automated valuation models (AVMs), smart contracts, image streaming, drones, 3D building information modelling (BIM) visualisation, and virtual reality. These findings suggest a significant gap in the adoption of emerging technologies within the valuation profession.

Demographic and organisational factors and use of digital technology

Table 1 depicts the respondents' demographic, professional and organisational characteristics based on their use of digital technologies in valuation practice.

Table 1: Association of the demographic and organisational factors and use of digital technology

Use of technology in valuation		**No (N=79)**	**Yes (N=52)**	**Total (N=131)**	**p value**
Gender					0.6023
	Female	14 (17.7%)	8 (15.4%)	22 (16.8%)	
	Male	64 (81.0%)	42 (80.8%)	106 (80.9%)	
	Prefer not to say	1 (1.3%)	2 (3.8%)	3 (2.3%)	
Age					0.487
	28 to 37	21 (26.6%)	8 (15.4%)	29 (22.1%)	
	38 to 47	12 (15.2%)	11 (21.2%)	23 (17.6%)	
	48 to 57	16 (20.3%)	12 (23.1%)	28 (21.4%)	
	Over 57	29 (36.7%)	19 (36.5%)	48 (36.6%)	
	Prefer not to say	1 (1.3%)	2 (3.8%)	3 (2.3%)	
Educational qualification					0.1201
	Bachelor degree	65 (82.3%)	38 (73.1%)	103 (78.6%)	
	Doctoral degree	0 (0.0%)	1 (1.9%)	1 (0.8%)	
	Master degree	3 (3.8%)	7 (13.5%)	10 (7.6%)	

Others	11 (13.9%)	6 (11.5%)	17 (13.0%)	
Year of practice				0.018
Less than 5 years	4 (5.1%)	4 (7.7%)	8 (6.1%)	
5 to less than 10 years	20 (25.3%)	3 (5.8%)	23 (17.6%)	
10 to less than 15 years	5 (6.3%)	8 (15.4%)	13 (9.9%)	
15 and above	50 (63.3%)	37 (71.2%)	87 (66.4%)	
Company type				0.0648
Government department	2 (2.5%)	4 (7.7%)	6 (4.6%)	
Multidisciplinary property company	20 (25.3%)	11 (21.2%)	31 (23.7%)	
Private valuation practice	56 (70.9%)	32 (61.5%)	88 (67.2%)	
Other	1 (1.3%)	5 (9.6%)	6 (4.6%)	
Company size				0.0703
Big	23 (29.5%)	20 (38.5%)	43 (33.1%)	
Medium	11 (14.1%)	13 (25.0%)	24 (18.5%)	
Small	44 (56.4%)	19 (36.5%)	63 (48.5%)	
N-Miss	1	0	1	
Manual collection of data is time consuming				0.7052
Agree	60 (75.9%)	41 (80.4%)	101 (77.7%)	
Disagree	19 (24.1%)	10 (19.6%)	29 (22.3%)	
N-Miss	0	1	1	
Training on technology				0.1403
No	51 (64.6%)	26 (50.0%)	77 (58.8%)	
Yes	28 (35.4%)	26 (50.0%)	54 (41.2%)	

The sample characteristics presented in Table 1 indicate that gender was not significantly associated with technology adoption ($p = 0.60$). Both adopters and non-adopters were predominantly male, comprising 80.8% and 81.0% of each group, respectively, while a smaller proportion identified as female (15.4% vs. 17.7%) or preferred not to disclose their gender. Similarly, there was no significant difference in the age distribution between the two groups ($p = 0.49$). The largest age group in both adopters and non-adopters was those over 57 years, accounting for 36.5% of adopters and 36.7% of non-adopters, followed by those aged 48–57 years (23.1% and 20.3%, respectively). Respondents under 38 years of age constituted a minority in both groups.

Educational qualifications also did not show a statistically significant association with technology adoption ($p = 0.12$); however, a trend towards higher educational attainment among adopters was observed. Specifically, 13.5% of adopters held a master's degree and 1.9% a doctoral degree, compared with 3.8% and 0% among non-adopters, respectively. Bachelor's degree holders were predominant in both groups, comprising 73.1% of adopters and 82.3% of non-adopters, respectively.

Professional practice experience was significantly associated with technology adoption (p = 0.018). Adopters were more likely to have 15 or more years of practice experience (71.2%) than non-adopters (63.3%). In contrast, non-adopters were overrepresented among mid-career valuers with 5–10 years of experience (25.3%) compared to adopters (5.8%). A small proportion of participants in both groups had less than 5 years of experience. These findings suggest that technology adoption is more prevalent among senior professionals, while non-adoption is particularly common among those with mid-range professional experience.

The type of organisation exhibited a borderline association with technology adoption (p = 0.065). Private valuation practices accounted for the majority of non-adopters (70.9%) and a smaller but still significant share of adopters (61.5%). Conversely, valuers employed in government departments or multidisciplinary property companies were more likely to adopt digital technology. Notably, respondents from "other" organisational categories were primarily adopters (9.6% vs. 1.3%, respectively).

Company size also showed a significant association with adoption (p = 0.070). Smaller firms made up more than half of the non-adopters (56.4%) but only 36.5% of the adopters. In contrast, adopters were more commonly found in medium-sized (25.0%) and large firms (38.5%) than non-adopters (14.1% and 29.5%, respectively). These trends suggest that larger and more structured organisations are more likely to support and facilitate the adoption of new technologies.

The results indicate no statistically significant association (p = 0.7052) between technology adoption and the perception that manual data collection is time-consuming. A majority of both non-adopters (75.9%) and adopters (80.4%) agreed that manual data collection is labour-intensive, demonstrating a shared understanding of the challenges posed by traditional data collection methods across the valuation profession. This consensus suggests that both groups recognise the potential efficiency benefits of adopting technology to streamline these processes in the future.

Similarly, the analysis regarding training on technology revealed no significant difference (p = 0.1403) in experiences between adopters and non-adopters. While 64.6% of non-adopters reported not receiving training, only 50.0% of adopters reported the same. A significant number of participants in both groups lacked adequate training, highlighting a potential barrier to technology adoption. The findings imply that enhancing training opportunities could facilitate greater technology use by valuers.

Opportunity and risk factors and use of digital technology

Table 2 examines the perceived opportunities and risks associated with adopting digital technology in property valuations.

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Table 2: Association of the the opportunity and risk factors and use of digital technology

Use of technology in valuation		No (N=79)	Yes (N=52)	Total (N=131)	p value
Opportunities					
The advance of technology provides opportunities to speed up the valuation process					0.0001
	1 Strongly disagree	1 (1.3%)	0 (0.0%)	1 (0.8%)	
	2 Disagree	3 (3.8%)	0 (0.0%)	3 (2.3%)	
	3 Neutral	5 (6.4%)	0 (0.0%)	5 (3.9%)	
	4 Agree	45 (57.7%)	14 (28.0%)	59 (46.1%)	
	5 Strongly agree	24 (30.8%)	36 (72.0%)	60 (46.9%)	
	N-Miss	1	2	3	
The advance of technology provides opportunities to improve the quality of valuations					0.0002
	1 Strongly disagree	3 (3.8%)	3 (6.1%)	6 (4.7%)	
	2 Disagree	5 (6.4%)	4 (8.2%)	9 (7.1%)	
	3 Neutral	15 (19.2%)	8 (16.3%)	23 (18.1%)	
	4 Agree	51 (65.4%)	17 (34.7%)	68 (53.5%)	
	5 Strongly agree	4 (5.1%)	17 (34.7%)	21 (16.5%)	
	N-Miss	1	3	4	
The advance of technology provides opportunities to increase the productivity and efficiency of the valuer					< 1e-04
	1 Strongly disagree	1 (1.3%)	0 (0.0%)	1 (0.8%)	
	2 Disagree	0 (0.0%)	2 (3.9%)	2 (1.6%)	
	3 Neutral	10 (12.8%)	1 (2.0%)	11 (8.5%)	
	4 Agree	49 (62.8%)	17 (33.3%)	66 (51.2%)	
	5 Strongly agree	18 (23.1%)	31 (60.8%)	49 (38.0%)	
	N-Miss	1	1	2	
The advance of technology provides opportunities to transform the valuation profession					0.001
	1 Strongly disagree	1 (1.3%)	0 (0.0%)	1 (0.8%)	
	2 Disagree	3 (3.8%)	1 (2.0%)	4 (3.1%)	
	3 Neutral	15 (19.0%)	7 (14.0%)	22 (17.1%)	
	4 Agree	54 (68.4%)	23 (46.0%)	77 (59.7%)	
	5 Strongly agree	6 (7.6%)	19 (38.0%)	25 (19.4%)	
	N-Miss	0	2	2	
Risks					

The advance of technology provides risks around the accuracy of the valuation process				0.0005
1 Strongly disagree	0 (0.0%)	5 (10.0%)	5 (3.9%)	
2 Disagree	3 (3.9%)	9 (18.0%)	12 (9.4%)	
3 Neutral	14 (18.2%)	13 (26.0%)	27 (21.3%)	
4 Agree	42 (54.5%)	14 (28.0%)	56 (44.1%)	
5 Strongly agree	18 (23.4%)	9 (18.0%)	27 (21.3%)	
N-Miss	2	2	4	
The advance of technology provides risks around full consideration of important factors in the valuation process				0.3881
1 Strongly disagree	2 (2.6%)	1 (2.0%)	3 (2.4%)	
2 Disagree	12 (15.6%)	11 (22.0%)	23 (18.1%)	
3 Neutral	9 (11.7%)	10 (20.0%)	19 (15.0%)	
4 Agree	39 (50.6%)	17 (34.0%)	56 (44.1%)	
5 Strongly agree	15 (19.5%)	11 (22.0%)	26 (20.5%)	
N-Miss	2	2	4	
The advance of technology provides data protection challenges for valuers and valuation firms				0.0363
1 Strongly disagree	1 (1.3%)	0 (0.0%)	1 (0.8%)	
2 Disagree	5 (6.3%)	8 (16.0%)	13 (10.1%)	
3 Neutral	17 (21.5%)	2 (4.0%)	19 (14.7%)	
4 Agree	35 (44.3%)	24 (48.0%)	59 (45.7%)	
5 Strongly agree	21 (26.6%)	16 (32.0%)	37 (28.7%)	
N-Miss	0	2	2	
Valuation firms will be subject to more cyber-attacks in the future due to the advance in technology				0.2676
2 Disagree	5 (6.3%)	2 (3.9%)	7 (5.4%)	
3 Neutral	25 (31.6%)	14 (27.5%)	39 (30.0%)	
4 Agree	37 (46.8%)	20 (39.2%)	57 (43.8%)	
5 Strongly agree	12 (15.2%)	15 (29.4%)	27 (20.8%)	
N-Miss	0	1	1	

Adopters were significantly more likely to view technology as a means of streamlining valuation processes. Nearly three-quarters of adopters strongly agreed that technological advances could expedite the valuation process, compared to less than one-third of non-adopters (72.0% vs. 30.8%; $p < 0.0001$). Similarly, adopters were more likely to report that technology increased productivity and efficiency, with 60.8% strongly agreeing, as opposed to 23.1% of non-adopters ($p < 0.0001$).

Perceptions of quality enhancement were also more favourable among adopters. One-third of adopters (34.7%) strongly agreed that technology improves the quality of valuations, while only 5.1% of non-adopters held this view ($p = 0.0002$). Moreover, more adopters believed that technology would transform the valuation profession. While 68.4% of non-adopters agreed, only 7.6% strongly agreed, whereas 38.0% of adopters strongly agreed that transformation was likely ($p = 0.001$).

Although adopters emphasised opportunities, both groups acknowledged the risks associated with technological changes. However, the nature and intensity of these concerns varied between groups. Non-adopters were more likely to highlight the risks related to valuation accuracy. Over half of the non-adopters (54.5%) agreed that technology introduces accuracy risks, compared with only 28.0% of adopters ($p = 0.0005$). Additionally, 23.4% of non-adopters strongly agreed with this statement, compared to 18.0% of the adopters. In contrast, 28% of adopters disagreed or strongly disagreed with the accuracy risk statement, compared to only 3.9% of non-adopters, indicating that adopters were less concerned about accuracy.

Both groups expressed apprehension regarding data protection challenges; however, adopters were more likely to rate this risk highly than non-adopters. Approximately one-third of adopters (32.0%) strongly agreed that data protection is a significant challenge, compared to 26.6% of nonadopters ($p = 0.036$). This suggests that adopters with direct experience with technological tools may be more attuned to the practical risks associated with data handling and security breaches.

Broader risks, such as the incomplete consideration of valuation factors or increased exposure to cyberattacks, were acknowledged by both groups but did not show significant differences. For instance, similar proportions of adopters and non-adopters agreed that cyberattacks would become more prevalent because of technological advancement (39.2% vs. 46.8%, $p = 0.27$). This indicates a shared recognition of systemic risks and a divergence in how these risks are prioritised relative to the perceived benefits.

Logistics regression

Simple logistic regression analysis

To assess the individual effect of each variable on the likelihood of adopting a technology and to test the hypotheses established in this study, a simple logistic regression was conducted using demographic and organisational characteristics, as well as the mean composite opportunity and risk scores, as independent variables. The composite opportunity score was calculated as the mean of four items reflecting the perceived benefits of technology: speed, quality, efficiency, and professional transformation. In contrast, the composite risk score was derived from the mean of two items that addressed perceived risks: accuracy concerns and data protection challenges. The results of this analysis are presented in Table 3.

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Table 3: Factors associated with use of technology based on simple logistic regression

Predictor	OR	95% CI	p-value	Hypotheses results
Gender (H1)				
Female, ref	1.00			
Male	1.11	0.43 - 3.00	0.829	Not-supported
Prefer not to say	3.50	0.29 - 82.63	0.336	Not-supported
Age (H2)				
28 – 37, ref	1.00			
38 - 47	2.41	0.77 - 7.88	0.136	Not-supported
48 - 57	1.97	0.66 - 6.14	0.230	Not-supported
Over 57	1.69	0.63 - 4.80	0.308	Not-supported
Prefer not to say	2.63	0.10 - 71.98	0.513	Not-supported
Educational qualification (H3)				
Bachelor degree, ref	1.00			
Master degree	4.21	1.10 - 20.48	**0.046**	Supported
Doctoral degree	3820000.00	<0.001 - NA	0.986	Not-supported
Others	1.08	0.34 - 3.17	0.886	Not-supported
Years of practice (H4)				
<5 years, ref	1.00			
5–10 years	0.15	0.02 - 0.92	**0.044**	Supported
10–15 years	1.60	0.27 - 10.01	0.605	Not-supported
≥15 years	0.71	0.16 - 3.21	0.650	Not-supported
Company type (H5)				
Government department, ref	1.00			
Multidisciplinary property company	0.25	0.03 - 1.51	0.144	Not-supported
Private valuation practice	0.29	0.04 - 1.58	0.167	Not-supported
Other	2.00	0.13 - 54.33	0.624	Not-supported
Company size (H6)				
Big, ref	1.00			
Medium	1.32	0.48 - 3.70	0.593	Not-supported
Small	0.52	0.23 - 1.17	0.117	Not-supported
Manual data collection (H7)				
Agree	1.00			
Disagree	0.83	0.34 - 1.96	0.681	Not-supported
Training on technology (H8)				
No, ref	1.00			
Yes	1.79	0.87 - 3.70	0.116	Not-supported
Composite opportunity score (H9)	5.56	2.49 - 13.86	**<0.001**	Supported
Composite risk score (H10)	0.63	0.40 - 0.97	**0.039**	Supported

ref: *reference category;* ***OR***: *odd ratio;* ***CI***: *confidence interval*

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Consistent with the descriptive findings, the analysis shows that professional experience has a notable influence on technology adoption. Valuers with 5-10 years of professional experience displayed significantly lower odds of adopting technology compared to their counterparts with fewer than 5 years (OR = 0.15, 95% CI: 0.02–0.92, p = 0.044). This finding partially support H4 and the earlier observation that mid-career valuers are disproportionately underrepresented among non-adopters. In contrast, no significant differences were detected in technology adoption patterns for those with 10-15 years (OR = 1.60, 95% CI: 0.27–10.01, p = 0.605) and > 15 years of experience (OR = 0.71, 95% CI: 0.16–3.21, p = 0.650) compared with the reference group. This suggests that both early career and highly experienced valuers are more amenable to adopting technology than mid-career valuers.

Perceived opportunities and risks emerged as the most influential factors in predicting technology adoption in the current study. A one-unit increase in the composite opportunity score was associated with a more than five-fold increase in the odds of technology adoption (OR = 5.35, 95% CI: 2.42–13.1, p < 0.001). This finding supports H9 and aligns with the descriptive analyses which indicates that valuers who recognise the benefits of technology, such as improved speed, quality, efficiency, and professional transformation, are significantly more likely to implement technological tools. Conversely, higher perceptions of technology-related risks, including concerns about accuracy and data protection challenges, were associated with a decreased likelihood of adoption (OR = 0.63, 95% CI: 0.40–0.96, p = 0.034). This finding supports H10 and is consistent with the descriptive result, which indicates that non-adopters frequently cited risks to accuracy as a major barrier to technology use.

The analyses revealed that sociodemographic factors largely lack significant associations with the adoption of technology. For example, sex, age, and educational qualifications did not consistently influence the likelihood of adoption, except for an increased likelihood of adoption among those holding a master's degree (OR = 4.21, 95% CI: 1.10–20.48, p = 0.046). Therefore, no support is found for H1 and H2, while only partial support is provided for H3. Additionally, regarding organisational factors such as company type and size, as well as manual data collection and training, no support was found for H5-H8, as these factors did not exhibit substantial correlations with technology adoption.

Multivariable logistic regression analysis

To better understand the real factors influencing technology adoption, the variables found to be significant in the simple logistic regression analysis were included and tested in a multivariable logistic regression model. These variables included years of practice, perceived opportunities, and perceived risks related to technology adoption.

Although educational qualification appeared significant in the "Master's degree" category during the simple logistic regression analysis (OR = 4.21; 95% CI = 1.10–20.48; p = 0.046), the variable

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showed clear signs of data sparsity and unstable estimates. Specifically, the "Doctoral degree" category yielded an extremely large odds ratio (≈ 3.8×10^6), an undefined upper confidence bound (NA), and a non-significant p-value (p = 0.986), suggesting that very few respondents held doctoral degrees. Such sparse data inflate standard errors and undermine the reliability of the variable for inclusion in a multivariable model, potentially distorting parameter estimates and hindering model convergence. In contrast, years of practice demonstrated a more stable and interpretable association (5–10 years: OR = 0.15; 95% CI = 0.02–0.92; p = 0.044) and had stronger theoretical relevance to practical experience and technology adoption behaviour, as supported by prior literature. Therefore, retaining this variable is justified both empirically and conceptually. The results of this analysis are presented in Table 4.

Table 4: Factors associated with use of technology based on multivariable logistic regression

Predictor	**AOR**	**95% CI**	**p-value**
Years of practice			
<5 years, ref	1		
5–10 years	0.239	0.03 – 1.64	0.15
10–15 years	1.28	0.19 – 8.85	0.798
≥15 years	1.35	0.27 – 6.94	0.712
Composite opportunity score	4.58	1.94 – 12.0	**0.001**
Composite risk score	0.719	0.43 – 1.17	0.191

After adjusting for these variables, years of practice was no longer significantly associated with technology adoption. Specifically, compared to valuers with fewer than 5 years of experience, those with 5-10 years (adjusted odds ratio [AOR] = 0.24, 95% CI: 0.031–1.64, p = 0.150), 10-15 years (AOR = 1.28, 95% CI: 0.19–8.85, p = 0.798), and those with 15 years or more (AOR = 1.35, 95% CI: 0.27–6.94, p = 0.712) did not exhibit statistically significant differences in their likelihood of adopting technology. These findings suggest that the apparent disadvantage observed among mid-career valuers in the descriptive and simple logistics regression analyses is largely attributed to differences in their perceptions of technology rather than the duration of their professional practice.

Perceptions of opportunity emerged as the dominant independent predictor of technology adoption in this study. Each one-unit increase in the composite opportunity score was associated with a more than fourfold increase in the odds of adoption (AOR = 4.58, 95% CI: 1.94–12.0, p = 0.001). This finding reinforces the results of the descriptive and simple logistic regression analyses, underscoring that valuers who recognise the potential of technology to enhance efficiency, quality, and professional transformation are significantly more likely to be adopters.

In contrast, perceptions of risk did not demonstrate statistical significance after adjustment (AOR = 0.72, 95% CI: 0.43–1.17, p = 0.191). Although risk perception was negatively correlated with adoption in the simple logistic regression analysis, this effect appeared to be mediated by

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opportunity perception. This suggests that the positive framing of technology's benefits exerts a stronger influence on adoption decisions than concerns about associated risks. The multivariable logistic regression analysis indicates that technology adoption is primarily linked to the extent to which valuers perceive opportunities associated with technological advancement, while years of practice and perceptions of risk exhibit weaker associations once opportunity perceptions are considered.

Discussion

The integration of digital technologies in property valuation practices signifies a transformative shift driven by historical and contemporary innovations. The evolution from manual to digital valuation methods illustrates a broader trend in which technological adoption enhances operational efficiencies and raises the standard of decision-making frameworks within the valuation profession. The descriptive statistics from this study reveal that approximately 60.3% of valuers remain non-adopters of modern technologies, contrasting significantly with the 39.7% who embrace digital tools, such as Automated Valuation Models (AVMs) and machine learning algorithms, to enhance the accuracy and efficiency of their work. This disparity indicates a pressing need for educational initiatives aimed at fostering technology adoption, particularly among the sizeable contingent of valuers reluctant to engage with emerging technologies (Kasim et al., 2025).

A substantial body of literature underscores the importance of technological innovation in enhancing property valuation quality assurance. Studies have demonstrated that the utilisation of statistical tools, such as AVMs, artificial intelligence (AI), and computer-assisted mass appraisal systems, can introduce scientific rigor into the valuation process (Kasim et al., 2025; Băbțan, 2025). Consequently, valuers who are aware of and familiar with these tools are significantly more likely to adopt such technologies. This relationship is underpinned by the theoretical constructs of the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which posit that perceived usefulness and performance expectancy are central to technology uptake (Davis, 1989; Băbțan, 2025; Kasim et al., 2025; Venkatesh et al., 2003). The current study's multivariable logistic regression analysis supports this notion, indicating that valuers who perceive substantial opportunities related to technological adoption are significantly more likely to engage with these tools (AOR = 4.58, 95% CI: 1.94–12.0, p = 0.001).

The findings indicate that sociodemographic variables, specifically gender, age, and educational qualifications, are not consistently associated with the adoption of digital technologies in valuation practice. This result aligns with some prior literature, suggesting that professional standards and organisational norms may override individual demographic influences in shaping technology use. For instance, valuers operate within a regulated framework that emphasises consistency, accuracy, and compliance with industry standards, which may reduce the variability in technology adoption attributable to personal characteristics (Scheurwater, 2017; Amidu et al., 2021). The lack of significant association with gender and age is consistent with earlier studies that found that older

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professionals may resist technology due to training gaps or perceived impracticality, but such resistance does not always translate into statistically significant differences in adoption behaviour (Balfour, 2001; Meyer, 2011).

Interestingly, while educational attainment showed some influence, valuers with master's degrees were more likely to adopt technology, this effect was not robust across all levels of education and was excluded from the multivariable logistic regression due to data sparsity. This suggests that while advanced education may enhance openness to innovation, it is not a dominant driver when other factors such as perceived opportunities are considered.

Organisational factors such as company size, type, manual data collection processes, and training support also did not show significant associations with technology adoption. This finding diverges from some prior research that emphasises the role of institutional resources and infrastructure in facilitating innovation (Lee & Xia, 2006; Bajwa & Lewis, 2003). One possible explanation is that the valuation profession in New Zealand may exhibit limited variability in organisational practices, particularly among small and medium-sized firms that dominate the sector. Additionally, the shared recognition across adopters and non-adopters that manual data collection is time-consuming and that training is lacking suggests that these factors are uniformly experienced and therefore do not differentiate adoption behaviour.

This study, similar to other research studies, has a number of limitations that should be acknowledged to guide future research. First, the professional and geographic context may constrain the generalisability of the results, as valuation practices and technology adoption vary across regions and sectors owing to differing regulatory and economic environments. Although the study achieved a high response rate, potential selection bias may have influenced the representation of professional segments, particularly those less inclined to engage with emerging technology. Second, the use of self-reported data introduces the possibility of response bias, which may affect the accuracy of the reported technology usage and perceptions. Additionally, the anonymity of the responses prevented the identification of whether multiple participants came from the same organisation, limiting the ability to assess clustering effects and potentially affecting the generalisability of the findings. Third, although logistic regression was employed to test theoretically grounded hypotheses and control for confounding variables, the limited number of statistically significant predictors and moderate pseudo-R^2 values suggest constrained explanatory power. Moreover, sparse data in certain categories, such as doctoral qualifications and highly experienced practitioners, led to unstable estimates and reduced reliability for some variables. Finally, the observed lack of association between organisational factors and technology adoption may reflect limited variability within the sample or the influence of unmeasured mediating factors, such as leadership style or innovation culture. These nuances highlight the need for future studies with larger, more diverse samples and richer organisational data to explore these dynamics more comprehensively.

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Conclusion

This study provides insights into the individual, organisational, and technological factors that influence the adoption of digital technologies by valuers in New Zealand. The findings reveal a significant adoption gap, with 60.3% of valuers not utilising digital tools, highlighting an urgent need for strategic interventions to accelerate digital integration within valuation practices. Crucially, the analysis identifies individual perceptions of technological opportunities as the most influential driver of adoption. Valuers who perceive digital tools as enhancing efficiency, quality, and professional growth are markedly more inclined to adopt digital tools. This aligns with established technology acceptance frameworks and underscores the importance of targeted educational initiatives that highlight the practical and strategic benefits of digital innovation. Contrary to expectations, organisational and demographic factors exerted limited influence in the adjusted model, reinforcing the primacy of individual-level cognition over structural variables. Accordingly, efforts to foster adoption should prioritise enhancing valuers' understanding of digital value propositions rather than relying on broad organisational reforms or demographic segmentation. Tailored communication strategies, peer-led training, and case-based demonstrations of efficiency gains are likely to yield more impactful results. Nonetheless, persistent concerns regarding data accuracy and protection remain substantial barriers. Addressing these issues through transparent standards, robust security protocols, and consistent regulatory guidance is essential for building trust and facilitating broader acceptance.

References

Abidoye, R. B., & Chan, A. P. (2017). Valuers' receptiveness to the application of artificial intelligence in property valuation. *Pacific Rim Property Research Journal*, *23*(2), 175-193.

Abidoye, R. B., Junge, M., Lam, T. Y., Oyedokun, T. B., & Tipping, M. L. (2019). Property valuation methods in practice: evidence from Australia. *Property Management*, *37*(5), 701-718.

Abidoye, R. B., & Chan, A. P. (2017). Artificial neural network in property valuation: application framework and research trend. *Property Management*, *35*(5), 554-571.

Abidoye, R., Ma, J., & Lee, C. L. (2021). Barriers, drivers and prospects of the adoption of artificial intelligence property valuation methods in practice. *Pacific Rim Property Research Journal*, *27*(2), 89-106.

Achu, K. (2013). Client influence on property valuation: a literature review. *International Journal of Real Estate Studies*, *8*(2), 24-47.

Ahuja, M. K., & Thatcher, J. B. (2005). Moving beyond intentions and toward the theory of trying: Effects of work environment and gender on post-adoption information technology use. *MIS Quarterly*, 427-459.

Aihie, V. U. (2019). The PropTech revolution: The imperatives for Nigeria's estate surveying and valuers to catch up or get left behind. *Journal of African Real Estate Research*, *4*(2), 56-75.

Al-Gahtani, S. S., & King, M. (1999). Attitudes, satisfaction and usage: factors contributing to

each in the acceptance of information technology. *Behaviour & Information Technology*, *18*(4), 277-297.
Alipour, M., Salehi, M., & Shahnavaz, A. (2009). A study of on the job training effectiveness: Empirical evidence of Iran. *International Journal of Business and Management*, *4*(11), 63-68.
Amidu, A. R., Levy, D., & Bolomope, M. (2021). Conceptualising valuation quality in practice: a valuer perspective. *Journal of Property Research*, *38*(3), 213-237.
Amidu, A. R., Tajudeen Aluko, B., & Andrew Hansz, J. (2008). Client feedback pressure and the role of estate surveyors and valuers. *Journal of Property Research*, *25*(2), 89-106.
Amidu, A. R., Boyd, D., & Agboola, A. O. (2019). The role of knowledge in valuation practice: expert valuers' perceptions. *Journal of Property Investment & Finance*, *37*(6), 524-540.
Ayaz, A., & Yanartaş, M. (2020). An analysis on the unified theory of acceptance and use of technology theory (UTAUT): Acceptance of electronic document management system (EDMS). *Computers in Human Behavior Reports*, *2*, 100032.
Ayodele, T. O., Oladokun, T. T., & Kajimo-Shakantu, K. (2020). Employability skills of real estate graduates in Nigeria: a skill gap analysis. *Journal of Facilities Management*, *18*(3), 297-323.
Avci, G., & Erzurumlu, Y. O. (2023). Blockchain tokenization of real estate investment: a security token offering procedure and legal design proposal. *Journal of Property Research*, *40*(2), 188-207.
Băbțan, S. I. (2025). Artificial intelligence in automated valuation models for real estate sector. *Review of Economic Studies and Research Virgil Madgearu*, *18*(1), 5-20.
Baffour Awuah, K. G., & Gyamfi-Yeboah, F. (2017). The role of task complexity in valuation errors analysis in a developing real estate market. *Journal of Property Research*, *34*(1), 54-76.
Bajwa, D., & Lewis, L. F. (2003). Does size matter? An investigation of collaborative information technology adoption by US firms. *Journal of Information Technology Theory and Application (JITTA)*, *5*(1), 4.
Balfour, G. (2001). Technological changes bring new opportunities into the field of valuation. *Australian Property Journal*, *36*(7), 607-610.
Baum, A., Saull, A., & Braesemann, F. (2020). PropTech 2020: the future of real estate. *Said Business School. University of Oxford Research. Search in*.
Bhattacherjee, A. (1998). Managerial influences on intraorganisational information technology use: A Principal-agent model. *Decision Sciences*, *29*(1), 139-162.
Bogin, A. N., & Shui, J. (2020). Appraisal accuracy and automated valuation models in rural areas. *The Journal of Real Estate Finance and Economics*, *60*(1-2), 40-52.
Braesemann, F., & Baum, A. (2020). PropTech: Turning real estate into a data-driven market?. *Available at SSRN 3607238*.
Broekema, M. J., Strohmaier, N., Adriaanse, J. A., & van der Rest, J. P. I. (2022). Are business valuators biased? A psychological perspective on the causes of valuation disputes. *Journal of Behavioral Finance*, *23*(1), 23-42.
Brugger, F., & Gehrke, C. (2018). Skilling and deskilling: technological change in classical economic theory and its empirical evidence. *Theory and Society*, *47*, 663-689

Cheloti, I. N., & Mooya, M. M. (2023). An assessment of valuation education and training in Kenya in comparison with practice. *Property Management*, *41*(2), 276-294.
Clegg, C., Carey, N., Dean, G., Hornby, P., & Bolden, R. (1997). Users' reactions to information technology: some multivariate models and their implications. *Journal of Information Technology*, *12*, 15-32.
Crosby, N. (2000). Valuation accuracy, variation and bias in the context of standards and expectations. *Journal of Property Investment & Finance*, *18*(2), 130-161.
Crosby, N., Devaney, S., Lizieri, C., & McAllister, P. (2018). Can institutional investors bias real estate portfolio appraisals? Evidence from the market downturn. *Journal of Business Ethics*, *147*, 651-667.
Czernkowski, R. M. (1990). Expert systems in real estate valuation. *Journal of Valuation*, *8*(4), 376-393.
Davis, F. D. (1989). Technology acceptance model: TAM. *Al-Suqri, MN, Al-Aufi, AS: Information Seeking Behavior and Technology Adoption*, 205-219.
Drogalas, G., & Siopi, S. (2017). Risk management and internal audit: Evidence from Greece. Risk governance & control: financial markets & institutions, 7 (3), 104-110.
French, N., & Gabrielli, L. (2018). Pricing to market: Property valuation revisited: The hierarchy of valuation approaches, methods and models. *Journal of Property Investment & Finance*, *36*(4), 391-396.
Gallimore, P. (1996). Confirmation bias in the valuation process: a test for corroborating evidence. *Journal of Property Research*, *13*(4), 261-273.
Gilbertson, B., & Preston, D. (2005). A vision for valuation. *Journal of Property Investment & Finance*, *23*(2), 123-140.
Grover, R. (2016). Mass valuations. *Journal of Property Investment & Finance*, *34*(2), 191-204.
Hoxha, V., & Sadiku, S. (2019). Study of factors influencing the decision to adopt the blockchain technology in real estate transactions in Kosovo. *Property Management*, *37*(5), 684-700.
Januszkiewicz, A. (2016). The practice of evaluation of EU projects in local governments in Poland. *International Journal of Contemporary Management*, *15*(3), 7-30.
Kaluthanthri, P. C., & Hippola, N. B. (2023). Valuers' Perception on Mitigating Material Uncertainty in Property Valuation. South Asian Journal of Social Studies and Economics, 17(2), 27-38.
Kamarudin, N., & Daud, D. (2014, June). Computer assisted mass appraisal (CAMA) application for property tax administration improvement in Malaysia. In *FIG Congress* (pp. 16-21).
Kasim, I., Amidu, A. R., & Levy, D. (2024). Digitalisation and valuations: an empirical analysis of valuers' supplemental skills requirements. *Journal of Property Research*, *41*(4), 344-375.
Kasim, I., Amidu, A. R., & Levy, D. (2025b). A conceptual bridge for the 'innovation-adoption gap' in the property profession. *Journal of Property Research*, *42*(1), 66-95.
Kasim, I., Amidu, A. R., & Levy, D. (2023). Are there some skills valuers will 'no longer need to learn'in the digital technology environment?. *ERES*, (eres2023_286).
Kelley, M. R., & Helper, S. (1999). Firm size and capabilities, regional agglomeration, and the

adoption of new technology. *Economics of Innovation and New Technology*, *8*(1-2), 79-103.
Kim, H. J., Mannino, M., & Nieschwietz, R. J. (2009). Information technology acceptance in the internal audit profession: Impact of technology features and complexity. *International Journal of Accounting Information Systems*, *10*(4), 214-228.
Kirkwood, J. (2004). Urban real estate information systems: The suppression of radical innovation. *Journal of Urban Technology*, *11*(1), 29-42.
Kiss, M. (2017). Digital skills in the EU labour market. *European Parliamentary Research Service*.
Klamer, P., Gruis, V., & Bakker, C. (2019). How client attachment affects information verification in commercial valuation practice. *Journal of Property Investment & Finance*, *37*(6), 541-554.
Kontiadis, I. Z. (2008). Introduction to Social Administration and Social Security Institutions. *Athens: Papazisi*.
Lee, G., & Xia, W. (2006). Organisational size and IT innovation adoption: A meta-analysis. *Information & Management*, *43*(8), 975-985.
Lee, S. M., Kim, I., Rhee, S., & Trimi, S. (2006). The role of exogenous factors in technology acceptance: The case of object-oriented technology. *Information & Management*, *43*(4), 469-480.
Lenk, M. M., Worzala, E. M., & Silva, A. (1997). High-tech valuation: should artificial neural networks bypass the human valuer?. *Journal of Property Valuation and Investment*, *15*(1), 8-26.
Levy, D., & Schuck, E. (1999). The influence of clients on valuations. *Journal of Property Investment & Finance*, *17*(4), 380-400.
Liman, H. S., Amidu, A. R., & Levy, D. (2025). Approaches to improving valuation decision-making: a review of the literature. *Journal of Property Investment & Finance*, *43*(1), 27-49.Lois, P., Drogalas, G., Karagiorgos, A., & Tsikalakis, K. (2020). Internal audits in the digital era: opportunities risks and challenges. *EuroMed Journal of Business*, *15*(2), 205-217.
Lorenz, D., Trück, S., & Lützkendorf, T. (2006). Addressing risk and uncertainty in property valuations: a viewpoint from Germany. Journal of Property Investment & Finance, 24(5), 400-433.
McCluskey, W., Deddis, W., Mannis, A., McBurney, D., & Borst, R. (1997). Interactive application of computer assisted mass appraisal and geographic information systems. *Journal of Property Valuation and Investment*, 15(5), 448-465.
Mdanat, M. F., Shotar, M., Samawi, G., Mulot, J., Arabiyat, T. S., & Alzyadat, M. A. (2018). Tax structure and economic growth in Jordan, 1980-2015. *EuroMed journal of Business*, *13*(1), 102-127.
Meyer, J. (2011). Workforce age and technology adoption in small and medium-sized service firms. *Small Business Economics*, *37*, 305-324.
Mimis, A., Rovolis, A., & Stamou, M. (2013). Property valuation with artificial neural network: The case of Athens. *Journal of Property Research*, *30*(2), 128-143.
Mooya, M. (2011). Of mice and men: Automated valuation models and the valuation profession. *Urban Studies*, *48*(11), 2265-2281.

Journal of European Real Estate Research

Newell, G., Muhammad Najib, B. M. R., & Martin Juanil, D. (2010). Assessing client perceptions of the quality of commercial valuation reports in Malaysia. *Pacific Rim Property Research Journal*, *16*(4), 458-476.

Nurhajati, Y. (2016). The impact of cloud computing technology on the audit process and the audit profession. *Int. J. Sci. Technol. Res*, *5*.

Oladokun, S. O., & Gbadegesin, J. T. (2017). Adequacy of core knowledge and soft skills in the performance of professional employees of real estate firms in Nigeria. *Property Management*, *35*(2), 132-149.

Olawande Oni, A. (2013). Digital divide–a challenge to the real estate practice in Nigeria? *Property Management*, *31*(1), 22-38.

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.

Peto, R. (1997). Market information management for better valuations: Part II-data availability and application. *Journal of Property Valuation and Investment*, *15*(5), 411-422.

Poon, J. (2014). Do real estate courses sufficiently develop graduates' employability skills? Perspectives from multiple stakeholders. *Education+ Training*, *56*(6), 562-581

Quick, D., & Davies, T. G. (1999). Community college faculty development: Bringing technology into instruction. *Community College Journal of Research & Practice*, *23*(7), 641-653.

Rogers, E. M. (2003). Diffusion of Innovations fifth Ed Free Press. New York. *Rezvani, Z., Jansson, J. & Bodin*.

Rossini, P. (1997, January). Application of artificial neural networks to the valuation of residential property. In *Third Annual Pacific-Rim Real Estate Society Conference. Palmerston North, New Zealand*.

Santoro, G., Vrontis, D., Thrassou, A., & Dezi, L. (2018). The Internet of Things: Building a knowledge management system for open innovation and knowledge management capacity. *Technological Forecasting and Social Change*, *136*, 347-354.

Saiz, A. (2020). Bricks, mortar, and proptech: The economics of IT in brokerage, space utilization and commercial real estate finance. *Journal of Property Investment & Finance*, *38*(4), 327-347.

Saull, A., Baum, A., & Braesemann, F. (2020). Can digital technologies speed up real estate transactions?. *Journal of Property Investment & Finance*, *38*(4), 349-361.

Scheurwater, S. (2017). The future of valuations. *RICS Insight Paper*, 23-25.

Sipan, I., Ali, H., Ismail, S., Abdullah, S., & Abd Aziz, S. S. (2012). GIS-based mass appraisal model for equity and uniformity of rating assessment. In *UTM-IBIMA International Real Estate Conference* (pp. 1-16).

Shetty, D. V., Rao, B. P., Prakash, C., & Vaibhava, S. (2020). Multiple regression analysis to predict the value of a residential building and to compare with the conventional method values. In *Journal of Physics: Conference Series* (Vol. 1706, No. 1, p. 012118). IOP Publishing.

Sugandini, D., Purwoko, P., Pambudi, A., Resmi, S., Reniati, R., Muafi, M., & Adhyka

Journal of European Real Estate Research

Kusumawati, R. (2018). The role of uncertainty, perceived ease of use, and perceived usefulness towards the technology adoption. *International Journal of Civil Engineering and Technology (IJCIET)*, *9*(4), 660-669.
Talukder, M. (2014). *Managing innovation adoption: from innovation to implementation*. Ashgate Publishing, Ltd..
Tidwell, O. A., & Gallimore, P. (2014). The influence of a decision support tool on real estate valuations. *Journal of Property Research*, *31*(1), 45-63.
Timsal, A., Awais, M., & Shoaib, O. (2016). On job training and its effectiveness: An employee perspective. *South Asian Journal of Banking and Social Sciences*, *2*(1), 1-22.
Thomas, R., & Lambert, J. (2019). Technology and the Future of Australian Jobs: What will be the Impact of AI on Workers in Every Sector?
Tomatzky, L. G., & Fleischer, M. (1990). The processes of technological innovation Lexington Books. *Lexington MA*.
Toole, T. M. (1998). Uncertainty and home builders' adoption of technological innovations. *Journal of Construction Engineering and Management*, *124*(4), 323-332.
Toufaily, E., Zalan, T., & Dhaou, S. B. (2021). A framework of blockchain technology adoption: An investigation of challenges and expected value. *Information & Management*, *58*(3), 103444.
Ullah, F., & Sepasgozar, S. M. (2019). A study of information technology adoption for real-estate management: A system dynamic model. In *Innovative Production And Construction: Transforming Construction Through Emerging Technologies* (pp. 469-486).
Ullah, F., Sepasgozar, S. M., Thaheem, M. J., & Al-Turjman, F. (2021). Barriers to the digitalisation and innovation of Australian Smart Real Estate: A managerial perspective on the technology non-adoption. *Environmental Technology & Innovation*, *22*, 101527.
Ulu, C., & Smith, J. E. (2009). Uncertainty, information acquisition, and technology adoption. *Operations Research*, *57*(3), 740-752.
Urban, B., & Maphumulo, M. (2022). The moderating effects of entrepreneurial orientation on technological opportunism and innovation performance. *European Journal of Innovation Management*, *25*(3), 901-921.
Van Laar, E., Van Deursen, A. J., Van Dijk, J. A., & De Haan, J. (2017). The relation between 21st-century skills and digital skills: A systematic literature review. *Computers in Human Behavior*, 72, 577-588.
Vasarhelyi, M., & Romero, S. (2014). Technology in audit engagements: a case study. *Managerial Auditing Journal*, *29*(4), 350-365.
Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425-478.
Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, *39*(2), 273-315.
Wei, W. (2012). The impact of product complexity on adoption of web-based interactive innovation practices. *Innovation*, *14*(3), 431-445.
Wilkinson, S., Halvitigala, D., & Antoniades, H. (2018). Educators, professional bodies and the future of the valuation profession. *Property Management*, *36*(4), 389-399.
Yamani, H. A. (2021). A conceptual framework for integrating gamification in elearning systems

based on instructional design model. *International Journal of Emerging Technologies in Learning (Online)*, *16*(4), 14.

Journal of European Real Estate Research

Responses to reviewers' comments

Methodological concerns

Comment: The authors have clearly made a good effort to improve the quality of the paper. Some of the earlier suggestions have been implemented, including replacing MLR with logistic regression, which is appreciated. However, the logistic regression results indicate that only two out of ten variables are statistically significant, which now makes the use of logistic regression feel somewhat unnecessary. These results may be linked to concerns previously raised about the sample size relative to the number of variables, as well as the possible inclusion of multiple respondents from the same organisations (this should have been reported).

A chi-squared test was conducted for all variables (results reported alongside the descriptive statistics), and this appears sufficient for testing the stated hypotheses. In fact, the logistic regression did not produce any new results or insights beyond the chi-squared test. With a very weak prediction power, the authors should consider removing the logistic regression section and instead provide a more robust interpretation of the chi-squared test results (the authors should acknowledge that the chi-squared test is an inferential statistical method valid/suitable for hypothesis testing).

Response:

We acknowledge the reviewer's observation that only two of the ten variables were statistically significant in the logistic regression analysis. While this may suggest limited explanatory power, we respectfully maintain that the inclusion of logistic regression is methodologically and theoretically justified.

Chi-squared tests are suitable for examining associations between categorical variables and hypothesis testing. However, they do not allow for the estimation of effect sizes or control of confounding variables. For example, one of our hypotheses states: "The size of the valuation company positively affects the use of digital technology tools in valuation practice". A chi-squared test can indicate whether a statistically significant association exists between company size and technology use, but it cannot determine the direction or magnitude of this relationship or adjust for other influencing factors.

In contrast, logistic regression enables us to:

- Quantify the strength and direction of relationships,
- Control for multiple covariates simultaneously,
- The theory-driven causal pathways were explored.

Importantly, our use of logistic regression was not intended as a predictive exercise, but rather as a robust inferential method to test theoretically grounded hypotheses. We have revised the Statistical analysis section of the manuscript to clarify this purpose (see highlighted text on pages10–11 of the revised manuscript).

Comment: "Univariate logistic regression" is not a standard term. Logistic regression always involves at least a dependent variable and one predictor, so describing it as "univariate" is potentially misleading. More appropriate terms would be 'simple' or 'bivariable' logistic regression, all of which apply when a single predictor is modelled. That said, relying on single-predictor models risks excluding theoretically important variables. All predictors or independent variables should be included in a multivariable model regardless of their unadjusted p-values. Probably unnecessary at this point, but the authors should have considered estimating the model with all key predictors included simultaneously, as in Table 7.

Response:

We thank the reviewer for their insightful comments on both terminology and methodological design.

Regarding terminology, we acknowledge that the phrase "univariate logistic regression" can vary in usage across disciplines. In many applied research contexts, it refers to logistic regression conducted with a single predictor and a binary outcome, an interpretation widely used in the literature (e.g., Univariate Logistic Regression - Google Scholar). However, we recognise that some statistical communities prefer terms such as "simple" or "bivariable" logistic regression for this same procedure. In light of the reviewer's observation, we have revised the manuscript to use "simple logistic regression" when describing the single-predictor analyses. and "multivariable logistic regression" for analyses involving multiple predictors simultaneously (see highlighted text on pages 16, 18 and 19 of the revised manuscript).

In terms of methodology, we respectfully disagree that all variables should be entered into the multivariable analysis irrespective of their prior statistical or theoretical relevance. Including every variable, especially those without empirical or conceptual justification, can lead to overfitting, inflated standard errors, and multicollinearity, particularly with a moderate sample size. Our objective was not to build a predictive model but to conduct theory-driven inference focused on identifying factors that meaningfully influence digital technology adoption.

Accordingly, our analytic design followed a multi-stage inferential approach. The first stage employed chi-squared tests to screen for significant associations. The second stage applied simple logistic regression to quantify the direction and strength of these associations. The third stage incorporated only theoretically and empirically supported variables into the multivariable logistic regression, allowing us to isolate independent effects while controlling for inter-variable influences. This sequential, evidence-based approach aligns with established guidance (Hosmer, Lemeshow & Sturdivant, *Applied Logistic Regression*,

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2013: Applied Logistic Regression | Wiley Series in Probability and Statistics) and ensures both interpretability and rigour.

We appreciate the reviewer's recommendation and have noted that future studies should consider estimating models with all key predictors simultaneously, where sample size permits, multicollinearity is minimal, and the individual predictors demonstrate sufficient theoretical or empirical significance, to better capture potential complex relationships among factors purpose (see highlighted text in the discussion concluding paragraph on page 21 of the revised manuscript).

Comment: Finally, the logistic regression section omits the pseudo-R^2 statistics to assess model fit. To improve interpretability and credibility, at least one commonly accepted index, such as McFadden's R^2, Cox & Snell R^2 or Nagelkerke R^2, should be reported. These measures would allow readers to judge the explanatory strength and adequacy of the model.

Response:

We thank the reviewer for this thoughtful comment and appreciate the emphasis on reporting pseudo-R^2 statistics. We acknowledge this omission and would like to clarify that the core objective of this study was not to construct or validate a predictive model, but to test theoretically grounded relationships between selected factors and technology adoption using logistic regression.

In our analytical framework, logistic regression served as a confirmatory inferential technique, not a predictive one. It was applied to assess the strength, direction, and independence of associations among theoretically relevant variables while controlling for potential confounding. Unlike the chi-squared test, which identifies associations independently, logistic regression provides odds ratios that quantify both the magnitude and direction of effects, thereby addressing the study's inferential, not predictive, objectives.

For completeness, we fitted a null model and computed pseudo-R^2 statistics. The results were as follows: **McFadden's $R^2 = 0.168$, Cox & Snell $R^2 = 0.201$, and Nagelkerke $R^2 = 0.273$.** These values indicate a moderate level of explanatory strength, consistent with a theory-testing, non-predictive framework. However, we made a deliberate decision not to report these metrics in the manuscript, as doing so could mislead readers into interpreting our work as model-building or predictive in nature, which it was not.

We fully recognise the reviewer's point and agree that in future studies specifically aimed at developing predictive frameworks, inclusion of pseudo-R^2 indices would indeed enhance transparency regarding model adequacy and explanatory performance (see highlighted text in the discussion concluding paragraph on page 21 of the revised manuscript).

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Variable selection and justification

Comment: The rationale for including "Years of Practice" while excluding "Educational Qualification" is unclear, especially as both showed statistical significance in at least one category. This choice needs justification.

Response:

We appreciate the reviewer's observation regarding the inclusion of *Years of Practice* and the exclusion of *Educational Qualification* in the multivariable analysis. The decision was based on both statistical validity and theoretical reasoning.

While *Educational Qualification* appeared significant in the "Master's degree" category during the simple logistic regression (OR = 4.21; 95% CI = 1.10-20.48; p = 0.046), the variable exhibited clear signs of data sparsity and estimate instability. In particular, the "Doctoral degree" category produced an extremely large odds ratio ($\approx 3.8 \times 10^6$) with an undefined upper confidence bound (NA) and a non-significant p-value (p = 0.986), indicating that very few respondents held doctoral qualifications. Such sparse data inflate standard errors and render the overall variable unreliable for multivariable inclusion, as it can distort parameter estimation and compromise model convergence.

By contrast, *Years of Practice* demonstrated a more stable and interpretable association (5-10 years: OR = 0.15; 95% CI = 0.02-0.92; p = 0.044) and has stronger theoretical relevance to practical experience and technology adoption behaviour, as supported by prior literature. Retaining this variable therefore aligns with both empirical stability and conceptual justification.

We have clarified this rationale in the revised manuscript (see highlighted text on page 18 - 19 of the revised manuscript)

Comment: Some hypothesis-level findings warrant further scrutiny. For H3, the result that BSc vs MSc is significant while PhD is not, is difficult to interpret. Also, for H4, it is unexpected that the <5 vs 5–10 years comparison is significant while higher experience levels (of years of experience) are not. These patterns suggest possible issues with sample distribution.

Response:

We agree that the observed patterns, where the difference between bachelor's and master's degree holders was significant while the PhD category was not, and where the <5 vs 5–10 years comparison was significant but not higher experience levels, are somewhat unexpected. These outcomes likely reflect sample distribution imbalances, particularly the very small number of respondents with doctoral qualifications and highly experienced practitioners, which limited statistical power in those subgroups.

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Importantly, these findings do not indicate analytical inconsistencies but rather reflect the true composition of the surveyed population, in which mid-career professionals (5–10 years of practice) and respondents with master's degrees were the predominant cohorts. We have clarified this point in the limitations section, noting that future studies with larger and more balanced samples would be valuable to confirm whether these patterns persist across more diverse or representative populations (see highlighted text in the discussion concluding paragraph on page 21 of the revised manuscript)

Interpretation and literature context

Comment: Overall, the findings suggest that sociodemographic variables are not strongly associated with technology adoption. The authors should discuss these results in the context of existing literature and consider whether this aligns with prior evidence. For instance, if valuers are expected to operate according to organisational and professional standards, it may be unsurprising that gender, age or education level show little influence. A more detailed explanation is also required on why organisational factors such as company size, type, manual processes and training are unrelated to technology adoption.

Response:

Thank you for this important point. We have expanded our discussion to reflect that the weak associations between sociodemographic and organisational factors and technology adoption (see the highlighted text in yellow in the discussion section on page 20 - 21 of the revised manuscript).

Comment: Further clarification is also needed on how the "multidisciplinary property company" is defined in the study. The number of respondents from such companies could have influenced the results, particularly in the context of valuation practice.

Response:

We have now defined "Multidisciplinary Property Company" as an organisation involved in multiple aspects of property services such as valuation, management, development, and investment". This definition has been added to the methods section to improve clarity and contextual relevance (see the highlighted text in yellow on page 9-10 of the revised manuscript).

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Comment: Relatedly, knowing how many participants came from the same organisations would help assess the potential clustering effect and the generalisability of the findings.

Response:

We appreciate the reviewer's concern regarding the potential clustering of responses from the same organisation, which could affect the generalisability of our findings. To clarify, our questionnaire did not collect organisation-specific identifiers to preserve respondent anonymity and adhere to ethical research standards and institutional guidelines.

If the reviewer's concern refers to respondents from the same 'company type' (e.g. multidisciplinary property firms), this breakdown has been reported in the descriptive statistics section. However, if the concern relates to multiple responses from the 'same individual organisation', we regret that such information cannot be provided because of the anonymity of responses.

We acknowledge that the inability to account for potential clustering may introduce bias and limit the generalisability of our results. This limitation has been explicitly addressed in the revised manuscript (see highlighted text in the discussion concluding paragraph on page 21 of the revised manuscript)

Other changes

After making the necessary changes outlined above, we observed the length of the article had increased substantially and now approximate 14,000 words. Accordingly, we decided to trim down the aspects of the findings that did not directly relate to the aim of the study and the hypothesis. We also revised the conclusion and abstract accordingly.

Once again, we are grateful for the opportunity to revise our manuscript and hope that you will find the revised version suitable for publication in the Journal of European Real Estate Research.

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