Intelligent Human Systems Integration (IHSI), Vol. 200, 2026, 901–910
https://doi.org/10.54941/ahfe1007151

Modern Technology Adoption in Property Valuation: Perceptions in South Africa

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ABSTRACT

Emerging technologies such as artificial intelligence (AI), automated valuation models (AVMs), geographical information systems (GIS) and other related technologies are reshaping the global property valuation industry. Debates on readiness for the adoption of digital technologies are at the forefront particularly in municipal valuations, where concerns of valuation accuracy are prevalent. This study investigates how property valuers perceive and adopt AI and other technologies in South Africa. The study employed a quantitative research design using an online national questionnaire survey distributed to capture the opinions of property valuers. A total of 340 valid responses were received and analysed using Statistical Package for Social Sciences (SPSS) version 30. Descriptive statistics, Spearman's rank-order correlation, Kruskal–Wallis H tests, and Pairwise Mann–Whitney U tests were applied to determine relationships and group differences. Findings indicate that AI adoption is minimal, with nearly half of property valuers reporting "never" using AI tools such as "ChatGPT" and only 1.8% reporting regular use. Statistically significant differences in adoption were observed across specialisation and registration class, with commercial and candidate valuers demonstrating higher adoption rates. Conversely, municipal and senior valuers displayed more conservative digital engagement patterns. Candidate valuers and valuers with less experience were more likely to experiment with AI tools, while property valuers specialising in municipal valuers were reported to be the most resistant to the use of AI and related emerging technologies. Confidence in GIS tools showed a high adoption rate with most respondents reporting consistent use. The findings indicate that South African property valuers are concomitantly progressive and conservative, with the use of GIS tools fully integrated in practice while AI and AVMs are yet to be adopted.

Keywords: Artificial intelligence (AI), Geographical information systems (GIS), Automated valuation models (AVMs), Technology adoption, South Africa

INTRODUCTION

Real estate is among the most significant assets within the global economy, forming part of one of the largest global markets and is integral for the effective functioning of the property market and economy of a country in general (Asres, 2023; Tzimas & Kritikos, 2022; Renigier-Bilozar, Zrobek & Walacik, 2022). Many authors concur that property valuations have a critical role in the functioning of the real estate market and ultimately the economy in general (Asres, 2023; Deppner, von Ahlefeldt-Dehn, Beracha & Schaefers 2023; Malkowska & Uhruska, 2022; Reinert 2021, Effiong & Mendi, 2019; Buuveibaatar, Lee & Lee, 2023). The accuracy of property

Received September 15, 2025; Revised November 10, 2025; Accepted November 25, 2025; Available online February 1, 2026

valuations, therefore, is of utmost importance (Deppner, von Ahlefeldt-Dehn, Beracha & Schaefers, 2023; Malkowska & Uhruska, 2022; Reinert, 2021; Effiong & Mendi, 2019; Buuveibaatar, Lee & Lee, 2023). Global technological advancements in property valuations such as AI, AVMs, GIS and other related technology could provide a viable solution to improved accuracy of property valuations and therefore needs to be investigated to establish their role in the property valuation environment.

The level of adoption among South Africa property valuers is unknown with no studies on either awareness or adoption of AI, AVMs, GIS and other technology. Furthermore, no study on both AI and GIS adoption have been done, further confirming the need for the research. This necessitates a robust national wide study of the South African valuation industry to establish the adoption level of AI, AVMs, GIS and other technologies. The findings should lead decision makers and policy makers to formulate evidence based strategies for technological adoption. The cost to disregards issues of adoption of technology in property valuation in South Africa can be massive, especially in a struggling economy.

The purpose of this paper is to: (i) establish the level of adoption of AI, AVMs, GIS and related technology in the South African valuation industry and (ii) establish how adoption of AI, AVMs, GIS and related technology vary between registration classes, experience levels, geographical locations and valuation speciality.

Adoption of Modern Technology in Property Valuations

This section reviews the adoption of modern technology in property valuations across various local and international contexts. Dimopoulos, Renigier-Bilozor, Ache and Janowski (2024) note that the real estate valuation industry is "undergoing a profound transformation, driven by the integration of advanced technologies such as Automated Valuation Models (AVMs) and Artificial Intelligence (AI)," signalling a shift toward data-driven valuation ecosystems. Droj, Kwartnik-Pruc, and Droj (2024) sought to use a literature review to investigate how modern technology, such as artificial intelligence (AI), geographical information systems (GIS) and satellite imagery, could be used to reduce the subjectivity of property valuations. The study found that GIS provides practical tools and solutions for mass valuations and automated valuation models (AVMs). Droj et al. (2024) concluded that integrating satellite imagery, AI or machine learning and GIS can improve the accuracy and objectivity of property valuations. However, the study also acknowledges that machine learning models have limitations and adjustments are required to improve errors and accuracy. Their review further emphasised that "advanced technologies, including artificial intelligence, GIS, and satellite imagery, can improve the subjectivity of traditional valuation approaches and thereby promote greater accuracy and productivity in real estate valuation" (Droj et al., 2024). Gbadebo & Adewusi (2025) focused on the awareness of AI technology among Nigerian valuers and found that, generally, the awareness of AI tools was low and poorly understood. Similarly, Adejumo, Ayodele, Oyewole, Adebara, Hassan &

Adeosun (2024) study revealed that although AI is not a new concept in the valuation industry, its adoption remains low. Complementing this, Adejumo, Olutayo & Adetola (2024) also found that AI adoption in Lagos, Nigeria, is below average, despite valuers above average willingness to embrace the technologies. A significant portion of respondents (67.5%) still exhibit low to very low awareness of AI valuation technologies, and similar studies in Malaysia "concluded that there is a low level of awareness of automated valuation models among valuation firms" (Mugunthany and Muhammad, 2008; Adewusi and Gbadebo, 2023). Other similar studies on the awareness of AI technology in property valuations have revealed low awareness, implying that adoption is also low in countries such as Malaysia and Hong Kong (Mugunthany & Muhammad, 2008; Abidoye, 2017). Although all these studies had relatively small sample sizes, a similar trend could be seen. This trend was further confirmed in a study by Abidoye, Ma & Lee (2021), which found the use of AI in Australia is limited, with traditional methods being favoured over machine learning methods. According to Abidoye et al. (2021), "traditional methods are being adopted by Australian valuers, but the advanced methods are seldomly popular and used in practice," although valuers "believe that AI will transform the property valuation profession." Yet more than 30 % indicated, "I will use AI valuation methods once I have learned it," suggesting readiness when training improves. In both developing and developed contexts, a common theme of low adoption and awareness of AI tools and related modern technology emerged. Nevertheless, the global literature recognises that "AI and AVMs are revolutionising real estate value, providing a roadmap for ethical and successful integration of AVMs and AI into the valuation process" (Dimopoulos et al., 2024), highlighting both the opportunity and the persistent implementation gap.

METHOLODY

The study was designed as a robust quantitative survey, consistent with inductive pragmatic ontological philosophy. Data collection was conducted using a national survey questionnaire by means of a five (5) point Likert scale compilation and only included registered property valuers in South Africa. The total population of valuers registered at the South African Council for the Valuers Profession (SACPVP) is 2452 and therefore a valid sample (n) was calculated using the formula $s = X^2NP(1-P) \div d^2(N-1) + X^2P(1-P)$ to be 332 respondents at a 95% confidence level (Krecijic & Morgan, 1970). A total of 340 valid response by a diverse respondent sample was achieved meeting and exceeding the required threshold. The survey was disseminated via e-mail and other electronic devices to all registered property valuers in South Africa. Google Forms was used to capture respondent responses and Excel and SPSS version 30 were used to analyse the data. Ethical clearance for the study was given by the University of the Free State, and all participants provided consent to take part in the survey. All respondents remained anonymised, and data was coded in line with Protection of Personal Information Act 4 of 2013.

Data analysis included descriptive statistics to identify the adoption of each technology, followed by inferential statistics like Spearman's correlation analysis to test the relationship between the technologies, Kruskal-Wallis H test to determine if adoption varies over demographic variables and finally Pairwise Mann-Whitney U test to determine which groups differ significantly.

RESULTS

This section aimed to identify the level of adoption of technologies such as AI, GIS, Satellite imagery, AVM's, 3D Laser/LiDAR and analytical dashboards within the South African valuation industry. Additionally, examine the correlations between these technologies and to test if the results vary significantly between provinces, experience, valuer specialisation and qualifications. The results are organised into five sections: (1) respondent demographics, (2) descriptive statistics describing the adoption of technology, (3) analysis of relationships between the technology, (4) differences across provinces, specialisations, qualifications, experience and registration class and (5) interpretation of the results.

Demographic Information

A total of 340 valid responses were achieved, representing a diverse sample of property valuers across all nine provinces of South Africa. Geographical representation was concentrated around the urban areas of South Africa where the majority of valuation practises are located, with the Western Cape representing 35.6%, Gauteng 34.7% and smaller proportions from the more rural areas like the Eastern Cape (6.2%), Kwazulu-Natal (5.9%), Mpumalanga (5.0%), North West (4.4%), Free State (3.5%), Northern Cape (2.6%) and Limpopo (2.1%).

The sample included valuers from all three registration classes, with 52.9% registered as Professional Valuers, 32.4% as Professional Associated Valuers and 14.7% as Candidate Valuers. In terms of qualifications 44.7% of respondents held a National Diploma, 17.6% a Bachelors degree, 22.4% an Honours degree, 14.4% a Master degree and less than 1% Doctoral degrees. Experience-wise a large proportion (37.6%) of the respondents had over 21 years' experience, 21.8% with 15 to 20 years, 15.0% with 6–10 years, 13.5% with 0–5 years and 12.1% with 11 to 15 years. Valuers specialising in commercial valuations dominated the sample with 37.4%, while 25.6% specialise in municipal valuations, followed by 21.8% in residential valuations and lastly, agricultural valuations with 15.3%.

Technology Adoption

To assess the adoption level of modern technology, respondents were asked to indicate how often they used the technologies listed in Table 1 below. Mean scores and standard deviations are summarised for each technology in Table 1 below.

Table 1: Descriptive statistics – level of technology adoption.

Technology	N	Mean	SD	Min	Max	Rank
GIS	340	4.46	0.82	1	5	1
Satellite imagery	340	4.40	0.89	1	5	2
Analytical dashboard	340	4.29	1.12	1	5	3
Automated valuation models	340	2.26	1.38	1	5	4
AI Programs like ChatGPT	340	2.11	1.09	1	5	5
3D Laser/LiDAR	340	1.65	1.02	1	5	6

The mean adoption of technology indicates a clear division between more established technologies and emerging automated technologies. GIS ranked no.1 with a mean score of 4.46, followed by Satellite Imagery at 4.40. Analytical dashboards ranked No.3 with a mean score of 4.29, while automated valuation models were remarkably lower at a mean of 2.26, AI programs at 2.11 and lastly 3D Laser or LiDAR technologies at 1.65. The relatively low standard deviations of between 0.82 and 1.12, indicate that these technologies moved beyond the early adopter phase into mainstream professional usage.

The findings further reveal that the spatial-visual technologies are widespread in the valuation industry, while AVM's, AI tools and 3D Laser/LiDAR scored well below the neutral point confirming limited adoption and experimental use only. Higher standard deviations imply greater dispersion, indicating heterogenous exposure and access. Nearly half of the respondents reported never using technologies like AI programs, with only approximately 1% reporting regular use, confirming unfamiliarity and scepticism. The findings support the first objective of the paper by revealing low adoption of emerging technologies in the valuation industry of South Africa.

Spearman's Correlation Analysis: Relationships Between Technologies

To test the relationship between the technologies, Spearman's rank-order correlation was used between the six technologies in the study. The correlation matrix is presented in Table 2 below.

Table 2: Spearman's correlation matrix.

	GIS	Satellite Imagery	Analytical Dashboards	AVM's	AI Programs	3D Scanning/ LiDAR
GIS	_	0.508*	0.169*	−0.066	0.036	−0.002
Satellite imagery	0.508*	_	0.305*	−0.016	0.124*	0.042
Analytical dashboards	0.169*	0.305*	_	0.057	0.141*	−0.021
AVM's	−0.066	−0.016	0.057	_	0.218*	0.218*
AI Programs	0.036	0.124*	0.141*	0.218*	_	0.175*
3D Scanning/ LiDAR	−0.002	0.042	−0.021	0.218*	0.175*	_

p < 0.05, **p < 0.01**

The results of Spearman's correlation revealed two distinct adoption clusters, namely the spatial-visual cluster and the AI-automation cluster. The spatial-visual cluster comprises GIS, Satellite Imagery and Analytical Dashboards, while the AI-automation cluster comprises AVM's, AI program and 3D Scanning/LiDAR.

A strong positive correlation was observed between GIS and Satellite Imagery ($p = 0.508$, $p < 0.001$) indicating that these technologies are used in conjunction. Furthermore, a moderate correlation with Analytical Dashboards was noted ($p = 0.305$, $p < 0.001$). In the AI-automation cluster, AVM's indicated a moderate correlation between AI programs ($p=0.218$, $p < 0.001$) and 3D Scanning/LiDAR ($p = 0.22$, $p < 0.001$). The further correlation between AI programs and LiDAR ($p = 0.175$, $p < 0.001$) confirms indications that these three technologies form an AI-automation cluster. A weak, not significant cross cluster correlation was noted, confirming prior indications that the clusters are independent.

Differences Between Demographic Groups

To determine whether adoption levels vary across different demographic groups, such as provinces, specialisation, qualifications, and experience, non-parametric Kruskal-Wallis H tests were conducted. Results for all four variables are summarised in Table 3 below.

Table 3: Kruskal-Wallis H tests.

Technology	Province (p)	Specialisation (p)	Qualification (p)	Experience (p)	Registration Class (p)
AI programs	0.368	0.001	0.437	0.072	0.185
GIS	0.334	<0.001	0.043	0.230	0.167
AVM's	0.176	0.029	0.753	0.060	<0.001
Satellite Imagery	0.980	0.001	0.352	0.994	0.050
3D Scanning/ LiDAR	0.539	<0.001	0.420	0.208	0.006
Analytical Dashboards	<0.001	<0.001	0.620	0.732	0.061

In terms of provincial differences, only Analytical Dashboards ($H(8) = 31.84$, $p < 0.001$) showed significant variations. The Western Cape, Gauteng and Northern Cape recorded higher mean ranks, possibly suggesting stronger digital infrastructure. No statistically significant differences were reported for AI programs, GIS, AVM's, Satellite Imagery and 3D Scanner/LiDAR use, indicating adoption of these technologies is similar across provinces.

Valuer specialisation indicated statistically significant differences, across all six technologies. Agricultural valuers had the highest adoption rate for GIS (mean rank = 205.17) and Analytical dashboards (mean rank = 200.76). This is attributed to the fact that agricultural valuers often rely on spatial tools due to the nature of the valuations. Similarly, Commercial valuers reported the highest use of AI programs/tools (mean rank = 191.94) and 3D scanning/LiDAR (mean rank = 179.14). Findings from residential valuers indicated a similar trend with AVM's (mean rank = 195.47) ranking the highest, possibly due to high volume valuation tasks. Interestingly, Municipal valuers ranked consistently low across all technologies suggestion that they are the most conservative in terms of technology adoption.

The adoption of GIS was significantly influenced by the repondents qualifications (H (4) = 9.83, p = 0.043). Higher mean ranks were achieved by respondents with Honours degrees and Bachelor's degrees, however no statistically significant results were yielded from other technologies, implying that practical exposure rather than education drives adoption. Furthermore, the respondents experience was found not to be a statistically significant predictor of any technology (p > 0.05). Nevertheless, younger valuers in the 0-5year experience group reported higher adoption of AI and AVM's compared to older valuers with >21years experience, confirming the general trend that digital readiness is related to generational differences. Registration class of valuers identified statistically significant differences, specifically for AVM's (H(2) = 14.809, p < 0.001), Satellite imagery (H(2) = 5.993, p = 0.050) and 3D Laser scanning/LiDAR (H(2) =10.157, p = 0.006). Patterns in the mean ranks further revealed that Candidate valuers' achieved higher mean ranks for AVM's (mean rank = 212.17), compared to Professional Associated valuers (mean rank = 175.70) and Professional valuers (mean rank = 155.74). A similar trend could be seen with Candidate valuers' adoption of 3D Scanning/LiDAR with a mean rank of 191.77 and AI programs/tools with a mean rank of 189.34.

Pairwise Mann-Whitney U Tests

As a result of the statistically significant contrasts of valuer specialisation and registration classes, a series of Pairwise Mann-Whitney U Tests were conducted to determine the specific valuer specialisation and registration classes that differed. Bonferroni adjustments were applied to mitigate Type I error inflation due to multiple comparisons, setting the adjusted at 0.05.

Comparison	Technology	Test Statistic (U)	z (Standard Test Statistic)	p (Sig)	Adjusted p Sig (Bonferroni)
Valuer specialisation					
Residential vs Commercial	AI	31.706	2.140	0.032	0.194
Agricultural vs Commercial	AVM's	–25.152	–1.630	0.103	0.618
Agricultural vs Municipal	Satellite Imagery	–20.022	–1.461	0.144	0.864
Residential vs Municipal	GIS	–56.154	–4.188	<0.001	0.000
Agricultural vs Residential	3D Scanning/ LiDAR	–42.038	–3.172	0.002	0.009

Continued

Comparison	Technology	Test Statistic (U)	z (Standard Test Statistic)	p (Sig)	Adjusted p Sig (Bonferroni)
Agricultural vs Municipal	Analytical Dash-boards	83.363	5.557	<0.001	0.000
Registration Class					
Candidate vs Professional valuer	AVM's	−56.426	−3.782	<0.001	0.000
Professional vs Candidate valuer	Satellite Imagery	29.606	2.145	0.032	0.096
Professional Associated vs Candidate valuer	3D Scanning/ LiDAR	−40.838	−2.857	0.004	0.013
Professional Associated vs Professional	AI Pro-grams	25.618	2.526	0.012	0.035
Professional vs Candidate	GIS	20.762	2.005	0.045	0.0135

Results from the Pairwise Mann-Whitney U test indicated that technology such as GIS, Analytical dashboards and 3D Scanning/LiDAR technology was adopted the most by Commercial valuers, compared to Residential and Municipal valuers. Significant differences were found primarily between municipal valuers and the other groups, especially commercial and agricultural valuers. For instance, municipal valuers reported significantly lower adoption of GIS (Adj. $p = 0.001$), AVMs (Adj. $p = 0.024$), and analytical dashboards (Adj. $p = 0.000$), indicating a lower level of digital integration in municipal practice. Agricultural valuers also demonstrated above-average adoption of Analytical dashboards and 3D Scanning/LiDAR. Two registration classes - Professional valuers and Candidate valuers illustrated significant differences on the adoption of AVMs. Candidate valuers (Adj. $p < 0.001$) reported significantly higher adoption of AVM's than Professional valuers, confirming earlier indications. It was further noted that Candidate valuers and Professional Associated valuers (Adj. $p = 0.013$) used Satellite imagery more than Professional Valuers (Adj. $p = 0.035$), confirming more responsive patterns towards technological advancements.

DISCUSSION

The findings of this study align closely with international research demonstrating uneven adoption of modern technologies in property valuation. Complementing the South African results, studies in Nigeria (Gbadebo & Adewusi, 2025; Adejumo et al., 2024) and Malaysia (Mugunthany & Muhammad, 2008) report that while awareness of artificial intelligence (AI) and automated valuation models (AVMs) is increasing, actual application remains minimal. Valuers continue to rely heavily on traditional methods, primarily due to limited data quality, high implementation costs, and scepticism regarding the accuracy of automated models (Abidoye, Ma & Lee, 2021). Conversely, spatial-visual technologies such as geographical information systems (GIS) and satellite imagery are widely integrated in both local and international valuation practices (Droj et al., 2024; Dimopoulos et al., 2024), supporting the study's identification of a mature spatial-visual adoption cluster. The observed divide between established tools and emerging automation mirrors global trends where GIS is mainstreamed while AI and AVMs remain experimental.

Institutional conservatism and generational differences also emerge as consistent barriers across contexts. Older and municipal valuers' slower adoption rates reflect the entrenched trust in manual valuation approaches observed internationally (Adejumo et al., 2024; Renigier-Bilozar et al., 2022). Literature further emphasises that effective adoption depends on continuous professional development and collaboration between professional bodies, academia, and regulators (Gbadebo & Adewusi, 2025). The South African results thus echo a global consensus: while technology offers pathways to improved valuation accuracy and efficiency, its integration requires coordinated investment in data infrastructure, ethical frameworks, and digital competence to realise the full benefits of AI-driven valuation practice.

CONCLUSION

The findings of this study successfully achieved its objectives by establishing the adoption levels of AI, AVMs, GIS and other technologies. Furthermore, the objective of identifying how the adoption varies between demographic variables has been satisfied. The results confirm that visual-spatial tools have been well integrated into valuation practices, while emerging technologies such as AI programs, AVM's and 3D scanning/LiDAR technology are yet to be adopted. These outcomes satisfied the first comprehensive national study into the adoption of technology in the property valuation field.

The findings further suggest that the adoption of technology is not uniform across all valuers in the profession. Significant differences were noted across valuer specialisation and registration class, with the most notable candidates and valuers specialising in commercial valuation reporting higher levels of adoption. Conversely, the results reported that valuers specialising in municipal valuations and valuers with more than 21 years of experience demonstrated a more conservative adoption pattern. Furthermore, the correlation analysis revealed that adoption transpire in two distinct clusters, spatial-visual and AI automation, highlighting that adoption takes place in complementary domains rather than holistically.

The study recommends that the South African Council for the Valuers Profession (SACPVP), South African Institute of Valuers (SAIV) and higher educational institutions provide continuing professional development (CPD) training events to enhance digital competencies. A combined effort from both higher educational institutions and the private sector to integrate technology in property valuation, could accelerate the adoption of AI, AVMs, GIS and related technology to ultimately improve valuation accuracy in South Africa.

Future research should expand similar studies through mixed-method designs, identifying barriers to the adoption of AI, AVMs and other related or emerging technologies. Furthermore, causal links between technology adoption and valuation accuracy should be examined.

ACKNOWLEDGMENT

The authors would like to acknowledge the University of the Free State for providing ethical clearance and institutional support for this study. Appreciation is extended to all registered property valuers across South Africa who participated in the national survey and contributed valuable insights to the research.

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