Paradigm

PROPERTY VALUATION, NEW TECHNOLOGIES AND DIGITALISATION CHALLENGES IN BOTSWANA

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ABSTRACT

In a 4IR world, with big data and machine learning technologies, wide differences in assessed values amongst valuers cannot be defended anymore; and yet a number of studies reveal slow adoption of these technologies amongst valuers in developing countries. Using Botswana as an example, this paper aims to show that this is not due to the lack of awareness amongst valuers on the potential of new technologies in reducing these variances but rather to a number of other doorstep challenges faced by practitioners. These have to be resolved first. The study adopted a mixed methods approach in which quantitative data was collected through the administration of 182 questionnaires amongst registered valuers and qualitative data through in-depth interviews with five Real Estate Advisory Council (REAC) members. The study found that, despite the availability of new technologies, a number of factors were hindering its application to real estate valuation, such as: paucity of property data, an insufficient legal framework, and a low level of competence and experience amongst valuers. The study thus points to areas for policy reforms and strengthening valuers' training and continuing professional development in Botswana.

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1. Introduction

Accurate representation of property values is an important task for the national economy and for individuals' wealth and welfare (Metzner & Kindt, 2018). The assessment of property values in the national economy is also important for politics, economy and society. Thus, property valuation is a critical component of the real estate industry, underpinning decisions from mortgage lending to investment analysis and portfolio management (Chan & Adiboye, 2019; Greer & Murtaza, 2020). For instance, financial institutions need to know the value of the assets behind a loan. Investors, on the other hand, need to determine the value of their assets in order to establish their reserves, selling and buying prices, and monitor the performance of their investment portfolio. Inconsistent valuations of assets can therefore make these decisions difficult and result in detrimental impacts on stakeholders. Thus, it is cardinal that valuations be accurate, fair, transparent and consistent.

A number of studies, though, show that, in many cases, property valuations are inaccurate, opaque and inconsistent, resulting in stakeholders' dissatisfaction (Munshifwa et al., 2016; Atilola et al., 2019; Yakub et al., 2021; Bellman, 2022). In many instances, there are wide differences in values for the same property assessed by two different valuers, what is now commonly referred to as "valuation variances" (Ayedun et al., 2012; Babawale, 2013; Mohammad et al., 2018; Evans et al. 2019; Cheloti & Mooya, 2021; Munshifwa, 2021). In the era of 4IR, new technologies have been presented as solutions to most of the industry's challenges, including in the field of property valuation. Thus, the application of new technologies is argued to offer opportunities for improving valuation accuracy.

Despite this realization, evidence shows slow uptake amongst practitioners. Using Botswana as an example, the paper investigated the adoption of new technologies in real estate valuation practice where a number of studies point to valuation inaccuracies similar to those seen in most developing economies (Dube, 2012; Mengwe, 2013; Kampamba, 2020). Studies attribute the prevalence of these valuation variances to low adoption of new technologies (Mosesane et al., 2021; Kampamba & Ratlou, 2021).

This paper acknowledges that valuation variances have been a recurring concern in Botswana. However, the paper goes further to argue that this is not because of lack of awareness amongst practitioners on the available technologies but other underlying factors. The paper is arranged as follows. After this introduction section, the paper reviews literature on the relationship between real estate valuation, new technologies and valuation variances. It then presents the research methodology used for this study before presenting the findings and discussions. The last section concludes the paper and points to the needed reforms in valuation practices in Botswana.

2. Real estate valuation, new technologies and valuation variances: a literature review

Valuation literature (Ayedun et al., 2012; Babawele & Omirin, 2012; Effiong 2015; Adegoke 2016; Oduyemi et al., 2016; Narayan et al., 2017; Abidoye et al., 2019; Atilola et al., 2019; Waters, 2019; Narayan & Biswas, 2020; Munshifwa, 2021; Oladokun & Mooya, 2023) point to various causes of valuation variances, with the use of different input variables, use of different valuation methods, human error, client influence, absence of national valuation standards, lack of market data, and level of knowledge and experience being key. In these studies, valuation variance is understood to be the disparities observed in estimated property values produced by different valuers. Adegoke (2016) explains valuation variance as the difference in opinion of values between two or more valuers regarding the same property and for the same purpose. Ashaolu and Bello (2022) explains that variance serves as a cross-sectional assessment conducted at a specific moment to assess the internal consistency within a specific cohort of valuers. Variances in property assessment can therefore be described as discrepancies and inconsistencies in property values of the same property among valuation professionals. The factors leading to variability in the outcomes among property valuers are varied.

Globally, valuers have argued for a tolerable difference in the assessed values, with a difference of between 5% to 15% seen as acceptable. For instance, in a landmark case in the United Kingdom of Singer & Friedlander vs John D Wood & Co [1977] it was ruled that the acceptable margin of error should be between + /- 10 of the correct figure or 15% in exceptional circumstances (Crosby, 2000). In Australia, Parker (1998) found that the acceptable margin of error ranges between +/-5% to +/-10%. Gambo and Anyakora (2013) explained that the margin of valuation error ranging from +/-5% to +/-15% should be adopted in Nigeria based on the complexity of the property and owing to the lack of databank on sale prices. While literature acknowledges variance in valuation practice, Addae-Dapaah (2001) argues that it is more important to focus on ways of reducing these valuation variances as opposed to justifying them.

Arguably, valuation variances arise from diverse sources. Methodological differences among various valuation approaches, such as the sales comparison, income approach, and cost approach, can lead to discrepancies in valuation estimates (Oduyemi et al., 2016; Abidoye et al., 2019). Additionally, variations in data quality, including issues related to accuracy, completeness, and timeliness, contribute to valuation variances (Ayedun et al., 2012; Oladokun & Mooya, 2023). Subjectivity and judgement, inherent in the valuation process, also play a role, as valuers must make subjective assessments regarding market trends, property conditions, and future income potential (Munshifwa, et al., 2016; Atilola et al., 2019; Waters, 2019; Ashaolu & Bello, 2022). Furthermore, market dynamics, regulatory factors, absence of national standards, and legal considerations influence valuation outcomes, further exacerbating variances (Kayode Babawale & Omirin, 2012; Effiong, 2015; Narayan & Biswas, 2020).

In light of these causes of variances, several studies, such as Aluko et al. (2004), Chaphalkar and Sandbhor (2013), Babawale (2013), Evans, et al., (2019), Renigier-Biłozor, et al., (2022) and others, have emphasized the need for valuers to use new technologies and statistical analysis in their valuation; this, they argue, would help minimize valuation variances and inaccuracies. In this sense, real estate technology can be defined as the hardware gadgets, software and online platforms used by different participants in the industry (Ullah, et al., 2018). This is argued to enhance operational efficiency, decision making and most importantly create new opportunities for investment growth (Naeem, et al., 2023). Various technologies have thus been utilized in the real estate industry, such as big data analytics (Zhou et al., 2015; Grybauskas et al., 2021; Naeem, et al., 2023; Root et al., 2023), Geographic Information Systems (GIS) (Gatheru & Nyika, 2015; Reddy, 2018), Automated Valuation Models (AMVs) (Greer & Murtaza, 2020; Kampamba & Ratlou, 2021; Bidanset & Rakow, 2022), Block chain technology (BCTech) (Adiliem, et al, 2024); Garcia-Teruel, 2020), Artificial Neural Networks (ANN) and others.

These studies specifically point to the use of new technologies as one of the solutions to valuation variances. For instance, Grybauskas et al. (2021) employed predictive analytics to analyze large data in real estate in the city of Vilnius, Lithuania. The study asserted that the real estate sector can reap numerous advantages from big data, including precise property valuations, enhanced transaction success rates, and informed decision-making. Thus, Grybauskas et al. (2021) argued that valuations and forecasts can now be done on the internet. Similarly, Kok et al. (2017) examined real estate big data, switching from human to automated valuation. The study argued that automated processes were more accurate than manual ones. Equally, Kang et al. (2021) used big data and machine learning to examine why house prices were rising in the Greater Boston Area of the United States. In this study, a sample of 21,928 houses was used. The study demonstrated how the real estate market's growth is significantly influenced by the use of data tactics.

Other studies (Boshoff & De Kock, 2013; Gatheru & Nyika, 2015; Chan & Abidoye, 2019 Bidanset & Rakow, 2022; Adilieme, Abidoye, & Lee, 2025) point to other tools such as Geographical Information Systems (GIS), Automated Valuation Models (AVMs), Artificial Neural Networks (ANN) and blockchain technologies as solutions to valuation variance problems. At its simplest, GIS is a data management and computer mapping system used to gather, store, organize, retrieve, analyze, and display spatial data (Reddy, 2018). It thus stores both geometric and attribute data. For instance, Droj et al. (2024) demonstrated how geographic information systems are used while appraising real estate.

Automated Valuation Models (AVMs), which are simply mathematical computer programs, are also touted as alternative tools for assessing market values of various real estate interests (Kok, et al., 2017; Metzner & Kindt, 2018; Bidanset & Rakow, 2022). They encompass a variety of valuation statistics and mathematical modeling techniques. AVMs are used especially in Australia, Canada, Sweden, USA and UK, and less common in developing markets (Downie & Robson, 2008). AVMs are part of bigger systems known as Computer-Assisted Mass Appraisals (CAMAs) (Bidanset & Raknow, 2022). These systems are argued to perform better than conventional processes in terms of consistency, objectivity, cost reduction and speedy delivery (Moore & Myers, 2010; Jahanshiri et al., 2011; Ibrahim, et al., 2023).

Machine learning and artificial intelligence (AI) tools have also found usage in the real estate industry. Artificial Neural Networks (ANNs), a subcomponent of AI, are algorithms designed to mimic processes in the human brain. They are thus based on deep learning, using data to train themselves, identify patterns and predict values (Peterson & Flanagan, 2009; Chiarazzo, 2014). Like AI systems, blockchain technology has equally been presented as a solution to real estate challenges. It is loosely defined as a collection of publicly accessible records arranged chronologically in "blocks" (Garcia-Teruel, 2020; Wouda & Opdenakker, 2019). They combine a digital ledger, peer network and cryptographic keys to ensure user privacy and data protection (Adilieme et al., 2024). Blockchain-based platforms are argued to offer speedy, transparent and safe real estate transactions (Hoxha & Sadiku, 2019; Water, 2022; Oluwumni, 2023).

Literature review acknowledged the challenges in valuation practice and the resultant value differences. Furthermore, a number of studies argued how new technologies can help in reducing these variances, and yet these solutions are not finding application in most developing real estate markets. An early notable feature of these new technologies is their heavy dependency on data. This paper explores the "why" question in the context of the Botswana real estate market and valuation practice.

3. Material and methods

This study was based on a mixed method approach, using surveys and in-depth interviews for data collection in Botswana's real estate market. The study's population consisted of a total of 332 property valuers registered with the Real Estate Institute of Botswana (REIB) and Real Estate Advisory Council (REAC). The simple random technique was used to select a sample of 182 Valuers at a 95% confidence interval. A total of 182 questionnaires were administered to practicing valuers out of which 135 were correctly filled and returned. This translates into a 74% response rate from the sample. According to Hendra and Hill (2018), high response rates are appropriate for scientific investigations, with an 80 percent response rate considered adequate. A response rate of 70% is considered acceptable (Pickett et al., 2018). Thus, the 74% response rate achieved for this study was adequate to draw meaningful conclusions. This high response rate was a result of the long length of time given to valuers to answer questionnaires and also constantly reminding the respondents to fill them out.

Table 1

Response rate analysis

Number of questionnaires administered	Number of questionnaires returned	Response rate (%)
182	135	74

Source: own study.

A five-point Likert scale was used for data collection and analysis. Respondents were asked to rank the factors according to the scale where they strongly disagreed (1), disagreed (2), neutral (3), agreed (4) and strongly agreed (5). The mean and average scores of each factor were then determined.

In-depth interviews were also conducted with Senior property valuers, as members of the Real Estate Institute of Botswana (REIB) and the Real Estate Advisory Council (REAC) underlined some of the findings from the survey. The senior valuers were purposively sampled as interview participants because they possess adequate knowledge about the property valuation industry in Botswana. These interview participants were distinct from the quantitative survey respondents, thus ensuring independent data streams for triangulation.

Ethical considerations for the study were adhered to through obtaining a research permit from the Department of Research under the Ministry of Lands and Agriculture. In regard to participant consent, for the survey, this was upon the voluntary completion and submission of the questionnaire, following a clear introductory disclosure that outlined the study's purpose, confidentiality protocols, and participants' rights. For the in-depth interviews, explicit written informed consent was formally obtained from each participant before their engagement. To ensure participant privacy, all data was handled with utmost confidentiality; survey responses were anonymized, and interview transcripts were meticulously de-identified.

In testing the reliability of the results, the Cronbach alpha test was done on the quantitative data. The research constructs were tested for dependability and the results are summarized in Table 2 below.

Table 2

Reliability statistics

Variable construct	Cronbach's alpha	Number of items
Perceived causes of variance	0.962	6
Barriers to technology adoption	0.759	6
Technologies in property valuation	0.691	8

Source: own study.

Table 2 above reveals that Cronbach's alpha for all study constructs was above 0.6. George and Malley (2003) developed the following guidelines: "0.9 – Excellent, 0.8 Good, 0.7 – Acceptable, 0.6 – Questionable, 0.5 – Poor, and less than 0.5 – Unacceptable," meaning that when the alpha is larger than 0.7, the instrument is generally adequate and acceptable. Taber (2018) concluded that a Cronbach's alpha of larger than 0.7 is usually suitable. The data set suggests that the items included in the study instruments for all variables were convergent and consistent, and hence the acquired data was regarded as reliable.

In order to provide additional transparency regarding the distributional properties of the Likert-scaled items, skewness and kurtosis coefficients were calculated and presented in Appendices A.1, A.2 and A.3. Skewness coefficients showed that the majority of the variables fell between -0.5 and 1, indicating moderate skewness. Specifically, these ranged between -0.787 to 0.014 on the perceived causes of valuation variances, -0.031 and -0.773 on the challenges of using technology in property valuation and -0.742 to 0.609 on the technologies used in property valuation. Equally, the majority of Kurtosis coefficients fell around 0, as "excess kurtosis", which was not far from normal. Specifically, these ranged between -0.238 and -0.912 on the perceived causes of valuation variances, -0.538 and 1.106 on the challenges of using technology in property valuation and -0.626 and 1.506 on the technologies used in property valuation.

3. Results

Real estate valuation practice in Botswana is regulated by the Real Estate Professionals Act of 2003. The purpose of the Act is to regulate the real estate practice and matters incidental thereto. The Act establishes the Real Estate Advisory Council (REAC), as the regulator of valuation practice. Additionally, property valuers are also regulated by professional bodies such as the Real Estate Institute of Botswana (REIB) and Botswana Institute of Valuers (BIV). Despite the establishment of regulatory bodies and the drive to adhere to international standards, different stakeholders in Botswana, especially in mortgage loans (bankers) and compulsory acquisition (general public), complain about variances in assessed values amongst practitioners; thus, prompting this study.

3.1. Profile of respondents

As already noted, the paper was based on the administration of questionnaires to practicing valuers. The characteristics of these respondents were 72% males, while the remaining 28% were females, indicating that most of the professionals in the real estate industry are males. The results also revealed that 41% of the respondents work in the private sector, 34% in the public sector, 12% in state-owned enterprises (SOEs) and the remaining 30% in non-governmental organizations. The private sector and government are the major employers of property valuers. This is because valuations for mortgage loans, insurance, tax, sale and investment purposes are needed by clients from private sector valuers. The government, on the other hand, requires valuation personnel mainly for rating purposes and valuation of government properties.

In terms of work experience, the study found that 29% had less than 5 years' experience, 31% had experience ranging from 6-10 years, 21% (11-16 years), 11% (16-20 years) and 8% had over 21 years' experience in the valuation profession. Thus, the majority of the respondents, that is 60%, had experiences ranging between 1-10 years, as shown in Table 3. With regards to educational qualifications, the survey revealed that 1% of the respondents had PhDs, 41% Masters qualifications and 58% had a Bachelor's degree. This is a clear indication that Botswana has sufficiently educated and skilled property valuers, able to provide informed responses for this study. The full profiles of these respondents are detailed in Table 3, that is, on their gender, educational qualification, level of experience, job designation and awareness of technologies used in property valuation. These features have an influence on how property valuers carry out valuation assessments as well as their ability to utilize new technologies.

Table 3

Detailed Profile of Respondents

Variables	Category	Frequency	Percentage
Gender	Male	97	72
	Female	38	28
	Total	135	100
Place of employment	Private sector	55	41
	Public sector	46	34
	Parastatal	16	12
	Non-governmental organization	18	13
	Total	135	100
Level of experience	Less than 5 years	39	29
	Between 6-10 years	42	31
	11-15 years	28	21
	16-20 years	15	11
	Above 21 years	11	8
	Total	135	100
Educational qualification	PhD	1	1
	Master's	55	41
	Bachelor's	79	58
	Higher Diploma	0	0
	Certificate	0	0
	Total	135	100
Job designation	Assistant property valuer	27	20
	Property valuer	61	45
	Manager	30	22
	Principal/ Managing partner	17	13
	Total	135	100

Source: own study.

Table 3 also shows that respondents had sufficient knowledge of property valuation and are therefore conversant with valuation assessments in that 21% of them work as Assistant Property Valuers, 45% as Property Valuers, 22% as Managers and 13% as Directors / Managing Partners in real estate companies. These respondents have been carrying out valuations on different types of properties, such as residential, commercial and industrial, and are therefore capable of providing valuable information for the study.

3.2. Perceptions on causes of valuation variances

Respondents were then asked to give their perceptions on the causes of variances in valuation assessments in Botswana. Using a five-point Likert Scale, respondents were asked to rank the responses and the mean score calculated. As shown in Table 4 below, a mean score of less than 1.49 meant that respondents strongly disagreed that the variable causes variances in valuation, while a mean score between 1.5 to 2.49 indicates that the respondents disagreed. A mean score ranging between 2.5 to 3.49 meant that respondents were not sure whether the variable causes valuation variances, and a mean score between 3.5 to 4.49 meant that respondents agreed that the variable causes variances in property valuation. Lastly, a mean score greater than 4.5 signifies that the respondent strongly agreed.

Table 4

Respondents' perceptions on causes of valuation variances in Botswana

Variables	Strongly disagree	Disagree	Neutral	Agree	Strongly agree	N Statistic	Mean scores	Remark
	(1)	(2)	(3)	(4)	(5)			
Valuers' competencies	0.0	4.7	30.6	47.1	17.6	135	3.78	Agree
Inadequate market data	0.00	14.1	17.6	56.5	11.8	135	3.65	Agree
Lack of proper legal framework	18.8	3.5	11.8	32.9	32.9	135	3.58	Agree
Valuers' level of experience	0.0	11.8	36.5	34.1	17.6	135	3.58	Agree
Property characteristics	20.0	3.5	10.6	32.9	32.9	135	3.55	Agree
Use of different methods of valuation	1.2	22.4	31.8	31.8	12.9	135	3.33	Neutral

Source: own study.

Table 4 reveals critical factors responsible for valuation variances in Botswana, with valuers' competencies cited as the highest followed by inadequate market data, as further discussed.

Valuer's competencies. It is evident from Table 3 that the competencies of valuers were identified as one of the causes for inconsistencies in property value estimates. This was shown by a high mean score of 3.78, which signified agreement among valuers. According to the International Valuation Standards (IVS), property valuers must have adequate technical skills and knowledge required to appropriately complete valuation assignments (IVSC, 2022). These findings are consistent with those of Ashaolu and Bello (2022) who noted that the high level of variances on value estimates indicate professional competence.

Inadequate market data. A key characteristic of emerging real estate markets is the paucity of market data. This was also found to be the case for Botswana. It was revealed by the majority of property valuers (68.3%) that inadequate market data contributed to differing values. On the other hand, the opinions on this matter of 17.6% were neutral and the remaining 14.1% disagreed that this variable caused valuation variances. Ajibola (2010) and Abiojola and Oletobo (2011) explained that dearth of market data has been identified as the most common cause of errors in property valuations particularly in developing countries where the property market is still at an immature stage. Cheloti and Mooya (2021) also opined that lack of access to comprehensive and reliable market data results in relying more on subjective judgments, intuition and limited comparable data which increases the risk of valuation errors and inconsistencies. Baffor Awuah et al. (2017) equally saw the lack of reliable data as a contributor to variances.

Inadequate legal framework. Property valuers also felt that Botswana has an inadequate legal framework to guide their work. This was coupled with the absence of national valuation standards. This was shown by results with a mean score of 3.58 (65.8%) agreeing, while 11.8% were neutral and 22.3% disagreed. Other studies, such as Effiong (2015), Komu

(2018) and Atilola, et al. (2019), also pointed to inadequate legal provisions and absence of valuation standards as contributors to valuation variances.

Sentiments on an inadequate legal framework were also echoed by interviewees. For instance, one key informant stated that *"There is a lack of transparency in information. Insufficient data about certain areas in Botswana results in valuers depending on unreliable sources of data to estimate property values."* In terms of the absence of a regulatory framework, another key informant pointed out that *"There is poor organisation of the profession. The valuation profession in Botswana is fragmented.''*

Level of experience. The valuation profession is relatively new in Botswana, with about 60% of valuers having 10 years or less in terms of practice. The lack of experience, especially when dealing with complex properties, does at times filter into valuation assessment, as indicated by a mean score of 3.58, showing that the majority of the respondents agreed with this assertion.

Property characteristics. The survey results indicated that valuers agreed that property characteristics contribute to variances in assessed values. A high mean score of 3.55 showed that 65.8% agreed while 10.6% were neutral and 23.5% disagreed. Effiong (2015) explained that the more individualized the physical and legal characteristics of a property, the lower the market activity, the smaller its transparency, and the greater its immaturity, the more difficult the objectivization process becomes. These results are consistent with the findings of Baffor Awuah & Gyamfi-Yeboah (2017), who explained that the more complex a property is, the more difficult the valuation assignment and the greater the errors in valuation estimates.

Use of different valuation methods: Findings show that property valuers were neutral on whether the use of different valuation methodologies contributed to discrepancies in values. This was shown by a low mean score of 3.33. Less than 50% of respondents (44.7%) agreed that this variable causes errors in valuations, while 31.8% were neutral. The remaining 23.6% disagreed. This result is inconsistent with the findings of Effiong (2015) and Ashaolu and Bello (2022) who explained that use of different valuation methods on the same valuation assignments results in valuers arriving at different figures, hence resulting in variances. This may be because property valuers in Botswana mostly use the same methods, i.e. the Sales Comparison method and Depreciated Replacement Cost method.

Differences in assessed values amongst practitioners have serious consequences on consumers of valuation services. When explaining how these challenges affect the valuation practice in Botswana, one key informant from REAC stated that, *"Practising valuers produce different valuation results with huge margins. This has led to an uprising in disputes that potentially cause large financial losses to the transacting institutions"*. Investors, financiers and developers are unable to make informed decisions when making property investments. They suffer financial losses which they could have avoided if proper estimates on values were given. In addition, variances in valuation make it difficult for valuers to gauge the performance of their investments. Investment analysis is important for investors to make decisions on whether to retain or dispose of assets. This was confirmed by a number of respondents who indicated that such variances resulted in distorted property prices, poor investment performance, delays in property sales, difficulties in managing real estate assets, loss of investors trust, denting of valuers credibility and integrity and an increase in investment risk. For instance, at least 49.4% of respondents (mean score = 3.51) agreed that valuation variances had the potential to cause distortions in the market, while 27.1% were neutral and 23.6% disagreed. These results are consistent with the findings of Baffor Awuah & Gyamfi-Yeboah (2017) and Abidoye & Chan (2018). The results are in consonance with those of Adegoke (2016) who noted that inconsistent property values cause fluctuation in property prices, thereby sending wrong signals to property buyers and sellers.

In addition, investor trust and valuers' credibility and integrity are also lost as their valuation estimates cannot be relied upon. This was revealed by 49.4% of the respondents (mean score = 3.54) although 28.2% were neutral. The remaining 22.4% disagreed that there is loss of investor trust due to variances in valuation. Variances in valuation estimates also expose valuers to negligence liability, loss of valuers' credibility and a reduction of valuers' integrity. Poor investment performance was identified as one of the impacts of inconsistent valuation values. A mean score of 3.66 was identified for this variable. The majority of the respondents, 55.3%, agreed that valuation errors in valuation cause poor returns in investments. This factor was also identified as one of the impacts of valuation variances. Adegoke (2016) explained that the higher the level of variance, the lower the performance of the investment.

Property valuers agreed that discrepancies in valuation estimates puts stakeholders at a greater risk in terms of their investments. A mean score of 3.60 was achieved for this variable with the majority of the respondents (54.1%) agreeing, 31.8% being neutral and the remaining 14.1% disagreeing. These results are consistent with the findings of Ajibola (2010) and Komu (2018). The survey respondents were neutral on whether variances in property value estimates resulted in delayed sales transactions. This was depicted by a low mean score of 3.39.

Another effect of variances in valuation is that the general public has lost trust and confidence in estimates given by registered valuers. One key informant pointed out that *"There have been discrepancies in valuations as well as mistrust on valuation estimates observed by professional valuers.''* Another informant said *"there is a growing concern on the lack of trust and diminishing confidence levels of the valuation professional services in Botswana. The possible explanation can be rooted in the growing apathy among the valuers to advance their professional skills in their areas of operations."*

These are damaging perceptions for a young valuation profession. Thus, having established the causes of valuation variances and their impacts on the real estate market, the study delved into examining the extent to which property valuers were using new technologies to minimize these variances. It was, however, important at this point to differentiate between having "knowledge" on the available technologies and actual use to solve the problem of valuation variances in the country. Table 5 presents these results.

Table 5

Respondents' perceptions of new technologies for reducing valuation variances

Variables	Strongly disagree	Disagree	Neutral	Agree	Strongly agree	N Statistic	Mean scores	Remark	Standard Deviation
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
Geographic Information Systems (GIS)	0.0	1.5	18.5	53.3	26.7	135	4.05	Agree	0.81
Block-chain technology	0.0	0.7	20.7	53.3	25.2	135	4.03	Agree	0.81
Big data analytics	0.7	3.7	17.8	51.9	25.9	135	3.99	Agree	0.70
Artificial Intelligence (AI) and Machine learning (ML)	0.7	4.4	15.6	54.1	25.2	135	3.99	Agree	0.82
Internet of Things (IoT)	6.7	11.1	55.6	18.5	8.1	135	3.10	Neutral	0.94
Cloud computing	3.7	25.9	60.7	6.7	3.0	135	2.79	Neutral	0.74
Mobile applications	18.5	39.3	31.1	6.7	4.4	135	2.39	Disagree	1.10
Augmented Reality (AR) and Virtual Reality (VR)	31.1	41.5	23.7	3.7	0.0	135	2.00	Disagree	0.83

Source: own study.

Survey results in Table 5 revealed strong agreements amongst property valuers on the use of Geographic Information Systems (GIS) to reduce valuation variances. This was shown by a high mean score of 4.05 and a standard deviation of 0.81. The majority of respondents, 80%, agreed, 18.5% were neutral and 1.5% disagreed. These findings are consistent with Gatheru and Nyika (2015) and Wang and Li (2019). These studies also argued that real estate value can be better modeled with a combination of artificial intelligence, geo-information systems, and mixed methods. Equally, the use of blockchain was highly supported by valuers, with a mean score of 4.03 and a standard deviation of 0.81. This represented at least 78.5% of respondents (25.2% strongly agree and 53.3% agree). However, 20.7% of respondents were neutral, while 0.7% disagreed or strongly disagreed; suggesting that while Block-chain technology is recognized as impactful, their perceived severity differs due to the perceived complexity of the technology or lack of expertise on how to use it. These results are in contrast with those of Adiliem et al. (2024) who noted that blockchain cannot be used to perform valuation tasks. Similarly, Liu et al. (2020) argued that the application of blockchain technology is limited. On the other hand this technology offers support in valuation in terms of data storage and creating a platform for valuers and clients to interact. Similarly, Adilieme et al. (2025) explain that blockchain technology offers transparency in transactions thus making it useful in property valuation. The disparity in findings may be due to perceived complexity of blockchain technology or a lack of expertise on how to effectively leverage it for valuation purposes.

Property valuers also identified Big Data Analytics as a crucial technology in mitigating the problem of valuation variances in Botswana. The overall mean score of 3.99 was achieved for this variable indicating a consensus amongst valuers. A significant majority, 77.8% agreed, 17.8% were neutral and 4.4% disagreed, thus demonstrating diverse perspectives regarding its influence on valuation variances. Other studies (Onwuanyi, 2020; Cheloti & Mooya, 2021) concurred that big data analytics has potential to reduce errors in valuation by providing accurate and comprehensive market data. This will also lead to discovering hidden patterns, trends and themes that valuers may not identify when using traditional methods.

In terms of the Internet of Things (IoT), the respondents were not sure whether this technology can reduce errors in valuation estimates. A low mean score of 3.10 was achieved for this variable, with 55.6% being neutral, 26.6% agreeing and 17.8% disagreeing. Most of the respondents (72.6%) disagreed that Augmented Reality (AR) and Virtual Reality (VR) technology reduced errors in valuation while 23.7% were neutral. Very few of the respondents (3.7%) agreed that AR and VR can minimize variance in valuation estimates. The mean score for this variable was 2.00, indicating that respondents disagree that the technology can reduce valuation variances. These results contradict that IoT, AR and VR can be useful in valuation. Discrepancies in findings may be due to valuers not having adequate knowledge about these technologies.

For Cloud computing, the majority of the respondents, i.e. 60.7%, were not sure whether this technology can minimize discrepancies in property values, while 29.7% disagreed. Only 9.7% agreed that Cloud computing can be used to reduce property valuation errors. A low mean score of 2.79 was achieved for this, signifying that respondents were neutral on whether the technology can produce reliable property value estimates. With mobile applications, property valuers disagreed that this technology can help minimize variances in valuations. This was indicated by a low mean score of 2.39, signifying overall disagreement among the respondents. The majority of the respondents (57.8%) disagreed, while 31.1% were neutral and 11.1% agreed.

Survey results revealed that property valuers agreed that GIS, Blockchain technology, Big Data Analytics and Artificial Intelligence (AI) and Machine Learning (ML) technologies can help to reduce inconsistencies in assessed property values. This is consistent with the fact that many studies (Yacim & Boshoff, 2014; Abidoye & Chan, 2016; Wang, Li, & Reddy, 2019; Teang & Lu, 2021) have demonstrated how AI and ML technologies can be used to provide accurate estimates in property values

3.3. Application of knowledge on new technologies to valuation practice

At this point, it was important to interrogate how much of this knowledge on the available technologies valuers were using in practice. Results in Table 6 showed that only 14% had adopted some of these technologies which was mainly restricted to Microsoft Excel, GIS and AVMs. The remaining 86% indicated that they are not using most of these technologies. When asked to give reasons why, the majority pointed to the high cost of software and equipment, lack of awareness on the suitability of the technologies and non-recognition of these technologies by local professional bodies (Table 6).

Results in Table 7 below highlight the challenges valuers encounter in the application of new technologies in property valuation in Botswana

Table 6

Application of Knowledge on new technologies to valuation practice

Technology adoption	Yes	19	14
	No	116	86
	Total	135	100
Technology awareness	Yes	100	74
	No	35	26
	Total	135	100

Source: own study.

Table 7

Challenges of using technology in property valuation practice

Variables	Strongly disagree	Disagree	Neutral	Agree	Strongly agree	N Statistic	Mean scores	Remark	Standard Deviation
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
Lack of expertise and technical skills	0.0	3.0	17.8	51.9	27.4	135	4.03	Agree	0.75
Fear of loss of jobs	0.0	3.0	17.0	57.0	23.0	135	4.00	Agree	0.72
High capital costs	0.0	5.2	19.3	48.1	27.4	135	3.98	Agree	0.82

Security and privacy concerns	0.7	3.7	17.0	54.8	23.7	135	3.97	Agree	0.79
Lack of adequate input property data	0.7	8.9	21.5	43.7	25.2	135	3.84	Agree	0.93
Limited internet access	8.9	19.3	38.5	21.5	11.9	135	3.08	Neutral	1.11

Source: own study.

Lack of expertise and technical skills. Survey results in Table 6 revealed that the lack of expertise and technical skills was one of the major challenges in the application of new technologies in valuation as shown by a high mean score of 4.03 with 79.3% of the respondents agreeing. Results also showed that 17.8% were neutral, while 3.0% disagreed. This is consistent with the findings of Demetriou (2016) and Kampamba et al. (2022) who also showed that the lack of technological skills and expertise among valuers is a major barrier to the adoption of innovative valuation technologies. Demetriou's study highlighted the importance of upskilling and training valuers to ensure they are comfortable and proficient in using technology-enabled valuation tools, which can ultimately improve the reliability and consistency of property value estimates.

Fear of job losses was also cited as a major hindrance. This was clear from at least 80.0% of respondents while 17.0% were neutral and 3.0% disagreed. The mean score of this variable was 4.00. This is consistent with the findings of Boshoff and De Kock (2013) who noted that valuers in South Africa fear that they might be replaced by AI. Similarly, Namangale and Chimalizeni (2022) reported that valuers in Malawi are non-receptive to using technology in valuation due to the fear of losing their jobs.

High-cost capital, for software and equipment, was also mentioned as a huge barrier that inhibits usage of technology in valuations. The overall mean score of 3.98 was achieved for this variable indicating a consensus amongst valuers. A significant majority, 75.5% agreed, 19.3% were neutral and 5.2% disagreed, thus demonstrating diverse perspectives from the respondents. Various results (Kampamba et al., 2022; Abidoye et al., 2021) concurred that high costs of technology and software deters valuers from using the same in property valuation practice.

Security and privacy concern. Most of the respondents (78.5%) agreed that security and privacy concerns are one of the challenges of using technology in property valuation. Only 17.0% of respondents were neutral while 4.4% disagreed. The mean score for this variable was 3.97, further underscoring the widespread perception that security and privacy are key obstacles in adopting technology-based valuation methods. The findings are consistent with those of Ullah et al. (2018) who explained that data owners do not want their sensitive information revealed and made available to unauthorized access. Valuers are responsible for handling clients' confidential information, and thus may be hesitant to adopt technologies that could potentially compromise data protection and privacy.

Lack of adequate input property data. Regarding the lack of adequate input property data for technology usage, respondents generally agree that this variable is a challenge in using technology in real estate valuation. The majority of valuers, 68.9% agreed, 21.5% were neutral while 9.6% disagreed. This results in a mean score of 3.84 and a standard deviation of 0.93. The property market in Botswana often lacks comprehensive, high-quality data that is necessary for technology driven valuations. Limited data makes it difficult for technology to accurately estimate property values. The plausible reason for this could the fragmented property market in Botswana. These findings corroborate those of Muzahem Alsahan and Ibraheem AlZaidan (2024) and Rampini and Re Cecconi (2022). Abidoye (2017) and Glumac and Des Rosiers (2021), explain that valuers serve as a critical tool in the valuation process, as they possess necessary market knowledge to estimate accurate figures.

Limited internet access. At least 38.5% of respondents were not sure whether limited internet access is one of the challenges that deters use of technology in valuations. On the other hand, 33.4% agreed that the lack of access to the internet makes it difficult to use technology in real estate valuation. A somewhat lower percentage, 28.2%, disagreed. A low mean score of 3.08 was achieved for this, signifying that respondents were neutral on whether limited internet access is a challenge in using technology to produce reliable property value estimates. The neutral perception expressed by the respondents on the impact of limited internet access could be attributed to the relatively developed telecommunications infrastructure and increasing internet penetration in Botswana compared to other countries in the African region.

As noted earlier, real estate valuation is a crucial sector of the economy in Botswana. Stakeholders such as investors, banks, pension funds and companies rely on valuers' estimates on property values to make informed decisions.

Key informants from REAC and REIB also revealed mixed perspectives on whether technology can be leveraged to reduce valuation variances in Botswana.

Key informant 1: *"The property market in Botswana is faced with a myriad of issues. There is a lack of data or comparables about some properties. In order for technology usage in valuations to work, there has to be sufficient property data available.*

Key informant 2: *''AI and technology-based valuation methods are better than human valuers, especially when it comes to accuracy.''*

Key informant 3: *''Technology eliminates human subjective judgment, thereby reducing bias in valuations. There has to be a shift towards automated processes in valuation.''*

Key informant 4: *'' AI methods are effective for generic property types, but less accurate for diverse property markets. They should complement, not replace, human valuation expertise.''*

Key informant 5: *''Technology may offer tools to enhance and supplement, but not substitute, the crucial process of physical inspections in property valuation.''*

These perceptions could probably be due to the limited expertise and skills on how to use technology and a reluctance to shift from traditional valuation methods to advanced methods. The respondents, however, highlighted the potential benefits of leveraging technology in property valuations, such as improved accuracy and reduced bias. They also emphasized the importance of addressing the underlying data challenges and recognizing the limitations of technology-driven approaches, particularly in developing real estate markets. It can therefore be concluded that while specific technological solutions like big data analytics and AI/ML hold promise, their successful implementation ultimately depends on the availability of high-quality, standardized data to power these tools. Addressing this data challenge can enable the use of technology in valuations, thereby eliminating errors, biases and inconsistencies. Most importantly, using technology will transform Botswana's valuation industry making it credible and trustworthy among stakeholders.

4. Discussion

This paper was underpinned by the assertion that the application of new technologies to minimize variances in valuation practice in Botswana is not necessarily due to the lack of awareness by insufficient detailed knowledge and skills. Property valuers are aware of the available technologies and how they can potentially help to solve valuation variance problems, yet their application is minimal. For instance, when asked on the major causes of valuation variances, the top four cited factors were valuer's competencies (mean score = 3.78), inadequate market data (mean score = 3.65), an inadequate legal framework (mean score = 3.58) and the level of experience in using these tools amongst valuers (mean score = 3.58). These findings are consistent with those of Ashaolu and Bello (2022) who noted that the high level of variances on value estimates indicate professional incompetence. Furthermore, Ajibola (2010), Ajibola and Oletobo (2011) also support the finding that dearth of market data was the most common cause of errors in property valuations particularly in developing countries where the property market is still at an immature stage. Cheloti and Mooya (2021), thus opined that the lack of access to comprehensive and reliable market data results in relying more on subjective judgments, intuition and limited comparable data, which increases the risk of valuation errors and inconsistencies. Baffour Awuah and Gyamfi-Yeboah (2017) added that the lack of reliable data contributes to variances. Having said that, it is also clear from these findings that the two of the major causes hinge on the level of knowledge and technical skills among practitioners in applying these new technologies. Thus, the Botswana market is suffering from similar shortcomings as other African countries.

When asked about the new technologies to help reduce valuation variances, the majority of respondents were clearly aware of what is on the market. For instance, the four main cited technologies included GIS (mean score = 4.05), Block chain technologies (mean score = 4.03), Big Data analytics (mean score = 3.99) and Artificial Intelligence and Machine Learning (3.99). This is not far off from reviewed literature, such as, Onwuanyi (2020), Cheloti and Mooya (2021) and others. For instance, Onwuanyi (2020) argued that, although the Nigerian government produces detailed statistics on GDP, foreign investment funds, etc. this is not the case for property data. Thus, the study argued that the shortage of property data creates challenges for the valuation profession.

Given these findings, it was thus important to understand why property valuers are not applying these new technologies given the fact that problems of variation variances have persisted. In other words, the study sought to distinguish the difference between being aware of the existence of the tools and having sufficient knowledge and skills to apply them in solving valuation challenges. Four major reasons cited included lack of expertise and technical skills (mean score = 4.03), fear of loss of jobs (mean score = 4.00), high capital costs (mean score = 3.98) and security and privacy concerns (mean score = 3.97). For instance, it was clear in the minds of property valuers that the application of AI and machine learning algorithms required large amounts of input data. In a market already thin on basic market data, this poses serious application challenges. In addition, human interaction is important for validation and verification of data through physical property inspections. This was also noted by Kampamba et al. (2022), and Rampini and Re Cecconi (2022). For instance, Rampini and Re Cecconi (2022) found that there are many applications for use in building asset management, however, there are also a number of challenges in their application. Thus, Muzahem Alsahan and Ibraheem AlZaidan (2024) pointed to more efforts from the profession in integrating AI into valuation practice, which was argued to be minimal at present.

This paper thus concludes that Botswana needs to look critically at four areas in order to enhance the integration of new technologies in valuation practice, namely: data challenges, legal framework, training of valuers and continuous development.

Conclusion

This study investigated the challenges hindering the adoption of new technologies in real estate valuation despite their potential to mitigate valuation variances. While acknowledging the global discourse on the benefits of digitalization in the 4IR era, the findings revealed that the slow uptake of technologies such as GIS, blockchain, big data analytics, and AI/ML in Botswana's valuation practice is not primarily due to a lack of awareness among valuers. Instead, the study identified several fundamental challenges that need to be addressed first.

The research highlighted that inadequate market data is a significant impediment, limiting the effectiveness of data-driven technologies. Furthermore, an insufficient legal framework and the absence of national valuation standards create an environment where consistent and technology-supported valuations are difficult to achieve. The study also pointed to the low level of competence and experience amongst valuers as a contributing factor to valuation variances and potentially hindering the effective utilization of advanced technologies. The consequences of these valuation variances are significant, leading to disputes, potential financial losses for transacting institutions and investors, distorted property prices, erosion of investor trust, and damage to the credibility of valuation professionals. While valuers in Botswana are aware of the potential of new technologies to address these issues, the foundational challenges related to data availability, legal and regulatory frameworks, and professional capacity need to be prioritized.

Therefore, this study emphasizes the need to develop a robust legal framework for the property valuation industry in Botswana. The current Real Estate Professionals Act is opaque and does not thoroughly regulate the property valuation profession. Comprehensive national valuation standards that focus on distinct characteristics of Botswana’s property market should also be developed. Furthermore, there is a clear imperative to strengthen valuers' training and continue professional development (CPD) to enhance their competence and equip them with the skills necessary to leverage new technologies effectively. Addressing these fundamental challenges will create a more conducive environment for the adoption of digitalization in real estate valuation, ultimately leading to greater accuracy, transparency, and consistency in property value assessments in Botswana. This, in turn, will benefit the national economy, increase individual wealth and welfare, and enhance trust in the real estate profession.

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Appendices

Table A.1

Perceived causes of valuation variances

	N	Minimum	Maximum	Mean		Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Std. Error	Statistic	Std. Error
Valuers' competencies	135	2.00	5.00	3.7778	.06705	.77908	-.165	.209	-.390	.414
Inadequate market data	135	2.00	5.00	3.6519	.07384	.85796	-.627	.209	-.238	.414
Lack of proper legal framework	135	1.00	5.00	3.5778	.12682	1.47348	-.787	.209	-.800	.414
Level of experience of valuers	135	2.00	5.00	3.5778	.07901	.91803	.002	.209	-.824	.414
Property characteristics	135	1.00	5.00	3.5481	.12951	1.50481	-.754	.209	-.912	.414
Use of different methods of valuation	135	1.00	5.00	3.3333	.08797	1.02214	.014	.209	-.857	.414
Valid N (listwise)	135									

Source: own study.

Table A.2

Challenges of using technology in property valuation

	N	Minimum	Maximum	Mean		Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Std. Error	Statistic	Std. Error
High capital costs	135	2.00	5.00	3.9778	.07090	.82378	-.528	.209	-.166	.414
Internet access	135	1.00	5.00	3.0815	.09582	1.11336	-.031	.209	-.538	.414
Expertise	135	2.00	5.00	4.0370	.06516	.75713	-.481	.209	-.018	.414
Security and privacy	135	1.00	5.00	3.9704	.06809	.79119	-.773	.209	1.106	.414
Loss of jobs	135	2.00	5.00	4.0000	.06221	.72276	-.482	.209	.306	.414
Lack of data	135	1.00	5.00	3.8370	.08022	.93208	-.566	.209	-.195	.414
Valid N (listwise)	135									

Source: own study.

Table A.3

Technologies used in property valuation

	N	Minimum	Maximum	Mean		Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Std. Error	Statistic	Std. Error
Blockchain	135	2.00	5.00	4.0296	.06035	.70118	-.173	.209	-.531	.414
GIS	135	2.00	5.00	4.0519	.06160	.71569	-.324	.209	-.238	.414
Big data analytics	135	1.00	5.00	3.9852	.06973	.81024	-.742	.209	.857	.414
AI and Machine learning	135	2.00	5.00	3.9778	.07090	.82378	-.528	.209	-.166	.414
Internet of Things	135	1.00	5.00	3.1037	.08095	.94058	-.100	.209	.491	.414
VR and AR	135	1.00	4.00	2.0000	.07208	.83755	.387	.209	-.626	.414
Cloud computing	135	1.00	5.00	2.7926	.06404	.74409	.246	.209	1.506	.414
Mobile applications	135	1.00	5.00	2.3926	.08677	1.00815	.609	.209	.244	.414
Valid N (listwise)	135									

Source: own study.