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Barriers, drivers and prospects of the adoption of artificial intelligence property valuation methods in practice

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ABSTRACT

Embracing technological advancement in the property valuation practice is unavoidable. However, studies show that valuers largely still adopt traditional methods of valuation. Hence, this study investigates the barriers, drivers, and prospects of the adoption of artificial intelligence (AI) valuation methods in practice. An online questionnaire survey was conducted on valuers practising in Australia. Their opinions about the topic were collected and analysed using frequency distribution and mean score ranking to establish the most significant factors. According to the valuers, the most important advantage of AI valuation methods is that they will help to reduce the cost of valuations. It was also found that the professional bodies that regulate the property valuation practice are the major driver of the adoption of AI valuation methods. The valuers expressed that AI valuation methods may produce accurate estimates. The valuers confirmed that the main prospect of adopting the AI valuation methods in practice is that it could transform the property valuation industry. It is evident that all the property valuation stakeholders should invest efforts in promoting the adoption of AI valuation methods in practice to bridge the gap between theory and practice. This will help reposition the property valuation profession.

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Introduction

Real estate assets remain one of the most common assets held by families and individuals in different countries around the world (Giacomini, Ling, & Naranjo, 2015). For instance, in Australia, property, particularly residential property is the largest single asset for almost 2/3 of Australian households (Al-Masum & Lee, 2020; Lee, Stevenson, & Lee, 2018). In other words, the activities in the property industry and property markets not only have a profound implication on individual households' wealth, but also the broader economy of a country (Chiang, Tao, & Wong, 2015; Lee et al., 2018). Furthermore, different stakeholders hold real estate for several varying purposes such as for investment, owner-occupation, prestige, social services etc. (Bangura & Lee, 2020, 2021). Irrespective of the purposes of holding a property, those stakeholders require an accurate and timely valuation of their assets in making property-related investment decisions (Glumac & Des Rosiers, 2020a; Mooya, 2011). The purposes of such property valuations include but are

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not limited to sales and acquisition, investment, mortgage underwriting, insurance, taxation, among others (Fortelny & Reed, 2005). Property valuation which is an “art” and “science” (Schneider, 2016), involvin the processing of the subject property and market information in arriving at a valuation figure is now tending towards more of data processing (science) (Abidoye, Junge, Lam, Oyedokun, & Tipping, 2019). The valuation process can be divided into three i.e. data, analysis and valuation and the quality of the valuation report is dependent on the accuracy of every step (Tretton, 2007). Getting the science right is very important because producing bad valuation figures could lead to a loss of trust in the process by the valuation report end-users (Adegoke, Olaleye, & Oloyede, 2013).

Valuers adopt different valuation methods in estimating properties values. Property valuation methods have been categorised into traditional and advanced property valuation methods (Pagourtzi, Assimakopoulos, Hatzichristos, & French, 2003). Traditional methods include investment, comparison, residual, cost and profit methods and they mostly rely on the comparison method of valuation (Yacim & Boshoff, 2014). The traditional methods have been established to be subjective, inaccurate, unreliable, costly among others (Zurada, Levitan, & Guan, 2006), and they are subjective which makes them unreliable in this data-driven age (Grover, 2016). In contrast, advanced valuation methods are mostly machine learning and mathematically based and they have been designed to address the limitations of the traditional methods in terms of speed, accuracy, cost and reliability (Abidoye, 2017). The advanced methods have gained popularity in the property valuation field globally in different property markets (Grover, 2016; Özkan, Yalpır, & Uygunol, 2007), and studies have shown that they tend to generate reliable and accurate valuation figures when compared to traditional methods (Abidoye & Chan, 2017a; Rossini, 1999). Mass and artificial intelligence (AI) valuations have been argued as a valuable tool to assist policymakers and property investors to make informed property investment and finance decisions (Trippi, 1990), such as value capture. As highlighted by Grover (2018) and Lee and Locke (2021), accurate and efficient land valuation are key success factors for a value capture mechanism.

Abidoye et al. (2019) found that traditional methods are being adopted by the Australian valuers, but the advanced methods are seldomly popular and used in practice. Nonetheless, it has been proven that the adoption of advanced methods could help to reposition the property valuation practice in becoming more sustainable and reliable (Gilbertson & Preston, 2005; Scheurwater, 2017). Elliott and Warren (2005) mentioned that for the Australian valuers to improve their services there is a need to embrace new technologies in practice. However, few studies have been devoted to understanding the key barriers for Australian valuers to adopt advanced valuation methods. Therefore, this study aims to investigate the barriers, drivers, and prospects of adopting the advanced valuation methods in practice for the first time.

As stated earlier, numerous studies have demonstrated the possibility of adopting AI technologies in property valuation, but the use of AI is still scanty, particularly in Australia. Unlike previous studies such as Glumac and Des Rosiers (2020b, 2020a) and Tajani, Morano, and Ntalianis (2018) etc., this study examines the barriers, drivers and prospects of the use of AI property valuation methods in practice from property valuers’ perspective. This provides policymakers, property valuers, property investors and other property valuation stakeholders a fuller understanding of the opportunity of adopting AI in property valuation in practice. The findings provide further insights to various property valuation stakeholders such as government, property investors, educational institutions, regulatory bodies, valuation firms etc. on how to reposition the property valuation practice and embrace technology and innovation.

The rest of this paper is divided into four parts. The next part presents a literature review and the research method adopted for this study. This is followed by the results and discussion section and the last section concludes the paper.

Literature review

The first application of AI in the property industry was in 1991 when Borst (1991) applied the AI technique in property valuation. However, AI is gaining popularity among real estate stakeholders and is being applied widely in different specialisations of the property industry. For instance, AI is used for property investment decision making by simulating future economic scenarios, assessing investment performance etc. (Chaillou, Fink, & Gonçalves, 2017; Hamzaoui & Perez, 2011; Rossini, 2000), by property managers for scheduling maintenance, analyses of rental trends etc. (Conway, 2018; Taylor, 2017), for property inspections (Scheurwater, 2017), among others.

Pagourtzi et al. (2003) provide detailed descriptions of the various advanced property valuation methods available in the literature, and Abidoye and Chan (2017a) and Peter, Okagbue, Obasi, and Akinola (2020) presented the review of the application of the artificial neural network (ANN) in property valuation in terms of the research trends, pattern, and the application framework. Their findings suggest that AI property valuation methods have been gaining more attention in the literature. More specifically, numerous studies have demonstrated the use of a number of AI techniques for property, land and Real Estate Investment Trust (REIT) valuation. These techniques include ANN (Abidoye & Chan, 2017a, 2017b; Brooks & Tsolacos, 2010; Fausett, 1994; García, Gámez, & Alfaro, 2008; Kathmann, 1993; Peterson & Flanagan, 2009; Yacim & Boshoff, 2014), decision-based models (Antipov & Pokryshevskaya, 2012; Reyes-Bueno, García-Samaniego, & Sánchez-Rodríguez, 2018), expert systems and decision support systems (Amidu & Boyd, 2018; Kilpatrick, 2011; Lam, Yu, & Lam, 2009; Naderi, Sharbatoghlie, & Vafaeimehr, 2012), and case-based reasoning (Gonzalez & Laureano-Ortiz, 1992; Yeh & Hsu, 2018).

It should be noted that no single AI property valuation method fits all real-life situations (Pagourtzi, Metaxiotis, Nikolopoulos, Giannelos, & Assimakopoulos, 2007; Tse, 1997). More recently, Wang and Li (2019) suggested that real estate value can be better modelled with a combination of artificial intelligence, geo-information systems, and mixed methods. Further, studies such as Lam, Yu, and Lam (2008), Grover (2016), Abidoye and Chan (2016), Kok, Koponen, and Martínez-Barbosa (2017), among others have discussed the advantages and disadvantages of different advanced property valuation methods. Elliott and Warren (2005), Downie and Robson (2008), Abidoye and Chan (2017b), Wilkinson, Halvitigala, and Antoniades (2017), Abidoye and Chan (2017a) have extensively discussed the drivers of the application of AI property valuation methods. Importantly, RICS (2016) found that the use of AI in property valuation has received increasing attention since the Global Financial Crisis (GFC). The advancement of this disruptive technology has also been seen as a significant challenge for property valuers.

To sum up, extensive studies have demonstrated the use of AI in the property industry. Numerous studies even provided empirical evidence to show the superiority of AI in producing accurate property valuations over traditional valuations. However, little study, to the best of our knowledge, has been devoted to the barriers of valuers to adopt a mass and AI program in property valuation.

Research methodology

In this study, a quantitative research approach was adopted. This is because a large study population was surveyed (Easterbrook, Singer, Storey, & Damian, 2008). A structured online questionnaire survey was conducted with Australian valuers as the target respondents (Abidoye et al., 2019). The questionnaire was designed using the Qualtrics survey platform hosted by the University of New South Wales (UNSW). Given this study aims to examine the perceptions of property valuers in terms of the barriers, drivers and prospects of AI adoption in property valuation, a survey emerges as an effective and efficient tool to assess humans' perceptions and attitudes as discussed by Newell, Lee, and Kupke (2015), Lee, Reed, and Robinson (2008) and Rogelberg and Stanton (2007). Further, previous studies have adopted the online questionnaire survey and it has produced robust data and results for property research. See, for instance, Mooya (2015), Abidoye, Chan, and Oppong (2018), Bulut, Wilkinson, Khan, Jin, and Lee (2020), Low, Ullah, Shirowzhan, Sepasgozar, and Lee (2020), Khan, Wang, and Lee (2021), among others.

In this study, valuers practising in the Australian property valuation space were the study population and research participants. Hence, the questionnaire was only administered to the valuers registered with the Australian professional body that regulations the practice, i.e. the Australian Property Institute (API) (Abidoye et al., 2019). Before the questionnaire administration, a pilot study was conducted with four property valuers that possess between five to 20 years of professional experience. The constructive comments received from the pilot study were used to revise the final copy of the questionnaire before administration. API sent the questionnaire link to about 8,000 registered members via the regular e-newsletter. Because API uses the e-newsletter to communicate with its members, it is assumed that all the members will be reached. However, members that are not computer savvy might not have responded to this survey. The survey period lasted for six weeks, and a reminder was sent in the third week. This was aimed at increasing the response rate for the survey. When the data collection period ended, a total of 73 responses were submitted and after the data cleaning process, only 64 responses were found to be valid and to be analysed in this study (Abidoye et al., 2019). The sample size is somewhat relatively small, but the sample size of this study can be representative of the total population under study and generate robust results that would be useful to all stakeholders. The reasons are 1) the characteristics of the respondents of this study are very similar to the characteristics of API membership. For instance, Australian Property Institute (2020) reported that the ratio of female to male members is 23% and 77%, respectively, and our study found this ratio to be 23.4% to 76.6%, respectively, 2) the difference between large and small sample size in terms of statistics is 32 (Levin & Rubin, 1998), 3) a sample size of 30 and above is regarded as a large sample size for this type of quantitative analysis (Ott & Longnecker, 2015; Verma, 2013), 4) low response rate is not uncommon in the built environment research (Akintoye & Fitzgerald, 2000), and some previous studies have also received low responses. For instance, Finlay and Tyler (1991) (25 responses), Effiong (2015) (38 responses), Abidoye et al. (2018) (21 responses), Adabre et al. (2020) (51 responses), among others. Particularly in Australia, Warren-Myers and Cradduck (2021) administered their questionnaire link to Australian valuers via API's e-newsletter (similar to this study) and got 21 valid responses.

The questionnaire invitation letter includes the aim of the survey and the description of both traditional and advanced property valuation methods. This was done to ensure that the respondents clearly understand the options provided to them. The rest of the questionnaire was divided into two parts. In the first part questions about the respondents' characteristics in terms of their age, gender, years of professional experience, practice location, highest educational qualification and area of specialisation were asked (Abidoye et al., 2019). The second section consists of questions that are the focus of this research. The valuers' opinion about the advantages of adopting AI valuation methods in practice, the driver of adopting AI in practice, the barriers of adopting AI in property valuation, and the prospects of adopting AI valuation methods in practice. The variables presented to the valuers were extracted from the literature (Abidoye & Chan, 2016, 2017b; Elliott & Warren, 2005; Glumac & Des Rosiers, 2020a; Grover, 2016; Kok et al., 2017; Wilkinson et al., 2017), and the authors' experience. Under those four questions, the valuers were requested to indicate their level of agreement with the different variables of each question. Their level of agreement was provided on a five-point Likert scale of "strongly disagree" (1) to "strongly agree" (5).

The statistical package for the social sciences (SPSS) version 23.0 software was used for the analysis of the collected data to conduct a frequency analysis, mean score (MS) ranking and Cronbach's alpha test. The internal consistency of the responses received was evaluated using Cronbach's alpha test. Cronbach's alpha values range between 0 and 1 and the lowest satisfactory threshold is 0.70 (Hair, Black, Babin, Anderson, & Tatham, 2010) and the highest satisfactory threshold is 0.90 (Tavakol & Dennick, 2011). Descriptive statistics in the form of frequency distribution was adopted to analyse the information about the characteristics of the respondents (section one of the questionnaire). Besides, it was adopted to analyse the opinions of the valuers presented for the questions in section two of the questionnaire. MS ranking was adopted to establish the significance of the variables under the questions in section two of the questionnaire. The adoption of the MS ranking analysis technique has been employed in the property literature (see, for instance, Abidoye & Chan, 2017b; Yu, Javed, Lam, Shen, & Sun, 2018). Since a five-point Likert scale was used in this study, the MS values will range between 1.000 and 5.000. Hence, a variable that gets the highest MS value under each category will be deemed to be more significant when compared with others. The calculation of the MS value for each variable was done using the formula expressed in Equation 1 (Abidoye, 2017).

$$\mathrm{MS} = \frac{5n_5 + 4n_4 + 3n_3 + 2n_2 + 1n_1}{N} \tag{1}$$

Where n is the score provided by the respondent on a five-point scale and N is the number of respondents that ranked the variable.

Results and discussion

In this study, a Cronbach alpha value of 0.78 was generated from the collected data (Abidoye et al., 2019). This value is satisfactory because it is above the threshold of 0.70 as suggested by Hair et al. (2010). Generating a satisfactory alpha value depicts that there is an acceptable internal consistency in the responses received and used in this study. Therefore, robust inferences and conclusions can be made from this study.

Table 1 contains information about the characteristics of the valuers. In terms of the gender of the valuers, about 77% of the valuers are male while the rest 23% indicated that they are female. Coincidentally, this statistic reflects the same gender distribution reported by the Australian Property Institute (2020), i.e. the members of API consist of 23% female and 77% male. This depicts that property valuation practice is dominated by male professionals. The age distribution shows that a majority (32.5%) are above 55 years old and the second most represented are those below 30 years (15.6%). This aligns with the findings of Wilkinson et al. (2017) that the API consists of an ageing membership.

Table 1. Valuer's characteristics.

Characteristics	Frequency	Percentage (%)
Gender		
Male	49	76.6
Female	15	23.4
Total	64	100.0
Age		
26–30 years	10	15.6
31–35 years	5	7.8
36–40 years	9	14.1
41–45 years	8	12.5
46–50 years	6	9.4
51–55 years	5	7.8
Above 55 years	21	32.5
Total	64	100.0
Educational qualification		
High school certificate/ Certificate I–IV	4	6.2
Diploma, Advanced diploma, Associate degree	10	15.6
Bachelor's degree and honours	27	42.2
Graduate certificate and Graduate diploma	13	20.3
Master's degree	10	15.6
Doctoral degree	0	0.0
Total	64	100
Years of experience		
0–5 years	12	18.8
6–10 years	4	6.3
11–15 years	7	10.9
16–20 years	12	18.8
Above 20 years	29	45.3
Total	64	100.0
Specialisation in practice		
Property valuation	57	89.1
Real estate agency	1	1.6
Consultancy/advisory service	2	3.1
Asset management	1	1.6
Property development	1	1.6
Others	2	3.1
Total	64	100.0

Source: Abidoye et al. (2019).

This implies that about 30% of the valuers could retire very soon, which is the situation in some other countries such as the UK, the US and South Africa, among others (Coyle, 2015; Downie & Robson, 2008).

For the highest educational qualification, the information shows that about 78% have acquired at least a bachelor's degree, which includes a graduate diploma, a graduate certificate and a master's degree (see Table 1). This depicts that the valuers are well educated and sought to acquire more knowledge through further higher education. Almost half (45.3%) of the valuers possess industry experience of above 20 years. This aligns with the age distribution of the valuers because expectedly ageing membership will translate to a majority having a good knowledge of the profession which suggest that the collected data in this study is provided by valuers that have a good knowledge of the property valuation practice. When considering the specialisation of the valuers, 89.1% of them specialise in property valuation. The specialisation of many of the valuers in property valuation is noteworthy for this study. Further, the experience of others that specialise in other areas is helpful in property valuation (Mooya, 2015).

The location of practice of the valuers is categorised into the six states in Australia. It was found that 42.2% practice in New South Wales, 23.4% in Queensland, 17.2% in Victoria, 6.3% in South Australia, 3.1% in Western Australia and Australian Capital Territory, respectively, and 4.7% prefer not to disclose this. The distribution of the valuer's location of practice shows that most of the valuers practice in big cities which is similar to the report of the Australian Property Institute (2020).

Advantages of AI valuation methods

Valuers' perception of the advantages of AI valuation methods could have an impact on their willingness to adopt the methods. Therefore, a list of potential advantages of AI valuation methods according to previous studies was presented to the valuers to indicate whether they agree or not. The MS are surprisingly low (Table 2). From the findings presented in Table 2, it can be seen that the valuers only agreed to one of the advantages which is it would "help reduce the cost of property valuation practice", with an MS value of 3.2344. This corroborates the positions of Grover (2016) and Kok et al. (2017) that automated valuation practice is cost-effective. Specifically, the AI mass valuation system assists valuers to achieve a lower cost/valuation, especially, for mass property valuation for taxation purposes. In such a valuation exercise, fewer human valuers will be required, and some processes will be automated. Although the setting up of an AI valuation system could require some capital, this can be recouped over time. Most valuers do not think AI valuation methods are better than human valuers, especially when it comes to accuracy. This result could probably be due to the low awareness level and low adoption rate of AI

Table 2. Valuers' opinion on the advantages of AI valuation methods.

Advantage	Mean score	Ranking
Help reduce the cost of property valuation practice	3.2344	1st
Work more efficiently than traditional property valuation methods	2.9063	2nd
Free human valuers from the onerous work of property valuation	2.8281	3rd
Reduce the subjective interference involved in a valuation	2.7813	4th
Provide more accurate estimates than traditional property valuation methods	2.3438	5th
Overall better than traditional valuation methods	2.2188	6th

valuation methods among the valuers (Abidoye et al., 2019). Additionally, it could be attributed to the fact that valuers are used to the adoption of the traditional methods in practice and feel that the AI methods will add no value to practice (Mooya, 2011).

Drivers of the adoption of AI valuation methods

A series of potential drivers of the adoption of AI valuation methods were presented to the valuers and they provided their opinion on them, and the MS ranking values of those drivers are listed in Table 3. It can be seen from Table 3 that valuers think that professional bodies are the most effective driver for the wide adoption of new technologies, which is in line with the results of Abidoye and Chan (2017b) that found that professional bodies are the most important stakeholders to drive the valuers' adoption of AI property valuation methods in practice. According to Abidoye and Chan (2016), valuers are quite willing to attend training on AI valuation methods, providing professional bodies with a good platform to promote AI valuation methods. The cooperation between AI software firms and property firms is the second most important driver. This could be because of the need to design bespoke software that will fit the professionals' need to build the bridge between theory and practice (Shmueli, 2010).

It is interesting to see that "AI methods to be introduced in schools' curriculum" is the least agreed driver based on the valuers' opinion. On the contrary, it has been argued in the literature that education is important in promoting the know-how of the AI valuation methods among valuers (Wilkinson et al., 2017), and researchers believe that education providers should equip their graduates with new technologies before entering the industry (Elliott & Warren, 2005). The reason for this difference might be that practitioners believe that the know-how of the AI valuation methods could be acquired through training, workshops and on the job rather than in the classroom.

Barriers to the adoption of AI valuation methods

A series of potential barriers to the adoption of AI valuation methods were listed based on the findings of previous studies. The MS ranking of the factors is presented in Table 4. The ranking in Table 4 reveals that valuers doubting the accuracy of AI valuation methods is the highest barrier to the adoption of them in practice with an MS value of 3.8594. The cost of the software and operative difficulty are also deemed as barriers, which are ranked as the second and third barriers, with MS values of 3.1563 and 3.0625,

Table 3. Valuers' opinion on the drivers of the adoption of AI valuation methods.

Drivers	Mean score	Ranking
Professional bodies (API, RICS, etc.) to organise conferences, seminar, workshop or courses on AI valuation topics	3.7031	1st
Closer cooperation between AI valuation software firms and property firms/organisations	3.6719	2nd
Easier access to market data	3.5781	3rd
The valuer's personal decision to try new technology	3.5625	4th
The software to be more user-friendly	3.5000	5th
AI methods to be introduced in schools' curriculum	3.3438	6th

Table 4. Barriers to the adoption of AI valuation methods.

Barriers	Mean score	Ranking
They may not provide accurate estimates	3.8594	1st
The software is expensive	3.1563	2nd
The models are difficult to operate (not user-friendly)	3.0625	3rd
Their adoption will not save time	2.9219	4th
I do not trust new technologies	2.6406	5th
It wastes time to learn new technology	2.4531	6th

respectively. This is different from the position of some scholars that argues that the adoption of AI is cost-effective and easy to operate by non-computer experts (Borst, 1991; Grover, 2016; Wong, So, & Hung, 2002). The last three barriers in terms of the adoption of AI valuation methods by the valuers are related to time-wasting and trust in the technology. This suggests that the valuers are relatively open to new technologies like AI valuation methods and the barriers to their adoption are surmountable. Once the accuracy, affordability and operative easiness of AI valuation software are improved and acceptable to valuers, valuers would be more likely to adopt these valuation methods in practice. And when the experience of the valuers are combined with new data-driven technologies, that would drive towards achieving more accurate valuation estimates (Schneider, 2016).

Prospect of the adoption of AI valuation methods

Some statements about the prospects of AI valuation methods adoption were listed in the questionnaire which are presented in Table 5. The valuers were requested to indicate their level of agreement with the statements. The first highly ranked statement is that valuers tend to believe that "AI will transform the property valuation profession in Australia" with an MS value of 3.3906. This result indicates that although valuers do not know or adopt AI valuation methods in practice, they are aware of the developing momentum of AI and its influence on society. It is believed that new technologies, including AI, are going to be embraced in the property valuation industry (Blass, 2016). Further, many companies such as APM Price Finder, CoreLogic are already adopting AVMs to generate property valuation reports (Wilkinson, Antoniades, & Halvitigala, 2018). Valuers might have realised the influence of new technologies and the survey result indicates that most of the valuers are prepared for the paradigm shift.

Table 5. Prospect of the adoption of AI valuation methods.

	Level of agreement (%)					Mean
Statements	SA	A	N	D	SD	score
AI will transform the property valuation profession	23.4	29.7	29.7	14.1	3.1	3.3906
I will use AI valuation methods once I have learned it	4.7	26.6	48.4	10.9	9.4	3.0625
AI will replace human valuers	18.8	28.1	10.9	23.4	18.8	3.0313
AI should be widely adopted in Australia	4.7	28.1	28.1	29.7	9.4	2.9219
The wide adoption of AI valuation methods will benefit the Australian property industry and the economy	9.4	12.5	23.4	29.7	25.0	2.6094

SA – Strongly agree A – Agree N – Neutral D – Disagree SD – Strongly disagree.

Secondly, more valuers (31.3%) are willing to adopt AI valuation methods based on the statement “I will use AI valuation methods once I have learned it” (see Table 5). While almost half (48.4%) of the valuers responded neutrally, more valuers agree (31.3%) than disagree (20.3%) with this statement. This corroborates the results of Abidoye and Chan (2017b) which reveals that 82% of the surveyed valuers indicated their willingness to adopt AI valuation methods in practice. The high percentage of neutral opinion in this study could be probably due to the low awareness of AI valuation methods. People tend to be conservative when talking about something they do not know. It is even more obvious when it comes to valuation. A profession where a practitioner tries to achieve higher accuracy using the methods they are best at, and avoid risks brought by uncertainty such as not-so-widely adopted new technologies. Thus, training that focuses on equipping the valuers with the knowledge of the AI valuation methods are important for the adoption of the AI methods in practice. Overall, the results indicate a positive tendency towards the adoption of AI valuation methods. More willingness to adopt the AI methods could be expected if the highly ranked drivers earlier discussed work effectively and the main barriers earlier established are eliminated.

Thirdly, more valuers believe that AI will replace human valuers in the property valuation industry. As shown in Table 5, 46.9% of the valuers agree and strongly agree that AI has the potential to replace human valuers, suggesting that valuers are apprehensive of the threats from AI to their jobs. AI is developing fast and gaining popularity (Abidoye, 2017), however, it is not designed to replace the human valuers rather complement their efforts (Lenk, Worzala, & Silva, 1997). Researchers like Motta and Endsley (2003) believe that AI will take over boring tasks, while humans focus on higher-level tasks. As property valuation exercise needs a large amount of information and intelligence, and there may not be enough robust data in some property markets to train the AI system, property valuers will not be entirely replaced by AI. As Motta and Endsley (2003) predicted, property valuers would be information arbiters, focusing more on market analysis in the future, leaving the boring information-gathering tasks to AI. On the other hand, valuation is an “art and science” (Bradford, 2014), hence, AI can handle the “science” part but cannot handle the “art” part, where a valuer’s good knowledge of the subject property helps to enhance the property valuation exercise (Shapiro, Mackmin, & Sams, 2012).

Fourthly, most valuers (39.1%) disagree and strongly disagree that “AI should be more widely adopted in Australia”. As shown in Table 5, the position of the valuers toward this statement is distributed evenly to some extent. However, the slightly higher percentage of disagreement (39.1%) than agreement (32.8%) indicates that valuers’ confidence in the wide adoption of AI valuation methods is not strong. This lack of enthusiasm is, to some extent surprising, compared to AI valuation methods’ popularity among researchers and used in practice in some property markets (Abidoye & Chan, 2017a). Wilkinson et al. (2018) stated that valuers should see AI valuation methods as a strategic partner instead of a threat and should leverage them. However, according to the response to this question, a large percentage of valuers do not see a bright future for these new technologies. If AI valuation is to be adopted nationwide, a lot more campaigns and promotions are necessary, and this could be carried out by professional bodies, educational institutions, valuation firms, etc. accordingly.

Lastly, most valuers, i.e. 54.7% of the valuers disagree and strongly disagree that "the wide adoption of AI valuation methods will benefit the Australian property industry and the economy". It is interesting to discover that although most people believe that AI is going to strike both the property valuation profession and the general economy, not many valuers believe that the impact would be beneficial. According to the response to this statement, only 21.9% of the valuers think AI will benefit the property industry and the economy (Table 5). This result is quite different from the position of some researchers such as Azmi, Nawawi, Ab Latif, and Ling (2013) and Abidoye and Chan (2017b) that reported that the adoption of AI property valuation methods would transform the Malaysian and Nigerian property valuation practice, respectively, and impliedly the national economy. Also, researchers have argued that AI valuation methods could help valuers to save time, cost and reduce inaccuracy (Abidoye & Chan, 2017a; Chaphalkar & Sayali, 2013; Morano, Tajani, & Torre, 2015; Taffese, 2006), which is beneficial to the property industry (Abidoye, 2017).

Overall, the valuers' attitude towards AI valuation methods is complicated and even a little self-contradictory. On one hand, valuers have shown a positive tendency to adopt these advanced methods and they agree that AI has the potential to replace human valuers and will transform the property valuation profession in Australia. On the other hand, they do not think AI valuation methods will be adopted nationwide or benefit the property industry and the economy. These self-contradictions reveal the valuers' mixed feelings with those techniques in the valuation industry. It can be suggested that with the improvement of the awareness level and adoption frequency of AI techniques, valuers' attitudes will become more consistent.

The relationship between the valuers' age and their opinion of the prospects of AI property valuation methods in practice was examined. The results of the cross-tabulation are presented in Table 6. It was found that the majority of the valuers in the age bracket of 51 years and above agreed and strongly agreed that the adoption of AI property valuation methods in practice will transform the valuation industry. It is interesting to know that senior valuers believe in the transformative power of information technology (IT) in the property valuation practice. This may be because they believe that this will serve as a support tool to the young valuers considering that there might be a shortage of valuers in the future because of the ageing population (Downie & Robson, 2008). The low agreement by the young valuers to this statement could be because of their already established awareness and attraction for trending IT (Abidoye, 2017), which has been applied in different disciplines (Glumac & Des Rosiers, 2020a). Also, presented in Table 6 are the responses of the valuers regarding the willingness to adopt AI property valuation methods in practice once learnt. It shows that valuers above 55 years are willing and eager to adopt AI valuation methods in practice. The plausible reason for this could be because they are approaching retirement and the window of opportunity of experiencing the practice transformation is getting closed. This is contrary to the findings of Boshoff and De Kock (2013) that reported that older valuers in South Africa are not inclined towards embracing the advanced property valuation methods in practice because of their familiarity with traditional valuation methods and that the wide adoption of AI valuation methods could lead to valuers' loss of jobs. However, AI valuation methods cannot replace valuers, they can serve as a support tool because the market knowledge of the valuer is necessary to estimate an accurate valuation figure (Abidoye, 2017; Gilbertson & Preston, 2005).

Table 6. Valuers' age and prospects of AI valuation methods cross-tabulation.

Statement	Age	Strongly disagree	Disagree	Neutral	Agree	Strongly agree	Total
AI will transform the valuation industry	26–30 years	1	0	7	2	0	10
	31–35 years	0	0	4	1	0	5
	36–40 years	0	0	7	1	1	9
	41–45 years	0	1	3	1	3	8
	46–50 years	0	0	1	4	1	6
	51–55 years	0	2	1	1	1	5
	Above 55 years	0	3	11	3	4	21
Total		1	6	34	12	10	64
I will use AI valuation methods once I have learned it	26–30 years	1	1	7	1	0	10
	31–35 years	0	2	3	0	0	5
	36–40 years	1	0	6	2	0	9
	41–45 years	1	1	2	3	1	8
	46–50 years	0	1	1	3	1	6
	51–55 years	0	0	2	2	1	5
	Above 55 years	3	2	10	6	0	21
Total		6	7	31	17	3	64

Conclusions

There is a mixed opinion on the importance of embracing the AI property valuation methods in addition to the traditional methods in practice among stakeholders. While some stakeholders, especially valuers, argues that the adoption of AI methods will be a game-changer in the valuation industry, some think otherwise. Therefore, this study was conducted to investigate the barriers, drivers, and prospects of the adoption of AI property valuation practice. An online questionnaire survey was conducted on valuer practising in Australia. Their opinion on the questions and factors posed to them was analysed using descriptive statistics and MS ranking.

According to the opinion of the valuers, it was found that the adoption of the AI valuation process in practice would help to reduce the cost of valuation exercise which suggests that valuation can be conducted more efficiently. On the drivers of the adoption of AI methods in practice, the professional bodies were the highest-ranked factor, reflecting that amongst the valuation stakeholders, professional bodies are closer to the valuers; thereby they can organise training, continuing professional development (CPDs) etc. to promote the use of AI. Valuers also indicated that the AI valuation methods may not produce accurate estimates is the most important barrier to their adoption in practice. Although studies have reported that AI valuation methods outperform traditional methods, the low adoption and awareness of AI methods amongst valuers could be the reason for this result. The two most important prospects of the adoption of AI methods are that it will transform the property valuation practice, and also the valuers indicated that they would adopt them in practice as soon as they acquire the know-how. Most senior valuers support the prospects of AI valuation in practice when compared with younger valuers.

Since valuers are willing to embrace AI valuation methods in practice, therefore, the professional bodies which are the major drivers need to strategise on how to promote this among the valuers. When this is achieved, the transformation that AI had brought to other fields of studies around the world will be experienced in the property valuation space which will lead to a sustainable practice. Sixty-four valid responses were analysed and reported in this study. This size is within the range of what were recorded in past studies and the characteristics of the respondents align with that of API. Hence, the sample size of this study should be borne in mind when interpreting the results, so as not to generalise it to the Australian property valuation practice. When more data are available, the results of this study may be different. Also, given that the awareness and adoption of AI valuation methods are still in their infancy, it isnecessary to investigate the role and the opportunity of professional bodies in promoting the adoption of AI among the valuers.

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References

Abidoye, R. B. (2017). Towards property valuation accuracy: A comparison of hedonic pricing model and artificial neural network. (Doctorate Degree), The Hong Kong Polytechnic University, Hong Kong. Retrieved December 20,2017, from http://ira.lib.polyu.edu.hk/bitstream/10397/70359/2/991021965755503411_pira.pdf (LG51 .H577P BRE 2017 Abidoye)

Abidoye, R. B., & Chan, A. P. (2016). A survey of property valuation approaches in Nigeria. *Property Management*, *34*(5), 364–380.

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

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

Abidoye, R. B., Chan, A. P. C., & Oppong, D. G. (2018, 23 – 24 April). *Property valuation practice in developed countries: A case of Hong Kong*. Paper presented at the RICS COBRA Conference, London, United Kingdom.

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.

Adabre, M. A., Chan, A. P., Darko, A., Osei-Kyei, R., Abidoye, R., & Adjei-Kumi, T. (2020). Critical barriers to sustainability attainment in affordable housing: International construction professionals' perspective. *Journal of Cleaner Production*, *253*, 119995.

Adegoke, O., Olaleye, A., & Oloyede, S. (2013). A study of valuation clients perception on mortgage valuation reliability. *African Journal of Environmental Science and Technology*, *7*(7), 585–590.

Akintoye, A., & Fitzgerald, E. (2000). A survey of current cost estimating practices in the UK. *Construction Management & Economics*, *18*(2), 161–172.

Al-Masum, M. A., & Lee, C. L. (2020). Modelling housing prices and market fundamentals: Evidence from the Sydney housing market. *International Journal of Housing Markets and Analysis*, *12*(4), 746–762.

Amidu, A.-R., & Boyd, D. (2018). Expert problem solving practice in commercial property valuation: An exploratory study. *Journal of Property Investment & Finance*, *36*(4), 366–382.

Antipov, E. A., & Pokryshevskaya, E. B. (2012). Mass appraisal of residential apartments: An application of Random forest for valuation and a CART-based approach for model diagnostics. *Expert Systems with Applications*, *39*(2), 1772–1778.

Australian Property Institute. (2020). Annual report 2019. Sydney Australia. Retrieved August 31, 2020, from https://www.api.org.au/wp-content/uploads/2020/05/2019-Annual-Report_Review_May-4-2020_V2A_website.pdf.

Azmi, A. S. M., Nawawi, A. H., Ab Latif, S. N. F., & Ling, N. L. F. J. (2013). Property valuers' receptive level on knowledge of computer aided valuation (CAV) system. *Procedia-Social and Behavioral Sciences*, *105*, 734–744.

Bangura, M., & Lee, C. L. (2020). Housing price bubbles in Greater Sydney: Evidence from a submarket analysis. *Housing Studies*, 1–36. doi:10.1080/02673037.2020.1803802

Bangura, M., & Lee, C. L. (2021). The determinants of homeownership affordability in Greater Sydney: Evidence from a submarket analysis. *Housing Studies*, 1–27. doi:10.1080/02673037.2021.1879995

Blass, E. (2016). The future role of 'the property professional'–is there a role for a valuer? Canberra. Retrieved September 17,2018, from www.api.org.au/sites/default/files/uploaded-content/website-content/20160912_future_the_future_role_of_the_property_professional.pdf

Borst, R. A. (1991). Artificial neural networks: The next modelling/calibration technology for the assessment community. *Property Tax Journal*, *10*(1), 69–94.

Boshoff, D., & De Kock, L. (2013). Investigating the use of Automated Valuation Models (AVMs) in the South African commercial property market. *Acta Structilia*, *20*(1), 1–21.

Bradford, J. (2014). Appraising: At the crossroads of art and science. *Mortgage Banking*, *74*(8), 100–101.

Brooks, C., & Tsolacos, S. (2010). *Real estate modelling and forecasting*. United States of America: Cambridge University Press.

Bulut, M., Wilkinson, S., Khan, A., Jin, X.-H., & Lee, C. L. (2020). Perceived benefits of retrofitted residential secondary glazing: An exploratory Australian study. *International Journal of Building Pathology and Adaptation*, *ahead-of-print*(ahead–of–print). doi:10.1108/IJBPA-09-2020-0083

Chaillou, S., Fink, D., & Gonçalves, P. (2017). Urban Tech on the Rise: Machine Learning Disrupts the Real Estate Industry. *Field Actions Science Reports*, (Special Issue 17), 38–43. https://journals.openedition.org/factsreports/4432

Chaphalkar, N. B., & Sayali, S. (2013). Use of artificial intelligence in real property valuation. *International Journal of Engineering and Technology*, *5*(3), 2334–2337.

Chiang, Y., Tao, L., & Wong, F. K. (2015). Causal relationship between construction activities, employment and GDP: The case of Hong Kong. *Habitat International*, *46*(1), 1–12.

Conway, J. (2018). *Artificial intelligence and machine learning: Current applications in real estate*. (Master of Science in Real Estate Development Master of Science), Massachusetts Institute of Technology, Massachusetts, United States. Retrieved September 15, 2020, from https://dspace.mit.edu/bitstream/handle/1721.1/120609/1088413444-MIT.pdf?sequence=1&isAllowed=y

Coyle, M. L. (2015). Future of valuation. *Working RE magazine, Editor's note*. Retrived July ,6, 2018 from www.workingre.com/wp-content/uploads/2015/09/future-of-valuation.docx

Downie, M.-L., & Robson, G. (2008, 4 November). *Automated valuation models: An international perspective*. Paper presented at the RICS Automated Valuation Models Conference: AVMs Today and Tomorrow, London.

Easterbrook, S., Singer, J., Storey, M.-A., & Damian, D. (2008). Selecting empirical methods for software engineering research. In F. Shull, J. Singer, & D. I. K. Sjøberg (Eds.), *Guide to advanced empirical software engineering* (pp. 285–311). London: Springer.

Effiong, J. B. (2015). A comparative study of valuation variance and accuracy between Nigeria and UK. *International Letters of Social and Humanistic Sciences*, *57*(4), 94–105.

Elliott, P., & Warren, C. M. (2005). The valuation profession in Australia: Profile, analysis and future direction. *Australian Property Journal*, *38*(5), 362–367.

Fausett, L. V. (1994). *Fundamentals of neural networks: Architecture, algorithms, and applications*. United States of America: Prentice-Hall International.

Finlay, P. N., & Tyler, S. B. (1991). The performance measurement of property investments. *Journal of Property Valuation and Investment*, *9*(4), 295–312.

Fortelny, A., & Reed, R. (2005). The increasing use of automated valuation models in the Australian mortgage market. *Australian Property Journal*, *38*(6), 681–685.

García, N., Gámez, M., & Alfaro, E. (2008). ANN+ GIS: An automated system for property valuation. *Neurocomputing*, *71*(4), 733–742.

Giacomini, E., Ling, D. C., & Naranjo, A. (2015). Leverage and returns: A cross-country analysis of public real estate markets. *The Journal of Real Estate Finance and Economics*, *51*(2), 125–159.

Gilbertson, B., & Preston, D. (2005). A vision for valuation. *Journal of Property Investment & Finance*, *23*(2), 123–140.

Glumac, B., & Des Rosiers, F. (2020a). Practice briefing–Automated valuation models (AVMs): Their role, their advantages and their limitations. *Journal of Property Investment & Finance*. doi:10.1108/JPIF-07-2020-0086

Glumac, B., & Des Rosiers, F. (2020b). Towards a taxonomy for real estate and land automated valuation systems. *Journal of Property Investment & Finance*. doi:10.1108/JPIF-07-2020-0087

Gonzalez, A. J., & Laureano-Ortiz, R. (1992). A case-based reasoning approach to real estate property appraisal. *Expert Systems with Applications*, *4*(2), 229–246.

Grover, R. (2016). Mass valuations. *Journal of Property Investment & Finance*, *34*(2), 191–204.

Grover, R. (2018). Betterment: A taxing problem. *Journal of Property Investment & Finance*, *36*(2), 217–226.

Hair, J., Black, W., Babin, B., Anderson, R., & Tatham, R. (2010). *Multivariate data analysis* (7th ed.). New Jersey: Prentice-Hall.
Hamzaoui, Y. E., & Perez, J. A. H. (2011, November 26 - December 4). *Application of artificial neural networks to predict the selling price in the real estate valuation process*. Paper presented at the 10th Mexican International Conference on Artificial Intelligence, Puebla, Mexico.
Kathmann, R. M. (1993). Neural networks for the mass appraisal of real estate. *Computers, Environment and Urban Systems*, *17*(4), 373–384.
Khan, M. A., Wang, C. C., & Lee, C. L. (2021). A framework for developing green building rating tools based on Pakistan's local context. *Buildings*, *11*(5), 202–225.
Kilpatrick, J. (2011). Expert systems and mass appraisal. *Journal of Property Investment & Finance*, *29*(4/5), 529–550. https://www.emerald.com/insight/content/doi/10.1108/14635781111150385/full/pdf?title=expert-systems-and-mass-appraisal .
Kok, N., Koponen, E.-L., & Martínez-Barbosa, C. A. (2017). Big data in real estate? From manual appraisal to automated valuation. *The Journal of Portfolio Management*, *43*(6), 202–211.
Lam, K. C., Yu, C., & Lam, C. K. (2009). Support vector machine and entropy based decision support system for property valuation. *Journal of Property Research*, *26*(3), 213–233.
Lam, K. C., Yu, C. Y., & Lam, K. Y. (2008). An artificial neural network and entropy model for residential property price forecasting in Hong Kong. *Journal of Property Research*, *25*(4), 321–342.
Lee, C. L., & Locke, M. (2021). The effectiveness of passive land value capture mechanisms in funding infrastructure. Journal of Property Investment & Finance, 39(3), 283–293. https://www.emerald.com/insight/content/doi/10.1108/JPIF-07-2020-0084/full/pdf?title=the-effectiveness-of-passive-land-value-capture-mechanisms-in-funding-infrastructure
Lee, C. L., Reed, R., & Robinson, J. (2008). An investigation on the risk perceptions of Australian property fund managers. *Pacific Rim Property Research Journal*, *14*(2), 199–221.
Lee, C. L., Stevenson, S., & Lee, M. L. (2018). Low-frequency volatility of real estate securities and macroeconomic risk. *Accounting & Finance*, *58*(1), 311–342.
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.
Levin, R. I., & Rubin, D. S. (1998). *Statistics for management*. New Jersey: Prentice Hall.
Low, S., Ullah, F., Shirowzhan, S., Sepasgozar, S. M., & Lee, C. L. (2020). Smart digital marketing capabilities for sustainable property development: A case of Malaysia. *Sustainability*, *12*(13), 5402.
Mooya, M. (2011). Of mice and men: Automated valuation models and the valuation profession. *Urban Studies*, *48*(11), 2265–2281.
Mooya, M. M. (2015). The education and professional practice of valuers in South Africa: A critical review. *Property Management*, *33*(3), 245–274.
Morano, P., Tajani, F., & Torre, C. M. (2015, 10-12 January). *Artificial intelligence in property valuations: An application of artificial neural networks to housing appraisal*. Paper presented at the 11th International Conference on Energy, Environment, Ecosystems and Sustainable Development (EEESD '15), Canary Islands, Spain.
Motta, T. A., & Endsley, W. E. (2003). The future of the valuation profession: Diagnostic tools and prescriptive practices for real estate markets. *The Appraisal Journal*, *71*(4), 345–350.
Naderi, I., Sharbatoghlie, A., & Vafaeimehr, A. (2012). Housing valuation model: An investigation of residential properties in Tehran. *International Journal of Housing Markets and Analysis*, *5*(1), 20–40.
Newell, G., Lee, C. L., & Kupke, V. (2015). The opportunity of residential property investment vehicles in enhancing affordable rental housing supply. *AHURI Positioning Paper Series*, *166*, 1–53.
Ott, R. L., & Longnecker, M. T. (2015). *An introduction to statistical methods and data analysis*. Boston, USA: Cengage Learning.
Özkan, G., Yalpır, Ş., & Uygunol, O. (2007, May 29 - June 1). *An investigation on the price estimation of residable real-estates by using artificial neural network and regression methods*. Paper presented at the 12th Applied Stochastic Models and Data Analysis International Conference (ASMDA), Crete, Greece.

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.
Pagourtzi, E., Metaxiotis, K., Nikolopoulos, K., Giannelos, K., & Assimakopoulos, V. (2007). Real estate valuation with artificial intelligence approaches. *International Journal of Intelligent Systems Technologies and Applications*, *2*(1), 50–57.
Peter, N. J., Okagbue, H. I., Obasi, E. C., & Akinola, A. O. (2020). Review on the application of artificial neural networks in real estate valuation. *International Journal of Advanced Trends in Computer Science and Engineering*, *9*(3), 2918–2925.
Peterson, S., & Flanagan, A. B. (2009). Neural network hedonic pricing models in mass real estate appraisal. *Journal of Real Estate Research*, *31*(2), 147–164.
Reyes-Bueno, F., García-Samaniego, J. M., & Sánchez-Rodríguez, A. (2018). Large-scale simultaneous market segment definition and mass appraisal using decision tree learning for fiscal purposes. *Land Use Policy*, *79*, 116–122.
RICS. (2016). Automated Valuation Models (AVMs) - Opportunity or Threat? London. Retrieved April , 24, 2020, from https://academy.rics.org/web-classes/residential-property/automated-valuation-models-opportunity-or-threat
Rogelberg, S. G., & Stanton, J. M. (2007). Introduction: Understanding and dealing with organizational survey nonresponse. *Organizational Research Methods*, *10*(2), 195–209.
Rossini, P. (1999, 26-30 January). *Accuracy issues for automated and artificial intelligent residential valuation systems*. Paper presented at the International Real Estate Society Conference, Kuala Lumpur, Malaysia.
Rossini, P. (2000, 24-27 January). *Using expert systems and artificial intelligence for real estate forecasting*. Paper presented at the Sixth Annual Pacific-Rim Real Estate Society Conference, Sydney, Australia.
Scheurwater, S. (2017). The future of valuations: The relevance of real estate valuations for institutional investors and banks –views from a European expert group. RICS, Parliament Square, London. Retrieved July 3, 2020, from https://www.rics.org/globalassets/rics-website/media/knowledge/research/insights/future-of-valuations-insights-paper-rics.pdf.
Schneider, H. (2016). Recapturing the art of appraising. *Mortgage Banking*, *76*(7), 30–31.
Shapiro, E., Mackmin, D., & Sams, G. (2012). *Modern methods of valuation* (11th ed.). London: Estates Gazette.
Shmueli, G. (2010). To explain or to predict?. *Statistical Science*, *25*(3), 289–310.
Taffese, W. Z. (2006). *A survey on application of artificial intelligence in real estate industry*. Paper presented at the 3rd International Conference on Artificial Intelligence in Engineering and Technology, Kota Kinabalu, Malaysia.
Tajani, F., Morano, P., & Ntalianis, K. (2018). Automated valuation models for real estate portfolios. *Journal of Property Investment & Finance*, *36*(4), 324–347.
Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education*, *2*(1), 53–55.
Taylor, A., (Producer). (2017, 13 April 2018). *6 ways artificial intelligence is transforming real estate investing.pdf*>.
Tretton. (2007). Where is the world of property valuation for taxation purposes going?. *Journal of Property Investment & Finance*, *25*(5), 482–514. https://www.emerald.com/insight/content/doi/10.1108/14635780710776684/full/pdf?title=where-is-the-world-of-property-valuation-for-taxation-purposes-going.
Trippi, R. R. (1990). Decision support and expert systems for real estate investment decisions: A review. *Interfaces*, *20*(5), 50–60.
Tse, R. Y. (1997). An application of the ARIMA model to real-estate prices in Hong Kong. *Journal of Property Finance*, *8*(2), 152–163.
Verma, J. P. (2013). *Data analysis in management with SPSS software*. India: Springer Science & Business Media.
Wang, D., & Li, V. J. (2019). Mass appraisal models of real estate in the 21st century: A systematic literature review. *Sustainability*, *11*(24), 7006.

Warren-Myers, G., & Cradduck, L. (2021). Physical and climate change-related risk identification in valuation practice: An Australian perspective. *Journal of Property Investment & Finance*, *ahead-of-print*(ahead–of–print). doi:10.1108/JPIF-10-2020-0114

Wilkinson, S., Antoniades, H., & Halvitigala, D. (2018). The future of the Australian valuation profession. *Property Management*, *36*(3), 333–344.

Wilkinson, S., Halvitigala, D., & Antoniades, H. (2017, 15-18 January). *The future of the valuation profession: Shaping the strategic direction of the profession for 2030*. Paper presented at the Annual Pacific Rim Real Estate Society Conference, Sydney, Australia.

Wong, K., So, A. T., & Hung, Y. (2002). Neural network vs. hedonic price model: Appraisal of high-density condominiums. In K. Wang & M. L. Wolverton (Eds.), *Real estate valuation theory* (pp. 181–198). New York: Springer.

Yacim, J. A., & Boshoff, D. G. (2014, 15-19 December). *Mass appraisal of properties*. Paper presented at the 2nd Virtual Multidisciplinary Conference, Zilina, Slovakia.

Yeh, I.-C., & Hsu, T.-K. (2018). Building real estate valuation models with comparative approach through case-based reasoning. *Applied Soft Computing*, *65*, 260–271.

Yu, A. T. W., Javed, A. A., Lam, T. I., Shen, G. Q., & Sun, M. (2018). Integrating value management into sustainable construction projects in Hong Kong. *Engineering, Construction and Architectural Management*, *25*(11), 1475–1500.

Zurada, J. M., Levitan, A. S., & Guan, J. (2006). Non-conventional approaches to property value assessment. *Journal of Applied Business Research*, *22*(3), 1–14.