THE RESIDUAL SKILLS TO AUGMENT PROPERTY VALUATION

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# Abstract

Artificial intelligence (AI) has the potential to redefine the way we value property, presenting the contemporary valuer with a new suite of skills to pursue. This research seeks to define the residual skills necessary to complete a valuation in today’s technology augmented practice.

This paper commences with a revisit of research into skills development within Australian universities and the emerging role of technology, specifically AI, in preparing valuations. The latter part of the research presents valuation as a framework, or environment, where tasks and roles are allocated. The mapping and allocation of tasks requires careful consideration of ecological and symbiotic relationships, between the human valuer and AI. The residual role of the property valuer defines the new skills necessary to complete a practical valuation.

Keywords: Artificial intelligence, skills, valuation, ecological and symbiotic relationships, Australian universities.

# Introduction

Artificial intelligence (AI) can perform tasks or make predictions, recommendations or decisions that usually require human intelligence. AI systems can perform these tasks and make these decisions based on objectives set by humans but without explicit human instructions.

These artificial systems have the potential to redefine the way we value property, presenting the contemporary valuer with a new suite of skills to pursue. For example, machine learning has enhanced automated valuation models and the mass appraisal of property. Advances in natural language understanding and generation has seen systems such as Chat GPT change the way we write, and potentially take point preparing a valuation report. Moving forward substantial advances in AI capabilities, especially robots, computer vision, and recommender systems, can enhance or replace physical inspections and, with appropriate training, bring further depth to property analysis, establishing highest and best use, or assessing value and worth.

This research seeks to define the residual skills necessary to complete a valuation in today’s technology augmented practice. It commences with a revisit of research into skills development within Australian universities and the emerging role of technology, specifically AI, in preparing valuations. The review commences with a discussion regarding learning, education theories and models. It then extends to AI and its emerging role in property valuation. The latter part of the research presents a property valuation report as a framework, or environment, where tasks and roles were allocated. The mapping and allocation considered the ecological and symbiotic relationships, between the human valuer and AI.

# Previous research

## Encouraging Learning

The study of learning has been the subject of research by psychologists, with theories of human knowledge construction shared and contested. Students, by their very nature, are said to be more inclined to adopt either surface or deep learning strategies in higher education (Biggs 1999; Biggs & Tang 2009). The focus of deeper learning is evident in Australian higher education with many institutions adopting, the Biggs and Tang (2009) perspective of good teaching, of ‘getting most students to use the level of cognitive processes needed to achieve the intended outcomes that more academic students use spontaneously’ (p. 11). Through property pedagogy research and a review of accredited property programs Boyd (2015) proposes the aim of an Australian property program may be served if their graduates can achieve the following five broad learning outcomes:

1. Describe and explain objective theories of property custodianship and the practical skills you require for a career in property.
2. Analyse the functioning of property and apply practical skills to make the best decisions in real-life property situations.
3. Communicate effectively as a professional with clients and colleagues in addressing real-life property situations.
4. Operate effectively and ethically as a team member in real-life property situations.
5. Reflect on your role as a property student and initiate transformative practices to guide your actions in an unknown future.

Traditionally designers of property education have focused on the development and application of objective theories of property ownership or custodianship, as defined in learning outcome one (Boyd 2015). Outcomes two through four specifically address skills and attributes development, often considered more practical and applied in nature. These outcomes may have even been regarded as those learned through a graduate program, or work integrated learning. To some academics, to place too much attention on these outcomes comes at a loss of deeper understanding of analysis and a shift in focus toward teaching what Palm and Pauli (2018) refer to as practicalities rather than engaging in deeper, more theoretical knowledge. Wilkinson, Halvitigala, and Antoniades (2018) make similar distinctions as they discuss the future of property education and technological interventions, contrasting training and education as:

…training involves learning how to use a technology or software, whereas education provides a deeper understanding of fundamental theories and the ability to question and continuously learn, evolve, and develop deeper understanding over time. It should be the case that universities retain this education role and do not become training [centers]. (Wilkinson et al. 2018, p.397)

In analysing South African property curriculum, Mooya (2015) is critical of the “how-to” philosophy of vocational education being prescriptively applied to the learning of valuation methodology. Specifically, he suggests that, by aligning each property type with a valuation approach, there is a loss of broad conceptual knowledge that should be the hallmark of university education (Mooya 2015).

While those designing education and learning may have an interest in developing the graduates a curious scholar employing deeper cognitive processes, higher education in Australia is being directed towards providing workplace ready graduates. This discussion and justification for change to university funding is addressed in nationally led workplace ready program materials including the Standing Committee on Education and Employment (Australian Government 2023) with

Australia needs better performing universities with increased focus on the national interest, and to ensure students and universities are incentivised to focus on work relevant qualifications that will support growth in a tertiary qualified workforce. (p.57)

The Standing Committee specifically refer to demand for job ready graduates in health care, teaching, and STEM related fields, including engineering and IT. They also touch on job automation and the skills presenting an ‘increase in automated systems raising task complexity and therefore requiring higher skill levels for entry-level positions’ (p.16). The higher skill levels are not explained further but are said to relate to STEM knowledge as well as being literate, numerate, and digitally literate (Australian Government 2023).

## Skills development in Australian Universities

In assessing competencies, Poon, Hoxley and Fuchs (2011) and Poon and Brownlow (2014) distinguish between knowledge, skills, and attributes. In a similar study, Tu, Weinstein, Worzala, and Lukens (2009) group knowledge, skills, and attributes in broader term as ‘skills and competencies’. The variation in interpretations is not specific to the discipline of property education but rather is regarded by some as a systemic issue in Australian higher education (Barrie 2006). According to Barrie, university communities have struggled to identify the combination of skills, attributes and knowledge to include in statements of graduate outcomes. While Barrie attributes the issue to factors including a misinterpretation of what constitutes generic graduate attributes, he cites Bowden et al. (2000) in defining his view of graduate attributes, as:

the qualities, skills and understandings a university community agrees its students should develop during their time with the institution. These attributes include but go beyond the disciplinary expertise or technical knowledge that has traditionally formed the core of most university courses. They are qualities that also prepare graduates as agents of social good in an unknown future. (Bowden et al. 2000, cited in Barrie 2006, p. 217)

For literary purposes, competencies, in this review, have been considered in two categories: ‘skills and attributes’ and ‘knowledge’.

### Skills and Attributes of Graduates

Tu et al. (2009) sought to test the empirical findings of Weinstein and Worzala (2008) via an online survey based on the authors’ prior empirical findings, to uncover the best ways to educate future property professionals. While the study focused on Northern American graduates of real estate schools, the findings, with respect to desired critical skills, would appear to be universal. Tu et al. (2009) tested 11 set skills and competencies against the preferences of stakeholders including faculty, students, graduates, and board members. On average, they found the top three student skills, as rated on a five-point Likert scale, comprised critical thinking, comprehensive knowledge of business, and quantitative/financial analysis skills. The comparison of skills and competencies by stakeholders, as found by Tu et al. (2009), is re-presented in Table1.

Table 1: Skills and Competencies by Stakeholders

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Student skill** | **Faculty/ admin** | **Students** | **Alumni** | **Board members** | **Average** | **Weighted average** |
| *n* | *111* | *474* | *346* | *39* | *4* | *970* |
| Comprehensive knowledge of business | 4.75 | 4.79 | 4.64 | 4.53 | 4.68 | 4.72 |
| Critical thinking | 4.84 | 4.74 | 4.77 | 4.78 | 4.78 | 4.76 |
| Understanding the current market trends | 4.54 | 4.73 | 4.55 | 4.28 | 4.53 | 4.63 |
| Writing skills | 4.58 | 4.21 | 4.44 | 4.22 | 4.36 | 4.33 |
| Oral communications skills | 4.72 | 4.57 | 4.59 | 4.66 | 4.64 | 4.60 |
| Quantitative/financial analysis skills | 4.58 | 4.69 | 4.77 | 4.59 | 4.66 | 4.70 |
| Negotiation skills | 4.11 | 4.43 | 4.18 | 4.19 | 4.23 | 4.29 |
| Leadership and management skills | 4.17 | 4.43 | 4.19 | 4.38 | 4.29 | 4.31 |
| Proficiency in tools used in the industry | 3.96 | 4.31 | 4.14 | 4.13 | 4.14 | 4.20 |
| Ability to work in teams | 4.31 | 4.45 | 4.45 | 4.53 | 4.44 | 4.44 |
| Ability to work individually | 4.36 | 4.50 | 4.47 | 4.44 | 4.44 | 4.47 |
| **Average** | **4.45** | **4.53** | **4.47** | **4.43** | **4.47** | **4.50** |
| Note: Likert scale 1–5, with 5 being extremely important (Tu et al. 2009, p. 113) | | | | | | |

Interestingly, students considered the objectivist attribute, ‘comprehensive knowledge about the property industry’, as most significant, whereas the other three groups placed more emphasis on the constructivist attributes and skills relating to critical thinking and the ability to analyse and communicate. The comparatively lower weighting of knowledge by alumni and board members may be attributable to the type of knowledge implied by the responders. Or, possibly, the future employers consider the type of knowledge delivered by the faculty does not align with that required to be a successful industry professional, a view shared by Leinhardt, McCarthy Young and Merriman (1995) and the Australian Property Institute (API) (2011). Apart from those examples, the study by Tu et al. (2009) reflected a relative consensus among the stakeholders.

Poon, Hoxley and Fuchs (2011), utilising previous studies, conducted a broad survey investigating 31 knowledge areas, 20 skills and 21 attributes. The questionnaire was directed towards RICS accredited course providers. The respondents were categorised into two groups, graduates, and employers. Employers were asked what they feel graduates require, while the graduates were asked what they feel they acquired during their studies (Poon, Hoxley & Fuchs 2011). Employers considered communication to be paramount, with the highest rated skill being ‘effective oral communication’ and six of the top 10 rated skills relating to various forms of communication, writing, and listening. Other skills ranked highly by employers included ‘numeracy’, ‘ability to define and solve problems’, and ‘information technology’ (Poon, Hoxley & Fuchs 2011). In broad terms, the graduates agreed they had acquired the primary skills, although ‘numeracy’ reflected a relatively lower score, representing a gap between the expectations of employers and the reflections of the graduates. Similarly, the graduates were less inclined to agree that they had acquired appropriate skills in ‘negotiation and industry-based software tools’ (Poon, Hoxley & Fuchs 2011).

There are variations between the skills sought from property graduates in the findings of Poon, Hoxley and Fuchs (2011) and the findings of Tu et al. (2009). Potentially, the variation in the desired skill set relates to the cultures of the employees and differences in learning and teaching practices between the United States of America and Europe. Nevertheless, high-rating skill sets from both regions and studies include communication in oral and written forms.

Employers, in the study by Poon, Hoxley and Fuchs (2011), rate ‘ability and willingness to update professional knowledge’, ‘professional attitude’, ‘interpersonal skills’, ‘ability to effectively work as part of a team’, and ‘enthusiasm’ as the top five attributes sought. Board members in the Tu et al. (2009) study support the desire for graduates to work effectively in teams. Had the studies been conducted in comparable ways with identical terms and categorisation, it is likely that further overlap in desired attributes may be witnessed.

In a subsequent research project, Poon and Brownlow (2014) sought to identify the competencies expected of property professionals in Australia. The study was, in part, an extension of Poon, Hoxley and Fuchs’s (2011) research from the United Kingdom as it utilised the same list of knowledge areas (31), skills (20) and attributes (21). In the later Australian study Poon and Brownlow utilised a quantitative survey tool administered through the API, specifically addressing the API’s membership.

With respect to skills, there are emergent themes across the studies by Tu et al. (2009), Poon, Hoxley and Fuchs (2011) and Poon and Brownlow (2014). Communication skills are popular, in both oral and written forms. In a study from the United Kingdom (Poon, Hoxley & Fuchs 2011), employers rated oral communication as most significant, while in the Australian study (Poon & Brownlow 2014) API members rated written communication and report writing as dominant. As illustrated in Table 2, oral and written skills were considered to be within the top three skills in the United States study, which included a broader diversity of stakeholder groups (Tu et al. 2009). The findings by Tu et al. (2009) diverged from the others, in that quantitative/financial analysis skills were considered the most sought after.

Table 2: Skills by Study

|  |  |  |  |
| --- | --- | --- | --- |
| **Rank** | **Tu et al. (2009) – US** | **Poon, Hoxley & Fuchs (2011) – UK** | **Poon & Brownlow (2014) – Australia** |
| 1 | Quantitative/financial analysis skills | Effective oral communication | Effective written communication |
| 2 | Oral communication skills | Report writing | Report writing |
| 3 | Writing skills | Effective written  communication | Effective oral communication |
| 4 | Negotiation skills | Numeracy | Decision-making |
| 5 | Leadership and management skills | Effective verbal presentation | Effective listening |

(Tu et al. 2009, Poon, Hoxley & Fuchs 2011, and Poon & Brownlow 2014)

The ability of and desire for a graduate or student to work effectively as part of a team and on their own are attributes shared across the three studies, as depicted in Table 3. In the United Kingdom and Australian studies referred to here, members of the respective institutions shared a desire for university graduates to have a professional attitude. While contestable in the nature of categorisation, the API members identified ‘practical experience’ as the most sought-after attribute (Poon & Brownlow 2014). The most striking variation from the studies relates to the attribute of critical thinking, which is rated as the most important in the United States study (Tu et al. 2009). While not specifically identified in the other studies, the somewhat related attribute of creativity was rated as least important in the responses from the Australian study (Poon & Brownlow 2014). Poon and Brownlow (2014) consider this response to echo previous research and they attribute the low weighting to:

property professionals are usually members of professional organisations such as the API or RICS, and their work is largely bound by legislations and therefore they have less flexibility to be creative. (Poon & Brownlow 2014, p. 277)

Table 3: Attributes by Study

|  |  |  |  |
| --- | --- | --- | --- |
| **Rank** | **Tu et al. (2009)** | **Poon, Hoxley & Fuchs (2011)** | **Poon & Brownlow (2014)** |
| 1 | Critical thinking | Ability and willingness to update professional knowledge | Practical experience |
| 2 | Ability to work individually | Professional attitude | Professional attitude |
| 3 | Ability to work in teams | Interpersonal skills | Ability and willingness to update professional knowledge |
| 4 | Leadership and management skills | Ability to effectively work as part of a team | Ability to work independently |
| 5 | — | Enthusiasm | Willingness and ability to accept responsibility |

(Tu et al. 2009, Poon, Hoxley & Fuchs 2011, and Poon & Brownlow 2014)

The Employer Satisfaction Survey, or ESS, is said to be the only national survey that measures how well graduates from Australian universities meet their employer needs (Social Research Centre Pty Ltd and Commonwealth of Australia 2023). According to the survey’s administrator, ‘data from the ESS are used to better understand the specific skills and attributes needed in business today, how well higher education is preparing graduates for the workforce and the varied employment pathways graduates are taking after completing their study’ (Social Research Centre Pty Ltd and Commonwealth of Australia 2023, np.).

## Skills Development Performance

The 2022 ESS survey found high levels of employer satisfaction across all attributes with:

* 93.0 per cent satisfaction with foundation skills – general literacy, numeracy and communication skills and the ability to investigate and
* integrate knowledge.
* 90.1 per cent satisfaction with adaptive skills – the ability to adapt and apply skills/knowledge and work independently.
* 88.2 per cent satisfaction with collaborative skills – teamwork and interpersonal skills.
* 92.7 per cent satisfaction with technical skills – application of professional and technical knowledge and standards.
* 86.8 per cent satisfaction with employability skills – the ability to perform and innovate in the workplace. (Social Research Centre Pty Ltd and Commonwealth of Australia 2023, np.)

In the field of Management and Commerce – Other, which contains most property degrees, 7 out of 10 employers consider the graduates well or very well prepared for current employment (Social Research Centre Pty Ltd and Commonwealth of Australia 2023).

Table 4: Employer Satisfaction Survey (2022)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Preparedness for current employment** | **Very Well** | **Well** | **Not Well** | **Not at All** | **Not Sure** |
| Number of Records | 200.0 | 493.0 | 118.0 | 76.0 | 85.0 |
| % | 20.6% | 50.7% | 12.1% | 7.8% | 8.7% |

(Social Research Centre Pty Ltd and Commonwealth of Australia 2023)

The ESS provides some assurance of graduates being work ready. That said, the grouping of information make it difficult to isolate property programs or drill down of skills specifically aligned to the emerging role of a property valuer. The survey does not specifically address emerging role of technology, or AI.

## Emerging Role of AI in Valuation

The practice of property valuation has evolved as new systems and technologies assist with automation and analysis. Saying that, in recent years PropTech development and its adoption have soared (Friedman 2020; Baum, Saull & Braesemann 2020; Braesemann & Baum 2020) due to the global COVID-19 pandemic and emergence of the next industrial revolution. The challenges presented by the pandemic, not just in terms of how to carry out valuations and determine value, but also in the reporting of those values (Aronsohn 2020) have been met with technological solutions. Industry 4.0, or the fourth industrial revolution, provided more than smart factories and smart products. According to Starr et al. (2020) it provided adaptable smart processes and systems driven by advances in artificial intelligence, cooperative robotics, and adaptive automation control. Outputs of Industry 4.0 are changing the property industry (Ullah, Sepasgozar, Thaheem & Al-Turjman 2021; Starr et al. 2020, Porter, Fields, Landau-Ward, Rogers, Sadowski, Maalsen, Kitchin, Dawkins, Young & Bates 2019) and the practice of property valuation (Abidoye & Chan 2017a; Abidoye & Chan 2017b; Abidoye et al. 2019; Valier 2020).

The most published threat to the practice of property valuation has been Automated Valuation Models, particular machine learning AVM models. These models are already more effective than the traditional hedonic approaches in assessing the market value of a property (Valier 2020). In Valier’s (2020) review of previous research there were 57 cases in which artificial intelligence models were more accurate in predicting value, compared to 13 cases in which regression performed better. That said, the studied machine learning models are data driven models and Valier concedes, their powerful predictive capacity runs the risk of being ineffective when confronted with new data, different from those with which it has trained.

The Valier concession is contested by advancements in machine learning, those enabled to refine their code over every iteration through an inbuilt feedback loop, or neural network. Marr (2016) and Baum et al. (2020), speak of machine learning as ‘the current application of AI based around the idea that we should really just be able to give machines access to data and let them learn for themselves’ (Marr 2016 cited in Baum et al. 2020, p.30). Providing access to data, especially geo spatial (Cheung 2017) and helping learn, may be our destiny whether we intend to advance machine learning or not. For example, in their review of emerging technologies, Starr et al. (2020) say our survival in this rapidly changing [Real Estate 4.0] environment requires us to embrace opportunity and ‘learn to experiment with emerging and maturing technologies’ (p. 165).

Before embracing or engaging AI there are a series of ethical considerations. With respect to digitisation, Landau-Ward and Porter (Porter et al. 2019) support Kitchin’s (2014) earlier assertion ‘digital disruptions cannot be viewed as simply neutral technologies that replace existing analogue processes, but are instead fundamentally social and political processes entwined with existing and emerging power relations’ (Kitchin’s 2014, cited in Porter et al. 2019). Braesemann and Baum (2020) echo these concerns discussing the importance and substantial efficiency gains from PropTech innovations while acknowledging their potential to ‘change the whole fabric of the real estate market’ (p. 20). They speak of datafied markets characterised by oligopolistic market structures, with a few firms or even monopolies offering the sole digital service available. To prevent the accumulation of market power Braesemann and Baum (2020) say ‘users and owners of real estate need to become aware of the value of the data they are generating in renting, buying, or managing real estate’ (p.20).

Our embrace of some technology, namely AI is remains conditional with the Gillespie, Lockey, Curtis, Pool, and Akbari (2023) recent survey showing nearly three-quarters (73%) of the 17,193-person sample express feelings of concern about the potential risks of AI. The respondents raised risks to cybersecurity and privacy breaches, manipulation and harmful use, loss of jobs and deskilling, system failure, the erosion of human rights, and inaccurate or biased outcomes (Gillespie et al. 2023).

Considerations of risk, and trust, in AI systems was found to be contextual and dependent on the specific application or use. Of the applications examined in the survey, Gillespie et al. (2023) found respondents are generally more willing to rely on, rather than share, information with AI systems, particularly recommender systems and security applications (Gillespie e al. 2023).

In their survey, Gillespie et al. (2023) found most people believe AI should have a role in managerial decision-making, with only a few people (8%) advocating for humans to have sole decision-making power. Almost half (45%) view a collaboration of 75% human and 25% AI as the most appropriate mix for managerial decision making with humans retaining more or equal control (Gillespie et al. 2023).

The McKinsey (2022) survey and review of AI has found adoption in business has more than doubled since 2017 with 50% of reporting business using AI in at least one business area. The average number of AI capabilities that organizations use, such as natural-language generation and computer vision, has also doubled, from 1.9 in 2018 to 3.8 in 2022 (McKinsey 2022). With respect to AI capabilities, robotic process automation and computer vision remain the most commonly deployed, with natural-language text understanding adoption increasing the most during the 5-year study period. The number of capabilities included in the survey has grown over time, from 9 in 2018 to 15 in the 2022 survey as demonstrated in Table 5, AI capability embedded in products or business.

Table 5: AI capability embedded in products or business.

|  |  |
| --- | --- |
| **Respondents who say given** **AI capability is embedded in products or business processes in at least one function or business unit** | **%** |
| Robotic process automation | 39 |
| Computer vision | 34 |
| Natural-language text understanding | 33 |
| Virtual agents or conversational interfaces | 33 |
| Deep learning (method that teaches computers to process data in a way that is inspired by the human brain) | 30 |
| Knowledge graphs (initial step of data sourcing, knowledge graphs are used for data lineage to track the data that feeds machine learning) | 25 |
| Recommender systems | 25 |
| Digital twins (virtual replicas of physical devices – assets, systems, or processes) | 24 |
| Natural-language speech understanding | 23 |
| Physical robotics | 20 |
| Reinforcement learning (algorithms that learn from outcomes and decide which action to take next) | 20 |
| Facial recognition | 18 |
| Natural-language generation | 18 |
| Transfer learning (where knowledge learned from a task is re-used in order to boost performance on a related task) | 16 |
| Generative adversarial networks (create new data instances that resemble training data. GANS can create images that look like human faces, even though the faces don’t exist) (GAN) | 11 |
| Transformers (a type of deep learning model used for natural language processing and computer vision tasks) | 11 |

(McKinsey 2022)

The application of these AI capabilities to property valuation has not been tested in research presented at the date of writing. That said, Abidoye, Ma, and Lee (2021) address research into AI property valuation methods supporting the assertion of that there is no single AI property valuation method fits all real-life situations. They bring attention to the work of Wang and Li (2019) who suggested that real estate value can be better modelled with a combination of artificial intelligence, geo-information systems, and mixed methods.

The review and previous research presents skills and attributes required for property valuers as well as the capabilities of AI. The studies vary in time with the assessment of skills and attributes performed before the intervention of AI and therefore, may no longer prove relevant. For example, in the Poon and Brownlow (2014) study the top two skills were identified as effective written communication, and report writing. Given the advances in natural-language understanding and generation, through AI systems such as Chat GPT, that role may be better suited to the AI rather than human valuer.

This gap in published research findings may, in part, relate to the rapid adoption of artificial intelligence. As such there is a limited foundation to empirically test, and iteratively build knowledge through research. For this reason, a novel approach, based on an existing industry framework, has been applied in this study with the findings requiring subsequent empirical evaluation.

The next part of the research presents valuation as a framework, or environment, where tasks and roles are allocated. The mapping and allocation of tasks require careful consideration of ecological and symbiotic relationships, between the human valuer and AI.

# Method

## Framework

The International Valuation Standards (IVS) Committee do not prescribe a report format however they do set a minimum matter to address in 30.1 being:

1. *the scope of the work performed*
2. *intended use,*
3. *intended users,*
4. *the purpose,*
5. *the approach or approaches adopted,*
6. *the method or methods applied,*
7. *the key inputs used,*
8. *the assumptions made,*
9. *the conclusion(s) of value and principal reasons for any conclusions reached, and*
10. *the date of the report (which may differ from the valuation date).*

(International Valuation Standards, pp.18-19)

From these standards the API has prescribed a more detailed valuation framework in the Guidance Note ANZVGP 111 Valuation Procedures – Real Property (API 2023). From the IVS and API guidance a valuation framework has been defined. The framework has the primary headings:

* Executive summary
* Introduction
* Nature of interest
* Land
* Improvements
* Occupancy details
* Valuation approach
* Valuation
* Appendices

This executive summary introduces no new information but rather brings salient material from the rest of the report to a summary. The Valuation and Appendices are simply the statement of the valuation presented in the Valuation approach section and additional supporting information.

The remaining sections from Introduction through to Valuation approach require the valuer to explore sources of information, conduct analysis and determine value. The information sources extend from materials available through external providers through to findings from physically inspecting the property. The Occupancy details and Valuation approach necessitate analysis with the valuer determining the highest and best use, choosing a valuation method, interpreting the market, applying the valuation method, and determining value. The framework assists with prescribing the information, tasks, and even skills to perform a valuation as presented in the column Tasks and associated skills and competencies, in Figure 1.

## AI and the Valuer

In determining the allocation of tasks and roles we have assumed two primary participants, the registered or certified valuer, and AI. With respect to identifying the AI we have adopted capability categorisations, as per the McKinsey (2022) survey. For ease of application, we have excluded systems that generally sit at the back end, integrate with other systems capabilities as such deep learning, knowledge graphs, reinforcement learning, generative adversarial networks, and transformers. This leaves the following for capability AI for the mapping:

1. Robotic process automation
2. Computer vision
3. Natural-language text understanding
4. Virtual agents or conversational interfaces
5. Recommender systems
6. Digital twins
7. Natural-language speech understanding
8. Physical robotics
9. Facial recognition
10. Natural-language generation

## Mapping Relationships

The mapping relationships between stakeholders and users of property is commonly applied in research and property industry practice. In the property industry larger developers spend considerable time and resources better understanding the stakeholders and how they may leverage opportunities to enhance their product or even advocate to have a development application supported. In developing a conceptual model for an eco-industrial park, Liwarska-Bizukojc, Bizukojc, Marcinkowski, and Doniec (2009), looked towards relationships in nature, specifically ecological relationships. Ecological relationships, whilst more complex and nuanced, can be categorised into 5 primary types:

1. Predation, where one organism eats another organism to obtain nutrients.
2. Competition, where individuals or populations compete for the same resource.
3. Commensalism, a relationship in where one organism benefits while the other is neither helped nor harmed.
4. Parasitism, a relationship where one organism benefits and the other organism is harmed, but not always killed.
5. Mutualism, where both species benefit.

These primary types of ecological relationships have been applied in the mapping performed by the authors. The mapping and allocation of tasks requires careful consideration of ecological and symbiotic relationships, between the human valuer and AI.

To undertake the AI identification and mapping, the authors have independently considered how the tasks inherent in performing the valuation may be best addressed through existing AI technology and a qualified valuer. In reviewing the selections, the following Valuation Capability and Relationship framework has been developed, Figure 1.

# Valuation capability and relationship

Figure 1: Valuation Capability and Relationship Mapping

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Heading** | **Content** | **Tasks and associated skills and competencies** | **AI Capability** | **Relationship** |
| 1. Executive summary | 1.2 Instructions  1.3 Prepared for  1.4 Brief description  1.5 Client reference  1.6 Date of valuation  1.7 Tenure type  1.8 Critical assumptions  1.9 Valuation  1.10 Valuer | Extract and present salient material from the body of the report. | Natural-language text understanding  Natural-language generation | Mutualism / Commensalism  Mutualism / Parasitism |
| 2. Introduction | 2.1 Instructions  2.2 Purpose  2.3 Date of valuation  2.4 Basis of value  2.5 Critical assumptions, qualifications and disclaimers | Understand and communicate an understanding of the instructions.  Identify and communicate the unique critical assumptions, qualifications and disclaimers as found to be applicable through the valuation process. | Computer vision  Natural-language text understanding  Virtual agents or conversational interfaces  Recommender systems  Digital twins  Natural-language speech understanding  Natural-language generation | Mutualism  Mutualism  Mutualism / Parasitism  Mutualism / Parasitism  Mutualism  Mutualism  Mutualism / Parasitism |
| 3. Nature of the interest | 3.1 Legal description  3.1.1 Real property description  3.1.2 Registered owner  3.1.3 Easements & Encumbrances | Understand and communicate understanding of the legal nature or dimension of the property interest.  Interpret maps and legal documents to identify unique property characteristics.  Analyse those unique characteristics as they apply to the property’s use and potential use. | Computer vision  Natural-language text understanding  Recommender systems  Digital twins  Natural-language speech understanding  Natural-language generation | Mutualism  Mutualism  Mutualism / Parasitism  Mutualism  Mutualism  Mutualism / Parasitism |
| 4. Land | 4.1.1 Dimensions and area  4.1.2 Location and locality  4.1.3 Services, amenities and access  4.1.4 Statutory land value assessment  4.2 Town planning  4.2.1 Local authority  4.2.2 Planning scheme zoning and classifications  4.3 Environmental hazards | Understand and communicate understanding of the land and its surrounding.  Physically conduct an inspection observing the land boundaries and characteristics.  Interpret maps, approvals, and planning schemes (including digital systems) to confirm compliance and identify unique property characteristics.  Analyse those unique characteristics as they apply to the property’s use and potential use. | Robotic process automation  Computer vision  Natural-language text understanding  Digital twins  Natural-language speech understanding  Physical robotics  Natural-language generation | Mutualism  Mutualism  Mutualism  Mutualism  Mutualism  Mutualism  Mutualism / Parasitism |
| 5. Improvements | 5.1.1 General description  5.1.2 Floor area  5.1.3 Construction  5.1.4 Accommodation and layout  5.1.5 Other improvements  5.1.6 Condition and functionality | Understand and communicate understanding of the improvements built on the land.  Physically conducting an inspection observing the improvements, their condition and assess the functional utility of the space.  Interpret plans (including digital systems) to measure and identify unique property characteristics.  Analyse those unique characteristics as they apply to the property’s use and potential use. | Robotic process automation  Computer vision  Natural-language text understanding  Digital twins  Natural-language speech understanding  Physical robotics  Natural-language generation | Mutualism  Mutualism  Mutualism  Mutualism  Mutualism  Mutualism  Mutualism / Parasitism |
| 6. Occupancy details | 6.1 Highest and best use  6.2 Income analysis | Communicate how the unique characteristics apply to the property’s use and potential use.  Understand and communicate understanding of the occupancy arrangements including analysing leases and occupancy agreements.  Interpret, analyse, and present income details. | Computer vision  Natural-language text understanding  Recommender systems  Digital twins  Natural-language speech understanding  Natural-language generation | Mutualism  Mutualism  Mutualism / Parasitism  Mutualism  Mutualism  Mutualism / Parasitism |
| 7. Valuation approach | 7.1 The market  7.2 Valuation method/calculations  7.3 Market evidence  7.4 Reconciliation and findings  7.5 Previous sale  7.6 Estimated selling period  7.7 Goods and Services Tax | Understand and communicate understanding of the economic environment and how it applies to the property.  Identify, analyse, and present salient market benchmarks and indices as they apply to the property.  Choose, apply, and communicate the valuation method. The method may relate to market, income or cost and include detailed financial analysis or benchmarking. Market and income approaches will require selection, analysis, and comparison of sales evidence. The cost approaches will require selection of market-based cost indices and application.  Reconcile and communication of the findings and results of the valuation method. | Computer vision  Natural-language text understanding  Recommender systems  Digital twins  Natural-language speech understanding  Natural-language generation | Mutualism  Mutualism  Mutualism / Parasitism  Mutualism  Mutualism  Mutualism / Parasitism |
| 8. Valuation |  | Communicate the adopted valuation | Natural-language text understanding  Virtual agents or conversational interfaces  Natural-language generation | Mutualism  Mutualism  Mutualism / Parasitism |
| 9. Appendices |  | Share additional supporting information referred to in the report. | Computer vision  Natural-language text understanding  Recommender  Digital twins | Mutualism  Mutualism / Commensalism  Commensalism  Mutualism / Commensalism |

# Findings

The framework and associated mapping, Figure 1: Valuation Capability and Relationship Mapping, present observable trends in the AI capability and relationships. That said, as raised by Gillespie et al. (2023), these relationships are to be interpreted in conjunction with the content as the functionality and use can change the dynamic. For example, recommender systems in the occupancy details (6.) and valuation approach (7.) sections can be quite different. An AI recommender system can learn from the human valuer in determining highest and best use (6.3). Highest and best use is dependent on many of the unique property characteristics detailed throughout the valuation process and it would take substantial training and testing for an AI system to master, implying much work and little direct reward for the human valuer. That said, having an AI recommender system analysing and suggesting sales evidence (7.3) could provide a direct and early benefit to the human valuer. In the past valuers may have an indication of value and pursue sales selection and analysis with that bias or end position in sight. The recommender system could help remove that search bias and present fresh evidence to explore which may enhance the quality and accuracy of the final assessment.

The physical property inspection, required to address the land and improvements component of a valuation (5.) has the greatest number of AI capabilities to explore. In particular, learning robots or drones with computer vision could enhance the current inspection process accessing areas where the human cannot, capturing and analysing far more unique characteristics than the human valuer can. This in turn can contribute to the development a digital twin, or even valuation report through natural language generation.

These AI capabilities have the potential to redefine the way we value property, presenting the contemporary valuer with a new role, one that relies more heavily on multidimensional observations, where options or pathways appear overwhelming, but the quality of their decision making is more important. In a similar manner to a director of a company, they will be under increasing pressure to make the right and ethical decision when presented with imperfect and sometimes misleading information.

## Residual Skills

The pursuit of job ready graduates, as per the Standing Committee’s recommendations (Australian Government 2023) is indirectly supported in these research findings. As the human valuer focuses on training AI, they may reduce their capacity to train a human assistant or graduate valuer, and in turn place more of that development responsibility on the higher education provider.

Training AI and the skills associated with that pursuit is a likely net addition to the skills already sought after in a human valuer. If this new role is added and expectations for more skilled entry level valuers is assumed (Australian Government 2023) then it would appear appropriate to look toward reducing the expectation for higher education providers to develop skills and attributes that would otherwise be assumed, or taken by AI.

After considering the emerging role of AI in property valuation we propose higher education providers focus on developing these residual skills:

1. Humanistic decision-making
2. Multidimensional information mastery (including numeracy and financial analysis)
3. Leadership and management skills
4. Time management
5. Effective communication (but not specifically report writing, oral or written)

All the attributes found in the studies by Tu et al. (2009), Poon, Hoxley & Fuchs (2011), and Poon & Brownlow (2014) appear relevant and even more important in an environment where the human valuer and AI work together to provide a property valuation. In particular, skills and attributes that lead toward ethical decision making will become more and more sought-after with further responsibility placed on fewer people.

# Limitations

This paper commenced with a revisit of research into skills development within Australian universities and the emerging role of technology, specifically AI, in preparing valuations. The review adopted a systemic approach to obtaining the literature and research to analyse. That said, such an exploration is subject to a series of predispositions. The perpetuation of a bias is possible as skills development is a difficult benchmark to assess with the only national measures, not specifically related to property courses. The same can be said for the emerging role of AI which is subject to much public discourse, with opinions in media and research.

The latter part of the research presents valuation as a framework, or environment, where tasks and roles are allocated. The framework provides a sound base for looking at valuation practice today, but AI and PropTech have the potential to reset the practice of valuation and in turn change the requirements for of nature of the valuation report.

The mapping and allocation of tasks requires careful consideration of ecological and symbiotic relationships, between the human valuer and AI. This has been untaken with the authors contributing to the framework and findings. Further contributions, from scholars and practitioners will help evaluate and refine the framework and mapping.

# Conclusions

AI is changing the way we value property, presenting the contemporary valuer with a new suite of skills to pursue. This research defines residual skills necessary to complete a valuation in today’s technology augmented practice.

This paper commenced with a revisit of research into skills development within Australian universities and the emerging role of technology, specifically AI, in preparing valuations. The latter part of the research presented a valuation as a framework, or environment, where tasks and roles were allocated. The mapping and allocation considered the ecological and symbiotic relationships, between the human valuer and AI. The outcome of this presented the residual role of the property valuer, one that relies more heavily on multidimensional observations, where options or pathways appear overwhelming, but the quality of their decision making is more important.

That said, before embracing this new AI enhanced valuation profession, or environment, there are a series of ethical considerations to explore. For example, the new AI valuer will not just replace existing analogue processes, but rather disrupt social and cultural systems and influence existing and emerging power relations. The first task for the contemporary valuer is to sceptically engage with a system that promises to enhance their practice while threatening the viability of their profession (Boyd 2021).

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