# Structuring Human-AI Collaboration in Residential Property Valuation Using Levels of Automation

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**DOI: https://doi.org/10.47772/IJRISS.2026.100500087**

**Received: 22 April 2026; Accepted: 28 April 2026; Published: 23 May 2026**

## ABSTRACT

The increasing adoption of artificial intelligence (AI) in residential property valuation has been driven largely by advances in automated valuation models and predictive analytics. However, existing research has focused predominantly on model performance and interpretability, offering limited guidance on how AI should be embedded within professional valuation practices that are judgement-intensive, regulated, and accountable. This study addresses this gap by reframing AI integration as a governance and workflow design problem rather than a purely technical challenge. Drawing on Levels of Automation (LOA) as an analytical lens, the study systematically maps human and AI roles across valuation workflows and identifies the limitations of conventional LOA frameworks in addressing professional authority and accountability. To overcome these limitations, the study introduces a Professional Governance Layer as a cross-cutting mechanism addressing decision authority, accountability ownership, override capability, and audit responsibility in AI-supported valuation. Using a systematic literature review and an expert-based Delphi approach, the study develops a Human-AI Hybrid Valuation Framework that structures human-AI collaboration while preserving non-transferable professional responsibility. The proposed framework contributes a process-oriented and professionally defensible approach to AI adoption in residential property valuation, offering practical implications for valuers, regulators, and system developers concerned with responsible and accountable AI integration.

**Keywords**: residential property valuation; artificial intelligence; human-AI collaboration; levels of automation; professional judgement; accountability; governance; decision support.

## INTRODUCTION

Artificial intelligence (AI) has gained increasing prominence in residential property valuation, particularly through automated valuation models and machine-learning-based prediction systems that aim to enhance analytical speed and consistency (Antipov & Pokryshevskaya, 2012). At the same time, valuation has long been understood as an interpretive practice requiring professional judgement, contextual insight, and experiential knowledge that resist full standardisation and quantification (Ahmad Muzir et al., 2026). However, despite rapid advances in AI-driven valuation techniques, existing studies remain predominantly model-centric, concentrating on predictive performance and diagnostics rather than providing guidance on how AI should be embedded within professional valuation workflows that require judgement, defensibility, and regulatory compliance (Cheung, 2024; Royal Institution of Chartered Surveyors (RICS), 2022; Board of Valuers, Appraisers, Estate Agents and Property Managers Malaysia (BOVAEP), 2021). This concern is consistent with prior conceptual work, which argues that current AI valuation research remains fragmented across disciplinary boundaries and has not yet been integrated within a coherent framework that reconciles professional judgement, methodological reasoning, and predictive analytics (Ahmad Muzir et al., 2026). This creates a practical and scholarly tension: valuation is not assessed solely by numerical output, but by whether the valuation reasoning is traceable, auditable, and professionally defensible under standards and dispute contexts (Cheung, 2024; BOVAEP, 2021; RICS, 2022).

The non-transferability of responsibility further distinguishes residential property valuation as a professional practice, as valuers remain accountable for valuation outcomes even when analytical tools are used to support parts of the workflow (BOVAEP, 2021; RICS, 2022). Relatedly, the hybrid epistemology literature also maintains that professional valuers retain ultimate accountability even when AI tools are used, reinforcing that analytical augmentation does not displace professional responsibility (Ahmad Muzir et al., 2026). In such a regulated setting, the uncritical adoption of AI as a decision-producing system risks creating a "responsibility vacuum," where decision authority and liability become ambiguous when AI outputs shape professional judgements (Matthias, 2004; Matysiak, 2023). While explainability and transparency are frequently proposed as remedies, post-hoc explanations alone do not resolve core governance questions about who retains authority, who can override system outputs, and who owns accountability for the final value opinion (Floridi et al., 2018). As a result, the central challenge is not whether AI can support valuation tasks, but how human and AI roles should be structured to preserve professional accountability while benefiting from analytical support (Teikari et al., 2025).

This paper addresses this gap by proposing a Human-AI Hybrid Valuation Framework structured using Levels of Automation (LOA). Unlike existing studies that focus primarily on improving predictive performance or model interpretability, this study explicitly reconceptualises AI integration as a governance problem. While prior applications of Levels of Automation (LOA) emphasise functional task allocation, they remain largely silent on accountability ownership and decision authority in professional contexts. This study extends LOA by introducing a cross-cutting Professional Governance Layer, ensuring that automation does not dilute non-transferable professional responsibility. In doing so, the study contributes a governance-oriented framework that aligns AI integration with the institutional and regulatory requirements of valuation practice.

LOA provides a principled way to describe how functions can be distributed between humans and automated systems along a continuum of support, rather than treating automation as a binary replacement of human work (Sheridan & Verplank, 1978). Subsequent work refined LOA as a functional model of human information processing—information acquisition, information analysis, decision/action selection, and action execution, highlighting that automation can be selectively applied to different cognitive functions rather than uniformly across the entire system (Parasuraman et al., 2000). Importantly, this study extends conventional LOA frameworks by introducing a Professional Governance Layer that operates across all stages, adding an explicit governance dimension concerning authority, control, and responsibility allocation, which is critical in professional domains where accountability is central to acceptable practice (Dumas et al., 2012). Consistent with this foundation, the proposed framework positions AI as decision support embedded within valuation workflows rather than as an autonomous decision-maker, reflecting the automation–augmentation paradigm in which AI complements human judgement (Raisch & Krakowski, 2021).

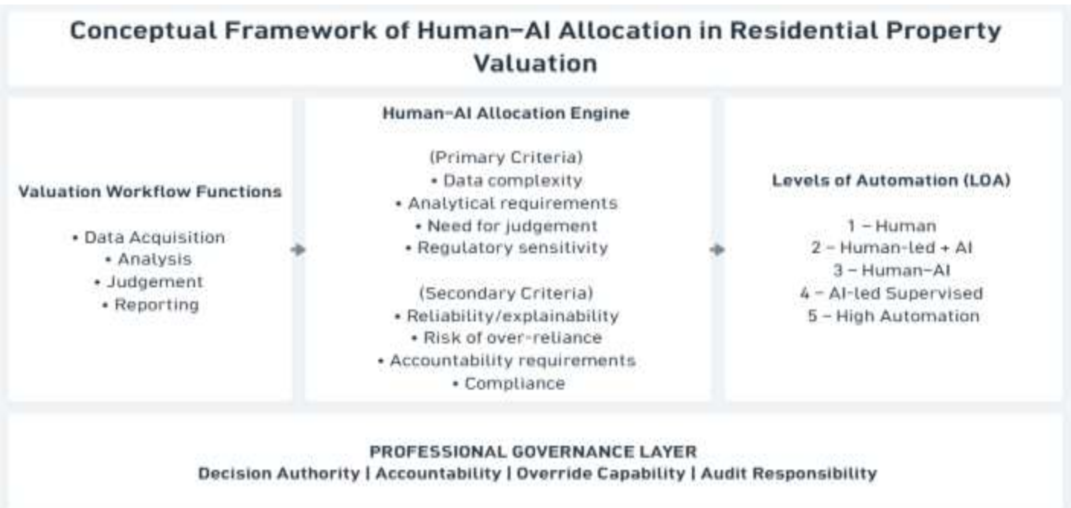


Figure 1. Conceptual Framework for Human–AI Allocation in Residential Property Valuation.

The figure presents a decision-centric framework that structures the allocation of human and AI roles across valuation tasks using Levels of Automation (LOA). Task allocation is determined through a Human–AI

Allocation Engine based on primary and secondary evaluative criteria, while a Professional Governance Layer operates across all stages and LOA levels to ensure decision authority, accountability, override, and audit responsibility remain with the valuer.

### Residential Property Valuation as a Judgement-Intensive Professional Practice

Residential property valuation is fundamentally a judgement-intensive professional activity rather than a purely computational exercise. Although valuation practice employs standardised methods and market evidence, the determination of market value ultimately requires professional interpretation, contextual understanding, and reasoned judgement exercised by a licensed valuer (Wyatt, 2013; RICS, 2022). This is also reflected in recent conceptual valuation scholarship, which emphasises that professional judgement remains essential in AI-enhanced valuation because algorithms cannot fully capture contextual nuances, qualitative factors, and emerging market dynamics recognised by experienced valuers (Ahmad Muzir et al., 2026). Valuation standards explicitly recognise that valuation outputs are opinions formed through the application of professional judgement to imperfect and context-dependent market information, rather than objective or deterministic truths (Cheung, 2024; Malaysian Valuation Standards (BOVAEP), 2021). Consequently, valuation outcomes cannot be evaluated solely on technical correctness or numerical accuracy, but on the credibility, transparency, and defensibility of the reasoning that underpins them.

A defining characteristic of professional valuation practice is its grounding in explicit regulatory and ethical obligations. In this context, valuation is not merely an analytical exercise but a professionally governed activity in which the valuer assumes formal responsibility for the outcome. Valuers are therefore subject to duty of care requirements, professional standards, and potential legal liability arising from their valuation opinions, particularly in contexts such as mortgage lending, taxation, compulsory acquisition, and dispute resolution. Valuation standards such as the RICS Global Valuation Standards (RICS, 2022) and the Malaysian Valuation Standards (BOVAEP, 2021) explicitly require that responsibility for valuation outcomes remains with the valuer, regardless of the analytical tools employed. These obligations necessitate that valuers document assumptions, justify methodological choices, and demonstrate that valuation conclusions are reasonable and supportable based on available evidence. Importantly, this establishes accountability as non-transferable: the valuer remains ultimately responsible for the final opinion of value, distinguishing valuation from data-analytic domains where responsibility may be distributed across systems and organisational processes (Cheung, 2024; Matysiak, 2023). Collectively, this non-transferable accountability forms the foundational constraint within which any AI integration in valuation must operate.

Within this professional context, analytical tools including statistical models, spreadsheets, geographic information systems, and increasingly AI-based systems have long been used to support valuation tasks. However, such tools have traditionally been framed as aids to professional judgement rather than substitutes for it (Wyatt, 2013). The growing incorporation of AI into valuation workflows therefore represents not merely a technological enhancement, but a potential shift in how judgement, reasoning, and responsibility are distributed across human and technological actors. If AI-generated outputs are treated as authoritative rather than advisory, there is a risk that professional judgement may be implicitly displaced without a corresponding reassignment of accountability, creating what recent literature has described as a “responsibility vacuum” in AI-supported professional decision-making (Matthias, 2004).

This risk is amplified by the fact that valuation decisions are frequently subject to ex post scrutiny. Valuation reports may be reviewed by auditors, challenged in court, or examined by regulators long after the original decision was made. In such circumstances, explainability alone is insufficient; valuers must be able to demonstrate who exercised judgement, who authorised key decisions, and on what basis alternative outcomes were considered or rejected (Floridi et al., 2018; Cheung, 2024). As a result, any framework for integrating AI into residential property valuation must explicitly preserve professional authority and accountability, ensuring that analytical support enhances rather than obscures the exercise of professional judgement.

### Human-Technology Interaction in Valuation: An Implicit Reality

Although professional property valuation has not historically employed formal automation taxonomies, interaction between human judgement and technological tools has long been embedded within valuation practice.

Contemporary valuation workflows routinely rely on digital databases, statistical software, geographic information systems, and market analytics platforms to support evidence gathering and analysis (Wyatt, 2013; RICS, 2022). These technologies assist valuers in processing large volumes of market data, identifying comparable transactions, and structuring analytical inputs, yet they do not independently determine valuation outcomes. Instead, their outputs are interpreted, contextualised, and selectively applied by valuers exercising professional judgement.

This implicit human-technology interaction reflects a gradual evolution of valuation practice rather than a discrete technological disruption. Over time, valuation tools have increasingly supported specific functional tasks such as information acquisition, data organisation, and preliminary analysis, while the authority to form and sign off valuation opinions has remained firmly with the valuer (Cheung, 2024; BOVAEP, 2021). As a result, valuation practice already embodies differentiated roles between humans and tools, even though these roles are not formally articulated through structured automation frameworks. The absence of explicit role definition does not imply the absence of automation, but rather that automation has been adopted incrementally and pragmatically without a unifying conceptual structure.

The recent introduction of AI-based systems into valuation workflows intensifies this longstanding interaction by expanding the scope of analytical support beyond descriptive statistics toward pattern recognition, prediction, and scenario exploration (Antipov & Pokryshevskaya, 2012; Deppner et al., 2023). Consistent with this, prior work on valuation epistemology characterises prediction as an augmentation to judgement and method rather than their replacement, positioning AI as an analytical extension that remains subject to professional oversight, consistent with the broader automation–augmentation perspective in which AI enhances, rather than replaces, human decision-making (Raisch & Krakowski, 2021). While such capabilities offer potential efficiency and consistency gains, they also blur established boundaries between analytical support and judgement formation. When AI systems generate valuation estimates or ranked recommendations, the distinction between assistance and decision-making becomes less clear, particularly if such outputs are treated as default benchmarks within professional workflows (Matysiak, 2023). In the absence of explicit structuring, these blurring risks shift cognitive authority toward technological systems without a corresponding redefinition of professional responsibility.

Crucially, existing valuation standards do not prohibit the use of advanced analytical tools, including AI, but they do require that valuers retain control over judgement, reasoning, and accountability for valuation outcomes (RICS, 2022; BOVAEP, 2021). This creates a structural tension: while technology increasingly participates in valuation tasks, standards continue to assign responsibility exclusively to the human professional. Without an explicit framework to govern this interaction, AI adoption may proceed in ways that are technically efficient but professionally ambiguous, particularly in contexts involving audit, dispute resolution, or legal challenge.

Recognising valuation as an implicitly socio-technical process provides an essential foundation for analysing AI integration. Rather than asking whether automation should replace professional judgement, the more pertinent question is how existing human-technology interactions can be systematically structured to support professional objectives while preserving accountability. Indeed, earlier conceptual work has already suggested the need for hybrid valuation protocols and human-AI collaboration models, but without specifying a task-level automation structure or governance mechanism for authority and accountability allocation (Ahmad Muzir et al., 2026). Addressing this question requires an analytical lens capable of distinguishing between different functional roles within valuation workflows and clarifying the boundaries of automation, an issue taken up in the following section through the application of Levels of Automation.

**Levels of Automation as an Analytical Lens (LOA1–LOA4)**

Levels of Automation (LOA) were originally developed to describe how functions within complex systems can be distributed between humans and automated technologies, emphasising that automation is not a binary choice between manual and autonomous operation but a continuum of support across different cognitive and operational functions (Sheridan & Verplank, 1978). Subsequent refinements conceptualised LOA around stages of human information processing information acquisition, information analysis, decision selection, and action execution, highlighting that automation can assist specific functions while leaving others under human control

(Parasuraman et al., 2000). Importantly, LOA was not designed to prescribe how work should be performed in a given profession, but to provide a structured framework for analysing human-automation interaction across tasks.

In this study, LOA is adopted explicitly as an analytical lens rather than as a representation of existing valuation practice. Its purpose is to systematically map functional task allocation within valuation workflows and to clarify where and how AI may support professional activities without implying the displacement of human judgement. Applied in this way, LOA1–LOA4 enable a functional decomposition of valuation work that aligns with observed practices described in Section 3, while remaining neutral with respect to professional authority and responsibility.

LOA1 (information acquisition) corresponds to tasks involving the collection and organisation of valuation-relevant data, such as transaction databases, property attributes, and spatial information. In contemporary valuation practice, these activities are already heavily supported by digital systems and data platforms, which enhance efficiency and coverage but do not determine valuation outcomes (Wyatt, 2013; RICS, 2022). LOA2 (information analysis) encompasses analytical processing, including statistical analysis, comparable selection, and pattern identification. AI systems are particularly well-suited to this level, offering capabilities in pattern recognition and data-intensive analysis that can augment professional insight (Antipov & Pokryshevskaya, 2012; Deppner et al., 2023). This division is broadly consistent with prior conceptualisations of hybrid valuation, where predictive systems contribute analytical optimisation while the valuer remains responsible for interpreting outputs, auditing their reasonableness, and determining the final value conclusion.

LOA3 (decision selection) involves the formulation of valuation judgements, such as selecting appropriate approaches, reconciling evidence, and forming an opinion of value. While automated systems may generate recommendations or indicative values at this stage, professional valuation standards require that decision selection remains a matter of human judgement, subject to contextual interpretation and professional reasoning (Cheung, 2024; BOVAEP, 2021). LOA4 (action execution) includes the preparation, documentation, and communication of valuation outputs, such as report generation and submission. Although automation can assist with formatting and documentation, the act of endorsing and issuing a valuation report remains a professional responsibility.

Viewed collectively, LOA1–LOA4 provide a coherent structure for distinguishing what functions within valuation workflows may be supported by AI and to what extent, without conflating analytical assistance with professional decision authority. However, while this functional perspective is valuable for clarifying task allocation, it does not address questions of who retains authority, who is accountable, or who may override automated outputs when professional judgement is required. These governance considerations are central to regulated valuation practice and fall outside the scope of conventional LOA models. As such, reliance on LOA1–LOA4 alone is insufficient for structuring AI integration in professional valuation contexts, necessitating an explicit extension to address accountability, an issue examined in the following section.

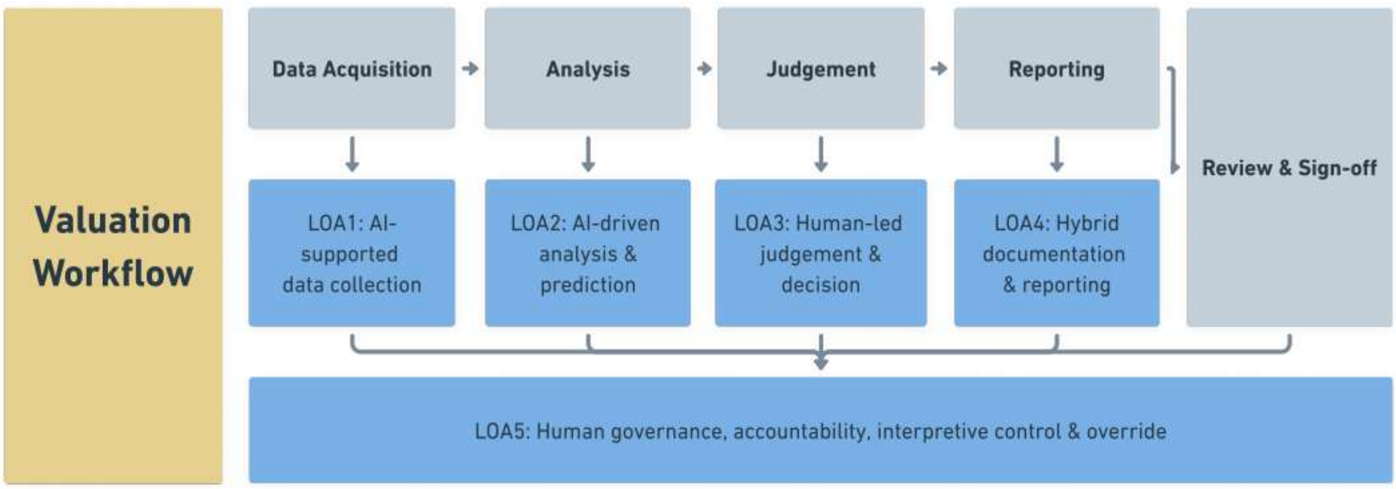


Figure 2. Mapping of Residential Property Valuation Workflow to Levels of Automation (LOA1–LOA4).

The figure presents a functional mapping of valuation workflow stages to Levels of Automation, showing how AI support is concentrated in data acquisition and analytical functions (LOA1–LOA2), while higher-order activities, including valuation judgement, reporting, and sign-off, remain human-led. The mapping also highlights the iterative interaction between analysis and judgement, where AI-generated outputs are interpreted, validated, and, where necessary, overridden by the valuer.

Table 1. Functional Roles of LOA1–LOA4 in Residential Property Valuation

| LOA Level | Core Function | Role of AI | Role of Human Valuer | Key Limitation |
|---|---|---|---|---|
| LOA1 | Data Acquisition | Automates data collection, cleaning, and structuring | Validates data relevance and contextual appropriateness | Data bias and incompleteness |
| LOA2 | Analysis & Prediction | Performs modelling, pattern recognition, and value estimation | Interprets analytical outputs and assesses reliability | Lack of explainability (black-box issue) |
| LOA3 | Valuation Judgement | Provides decision support or suggested value ranges | Exercises professional judgement and determines the final value | Risk of over-reliance on AI |
| LOA4 | Reporting & Documentation | Assists in report generation and standardisation | Reviews, refines, and formally approves valuation reports | Formal responsibility remains human-bound |
| Note: A professional governance layer operates across all levels to maintain accountability and control. | | | | |

Table 1 summarises the functional roles of each level of automation within the valuation context. While LOA1-LOA2 are primarily associated with computational efficiency and analytical enhancement, LOA3-LOA4 increasingly require human interpretive involvement. Notably, a Professional Governance Layer is introduced as a cross-cutting mechanism absent in conventional automation models, explicitly recognising the valuer's ultimate authority, accountability, and responsibility across the valuation process.

**Limitations of Conventional LOA In Professional Valuation Contexts**

While LOA1–LOA4 provide a useful structure for analysing functional task allocation between humans and automated systems, their applicability to professional valuation contexts is inherently limited. Conventional LOA frameworks were developed primarily for technical and operational domains, such as aviation, manufacturing, and human-machine systems engineering, where the primary concern is optimising performance, safety, and efficiency across task execution stages (Sheridan & Verplank, 1978; Parasuraman et al., 2000). In these domains, questions of authority and accountability are often embedded within organisational hierarchies or system design assumptions rather than treated as explicit analytical dimensions.

In contrast, residential property valuation operates within a regulated professional environment where authority, responsibility, and accountability are not incidental but foundational. Valuation outcomes carry legal, financial, and ethical consequences, and professional standards explicitly assign responsibility for valuation opinions to licensed valuers, irrespective of the analytical tools employed (RICS, 2022; BOVAEP, 2021). Conventional LOA frameworks do not account for this non-transferable responsibility, as they focus on what tasks are performed by whom rather than who bears responsibility for the consequences of those tasks. As a result, applying LOA1-LOA4 alone to valuation workflows risks conflating analytical support with professional authority. This limitation becomes more salient in light of valuation scholarship that highlights transparency, trust, and accountability as central concerns in AI-supported valuation, particularly where black-box systems may undermine professional defensibility and dispute resolution (Ahmad Muzir et al., 2026).

A key limitation of LOA1-LOA4 in valuation contexts is their silence on decision authority and override capability. AI systems operating at LOA2 or LOA3 may generate analytical outputs or recommended decisions that exert significant cognitive influence on valuers, particularly when such outputs are perceived as objective or statistically superior. However, LOA1-LOA4 do not specify who retains the authority to accept, reject, or override these outputs, nor do they clarify how such interventions should be documented and justified within professional reporting standards (Cheung, 2024; Matysiak, 2023). This omission is particularly problematic in valuation practice, where the ability to demonstrate reasoned departure from analytical outputs is often essential to professional defensibility.

Furthermore, conventional LOA frameworks do not address accountability ownership in post-decision contexts. Valuation decisions are frequently subject to retrospective scrutiny through audits, regulatory reviews, or legal proceedings, requiring clear attribution of responsibility for both the decision-making process and the outcome (Matthias, 2004). While LOA1-LOA4 can describe how information was acquired or analysed, they do not provide a mechanism for tracing accountability when automated outputs influence professional judgement. This gap creates what has been described in the literature as a “responsibility vacuum,” in which neither the human professional nor the technological system is clearly accountable for contested outcomes (Floridi et al., 2018).

These limitations indicate that while LOA1-LOA4 are effective for clarifying functional roles within valuation workflows, they are insufficient for governing AI integration in a professional context where accountability is central. Addressing this deficiency requires complementing LOA with a governance layer to incorporate authority, responsibility, and accountability as core analytical dimensions. The following section introduces such an extension through the incorporation of a Professional Governance Layer, aligning automation analysis with the institutional and ethical requirements of professional valuation practice.

**Extending LOA with Governance: Introducing a Professional Governance Layer**

The limitations identified in conventional Levels of Automation highlight a fundamental mismatch between functional automation frameworks and the governance requirements of professional valuation practice. While LOA1–LOA4 are effective for analysing how tasks are distributed between humans and automated systems, they do not address who retains authority, who is accountable for outcomes, or how responsibility is exercised when automated outputs influence professional judgement. In regulated domains such as residential property valuation, these questions are not peripheral; they are central to the legitimacy and defensibility of professional decisions (RICS, 2022; BOVAEP, 2021).

To address this gap, this study introduces a Professional Governance Layer that operates alongside, rather than within, conventional LOA frameworks. Importantly, it does not extend Levels of Automation numerically but structurally, by decoupling governance from automation and repositioning it as a cross-cutting professional control layer. This clarification is essential to avoid misinterpreting governance as an additional level of automation. Instead, the layer specifies decision authority, accountability ownership, override capability, and audit responsibility when AI systems are embedded within valuation workflows. In doing so, it reconceptualises automation analysis from a purely functional perspective to one aligned with professional and institutional requirements.

The necessity of this governance structure becomes particularly evident in situations where AI-generated outputs exert strong cognitive influence on valuation decisions. Systems operating at LOA2 or LOA3 may produce statistically robust estimates or ranked recommendations that shape professional judgement, even if final decisions remain formally human-led. Without an explicit governance mechanism, such influence risks creating ambiguity regarding responsibility for outcomes, especially when AI-supported decisions are later subject to audit, regulatory review, or legal challenge (Matysiak, 2023). The introduction of this layer addresses this risk by clearly delineating the advisory role of AI while preserving the authority and accountability of the human valuer.

In operational terms, this governance layer encompasses four interrelated functions. First, decision authority clarifies who has the legitimate power to accept, modify, or reject AI-generated recommendations. Second, accountability ownership specifies who bears professional and legal responsibility for valuation outcomes, irrespective of the degree of analytical support provided by AI. Third, override capability ensures that valuers retain both the ability and obligation to depart from automated outputs when professional judgement or contextual considerations warrant such action. Fourth, audit responsibility establishes clear ownership of the reasoning and documentation required to justify valuation decisions under regulatory or legal scrutiny. Together, these functions ensure that AI integration enhances analytical support without diluting professional responsibility.

In this context, explainable AI (XAI) mechanisms may play a complementary role in supporting the Professional Governance Layer, particularly in relation to audit responsibility. By improving the interpretability of AI-generated outputs, XAI enables valuers to understand, justify, and communicate the reasoning underlying AI-assisted decisions. This is critical in ensuring that valuation outcomes remain transparent, defensible, and compliant with professional standards, especially in situations subject to regulatory review or legal scrutiny.

Importantly, the introduction of this layer aligns with broader principles of human-centred automation and responsible AI, which emphasise that automation should support human decision-makers rather than displace them in contexts involving high-stakes judgement and accountability (Parasuraman et al., 2000; Floridi et al., 2018). In valuation practice, this alignment is not merely desirable but essential, given that professional standards explicitly prohibit the delegation of responsibility to non-human actors (Cheung, 2024; RICS, 2022).

By complementing LOA with an explicit governance layer, this study advances a framework that is both analytically rigorous and professionally defensible. The governance structure ensures that AI functions as structured decision support embedded within valuation workflows, while preserving the authority, responsibility, and accountability of the licensed valuer. This extension forms the foundation for the Human-AI Hybrid Valuation Framework presented in the following section.

**The Human-AI Hybrid Valuation Framework**

Building on the governance rationale established in Sections 4-6, this study proposes a Human-AI Hybrid Valuation Framework that structures human-AI collaboration across residential valuation workflows using Levels of Automation (LOA1-LOA4). The framework incorporates a Professional Governance Layer as established in Section 6. In doing so, it translates abstract principles of responsible AI and professional governance into a concrete workflow structure that is compatible with valuation standards and practice.

At the core of the framework is the recognition that residential valuation is a staged workflow comprising interrelated activities rather than a single analytical event. These stages typically include (i) data acquisition and verification, (ii) market and property analysis, (iii) valuation judgement and reconciliation, and (iv) reporting, review, and sign-off. Within each stage, the framework distinguishes between tasks that may be supported by AI and those that must remain under human professional control, ensuring that analytical assistance does not become de facto decision authority.

LOA1 (information acquisition) and LOA2 (information analysis) capture the domains where AI can provide the greatest analytical value with minimal governance risk. At these levels, AI systems may support data aggregation, cleansing, pattern recognition, and exploratory analysis, enhancing efficiency and consistency without determining valuation outcomes. LOA3 (decision selection) marks a critical boundary: while AI may generate indicative values or recommendations, the framework requires that such outputs remain advisory, with professional judgement exercised by the valuer to select, adjust, or reject recommendations based on contextual considerations and standards. LOA4 (action execution) includes report preparation and documentation support, where automation may assist formatting and consistency, but professional endorsement remains a human responsibility.

The dynamic nature of the framework can be illustrated through practical valuation scenarios. For instance, in a standard residential valuation, AI systems may support comparable data selection and value estimation at LOA2, with the valuer interpreting and validating outputs before forming the final judgement. In contrast, for complex properties such as high-value or unique assets, greater reliance on human expertise at LOA3 is required due to higher uncertainty, data limitations, and contextual considerations. This demonstrates that LOA allocation is not fixed but varies depending on task complexity, data availability, and professional judgement requirements.

Beyond these functional levels, the framework incorporates a Professional Governance Layer. This layer functions as an overarching control mechanism that spans all workflow stages. It explicitly assigns decision authority, accountability, ownership, override capability, and audit responsibility to the licensed valuer, irrespective of the degree of analytical support provided by AI at other levels. By operating across all stages of the framework, the model ensures that accountability is continuous rather than episodic, extending from initial data use decisions through to final report sign-off and post-decision scrutiny. This addresses the accountability gap identified in prior sections and aligns AI integration with non-transferable professional responsibility requirements set out in valuation standards (RICS, 2022; BOVAEP, 2021).

Importantly, the framework is process-oriented rather than technology-specific. It does not prescribe particular AI techniques or systems, allowing flexibility for future technological developments while preserving governance integrity. This design choice ensures that the framework remains applicable across varying organisational contexts and regulatory environments, and that it can function as a blueprint for responsible AI adoption rather than a fixed technical architecture. In this respect, the framework advances earlier conceptual work which argued that valuation outcomes are strengthened when contextual judgement, methodological validation, and predictive support are treated as complementary rather than competing forms of knowledge (Ahmad Muzir et al., 2026). By structuring collaboration instead of maximising automation, the Human-AI Hybrid Valuation Framework positions AI as an enabling capability that strengthens, rather than undermines, professional valuation practice.

**Methodological Justification**

This study adopts a qualitative, expert-driven research design to address normative and governance-oriented questions concerning human-AI role allocation, authority, and accountability in residential property valuation. The research objective is not to test algorithmic performance or predict market values, but to develop a professionally defensible framework that structures how AI should be embedded within judgement-intensive and regulated valuation workflows. Accordingly, methods that prioritise statistical inference or model validation are not appropriate for the type of knowledge problem addressed in this study.

A systematic literature review (SLR) was first undertaken to synthesise existing research on AI-enabled valuation, professional judgement, automation governance, and valuation standards. The SLR enabled the identification of key valuation workflow components, existing approaches to AI integration, and persistent gaps related to accountability and authority. This synthesis provided the theoretical and contextual foundation for the development of the Human-AI Hybrid Valuation Framework and ensured that the framework was grounded in established knowledge rather than ad hoc conceptualisation.

Following the SLR, the Delphi method was employed to elicit structured expert judgement regarding appropriate task allocation, Levels of Automation, and accountability arrangements within AI-supported valuation workflows. The Delphi technique is particularly well suited to this study because it facilitates convergence of expert opinion on complex issues where empirical data alone is insufficient and where professional norms, experience, and regulatory considerations are central (Hsu & Sandford, 2007; Okoli & Pawlowski, 2004). Through iterative rounds and controlled feedback, the Delphi process supports the development and validation of a framework that reflects both theoretical coherence and professional acceptability.

This methodological approach aligns with a pragmatic epistemological stance, which emphasises the suitability of methods to research objectives rather than adherence to a single methodological tradition (Creswell & Plano Clark, 2018; Morgan, 2014). By combining systematic literature synthesis with expert consensus building, the study ensures that the proposed framework is analytically grounded, context-sensitive, and aligned with professional valuation practice. Importantly, the absence of empirical AI model testing reflects a deliberate methodological boundary rather than a limitation, as the primary contribution of the study lies in structuring accountable human–AI collaboration rather than advancing predictive techniques.

It is important to emphasise that empirical testing of AI models is intentionally beyond the scope of this study, as it does not directly address the core research problem of structuring accountability and governance in human–

AI collaboration. The objective of this research is to develop a conceptual and professionally grounded framework, rather than to evaluate predictive performance.

# DISCUSSION

## Contributions and Implications

### Theoretical Contributions

This study contributes to the literature in three key ways. First, it reframes AI integration in residential property valuation as a governance and workflow design problem rather than a purely technical or predictive challenge. Second, by adopting Levels of Automation (LOA) as an analytical lens and introducing a Professional Governance Layer that operates alongside, rather than within the LOA structure, the study extends automation theory into a professional domain where authority, responsibility, and accountability are central. Third, it demonstrates that functional task allocation alone is insufficient to ensure professional defensibility and that the explicit incorporation of accountability as an analytical dimension is necessary to align automation analysis with the institutional realities of regulated professional practice.

The Human-AI Hybrid Valuation Framework also contributes to valuation theory by operationalising a socio-technical perspective on valuation workflows. Rather than treating valuation as a singular analytical outcome, the framework conceptualises valuation as a staged process in which analytical support, judgement formation, and professional endorsement interact. This process-oriented view provides a theoretical bridge between human-centred automation, responsible AI principles, and the long-established understanding of valuation as a judgement-intensive professional activity. It also extends prior epistemological work in valuation that conceptualised judgement, method, and prediction as complementary dimensions of valuation knowledge, by translating that conceptual integration into a governance-oriented workflow structure for human-AI collaboration. In doing so, the study complements emerging epistemological discussions on the relationship between prediction and professional judgement by offering a concrete structure through which this relationship can be governed in practice.

By explicitly incorporating accountability as a core analytical dimension, this study extends conventional automation theory beyond functional task allocation toward governance-oriented system design, particularly in professional domains characterised by non-transferable responsibility.

### Practical Implications for Valuation Practice and Governance

From a practical perspective, the proposed framework offers a blueprint for responsible AI adoption in residential property valuation. For practising valuers, the framework clarifies where AI can add analytical value, particularly at LOA1 and LOA2, without encroaching upon professional judgement or accountability. By explicitly distinguishing advisory AI outputs from authoritative valuation decisions, the framework supports valuers in leveraging advanced analytics while maintaining compliance with professional standards and duty of care requirements.

For regulatory bodies and professional institutions, the framework provides a structured basis for developing guidance, policies, or audit criteria related to AI use in valuation. Rather than evaluating AI tools in isolation, regulators can assess whether valuation workflows appropriately allocate authority and accountability in accordance with cross-cutting governance layer principles. This process-oriented perspective may be particularly valuable in contexts where AI-supported valuations are subject to heightened scrutiny, such as mortgage lending, taxation, or compulsory acquisition.

The framework also has implications for organisations and technology developers involved in valuation services. By making governance requirements explicit, the model encourages system designers to embed accountability features such as override mechanisms, documentation support, and audit trails into AI-enabled valuation systems. This alignment between system design and professional governance can reduce organisational risk and support more sustainable adoption of AI within valuation practice.

To enhance the practical applicability of the proposed framework, an indicative implementation pathway may be considered. At an initial stage, valuation firms may adopt AI support primarily at LOA1–LOA2 for data acquisition and analysis, where governance risk is relatively low. As organisational capability matures, controlled integration into LOA3 may be introduced under strict professional oversight. Throughout all stages, the Professional Governance Layer remains constant, ensuring that decision authority, accountability, and audit responsibility are preserved. This staged approach allows organisations to gradually integrate AI while maintaining compliance with professional standards and governance requirements.

**Implications for Future Research**

The findings of this study suggest several avenues for future research. First, the Human-AI Hybrid Valuation Framework may be empirically examined through case studies or pilot implementations to explore how LOA-based task allocation and accountability structures operate in real-world valuation settings. Such studies could investigate practitioner responses, organisational adaptations, and regulatory perceptions of AI-supported valuation workflows.

Second, the framework may be extended or adapted to other professional domains characterised by judgement-intensive and regulated decision-making, such as accounting, auditing, or financial advisory services. Comparative studies across professions could further refine the role of accountability as a core dimension of automation governance. Finally, future research may explore how emerging AI capabilities interact with Professional Governance Layer mechanisms, particularly as systems become more autonomous or integrated across organisational boundaries.

## CONCLUSION

The increasing use of artificial intelligence in residential property valuation presents both analytical opportunities and governance challenges. While existing research has demonstrated the technical potential of AI-driven valuation models, it has offered limited guidance on how such technologies should be embedded within professional valuation practice, which is fundamentally judgement-intensive, regulated, and accountable. This study addresses that gap by reframing AI integration as a problem of workflow structuring and accountability governance, rather than one of predictive performance alone.

By adopting Levels of Automation as an analytical lens, the study clarifies how functional tasks within valuation workflows may be supported by AI without displacing professional judgement. More importantly, the introduction of a Professional Governance Layer complements conventional LOA frameworks by explicitly incorporating decision authority, accountability, ownership, override capability, and audit responsibility as core design dimensions. This extension responds directly to the non-transferable responsibility requirements of professional valuation standards and mitigates the risk of responsibility ambiguity in AI-supported valuation decisions.

The resulting Human-AI Hybrid Valuation Framework provides a process-oriented and professionally defensible approach to AI adoption in residential valuation. Rather than advocating increased automation, the framework emphasises structured human-AI collaboration that preserves professional authority while leveraging analytical support. As AI continues to evolve and permeate valuation practice, such governance-oriented frameworks will be essential to ensuring that technological innovation strengthens, rather than undermines, the integrity and legitimacy of professional valuation.

In doing so, the study repositions AI not as a replacement for professional judgement, but as a governed decision-support mechanism embedded within a framework of accountability, authority, and professional responsibility.

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