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# BEST PRACTICES FOR LEVERAGING GENERATIVE AI IN ARCHITECTURAL DESIGN TO PROMOTE INVESTMENT OPPORTUNITIES: AN AHP-WEIGHTED FRAMEWORK APPLIED TO THE ASEER REGION, SAUDI ARABIA

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**Abstract**

Generative artificial intelligence (AI) is reshaping architectural practice, yet the literature offers little guidance on which practices matter most when the objective is not design production alone but the marketing of real-estate investment opportunities in a culturally distinct region. This study develops and empirically weights a best-practice framework for leveraging generative AI in architectural design to promote investment opportunities, using the Aseer Region of south-western Saudi Arabia as its application context. A structured review of the recent literature was synthesised into a hierarchy of five dimensions and seventeen practices, which was then weighted through the Analytic Hierarchy Process (AHP). Fifteen domain experts—architects, real-estate developers and academics—completed thirty-one pairwise comparisons each; judgements were aggregated by the geometric mean and the aggregated matrices proved highly consistent (consistency ratio = 0.024 at the dimension level). Contrary to a technology-first expectation, experts ranked *governance, ethics and trust* highest (26.7%), followed by *local-identity localisation* (21.0%), ahead of generative technology itself (15.5%). A sensitivity analysis excluding the least-consistent respondents confirmed the stability of this ordering (Spearman's ρ = 0.93–0.99). The findings are illustrated through a set of AI-generated visualisations produced for an Aseer investment site, and translated into actionable guidance for practitioners and decision-makers pursuing Vision 2030-aligned development.

**Keywords:** Generative AI; Architectural Design; Analytic Hierarchy Process; Investment Marketing; Aseer Region; Vision 2030.

**Article Highlights**

- Experts rank governance and local identity above generative technology itself.
- An AHP framework weights 17 AI best practices for investment-led architecture.
- Sensitivity analysis confirms a stable priority order across all scenarios.

## 1. INTRODUCTION

Over the past five years, generative artificial intelligence (AI) has moved from a research curiosity to an instrument that practising architects use daily. Text-to-image diffusion models and large language models now compress the early ideation cycle from days to minutes, producing photorealistic façades, massing studies and atmosphere images directly from natural-language prompts [1], [2]. Reviews of the field document gains in creativity, spatial organisation and environmental performance, while cautioning that the same tools introduce risks of algorithmic bias, opacity and the erosion of place-specific architectural identity [3], [4]. The result is a widening gap between what the technology *can* do and a disciplined understanding of how it *should* be deployed in professional settings.

This gap is especially consequential when generative AI is used not for design production in the abstract but as an instrument of *investment marketing*—the task of rendering a development opportunity legible and attractive to investors, financiers and public decision-makers.

In this mode the AI-generated image is simultaneously a design artefact and a persuasion device, and its credibility, cultural fit and ethical framing become economic variables. Marketing scholarship has examined the promise and the pitfalls of AI in customer-facing contexts [5], [6], but it has rarely been connected to the specific workflow of architectural visualisation for real-estate promotion.

The Aseer Region of south-western Saudi Arabia offers a revealing setting for this question. Its highland topography, temperate climate and distinctive vernacular—most recognisably the decorated Al-Qatt Al-Asiri interiors and the terraced stone settlements of the Sarawat range—give it an architectural identity unlike the Gulf's coastal cities.

Under Saudi Vision 2030 the region is positioned as a tourism and investment destination, which places a premium on development imagery that is at once internationally compelling and locally authentic. Empirical work on the Kingdom's architecture, engineering and construction sector confirms both strong interest in AI and uneven readiness to adopt it [7], making Aseer a microcosm of a broader regional challenge.

Despite this, no study to the author's knowledge offers a *weighted* account of best practice—one that establishes not merely a list of things architects might do with generative AI, but a defensible ordering of their relative importance for the investment-marketing objective in a specific cultural context.

The present work addresses three questions: (i) which dimensions and practices constitute leveraging generative AI in architectural design for investment marketing; (ii) how domain experts prioritise these practices for the Aseer Region; and (iii) what the resulting priority structure implies for practitioners and decision-makers. The contribution is threefold: a literature-grounded framework, its empirical weighting through the Analytic Hierarchy Process with a sensitivity check, and an illustrative application to an Aseer site using author-produced AI visualisations.

The study builds directly on a recent systematic review of AI in architectural design published in this journal [3], extending its synthesis from a description of capabilities to a prioritised, context-specific decision framework.

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## 2. LITERATURE REVIEW

The reviewed literature clusters into five themes, which together motivate the five dimensions of the proposed framework.

### 2.1 Generative technology and workflow integration

The foundational reviews map how AI methods—from evolutionary algorithms and cellular automata to deep generative models—support conceptual design [8]. Subsequent work shows text-to-sketch and sketch-to-image systems generating exterior concepts that match a stated design intent with high fidelity, collapsing tasks that once took weeks [9], and surveys the rapid diffusion of these models across the design studio [2].

Parallel research integrates AI with building information modelling and parametric pipelines, and applies optimisation to façade, shading and energy performance [10], [11]. The consistent finding is that value accrues less from any single tool than from its coherent integration into an existing professional workflow.

### 2.2 Local-identity localisation and contextual adaptation

A distinct strand trains or fine-tunes generative models on place-specific data so that outputs resonate with regional identity. The most cited example develops local-identity-trained models to render façades that reflect the character of a specific district, demonstrating that identity can be encoded and reproduced through weight adjustment and prompt engineering [1].

Comparative experiments on Midjourney, DALL·E and Stable Diffusion for regional residential design reach a pointed conclusion: leading models struggle to represent vernacular elements reliably without region-specific fine-tuning [12]. Earlier work likewise frames identity-aware generation as central to the discipline's engagement with AI [13].

### 2.3 Human capital and hybrid human–AI collaboration

Reviews of AEC practice and education converge on upskilling as the binding constraint: realising AI's potential depends on continuous professional development, prompt-engineering competence and curricular reform [4].

Studio-based studies report that students using AI tools achieve more creative outcomes, but only under structured guidance [14], and classifications of early-stage techniques stress keeping human judgement in the loop rather than automating it away [15]. Cross-sectional evidence from Saudi architectural education identifies faculty-readiness gaps as a specific regional barrier [16].

### 2.4 Governance, ethics and trust

As AI enters planning and design decisions, scholars foreground bias, transparency, accountability and privacy. A prominent treatment of AI ethics in urban planning argues that practitioners must act proactively to detect and document bias rather than treat fairness as automatic [17].

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Work on data ethics and governance in AI-powered analytics stresses fairness, transparency and compliance as design requirements, not afterthoughts [18], and consumer-market research catalogues the ethical paradoxes that arise when AI mediates trust [6]. For investor-facing imagery, these concerns crystallise around the honest disclosure of synthetic visuals.

### 2.5 AI and the marketing of investment opportunities

Marketing scholarship frames AI through higher-order learning and its attendant dangers—poorly specified objectives, biased models and limited explainability [5]. Studies of small and medium enterprises show that AI-based business-to-business practice depends on organisational antecedents and yields competitive consequences [19], while reviews of adoption in smart cities identify the institutional and skills barriers that gate uptake [20].

Applied to real estate, these insights suggest that AI visuals are most effective when embedded in a wider decision and communication process rather than treated as standalone renders.

### 2.6 Research gap

Across these themes the literature is rich in capability and case study but silent on *relative priority*. No study weights these practices against one another for the investment-marketing objective, and none does so for a culturally distinct Saudi context such as Aseer. The present study addresses this gap with an expert-weighted, sensitivity-tested framework.

## 3. METHODOLOGY

### 3.1 Research design

The study follows a three-stage mixed design. First, the literature was synthesised into a hierarchical framework of dimensions and practices.

Second, the framework was weighted empirically using the Analytic Hierarchy Process (AHP) on judgements elicited from a panel of domain experts.

Third, the resulting priorities were interpreted and illustrated through an application to an Aseer investment site. This design couples the breadth of a structured review with the decision-theoretic rigour of pairwise prioritisation.

### 3.2 The hierarchical framework

Synthesis produced a three-level hierarchy: an overall goal, five dimensions (D1–D5) and seventeen practices (P1.1–P5.4). Each practice is traceable to the reviewed sources, ensuring content validity. Figure 1 presents the structure.

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Figure 5. Hierarchical decision structure of the AHP model (5 dimensions, 17 best-practice criteria)

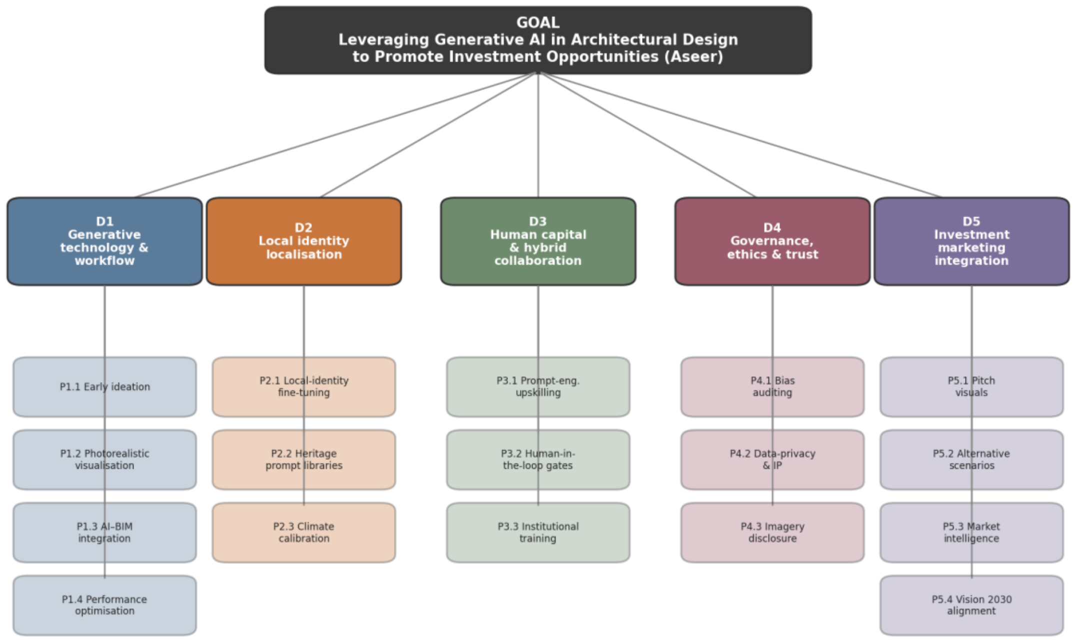


**Figure 1: Hierarchical decision structure of the AHP model (five dimensions, seventeen best-practice criteria)**

### 3.3 The Analytic Hierarchy Process

AHP derives priority weights from pairwise comparisons judged on Saaty's fundamental 1–9 scale, where 1 denotes equal importance and 9 denotes the extreme dominance of one element over another [21]. For a set of $n$ elements, judgements populate a reciprocal comparison matrix $A = [a_{ij}]$, with:

$$a_{ij} > 0 , \quad a_{ji} = 1 / a_{ij} , \quad a_{ii} = 1$$

The priority vector $w$ is the normalised principal eigenvector of $A$, satisfying:

$$A \cdot w = \lambda max \cdot w$$

where λmax is the principal eigenvalue. Consistency is assessed through the consistency index (CI) and consistency ratio (CR):

$$CI = (\lambda max - n) / (n - 1) \; ; \quad CR = CI / RI$$

RI is the random index for a matrix of order $n$. A CR not exceeding 0.10 indicates acceptable consistency [21].

### 3.4 Expert panel

Fifteen experts were purposively selected for direct professional engagement with architecture, real-estate development or investment in the study region. AHP relies on the quality rather than the statistical representativeness of judgements, and panels of this

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size are well established in the method's literature. Figure 2 summarises the panel: it is weighted towards architecture and urban design, complemented by real-estate development and academia, with most members holding sixteen or more years of experience.

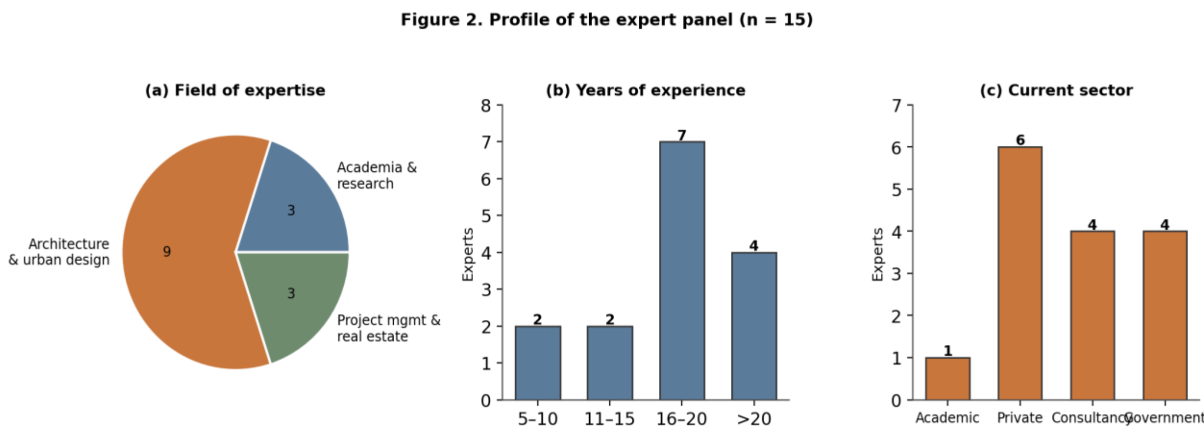


**Figure 2: Profile of the expert panel (n = 15)**

### 3.5 Data collection

Judgements were collected through a bilingual (Arabic–English) online questionnaire. After informed consent and a short profile section, each expert completed thirty-one pairwise comparisons—ten among the five dimensions and twenty-one among practices within their parent dimensions—using the verbal 1–9 scale. Two open questions captured the perceived principal barrier and opportunity for generative AI in Aseer's investment marketing.

### 3.6 Aggregation and consistency

Individual judgements were combined using the Aggregation of Individual Judgements (AIJ) approach, taking the geometric mean of each pairwise entry across experts—the theoretically appropriate operator for AHP because it preserves the reciprocal property of the matrices:

$$a_{ij}(group) = \left( \Pi_{k=1}^{M} a_{ij}^{(k)} \right)^{(1/M)}$$

for $M$ experts. Local weights were obtained for every matrix and global practice weights computed as the product of each practice's local weight and its parent dimension's weight. Consistency was evaluated for every aggregated matrix.

### 3.7 Sensitivity analysis

Because individual reciprocal matrices elicited with the verbal scale frequently exceed the 0.10 consistency threshold, the robustness of the aggregated priorities was tested directly. Each expert's overall inconsistency was indexed by the maximum CR across their six matrices; the analysis then recomputed the full weighting after excluding the one, two, three and five least-consistent respondents. Stability was assessed by tracking the

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dimension weights and by Spearman's rank-correlation coefficient between each scenario's seventeen-criterion ordering and the baseline.

### 3.8 Use of AI tools and disclosure

All analyses were implemented by the author in Python (NumPy). The architectural visualisations in Figure 6 were generated by the author using the Midjourney text-to-image model as part of an investment-marketing study for a site in the Aseer Region; they are illustrative of the practices under study and are explicitly disclosed as AI-generated, consistent with the governance practice (P4.3) that the framework itself identifies. No generative model was used to fabricate data, results or references; bibliographic sources were verified individually against their digital object identifiers.

## 4. RESULTS

### 4.1 Panel and consistency

The aggregated comparison matrices were highly consistent, with a dimension-level CR of **0.024** and within-dimension CRs ranging from **0.010** to **0.063**, all comfortably below the 0.10 threshold. Aggregation therefore yields a coherent group priority structure.

### 4.2 Dimension weights

Figure 3 and Table 1 report the dimension weights. Experts assigned the highest priority to *Governance, ethics & trust* (**26.67%**), followed by *Local architectural identity localisation & contextual adaptation* (**20.95%**). Generative technology itself ranked last (**15.47%**), a striking inversion of a technology-first expectation.

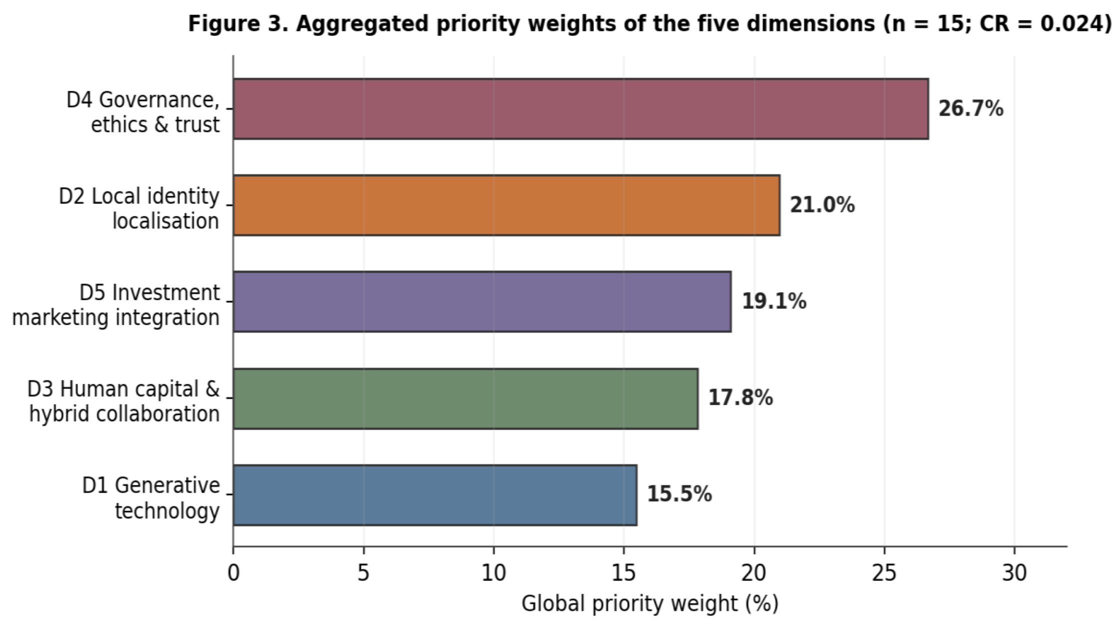


**Figure 3: Aggregated priority weights of the five dimensions (n = 15; CR = 0.024)**

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**Table 1: Aggregated dimension weights and rank**

| Rank | Dimension | Weight |
|---|---|---|
| **1** | D4 — Governance, ethics & trust | 26.67% |
| **2** | D2 — Local architectural identity localisation & contextual adaptation | 20.95% |
| **3** | D5 — Integration with investment-opportunity marketing | 19.09% |
| **4** | D3 — Human capital & hybrid human–AI collaboration | 17.82% |
| **5** | D1 — Generative design technology & workflow integration | 15.47% |

### 4.3 Local and global practice weights

Table 2 reports each practice's local weight (within its dimension) and global weight (across the whole model), and Figure 4 ranks all seventeen practices globally. The three highest-priority practices are *data-privacy and IP safeguards* (**10.87%**), *bias-auditing and transparency* (**8.94%**) and *fine-tuning models on local-identity data* (**7.76%**). Two governance practices thus occupy the top tier, with local-identity practices immediately behind—mirroring the dimension-level pattern.

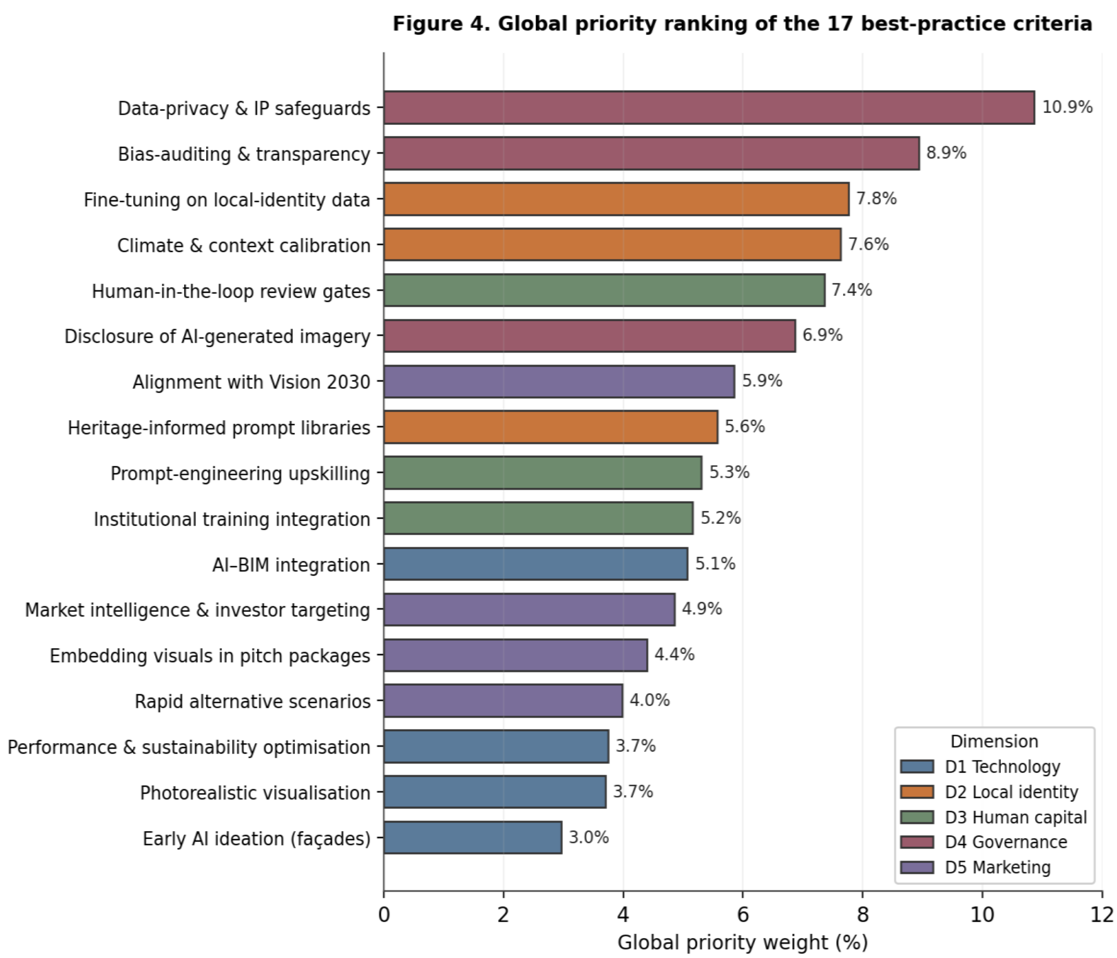


**Figure 4: Global priority ranking of the seventeen best-practice criteria**

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**Table 2: Local and global weights of the seventeen practices**

| Practice | Local wt. | Global wt. |
|---|---|---|
| P1.1 Early AI ideation of concepts and façades | 19.13% | 2.96% |
| P1.2 Photorealistic visualisation for stakeholder communication | 23.92% | 3.70% |
| P1.3 AI–BIM integration across design stages | 32.76% | 5.07% |
| P1.4 AI-driven performance and sustainability optimisation | 24.19% | 3.74% |
| P2.1 Models fine-tuned on local-identity datasets | 37.04% | 7.76% |
| P2.2 Heritage-informed prompt libraries | 26.56% | 5.56% |
| P2.3 Climate- and context-responsive calibration | 36.40% | 7.63% |
| P3.1 Prompt-engineering and AI-literacy upskilling | 29.77% | 5.31% |
| P3.2 Human-in-the-loop review at defined design gates | 41.29% | 7.36% |
| P3.3 Institutional training and education integration | 28.94% | 5.16% |
| P4.1 Bias-auditing and transparency protocols | 33.51% | 8.94% |
| P4.2 Data-privacy and IP safeguards | 40.75% | 10.87% |
| P4.3 Disclosure of AI-generated imagery in investor materials | 25.75% | 6.87% |
| P5.1 Embedding AI visuals in pitch and feasibility packages | 23.05% | 4.40% |
| P5.2 Rapid generation of alternative development scenarios | 20.86% | 3.98% |
| P5.3 AI-supported market intelligence and investor targeting | 25.43% | 4.86% |
| P5.4 Alignment with Vision 2030 and digital-transformation enablers | 30.66% | 5.86% |

### 4.4 Sensitivity and robustness

Figure 5 reports the sensitivity analysis. Across every exclusion scenario, *Governance, ethics & trust* remained the highest-weighted dimension and generative technology the lowest; dimension weights varied within a band of roughly two to four percentage points. Spearman's ρ between each scenario's full ordering and the baseline ranged from **0.929 to 0.990**, indicating that the priority structure is not an artefact of a few inconsistent respondents but a robust property of the panel's collective judgement.

**Figure 5. Sensitivity analysis confirming robustness of the priority structure**

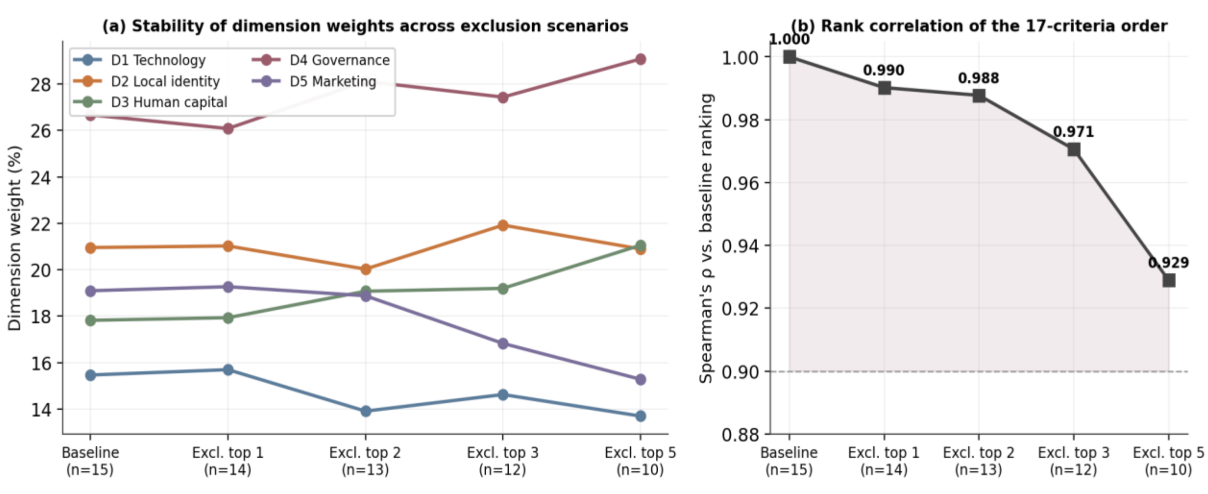


**Figure 5: Sensitivity analysis confirming robustness of the priority structure: (a) dimension-weight stability; (b) rank correlation with the baseline ordering**

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### 4.5 Qualitative findings

Open responses reinforced the quantitative pattern. The barriers most frequently named were the *reliability and provenance of data*, limited understanding of how the underlying models are constructed, and a shortage of trained personnel—concerns that map onto the governance and human-capital dimensions. The opportunities most often cited were AI-supported *investment-oriented land-use planning*, the cultivation of computational design skills, and the systematic incorporation of user feedback—each aligned with the marketing-integration dimension.

## 5. DISCUSSION

### 5.1 Why governance leads

That experts placed governance, ethics and trust above every other dimension is the study's most consequential result. It is consistent with planning and marketing scholarship warning that unmanaged bias, opacity and privacy failures undermine the very trust on which AI's value depends [17], [6].

In an investment-marketing setting the logic sharpens: a visualisation that misleads an investor, or that cannot be defended as an honest representation, is not merely an ethical lapse but a commercial liability. The high weight on data-privacy, IP safeguards and bias-auditing signals a professional community that regards trustworthiness as the precondition for everything else generative AI offers.

### 5.2 Local identity above raw technology

The second finding—local-identity localisation outranking generative technology itself—speaks directly to the Aseer context. Experts evidently judge that the persuasive and developmental value of AI imagery rests on its cultural authenticity, not on technical novelty.

This echoes evidence that leading models cannot reliably represent vernacular elements without region-specific fine-tuning [12], and that identity-trained models are precisely what allow outputs to resonate locally [1]. For a region whose competitive advantage is its distinctive highland heritage, identity is not decoration but the core of the value proposition.

### 5.3 Application to the Aseer Region

Figure 6 illustrates the framework through visualisations produced by the author for an Aseer investment site. The set deliberately spans the priority structure: heritage-rooted highland settlement imagery and mountain-contextual residential fabric exemplify the high-priority local-identity dimension (D2), while the mixed-use commercial cluster and the sports-and-wellness destination demonstrate marketing-integration practices (D5)—the visual products that populate pitch and feasibility packages. The images make concrete how high-ranked practices translate into investor-facing artefacts.

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(a) Heritage-rooted highland settlement: Sarawat stone typology and terraced topography [D2: local identity]

(b) Contemporary residential fabric set against the Asir mountain context [D2: contextual calibration]

(c) Iconic mixed-use commercial cluster: a high-value investment product [D5: investment marketing]

(d) Sports & wellness destination within a highland masterplan [D5: pitch & feasibility visuals]

**Figure 6: AI-generated visualisations (Midjourney) produced by the author for an investment-marketing study of a site in the Aseer Region, annotated against the framework's dimensions. Images are disclosed as AI-generated in accordance with practice P4.3**

### 5.4 A self-applying framework

The treatment of Figure 6 enacts the framework's own highest-tier guidance: the imagery is explicitly disclosed as AI-generated (P4.3) and is presented as a communication aid within a wider analytical argument (D5) rather than as a freestanding render. This reflexive consistency—applying to the study's own visuals the governance practice that experts ranked most important—strengthens rather than weakens the analysis.

### 5.5 Theoretical and practical contributions

Theoretically, the study advances a transferable, weighted framework that reframes generative AI in architecture from a catalogue of capabilities into a prioritised decision structure tied to a marketing objective. Practically, the weights offer an explicit checklist: practitioners and municipal decision-makers in Aseer—and in comparable heritage regions—should invest first in governance safeguards and local-identity fine-tuning, then in human-in-the-loop capability, before treating raw generative throughput as the differentiator.

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## 5.6 Limitations

Three limitations qualify the findings. First, although the aggregated matrices were highly consistent and the ordering proved robust, several individual matrices exceeded the 0.10 consistency threshold—an expected consequence of the verbal scale that the sensitivity analysis was designed to address rather than eliminate. Second, the panel, while expert, is modest in size and regionally focused, so generalisation beyond comparable contexts should be cautious. Third, the application in Figure 6 is illustrative; it demonstrates the framework's use rather than measuring investment outcomes, which remain a subject for future field evaluation.

## 6. CONCLUSION

This study asked which practices matter most when generative AI is used to promote architectural investment opportunities in the Aseer Region, and how experts prioritise them. Synthesising the literature into five dimensions and seventeen practices and weighting them through AHP, it found that domain experts place governance, ethics and trust first and local-identity localisation second, ahead of generative technology itself—an ordering shown to be robust through sensitivity analysis. The framework reframes the conversation from technical possibility to disciplined, context-aware priority, and its illustrative application demonstrates how high-priority practices become investor-facing artefacts. For practitioners and decision-makers pursuing Vision 2030-aligned development, the message is clear: the returns to generative AI in heritage regions are unlocked not by the most powerful model but by the most trustworthy and locally grounded practice. Future research should extend the framework through analytic network modelling to capture interdependence among practices, widen the panel geographically, and evaluate investment outcomes empirically.

### Declarations

**Funding:** This research received no external funding; it was entirely self-funded by the authors.

**Ethics declaration:** Participation in the expert survey was voluntary and anonymous; no personally identifying data were collected, and the study did not involve any procedure requiring institutional ethics-committee approval.

**Conflict of interest:** The authors declare that they have no competing interests.

**Data availability:** The anonymised judgement matrices analysed in this study are available from the corresponding author on reasonable request.

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