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Research Design for Doctor of Business Administration (DBA) Studies: A Decision-Oriented Framework

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ABSTRACT

DBA students often encounter research-design guidance as separate methodological choices, making it difficult to align the research question, design, sampling, analysis, and quality criteria. This paper addresses that integration problem by developing a narrative, decision-oriented conceptual synthesis for management research. It draws purposively on established research-methods texts and recent peer-reviewed applied studies and compares seven interdependent areas: framing the topic and terms of reference; selecting correlational, predictive, or experimental designs; choosing probability or non-probability sampling; determining when and how to integrate mixed methods; matching scoping or systematic reviews to field maturity; selecting content or thematic analysis; and establishing validity and reliability. The synthesis shows that these are not standalone decisions: the intended claim determines the design, the design constrains sampling, method and review choices must fill a stated evidentiary need, and validity and reliability provide cross-cutting tests of coherence. Its contribution is to connect existing methodological guidance into an ordered framework with explicit decision links and practical checks, rather than propose a new empirical method. DBA students can use it to plan and justify a study and identify downstream consequences before data collection. The framework is a planning aid, not a validated protocol, and is applicable to management-focused DBA studies.

INTRODUCTION

In management research, the topic directs the work, while the terms of reference (ToR) act as a compass that governs the aim, objectives, and research questions. Topic selection considers relevance, evidence, and feasibility (Creswell, 2007). This should ignite a “burning desire” to tackle a problem (e.g., a business challenge) that is visible in practice. Such a problem must be systematically reframed within a plan, so that it can provide empirical, verifiable and ethical conclusions (Booth *et al.*, 2024; Denscombe, 2010).

This procedural reframing necessitates an academic basis: the topic should be positioned in the relevant literature to know what was established, what has been investigated, debated or paradoxically presented, and what remains uncertain to help clarify the intended contribution (Bell *et al.*, 2022).

The researcher may “replicate with adjustment” and so build upon an existing study while changing scope, context, or population but avoiding a “trivial contribution” (Saunders *et al.*, 2023). Another route is “development of earlier work” where the topic is taken further through a modern theory with improved data but without scope creep (Denscombe, 2010). A third route is “convenient access”, where data availability shapes the plan that shall be deliberately linked to relevant theories (Taylor *et al.*, 2016). ToR, the governance mechanism of the route, ensures a systematic sequence and rigor (Page *et al.*, 2021) and prevents haphazard inquiry (Walliman, 2011). The aim defines an ultimate purpose while the objectives translate that aim into a small set (typically 3–4)

of SMART deliverables; then research questions define what scientifically counts as an answer and therefore determine the appropriate design and evidence (Bougie & Sekaran, 2019; Creswell, 2009).

As an example, the “burning desire” may start with an aim “to improve employee engagement” then ToR set objectives like diagnose current engagement drivers, explore root causes qualitatively, and propose and prioritize interventions. Questions could be then: what is the current level of employee engagement, and which interventions are most feasible to improve engagement.

Ethics and integrity are critical for each component and must surround the whole work (Creswell, 2023; Taylor *et al.*, 2016). When these elements align with each other through “acceptable scientific method”, they strengthen research credibility and reliability by (a) matching claims to evidence and (b) making conclusions transparent and replicable (Miles *et al.*, 2014).

In conclusion, research must be systematic, controlled, rigorous, verifiable, objective, empirical, and critically scrutinized. These concepts act as guiding principles which indicate research plan through proper collection and interpretation of data as well as scrupulous explanations (Jackson, 2008; Shadish *et al.*, 2002).

LITERATURE REVIEW

Quantitative Research Designs

Research design is a systematic plan that links ToR with these procedures applied for collecting and analyzing evidence to ensure overall coherence in a way that increases credibility and replicability (Creswell, 2023). In

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quantitative research, designs are commonly differentiated by the type of claim they support, or in other words, by their aim to examine association, to analyze prediction, or to establish causal effect relationship between variable (Jackson, 2008).

Correlational design examines whether two or more variables co-vary. It analyzes the direction as well as strength of their association (e.g., whether they increase or decrease together) using naturally occurring variation rather than researcher manipulation (Bougie & Sekaran, 2019; Jackson, 2008).

It is generally weaker in terms of internal validity because, without manipulation, it is difficult to block out confounding variables or reverse causality. However, it can offer good generalizability when conducted in natural settings and with sufficiently large and diverse samples, and thus they are typically feasible due to lower cost and easier access to data through surveys or organizational records. It also typically poses lower ethical risk than interventional studies because it does not alter participants' conditions. Nevertheless, informed consent, confidentiality (i.e., anonymity), and harm minimization remain essential, particularly when using sensitive data or studying contexts shaped by organizational power dynamics.

Overall, correlational design supports informed decision making primarily through diagnostic insight as it helps mapping patterns and identifying candidate factors for further testing rather than demonstrating causal effects (Bell *et al.*, 2022). Predictive design focuses on forecasting an outcome variable from one or more predictors using statistical modelling (e.g., regression) to support forward-looking decision making (Sheard, 2018), but even high accuracy does not demonstrate how variables cause the outcome because models may capture correlations or confounding rather than underlying mechanisms.

Since predictive models can lose accuracy when environments change, their generalizability depends on both the training data and the stability of conditions over time, thus validation and recalibration are essential. This design's feasibility is often high when relevant datasets are available. However, this requires extensive data preparation and appropriate quality controls, especially that it may carry ethical considerations when predictions influence decisions about individuals or groups, raising concerns around bias, transparency, privacy, and misuse; therefore, governance becomes highly important. Overall, it is highly useful for operational decisions, such as early warning, prioritization, and resource targeting while the conclusions should be framed as forecasts rather than causal claims (Sheard, 2018). Experimental design involves deliberate manipulation of the independent variable and comparison of outcomes under controlled conditions, which supports stronger causal inference than non-interventional designs (Creswell, 2023).

When implemented as a true experiment with random assignment and a control group, it reduces the influence

of confounding factors and enables more confident claims about whether a specific intervention results in a significant effect. However, experiments often face feasibility and ethical constraints: they can be expensive, time-consuming, and operationally difficult, whereas randomization may be impractical or ethically inappropriate in real organizational or social settings. Generalizability can also be limited if the study context is artificial or the sample is narrow, and participants may change their behavior because they know they are being studied. For these reasons, applied research frequently relies on quasi-experimental alternatives, but these typically provide weaker causal confidence than well-executed randomized experiments (Shadish *et al.*, 2002).

Data Sampling

Since it is almost impossible to conduct research on the whole study population, researchers perform sampling with rigor (Aguinis *et al.*, 2021); that is a transparent process of selecting a subset of cases in scope. By this, they collect and analyze sample data then draw conclusions about that wider population with greater replicability and confidence (Denscombe, 2010).

In contrast to probability (representative) sampling, where each population member has a known and non-zero chance of selection, non-probability (judgmental) sampling involves unequal or unknown selection chances, and some members may have no chance of inclusion (Fowler, 2002).

Probability sampling uses random selection techniques, such as simple random, stratified, and cluster, which support stronger generalizability because (a) the selection is not driven by intervention, and (b) the results are less exposed to bias. Nevertheless, researchers must manage sampling error and related threats (e.g., non-response) to protect the quality of inferences (Miller, 1991).

Having an available, harm-free sampling frame, probability sampling becomes the most appropriate especially when the purpose is to estimate population parameters, such as behavioral patterns, satisfaction levels, non-conformity, or differences between demographic groups (Babbie, 1990). Table 1 shows a few examples of probability sampling.

Non-probability sampling selects participants without randomization but via convenience, purposive, quota, or snowball techniques (Fowler, 2002). It is usually more feasible, faster, cheaper, and practically justified when a full, risk-free sampling frame is unavailable, or when access to data is restricted. It allows purposive inclusion of cases with relevant experience and paves the way for higher response rate (Ting *et al.*, 2025).

Researchers may consider non-probability methods when (a) the aim is exploratory, (b) when studying specialized subgroups, (c) when the population is hard to reach, or (d) when a potential harm is addressed (Aguinis *et al.*, 2018; Bell *et al.*, 2022). Table 2 shows a few examples of justified non-probability sampling.

Table 1: Probability Sampling Examples.

Example	Description
Employee engagement	In 2019, the ADP Research Institute conducted a global survey to measure levels of over 19,000 workers' engagement as well as the work conditions that are most likely to attract and keep them. They surveyed a random sample of approximately 1,000 workers across 19 countries (Hayes <i>et al.</i> , 2019). This approach offered scanning myriad factors beyond employer's control.
Customer satisfaction	In 2020, Kenya Bankers Association applied simple random sampling in a study that collected 15,179 respondents from all the 47 Counties which make up Kenya to analyze the unprecedented impact of the health crisis on the banking industry. This approach supported reliable estimates across the full geographic scope (Kenya Bankers Association, 2020).
Food inspections	U.S. Food Safety and Inspection Service (FSIS) pathogen monitoring program, as described by Williams <i>et al.</i> (2025), performed surveillance samples collected from slaughter and processing establishments. Their sampling was a close approximation of either stratified sampling or a two-stage cluster sampling design, which enabled population-level estimates of pathogen occurrence and supported monitoring changes over time (Williams <i>et al.</i> , 2025).

Note: Compiled by the author from the sources cited in the table.

Table 2: Non-Probability Sampling Examples.

Example	Description
Technical assessments	In 1995, the Office of the Inspector General (U.S. Department of Defense) assessed nonconformances in resistors, semiconductors, and connectors managed by the Defense Logistics Agency and discussed the use of statistical sampling in quality assurance. At the time of the assessment, DESC's testing program did not use statistical random sampling for test sample selection; instead, items were selected using operational judgement based on factors such as criticality, value, prior deficiency history, and vendor experience. In parallel, the assessment documented a layered sampling approach for the technical review. Practical constraints limited the extent to which fully random selection could be executed (Office of the Inspector General, Department of Defense, 1995).
Niche expert practices	Roch <i>et al.</i> (2024) studied security experts' perspectives on augmented intelligence in cybersecurity. Their sample was recruited mainly through purposive sampling to ensure participants matched the target group in terms of role and level of expertise (including a minimum experience threshold), and they used additional snowball sampling (peer identification or referrals) to reach relevant experts. This approach was appropriate since the population was specialized and not easily captured by a complete sampling frame whereas the resulting findings should have been presented as expert-informed insights rather than statistically population-representative estimates (Roch <i>et al.</i> , 2024).
Early-stage user feedback	Wedig <i>et al.</i> (2025) developed a preliminary web-based application and conducted an initial round of usability testing with the intended users (i.e., physical therapists) to identify early design issues and improvement opportunities. Because the purpose was formative feedback rather than population estimation, the authors used a convenience sample of five physical therapists for the first iteration of usability testing (Wedig <i>et al.</i> , 2025).

Note: Compiled by the author from the sources cited in the table.

In summary, researchers should clarify their sampling procedures answering questions about (a) which population was targeted, (b) which cases were eventually included in the study (c) how did they select and recruit them, and (d) what data sources were used? (Aguinis *et al.*, 2021; Saunders *et al.*, 2023).

To do so, they may follow a decision tree that helps determine the most appropriate sampling approach as shown in Figure 1:

Mixed-Methods Research

Mixed-method research in management combines qualitative and quantitative approaches within a single study to address questions that are both measurable and socially constructed (Lall, 2021). Its value is derived from its strong chain of reasoning and improved accuracy (Denscombe, 2010). For instance, numbers can show patterns and magnitude, while qualitative evidence can explain unspoken meaning, psychological context, and

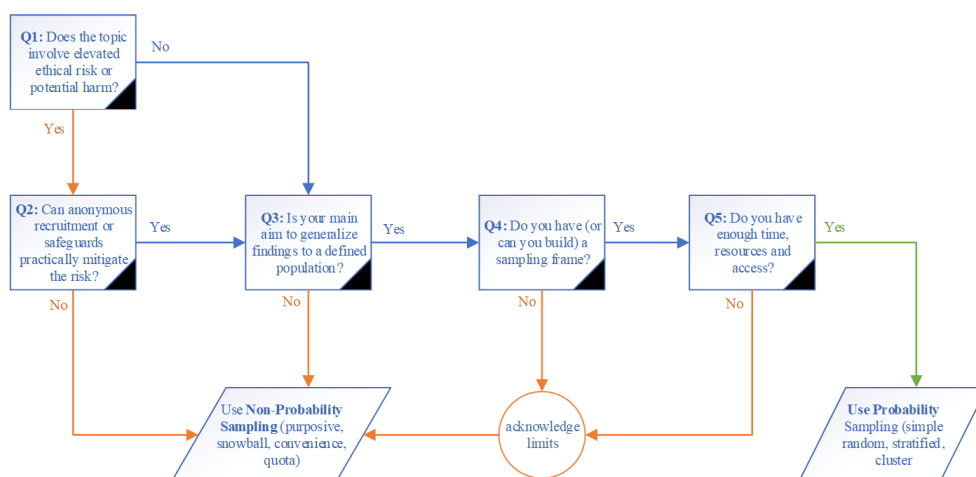


Figure 1: Suggested Decision Tree for Sampling Approach.

Note: Created by the author.

underlying process. However, this is a complex research design. It requires careful sampling choices, additional time and skill, clear integration and serious consideration of revealed contradictions (Denscombe, 2010). Therefore, the practical use and application of such a mixed design must serve the inadequacy (e.g., limitation) of a mono method for the subject ToR and shall maintain the rigor that keeps such an integration credible (Creswell, 2023).

Analyzing the Use of Mixed-Methods Design (Why and When)

Researchers in management typically choose mixed methods when a single approach leaves important gaps (Denscombe, 2010). Common rationales include: (a) triangulation, where two strands examine the same issue to test whether findings align; (b) complementarity, where one strand adds explanation or detail to the other; (c) development, where results from one strand shape the tools, sampling, or hypotheses of the next; (d) expansion, where different strands answer different parts of a wider problem; and (e) initiation, where contradictions are deliberately explored rather than avoided (Caruth, 2013; Venkatesh *et al.*, 2013).

These rationales guide design selection: convergent designs fit triangulation and contradiction-checking; explanatory sequential designs fit situations where quantitative results need interpretation; and exploratory sequential designs fit cases where qualitative insights are needed to build measures or categories for later testing (Creswell, 2023).

Analyzing the Application of Mixed-Methods Design (How and Where)

In practice, the quality of mixed-method design depends on explicit integration decisions: which strand leads (or whether both are equal in priority), whether strands run in parallel or in phases, how participants/sources are connected across strands, and where integration occurs (in design stage, data collection, analysis, or final interpretation) (Creswell, 2023).

Good convergent studies specify how results will be

compared and what will be done if findings diverge; and similarly, good sequential studies explain the “bridge” between phases; for instance, what quantitative pattern triggered follow-up interviews, or how qualitative codes became survey items (Dawadi *et al.*, 2021).

Weak application often appears as parallel reporting, unclear dominance, or vague statements such as “results were combined” without showing how (Caruth, 2013).

In conclusion, mixed-method design is most convincing in management research when the research question requires both measurement and interpretation, and when the study shows a transparent rationale with a well-planned integration route (Salehi & Golafshani, 2010).

Scoping and Systematic Reviews

Scoping reviews and systematic reviews are structured approaches in studying literature, through the extraction and analysis of data from existing research, to examine current knowledge, debates, and unresolved issues. While both approaches support the development of research questions through predefined inclusion and exclusion criteria, they differ significantly in purpose, analytical depth, and evidence strength (Smith & Duncan, 2022).

A scoping review requires less time and resources. It is exploratory in nature, thus, is suitable when a research field is emerging or conceptually fragmented. Its main strength lies in mapping the breadth of existing literature, clarifying key concepts, identifying theoretical perspectives, and highlighting research gaps rather than producing definitive answers (PRISMA, 2018). This breadth allows researchers to set meaningful boundaries and identify trends across industries or interdisciplinary domains. However, this flexibility also represents a limitation since it involves limited critical appraisal of study quality and variables, which weakens the capacity to support strong evaluative claims. For example, Heikinniemi *et al.* (2025) used a scoping review to answer the question: What is the role of employee surveys in promoting physical health and healthy lifestyles at the workplace?

In contrast, a systematic literature review is designed to

answer a precise, well-defined research question through a rigorous and transparent process. Its strength lies in methodological discipline, including comprehensive searching, standardized data extraction, and formal quality assessment, which together reduce bias and enhance reproducibility. As a result, systematic reviews generate more defensible and evidence-based conclusions (PRISMA, 2021). However, they are resource-intensive and less appropriate for immature research domains where evidence is sparse, heterogeneous, or conceptually underdeveloped. In such contexts, strict inclusion criteria may lead to overly narrow or inconclusive findings. For instance, Kekkonen *et al.* (2025) conducted a systematic review to answer the question: What is the effectiveness of work ability interventions on productivity outcomes? Overall, scoping reviews are more compelling for exploration and theory development, whereas systematic reviews are superior for evidence-based precise inquiry.

Content and Thematic Analysis

Content analysis helps researchers code segments of qualitative data using key categories that systematically summarize what is explicitly present in the dataset and, where relevant, report the distribution of categories across cases. It may be inductive, allowing categories to emerge from the data, or deductive (directed), applying a pre-existing framework and mapping segments of text to predefined categories (Schreier, 2012).

In contrast, thematic analysis aims to interpret and report patterns of meaning and their relationships rather than focusing on wording frequency. The output is a set of themes and sub-themes supported by evidence from the dataset (Guest *et al.*, 2012). This requires deeper interpretation as it moves beyond surface content

to consider both explicit and implicit meanings in participants' accounts (Maguire & Delahunt, 2017).

Although both approaches involve iterative, non-linear coding, content analysis is often more descriptive and structured, which can risk overlooking relevant categories if the coding frame is too narrow, whereas thematic analysis can provide richer, more nuanced insight but may introduce greater interpretive variability between analysts (Vears & Gillam, 2022).

In both methods, rigor is strengthened by transparent procedures and by presenting sufficient supporting evidence from the original data to demonstrate how interpretations were generated (Guest *et al.*, 2012; Schreier, 2012).

Content Analysis Example

Deshpande and Sharp (2022) provided a strong example of qualitative content analysis applied to stakeholder identification for responsible artificial intelligence (AI) systems, based on 45 shortlisted articles.

The authors applied a deductive coding frame using probes adapted from ISO 26000:2010 (see Table 3).

Upon analysis, the authors systematically coded relevant text segments, extracted and categorized (a) stakeholders likely to be impacted by responsible AI systems and (b) stakeholders expected to address those impacts. The purpose was to develop a structured stakeholder view that can support executive-level decision making on responsible AI.

The key output was a categorized long list of stakeholders organized across three levels: individual, organizational, and national/international (see Figure 2), illustrating how content analysis produces transparent, structured categories grounded in coded documentary evidence.

Table 3: Coding Probes.

	ISO 26000:2010 clause 5.3.2	Probes for content analysis (Relevant research questions)
1	To whom does the organization have legal obligations?	To whom could the responsible AI system have legal obligations? (RQ01)
2	Who might be positively or negatively affected by the organization's decisions or activities?	Who might be [positively or negatively] impacted by the responsible AI system's decisions or activities? (RQ01)
3	Who is likely to express concerns about the decisions and activities of the organization?	Who is likely to express concerns about the decisions and activities of the responsible AI system? (RQ01 and RQ02)
4	Who has been involved in the past when similar concerns needed to be addressed?	Who has been involved in the past when concerns about responsible AI systems needed to be addressed? (RQ02)
5	Who can help the organization address specific impacts?	Who can help the responsible AI system address specific impacts and meet its responsibilities? (RQ02)
6	Who can affect the organization's ability to meet its responsibilities?	This was considered as part of Who can help the responsible AI system address specific impacts and meet its responsibilities?
7	Who would be disadvantaged if excluded from the engagement?	Who would be disadvantaged if excluded from the engagement with the responsible AI system? (RQ01 and RQ02)
8	Who in the value chain is affected?	This was considered as part of Who might be [positively or negatively] impacted by the responsible AI system's decisions or activities?

Note: Adapted from Deshpande and Sharp (2022).

- Individual stakeholders i.e. users, developers, engineers, researchers, AI experts, HCI researchers and experts, non-users of AI systems, non-AI experts;
- Organisational stakeholders i.e. technology companies, professional bodies such as ACM, IEEE, learned societies such as the Japanese Society for Artificial Intelligence, and research institutes such as the Future of Life Institute and the Alan Turing Institute; and
- National/international stakeholders engaged in making laws, rules, and regulations i.e. nation states (EU, US, UK, China, Australia etc.), regional/national legislative/regulatory agencies, OECD, UNICEF etc.

Figure 2: Stakeholder Groups Exposed to AI Impact

Note: Adapted from Deshpande and Sharp (2022).

Thematic Analysis Example

Miller (2022) provided another clear example of thematic analysis applied to AI project governance from 47 shortlisted articles. The study reviewed academic literature on stakeholder involvement in AI projects and used thematic coding to interpret recurring patterns of meaning in how stakeholders are described and positioned based on their power, legitimacy, urgency, and harm. Rather than counting and categorizing roles into levels (Deshpande & Sharp, 2022), this analysis synthesized the evidence into coherent themes that represent AI community members resulting in “34 AI community

members”, grouped under: Developing Organization, Funding Entity, Performing Entity and Operating Organization in addition to Society Member (see Figure 3). These stakeholders have been finally classified into six roles (see Figure 4).

This thematic interpretation also supported a conceptual extension to stakeholder salience by introducing “harm” as an attribute to capture passive stakeholders affected by AI outcomes. The study provided, practically, an interpreted set of themes (stakeholder roles and their relationships) grounded in qualitative evidence from the reviewed research (Miller, 2022).

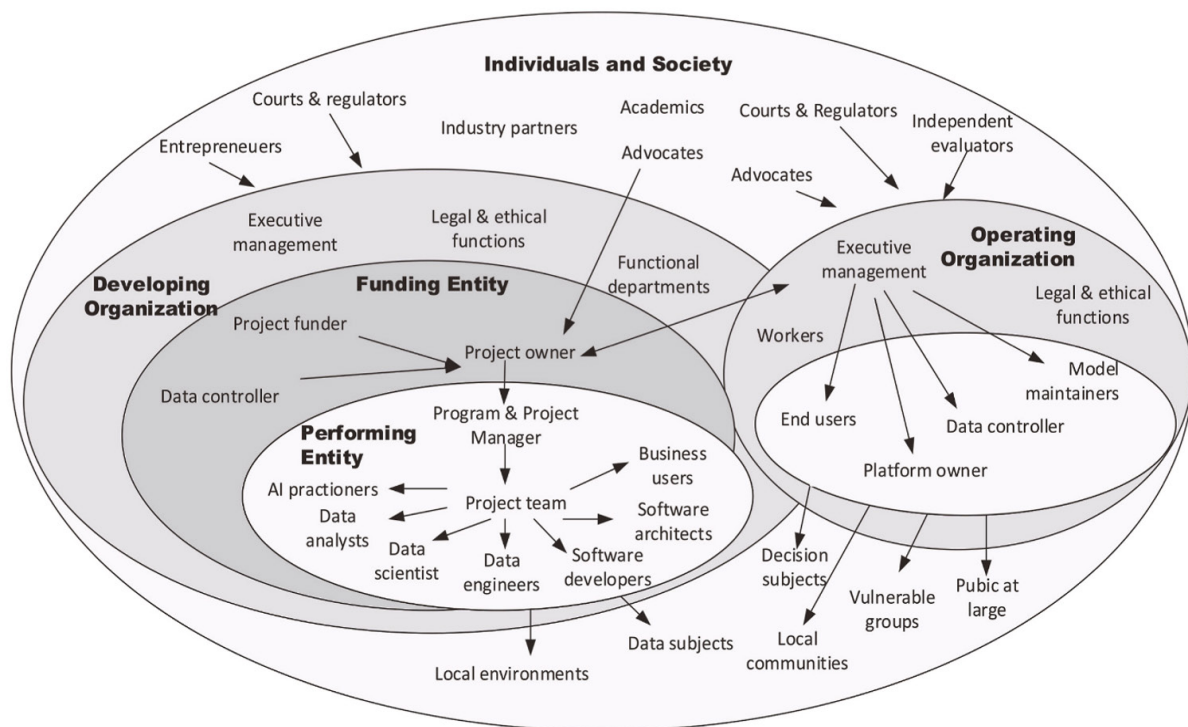


Figure 3: Groups of AI Community Members.

Note: Adapted from Miller (2022).

Stakeholder project role	Project role
Client	Operating organization, model maintainers, platform owners
Reference	Data controller and data custodian, functional departments, legal and ethical functions
Decision maker	Developing organization, executive management, project funder project and program managers, project owner, project team, operating organization, *end users
Designer	Project owner, project team (business users, data analyst, data scientist, data engineer, software architects, software developers, AI practitioners)
Passive	Data subjects, decision subjects, *end users, entrepreneurs, local communities, local environments, public at large, vulnerable groups, workers
Representatives	Advocates, courts and regulators, independent evaluators, labor unions
Note: * Extremely context dependent.	

Figure 4: Stakeholder Roles Within AI Projects.

Note: Adapted from Miller (2022).

Validity and Reliability

Validity and reliability are core quality criteria in research. They determine whether findings and conclusions are both “accurate” and “consistent”, which make them confidently usable for decision-making and further research (American Educational Research Association *et al.*, 2014).

Validity refers to the extent to which a study (or its instrument) correctly measures what it intends to examine and thus supports appropriate inferences from the data. This includes the adherence of construct to theory as well as content defensible measurement and criteria appropriateness. Reliability refers to the consistency and stability of measurement results when repeated under comparable/similar conditions, indicating that findings are not primarily driven by random error (Andersson *et al.*, 2024).

In quantitative designs, validity has two dimensions: (a) internal, which concerns whether observed effects represent the truth for the study population and are not driven by methodological problems such as measurement error or biased selection; and (b) external, which addresses the extent to which the findings are generalizable to other settings, groups, or contexts (Patino & Ferreira, 2018). Weak internal validity undermines causal or explanatory claims, whereas weak external validity limits applicability beyond the sample, even when results are internally sound. Reliability here is demonstrated through reproducibility metrics such as test–retest reliability, inter-rater reliability, and internal consistency, each addressing a different source of potential inconsistency (Shadish *et al.*, 2002).

In qualitative research, the equivalent concern is demonstrated through rigor and trustworthiness (such as credibility, dependability, and confirmability) supported by transparent procedures, audit trails, triangulation, and reflexive practice (Noble & Smith, 2015).

Reliability is significant because low reliability (a) attenuates observed effect sizes, (b) reduces statistical power, and (c) makes conclusions less precise; therefore, reliable measurement is a prerequisite for credible interpretation and quality study design. However, reliability alone is insufficient. A measure may show consistent results while still being invalid if it consistently captures the wrong construct or is systematically biased (Matheson, 2019). Together, validity and reliability strengthen confidence that research outcomes are both defensible and meaningful.

MATERIALS AND METHODS

This paper is a narrative, conceptual synthesis rather than an empirical study; no primary data were collected. Consistent with the “convenient access” and “development of earlier work” routes to a topic described above (Denscombe, 2010; Taylor *et al.*, 2016), material was drawn purposively from established research-methods texts (e.g., Bell *et al.*, 2022; Bougie & Sekaran, 2019; Creswell, 2023; Saunders *et al.*, 2023) and from recent peer-reviewed studies chosen to illustrate each concept in applied use (e.g., Deshpande & Sharp, 2022; Heikinniemi *et al.*, 2025; Kekkonen *et al.*, 2025; Miller, 2022).

Sources were selected against the seven areas that structure the paper: framing a topic through terms of reference; the correlational/predictive/experimental typology of quantitative designs; probability and non-probability sampling; the rationale and application of mixed methods; scoping versus systematic literature reviews; content versus thematic analysis; and validity and reliability. For each area, a small number of foundational texts was paired with one or two applied examples, and the material was organized to move from framing, through design and data-collection choices, to the quality criteria that judge the whole. Because the aim is to build

a decision-oriented framework for DBA students rather than to test a hypothesis, no sampling frame, instrument, or statistical procedure was applied, and no PRISMA-style systematic search protocol was followed.

RESULTS AND DISCUSSION

Read together, the reviewed material points to a single chain of reasoning that a DBA student can follow when designing a study. The topic and its terms of reference come first, because the aim and objectives determine what would count, scientifically, as an answer, and that in turn dictates whether a correlational, predictive, or experimental design is appropriate: correlational designs suit diagnostic mapping of patterns, predictive designs suit forecasting for operational decisions, and experimental designs suit causal claims, each trading internal validity against feasibility and generalizability in a different way (Jackson, 2008; Shadish *et al.*, 2002; Sheard, 2018).

Sampling strategy follows directly from that design choice: probability sampling is preferred when the purpose is to estimate population parameters with generalizable confidence, whereas non-probability sampling is often the more defensible option when the aim is exploratory, the subgroup is specialized, or a full sampling frame is unavailable (Aguinis *et al.*, 2018; Babbie, 1990; Fowler, 2002). Mixed-method designs become relevant when a single strand, quantitative or qualitative, would leave an important gap; their credibility rests less on combining two methods than on a transparent integration plan that specifies which strand leads, when the strands connect, and what will be done if findings diverge (Caruth, 2013; Creswell, 2023).

The choice between a scoping and a systematic literature review should track the maturity of the field: scoping reviews suit emerging or fragmented areas where the goal is to map concepts and gaps, while systematic reviews suit precise, well-defined questions where methodological discipline is needed to reduce bias (PRISMA, 2018; PRISMA, 2021; Smith & Duncan, 2022). A parallel logic applies to qualitative analysis: content analysis offers a structured, descriptive account of what is explicitly present in the data, while thematic analysis offers deeper interpretation of patterns of meaning, at the cost of greater variability between analysts (Guest *et al.*, 2012; Schreier, 2012; Vears & Gillam, 2022).

Validity and reliability cut across every one of these choices rather than sitting apart from them: a design can only be judged defensible once it is clear that it measures what it claims to measure (validity) and would produce consistent results under comparable conditions (reliability). Weak reliability erodes statistical power and precision, while a reliable but invalid measure still produces confidently wrong conclusions (Andersson *et al.*, 2024; Matheson, 2019). The overall implication for a DBA student is that framing, design, sampling, method, and literature strategy are not independent decisions; each constrains the next, and validity and reliability are the criteria against which the coherence of the whole chain should finally be checked.

CONCLUSION

Research must be systematic, controlled, rigorous, verifiable, objective, empirical, and critically scrutinized if its conclusions are to be trusted (Jackson, 2008; Shadish *et al.*, 2002). For a DBA student, this paper's practical recommendation is to work through the design choices in sequence rather than in isolation: start by fixing the aim, objectives, and research questions before selecting a design; let the nature of the intended claim, association, prediction, or causation, decide between correlational, predictive, and experimental designs; choose a sampling strategy that matches the design's purpose and is honestly reported; adopt a mixed-method design only where a clear integration rationale justifies the added complexity; match the type of literature review to the maturity of the field; select content or thematic analysis according to whether a descriptive or an interpretive account of the qualitative data is required; and treat validity and reliability as design criteria to be built in from the outset, not checks to be performed at the end. Following this sequence, and documenting the reasoning behind each step, is what allows a study's conclusions to be both defensible and useful for further research and practice.

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