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# Selling What Buyers Cannot Verify: Credence-Claim Conversion in the B2B Sale of AI-Enabled Diagnostic Equipment

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**Abstract:-** Artificial intelligence (AI) is increasingly embedded in the equipment that firms sell to organisational buyers, yet little is known about how AI claims are sold and evaluated when AI is the offering rather than the seller's tool, particularly in emerging markets where verification infrastructure is thin. Drawing on buying-centre, value-proposition and signalling theories, and treating AI performance as a difficult-to-verify credence attribute, this study examines the business-to-business sale of an AI-enabled dry haematology analyzer to hospitals and laboratories in Lagos and Abuja, Nigeria. An embedded single-case design combined 22 interviews; 10 with vendor-side actors and 12 with buyer-side participants from nine facilities—with nine sales, demonstration and tender documents. Vendors reported learning to position AI as supporting evidence rather than as the headline; buyers required evidence before crediting AI claims and ranked servicing, spare parts and cost per test first. None of the three tender documents scored AI-specific features, leaving user-level interest without a formal route into award criteria. The study theorizes credence-claim conversion: vendors make a hard-to-verify AI claim actionable through (1) attribute translation into observable operational benefits, (2) verification substitution through own-sample demonstrations and placements, and (3) borrowed trust in local service teams and peers. Conversion was associated with shorter decision pathways and with infrastructure conditions that favoured the dry format. The findings extend value-based selling and buying-centre theory to AI-enabled offerings, identify accountability allocation as a potential buying criterion, and yield six propositions for testing across markets.

**Keywords**: AI-enabled offerings, credence attributes, buying centre, value-based selling, emerging markets.

## 1. Introduction

Artificial intelligence (AI) is rapidly becoming part of what business-to-business (B2B) firms sell, not only how they sell. Industrial marketing research has examined AI mainly as an instrument of the selling firm: a source of market knowledge, a support for lead generation and forecasting, and a partner to the salesperson along the sales funnel [1], [2], [3], and as a capability whose adoption reshapes power within marketing organisations [4]. Far less is known about the reverse situation, in which AI is embedded in the offering and must itself be sold to an organisational buying centre. In that situation the vendor must persuade several buyers of the value of a capability that they usually cannot inspect, cannot easily test, and may not be able to evaluate even after purchase.

This problem sits uneasily with the dominant account of value-based selling. Value-based selling assumes that the supplier can understand the customer's business, quantify the value its offering creates, and communicate that value convincingly [5], [6], [7]. AI performance strains each assumption. Its benefits are probabilistic, depend on local data and workflows, and are difficult to verify before use; in economic terms, they resemble credence attributes whose quality buyers cannot readily ascertain [8], [9]. Signalling theory suggests that buyers facing such uncertainty will look for costly, credible signals [10], [11], [12], and recent experimental work shows that the effectiveness of B2B value-proposition signals depends on the buyer's context [13]. Yet little is known about which signals carry AI claims through a real, multi-actor purchase, or what happens to those claims when different members of the buying centre apply different criteria.

The problem is sharper in emerging markets. In many such markets the institutions that normally make product claims verifiable, such as independent testing, local clinical validation and strong regulatory signalling, are thin or absent, a condition described as institutional voids [14], [15]. Health systems in low- and middle-income countries also face a long-standing mismatch between imported medical devices and local infrastructure, staffing and maintenance capacity [16], [17]. Research on AI in Nigerian healthcare, which is growing quickly, has concentrated on clinicians' knowledge and attitudes, readiness and governance [18], [19], [20], [21]. It has not examined the commercial process through which AI-enabled equipment actually reaches hospitals and laboratories.

This study addresses that gap through an embedded case study of the B2B sale of an AI-enabled dry haematology analyzer by a multinational manufacturer in Lagos and Abuja, Nigeria. The analyzer combines sealed, room-temperature reagent cartridges with AI-driven image interpretation of blood-cell morphology, and competes against an entrenched installed base of conventional wet haematology analyzers that rely on liquid reagents and, often, manual microscopic review. The case is analytically valuable because the vendor must sell two things at once: a hard-to-verify AI capability and a change in workflow format. This allows the study to examine the role of AI alongside the role of the technology shift in which it is embedded. The study is guided by one central question and three sub-questions:

**RQ:** How is AI constructed and communicated as a value proposition in the B2B sale of AI-enabled diagnostic equipment, and how does this shape buying-centre decision-making in an emerging market?

RQ1: How do vendor actors frame AI-related value propositions, and how do they report adapting this framing?

**RQ2:** What criteria do buying-centre members use to credit, discount or set aside AI-related claims?

RQ3: How do participants describe institutional and infrastructural conditions in relation to whether AI claims are converted into purchase decisions?

Drawing on 22 interviews with vendor-side and buyer-side actors across nine facilities and nine sales and tender documents, the study makes three contributions. First, it conceptualizes AI performance as a difficult-to-verify credence claim in this setting and develops a model of credence-claim conversion, which explains how vendors make a hard-to-verify claim more actionable through attribute translation, verification substitution and borrowed trust. This extends value-based selling, which presupposes that value can be quantified and demonstrated, to offerings whose core value is opaque. Second, it extends buying-centre theory by identifying claim–criteria decoupling: AI claims were presented to and evaluated by users and influencers, while the tender criteria reviewed did not score AI-related features. It also identifies accountability allocation, captured in the buyer question "who checks it?", as a potential evaluation criterion in this case. Third, it suggests how institutional voids reshape signalling: in the absence of local validation infrastructure, buyers relied on relational and local-service signals, and participants attributed the innovation's appeal mainly to its fit with poor infrastructure rather than to its AI.

The researcher is employed in the manufacturer's commercial function. This insider position provided access to vendor-side actors and documents that are usually closed to researchers, and it is treated throughout as a source of both insight and potential bias, with safeguards described in Section 3.2. The remainder of the paper reviews the literature and theoretical background, describes the methodology, presents the findings, and develops the conversion model, propositions and implications.

## 2. Literature Review and Theoretical Background

### *2.1 Selling AI-Enabled Offerings in Business Markets*

The industrial marketing literature on AI has developed along two lines. The first treats AI as a tool for marketing and sales: AI generates market knowledge [1], augments salespeople at each stage of the funnel [2], [3], and is adopted through negotiated changes in power within marketing functions [4]. The second, much smaller line examines how buyers respond to vendor value propositions for new technologies. Aksoy and Schnellbächer [13], for example, show experimentally that monetization, certification and risk-based strategies for communicating

sustainable value propositions each raise B2B purchase intentions for green technologies, and that buyers' market turbulence changes which strategy works best. Neither line has examined offerings in which AI is the core of what is sold to an institutional buying centre.

Value-proposition research provides the most relevant normative account. Anderson et al. [5] argues that effective customer value propositions in business markets focus on a few points of difference that matter most to the customer and are substantiated with documented, quantified evidence of value. Subsequent work has extended the value proposition from a seller's statement to a reciprocal, communicated promise that is shaped by the buyer's own value-in-use [22], [23], and has conceptualised value-based selling as a set of capabilities for understanding, crafting and communicating customer value [6], [7]. This literature presumes that value, once understood, can be demonstrated and quantified. It says little about offerings whose central value proposition is difficult to verify before purchase, which is precisely the condition of AI-enabled diagnostic equipment.

### *2.2 AI Performance as a Credence Attribute*

Information economics distinguishes search attributes, which buyers can evaluate before purchase; experience attributes, which they can evaluate only through use [9]; and credence attributes, which they cannot readily evaluate even after use [8]. Where quality is hidden, markets are vulnerable to adverse selection [24], and sellers of high-quality offerings need signals that low-quality sellers find costly to imitate [10], [11], [12].

In this setting, the performance of an AI-based diagnostic function had credence characteristics because buyers lacked independent reference standards with which to assess its accuracy. A demonstration could expose buyers to the system's operation, but it did not by itself establish diagnostic accuracy. A laboratory can observe whether an analyzer produces results quickly, but whether its automated morphology classification is correct, and under what conditions it fails, depends on validation that the buyer typically cannot perform. Clinical AI research documents that performance reported in development can degrade with new populations, equipment and workflows [25], [26]. Research on human responses to algorithms adds a behavioural layer: people discount algorithms after seeing them make errors [27], resist medical AI in particular [28], and calibrate their trust in AI through its tangibility, transparency and reliability [29]. In Nigeria, concern about unverified vendor performance claims for deployed health AI has begun to emerge [30]. Together, these strands imply that an AI claim is unlikely to persuade a professional buyer on its own; the question is what the vendor can do to make it credible.

### *2.3 Buying Centres and Institutional Purchasing of Medical Equipment*

Webster and Wind [31] conceptualized organisational purchasing as a multi-actor process involving users, influencers, buyers, deciders and gatekeepers, shaped by environmental, organizational, interpersonal and individual factors. Later work showed that the structure and interaction patterns of the buying centre vary with the complexity and risk of the purchase [32] and integrated these insights into broader models of organisational buying behaviour [32]. A consistent implication is that a vendor's claim does not meet "the buyer" but a distributed set of actors with different criteria and different degrees of formal power.

Purchasing of medical equipment in low- and middle-income countries adds two features. First, procurement is frequently governed by formal tender procedures and prioritization methods, which codify decision criteria in documents [16]. Second, a recurrent mismatch between imported devices and local infrastructure, maintenance capacity and staffing mean that after-sales service and supply continuity weigh heavily in decisions [17]. In such markets, buyer–seller trust is not merely an outcome of the relationship [33], [34] but a substitute for missing institutional guarantees. Zucker [35] distinguishes process-based, characteristic-based and institution-based sources of trust; where institutional sources are weak, as in contexts marked by institutional voids [14], [15], process-based and relational sources may carry more of the load.

### *2.4 Disruption and Diffusion in Resource-Constrained Health Systems*

Disruptive innovation theory holds that disruptive offerings typically enter through a low-end or new-market foothold, offering simplicity, convenience or affordability to customers, that incumbents overserve or ignore, rather than outperforming incumbents on established dimensions [36], [37]. Its application to health care emphasizes business-model and workflow simplification [38], [39]. Christensen et al., [37] caution against

labelling any radical technology as disruptive; the theory concerns the trajectory of market entry, not novelty per se, and its predictive claims remain debated [40]. Related work on frugal innovation in emerging markets similarly stresses robustness and fit with local constraints [41].

Diffusion of innovations theory complements this view by identifying relative advantage, compatibility, complexity, trialability and observability as attributes that shape adoption [42]. Health-service research shows that these attributes interact with organizational readiness, system antecedents and the wider context [43], and that technologies are frequently abandoned or fail to scale because of complexity across multiple domains [44]. For the present case, these lenses raise a specific question: is the disruptive appeal of an AI-enabled dry analyzer carried by its AI, by its format, or by both?

### *2.5 AI in Nigerian Healthcare and the Research Gap*

Research on AI in Nigerian and African healthcare has documented promise alongside barriers of infrastructure, data, skills and governance [45], [46]. Surveys of Nigerian health professionals report favourable attitudes towards AI together with concerns about guidelines, privacy, bias and infrastructure [18], [47]. Consultant doctors in tertiary hospitals describe AI as potentially transformative but dependent on training, regulation and infrastructure [21]. Reviews characterize AI deployment in Nigeria as limited and sparsely documented [19], [20]. A perspective by investigators involved in the SPEC-AI Nigeria trial discusses contextual challenges related to human resources and infrastructure [48], and a multi-case study of Nigerian healthcare leaders who implemented AI-based devices identifies financing and infrastructure as central adoption factors, without vendor-side data [49].

Read together, these literatures leave a specific gap. B2B research on AI has studied AI as the seller's tool rather than as the offering; value-based selling presumes verifiable value; signalling research on B2B value propositions has been conducted largely in high-income, experimental settings; and Nigerian AI-in-health research has examined clinicians, policymakers and implementers but not the commercial process through which AI claims are constructed, communicated and weighed. Within the literature reviewed, no study traces how an AI claim travels through a real buying centre for diagnostic equipment in an emerging market.

### *2.6 Sensitizing Framework*

Figure 1 summarizes the a priori framework that sensitized the inquiry. It positions the vendor's AI-related value proposition as a set of signals that pass through the buying centre, where users, influencers, buyers, deciders and gatekeepers evaluate them against role-specific criteria, and through contextual filters of infrastructure, finance and procurement rules before reaching a purchase decision. Three sensitizing propositions informed, but did not constrain, the analysis: (a) vendors construct AI claims differently depending on how far they judge the buyer to understand and trust the underlying technology shift; (b) buyers weigh AI claims against, and frequently subordinate them to, established non-AI criteria such as servicing, financing and workflow familiarity; and (c) Nigeria-specific conditions shape not only whether AI-enabled equipment is purchased but how its value can credibly be communicated. Section 5 revisits each proposition in light of the findings.

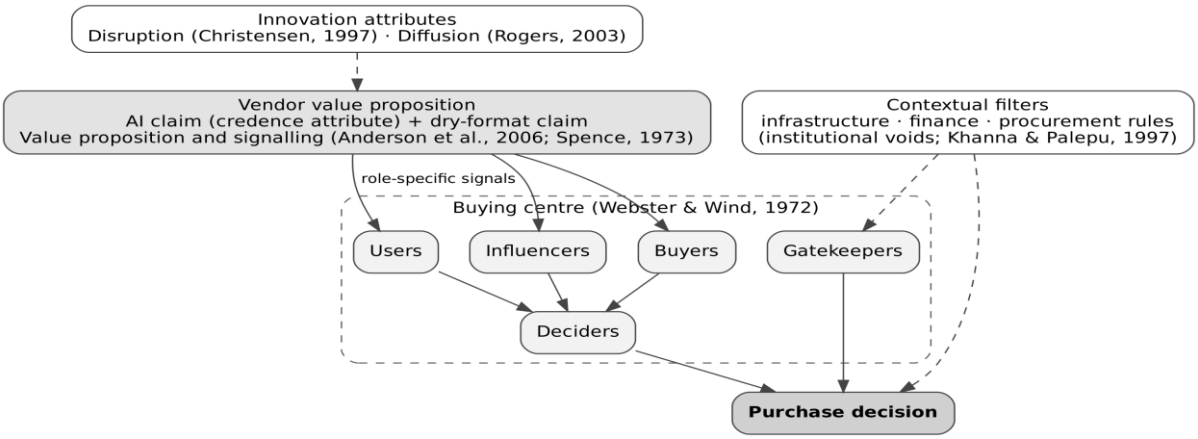



***Figure 1.*** *Sensitizing framework guiding the inquiry.*

## 3. Methodology

### *3.1 Research Design and Case Selection*

The study adopted a qualitative, interpretive case design suited to "how" questions about processes that unfold over time in their real-world context [50] and to theory elaboration where existing constructs are only partly adequate [51]. Following the systematic-combining approach common in industrial marketing case research, the analysis moved iteratively between the empirical case, the sensitizing framework and the literature, revising the framework as the case revealed unanticipated patterns [52], [53].

The case is the Nigerian market entry of a multinational manufacturer's AI-enabled dry haematology analyzer. It was selected purposively as a theoretically revealing case [50] for two reasons. First, the vendor must sell both an AI capability that buyers cannot readily verify independently and a change of format (dry cartridges versus wet reagents), which supports examining the role of AI alongside the role of the technology shift. Second, the setting combines an import-dependent device market, a strong incumbent installed base and thin local verification infrastructure, conditions under which the credence problem described in Section 2.2 should be pronounced. The design is embedded [50], with two units of analysis: (a) vendor sales encounters, where the value proposition is constructed and communicated; and (b) buying-centre evaluations in hospitals and laboratories, where the proposition is interpreted and weighed. Examining both units allow the study to trace a value proposition from construction to reception, and to identify where vendor and buyer accounts converge and diverge. Lagos and Abuja were included to capture variation in institutional settings, not to represent either city or Nigeria as a whole; the aim is analytical rather than statistical generalisation.

The analyzer and manufacturer are referred to generically to protect commercial confidentiality and reduce the risk of deductive identification in this small, insider-research setting. The study examines how AI-related value propositions are communicated and evaluated in organisational purchasing; it does not assess the device's diagnostic accuracy, regulatory status or clinical effectiveness, which are outside its scope.

### *3.2 Researcher Position and Safeguards*

The research is employed in the focal manufacturer's commercial function. Insider research offers access, pre-understanding and the ability to interpret tacit practice, but carries risks of role duality, over-familiarity and social desirability [54], [55]. These risks are acute in the present design because buyer-side participants were current or prospective customers. The following safeguards were applied. Participants were informed that the study was academic, voluntary and independent of any commercial process, and that declining or withdrawing would have no commercial consequence. Vendor-side participants were recruited through a neutral, non-managerial channel, and no participant reported to the researcher. All interviews, including those with buyer-side participants, were conducted by the researcher, who introduced himself in his academic capacity, did not discuss prices, offers or orders, and assured buyers that their comments would not be shared in identifiable form with the vendor's sales team. Interviews began with general questions about equipment purchasing before turning to the focal product, and participants were explicitly invited to describe negative experiences and competing products. Commercially sensitive information was excluded. A reflexive journal was kept throughout; for example, an early entry recorded the researcher's expectation that AI would be the decisive selling point; repeated buyer accounts that ranked servicing and cost per test first led to this assumption being abandoned and informed the development of the attribute-translation code. The manufacturer gave written permission to conduct and publish the study but did not review or approve the manuscript before submission. The researcher's employment is declared in the conflict-of-interest statement.

### *3.3 Sampling Strategy and Participants*

Participants were selected purposively, combining criterion and maximum-variation strategies [56]. Criterion sampling ensured that every participant had direct experience of constructing or evaluating an AI-related value proposition for diagnostic equipment; maximum-variation sampling sought diversity in role, facility ownership and type, location and decision outcome. The vendor-side group comprised sales representatives, sales and marketing managers, and distributor staff with direct experience of selling diagnostic equipment in Nigeria. The

buyer-side group comprised buying-centre members who had taken part in evaluating or approving haematology analyzer purchases in Lagos or Abuja. Individuals without a direct role in the purchase process and individuals reporting to the researcher were excluded. Participants were approached directly or by referral and received study information and consent materials in advance.

Table 1 shows the planned sampling frame. The final sample comprised 22 participants: 10 vendor-side and 12 buyer-side, all within the planned range for each group. Sample adequacy was judged by information power rather than by saturation [57], [58]: the study aim was narrow, participants were highly specific to it, the analysis was supported by established theory, interview dialogue was rich, and the analysis compared cases within an embedded design. Table 2 presents participant profiles. Buyer-side participants represented nine facilities: three public tertiary facilities, three private secondary or tertiary facilities, and three stand-alone laboratories. At the time of data collection, four facilities had purchased the analyzer, three were evaluating it, and two had declined.

**Table 1.** ***Planned sampling frame and achieved sample***

| Participant group | Buying-centre or vendor role | Target n | Achieved n | Settings |
|---|---|---|---|---|
| Vendor: sales representatives | Construct and deliver the value proposition | 4–5 | 4 | Lagos, Abuja |
| Vendor: sales and marketing managers | Shape positioning, training and pricing approach | 2–3 | 3 | Lagos, Abuja |
| Vendor: distributor staff | Mediate between manufacturer and buyer | 2–3 | 3 | Lagos, Abuja |
| Buyer: procurement officers | Buyers and gatekeepers | 3–4 | 3 | Public and private facilities |
| Buyer: laboratory scientists and biomedical engineers | Users (scientists); influencers (engineers) | 4–5 | 5 | Public and private facilities |
| Buyer: medical and laboratory directors, consultant pathologists | Deciders (directors); influencers (pathologists) | 3–4 | 4 | Public and private facilities |
| Total | | 18–24 | 22 | |

**Table 2.** ***Participant profile***

| Code | Group and role | Facility | Facility type and ownership | Location | Decision outcome |
|---|---|---|---|---|---|
| V01 | Vendor: sales representative | – | – | Lagos | – |
| V02 | Vendor: sales representative | – | – | Abuja | – |
| V03 | Vendor: sales representative | – | – | Lagos | – |
| V04 | Vendor: sales representative | – | – | Abuja | – |
| V05 | Vendor: sales and marketing manager | – | – | Lagos | – |
| V06 | Vendor: sales and marketing manager | – | – | Lagos | – |
| V07 | Vendor: sales and marketing manager | – | – | Abuja | – |
| V08 | Vendor: distributor staff | – | – | Lagos | – |
| V09 | Vendor: distributor staff | – | – | Lagos | – |
| V10 | Vendor: distributor staff | – | – | Abuja | – |
| B01 | Buyer: procurement officer | F1 | Public tertiary | Lagos | Evaluating |
| B02 | Buyer: laboratory scientist | F1 | Public tertiary | Lagos | Evaluating |
| B03 | Buyer: consultant pathologist | F2 | Public tertiary | Abuja | Declined |
| B04 | Buyer: procurement officer | F2 | Public tertiary | Abuja | Declined |
| B05 | Buyer: biomedical engineer | F3 | Public tertiary | Abuja | Evaluating |
| B06 | Buyer: medical director | F4 | Private secondary/tertiary | Lagos | Purchased |
| B07 | Buyer: laboratory scientist | F4 | Private secondary/tertiary | Lagos | Purchased |
| B08 | Buyer: procurement officer | F5 | Private secondary/tertiary | Lagos | Purchased |
| B09 | Buyer: laboratory scientist | F6 | Private secondary/tertiary | Abuja | Declined |
| B10 | Buyer: laboratory scientist | F7 | Stand-alone laboratory | Lagos | Purchased |

| Code | Group and role | Facility | Facility type and ownership | Location | Decision outcome |
|---|---|---|---|---|---|
| B11 | Buyer: laboratory director | F8 | Stand-alone laboratory | Lagos | Purchased |
| B12 | Buyer: consultant pathologist | F9 | Stand-alone laboratory | Abuja | Evaluating |

**Note.** Facility codes allow the facility-level outcome counts in the text (four purchased, three evaluating, two declined) to be traced to participants.

### *3.4 Data Collection Methods*

Semi-structured, one-to-one interviews were conducted between June and August 2026 using parallel guides for vendor-side and buyer-side participants (Appendix A). Interviews were conducted in English, in person at participants' workplaces or by video call where travel was impractical, and were audio-recorded with permission and transcribed verbatim. Interviews lasted 41 to 67 minutes (mean 53). After each interview the researcher wrote field notes and a reflexive memo recording context, non-verbal cues and emerging interpretations.

Nine documents supplemented the interviews to triangulate participants' accounts with documentary evidence: four sales brochures, two demonstration protocols, and three customer tender documents containing specifications and evaluation criteria. Tender documents were provided by the issuing facilities with the permission of their procurement units, or were obtained from publicly advertised tender notices. Documents containing pricing or other commercially sensitive terms were excluded or redacted. The documents were used to examine whether, and how, AI-related features appeared in vendor communication and in formal procurement criteria.

### *3.5 Data Analysis Procedures*

The analysis used codebook thematic analysis [57], [59] embedded in a systematic-combining logic [52]. This choice reflects the study's abductive design: a provisional codebook was derived from the sensitizing framework and the interview guides (Appendix B), and was then revised, merged and extended inductively as the analysis proceeded. Three codes developed inductively (accountability for AI error, borrowed trust and new supplier dependence) proved central to the final model. NVivo was used to manage data and analytic records.

The analysis proceeded in four steps. First, transcripts, field notes and documents were read repeatedly and coded line by line, with attention to participants' own language. Second, vendor-side and buyer-side materials were coded separately and then compared for convergence and divergence; buyer-side accounts were further compared by location, facility ownership and decision outcome. Third, codes were clustered into 14 sub-themes and five themes, which were reviewed against the full data set. Fourth, the themes were synthesized into five aggregate dimensions, one of them cross-cutting, that inform the conversion model in Section 5. Figure 2 uses the first-order concepts, second-order themes and aggregate dimensions terminology associated with Gioia et al.,[60] to display the analysis; codebook thematic analysis, rather than the full Gioia methodology, was the analytic approach.

A second analyst (an experienced qualitative researcher not employed by the manufacturer) independently reviewed approximately 20% of transcripts against the codebook. Differences were resolved through discussion and used to refine code definitions, rather than to compute inter-coder reliability coefficients. Participant counts are reported in the findings to indicate how widely a pattern was shared within this sample (Table 4); they describe the sample and are not estimates of prevalence.

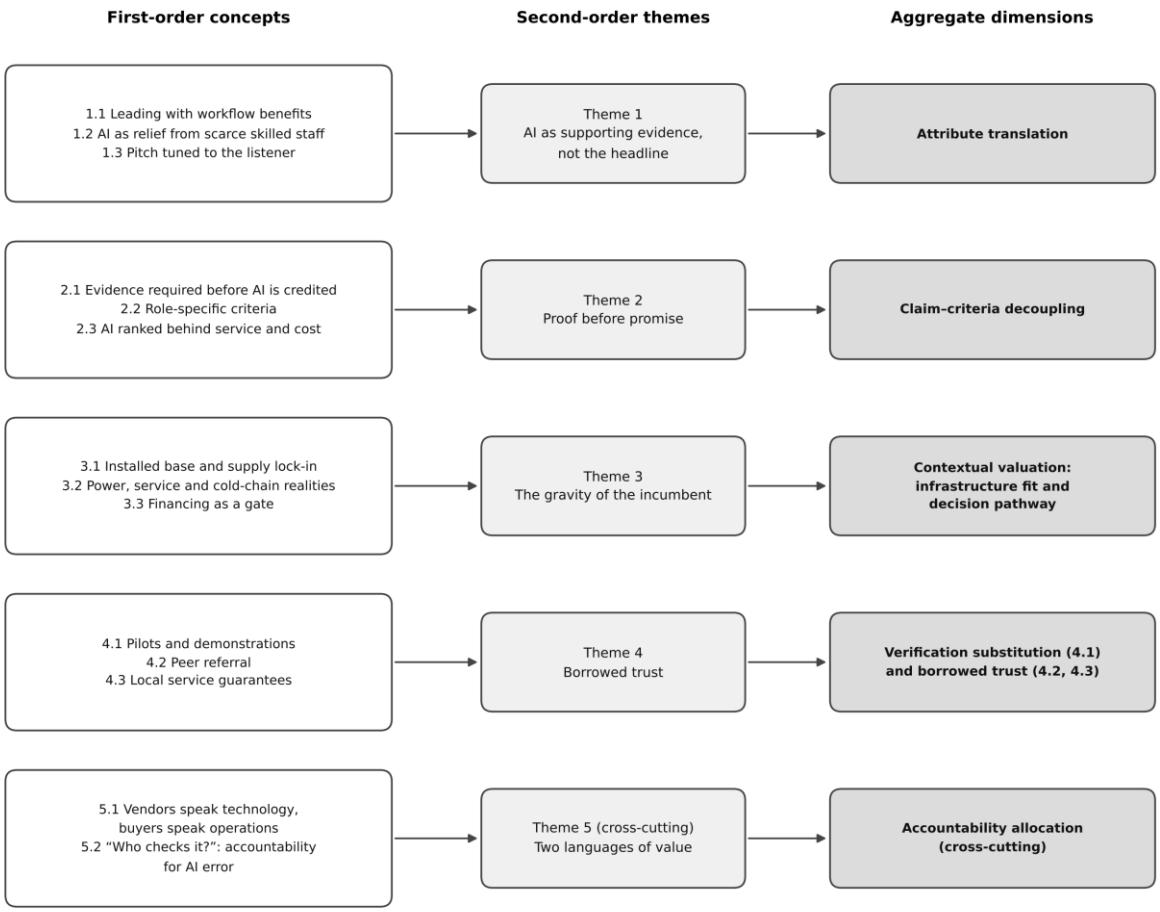



**Figure 2.** Data structure [60]

### *3.6 Trustworthiness and Ethics*

Table 3 summarises the tactics used to address the trustworthiness criteria of credibility, transferability, dependability and confirmability [61]. Reporting follows the COREQ checklist [62] and the recommendations of Lindgreen et al.,[63] for writing up case-study methodology in industrial marketing.

**Table 3. Trustworthiness criteria and tactics**

| Criterion | Tactics used in this study |
|---|---|
| Credibility | Triangulation across vendor-side accounts, buyer-side accounts and documents; member checking of emerging themes with five participants (two vendor-side and three buyer-side), which led to clarified theme labels but no substantive change in interpretation; retention and reporting of disconfirming cases; review of approximately 20% of transcripts by a second analyst. |
| Transferability | Thick description of the case, product, market and facility types; explicit boundary conditions; propositions formulated for testing in other contexts. |
| Dependability | Audit trail of codebook versions, memos and analytic decisions in NVivo; documented interview guides and procedures (Appendices A and B). |
| Confirmability | Reflexive journal and post-interview memos; insider safeguards (Section 3.2); systematic comparison of vendor and buyer accounts to detect vendor-favourable bias. |

The study examined professional purchasing practices through interviews with adult professionals and commercial documents, without involving patients, clinical interventions, or patient-level data. Participation was voluntary, while written informed consent was obtained from all participants, and people, facilities, and commercially sensitive terms were anonymized. To reduce the risk of deductive identification, participant roles are reported at a general level and facilities are identified only by code.

## 4. Findings

### *4.1 Overview*

The analysis generated five themes and 14 sub-themes, abstracted into five aggregate dimensions (Figure 2; Table 4). Themes 1 to 4 correspond to the sub-questions; Theme 5 cuts across them. Vendor-side and buyer-side accounts are presented together to show where they converge and diverge. Participants are identified by code, role and setting. Theme 4 informs two of the three conversion mechanisms developed in Section 5.1: demonstrations and placements (sub-theme 4.1) underpin verification substitution, whereas peer referral and local service guarantees (sub-themes 4.2 and 4.3) underpin borrowed trust. Findings report participants' accounts and the documents reviewed; counts describe this sample and are not estimates of prevalence.

**Table 4. Data structure: themes, sub-themes and contributing participants**

| Aggregate dimension | Theme | Sub-themes | RQ | Vendor (of 10) | Buyer (of 12) |
|---|---|---|---|---|---|
| Attribute translation | 1. AI as supporting evidence, not the headline | 1.1 Leading with workflow benefits; 1.2 AI as relief from scarce skilled staff; 1.3 Pitch tuned to the listener | RQ1 | 10 | 10 |
| Claim–criteria decoupling | 2. Proof before promise | 2.1 Evidence required before AI is credited; 2.2 Role-specific criteria; 2.3 AI ranked behind service and cost | RQ2 | 10 | 12 |
| Contextual valuation | 3. The gravity of the incumbent | 3.1 Installed base and supply lock-in; 3.2 Power, service and cold-chain realities; 3.3 Financing as gate | RQ3 | 10 | 11 |
| Verification substitution and borrowed trust | 4. Borrowed trust | 4.1 Pilots and demonstrations; 4.2 Peer referral; 4.3 Local service guarantees | RQ1, RQ3 | 10 | 10 |
| Accountability allocation (cross-cutting) | 5. Two languages of value | 5.1 Vendors speak technology, buyers speak operations; 5.2 "Who checks it?": accountability for AI error | All | 7 | 8 |

**Note.** Counts show how many participants contributed to each theme in this sample; they are not estimates of prevalence. Documentary evidence: Theme 1, four sales brochures; Theme 2, three tender documents; Theme 3, three tender documents (weighting of servicing and delivery terms); Theme 4, two demonstration protocols.

### *4.2 Theme 1: AI as Supporting Evidence, Not the Headline*

Vendors presented the AI component as supporting evidence for an operational case rather than as the headline of the sale (RQ1). They described introducing the analyzer through its operational features and bringing in the AI afterwards. Seven of the ten vendors framed the AI chiefly as a way to reduce dependence on scarce skilled staff for slide review, whereas three emphasized the consistency of cell classification. Vendors described this framing as learned. Nine of ten said they had stopped leading with the term "AI" after early meetings in which it prompted questions they could not answer to the buyer's satisfaction; the exception, a distributor (V08), still regarded AI as decisive for younger laboratory staff (Section 4.7). Vendors also tuned their language to the listener: engineers heard about sealed cartridges and maintenance, directors about turnaround time, and procurement officers about cost per test.

"I used to open with the AI. Now I open with what it saves them: no reagent handling, no waiting for the one person who can read slides. The AI comes in when they ask how it knows." (V03, sales representative, Lagos)

Buyer-side accounts largely matched this framing, but with a different emphasis. Ten of twelve recalled the AI element as secondary or unclear in the first presentation; seven of them could describe the operational benefits accurately but not what the AI actually did. Two described the AI claim as marketing language until they saw a live demonstration. Vendors and buyers diverged on the purpose of the AI message: vendors intended it as reassurance, whereas several buyers heard it as a reason for caution.

"They said it was AI-driven and I thought, fine, but what happens when it is wrong? Nobody told me who checks it." (B05, biomedical engineer, public tertiary facility, Abuja)

The shift from wet to dry analysis, by contrast, was readily understood. Eight of ten vendors and nine of twelve buyers named room-temperature storage and the absence of liquid reagent handling as the most tangible difference. Three buyers worried whether clinicians used to wet-analyzer output would accept results from a dry system, a concern absent from vendor accounts. For most participants the format shift was easier to grasp and weigh than the AI component. Analytically, vendors were translating a credence attribute (the correctness of AI classification) into search and experience attributes that buyers could observe (no reagent handling, less dependence on scarce staff, faster turnaround). This mechanism is termed here attribute translation.

### *4.3 Theme 2: Proof Before Promise*

Most buyers said they required verifiable evidence before crediting AI claims, and they generally ranked servicing, spare parts and cost per test ahead of AI features (RQ2). Vendors anticipated this: they believed buyers decided mainly on price per test, servicing and financing. Eight of ten said laboratory scientists were the most receptive to AI claims and procurement officers the least, and several said directors tended to defer to what their scientists reported.

"The scientist wants to see it work. The procurement officer wants to see the contract. Neither is moved by the word AI." (V06, sales and marketing manager, Lagos)

Buyers described role-specific criteria. Eleven of twelve said they would not credit an AI claim without evidence they could verify. The forms of evidence they named were a demonstration on their own samples (nine), results from a peer facility (seven) and published validation (four). All three procurement officers ranked servicing and total cost above any technology feature. Laboratory scientists were more open to AI but wanted to know how results could be reviewed and overridden. The medical director and the laboratory director regarded AI features as relevant mainly if they shortened turnaround time for clinicians (Table 6).

"Before I approve anything I ask three questions: who services it, how fast do they come, and what happens when the reagent runs out. The AI is the fourth question, if I get to it." (B08, procurement officer, private facility, Lagos)

Past disappointments made verification demands durable. Three buyers described an earlier purchase, not from the focal manufacturer, in which advertised automation features were unavailable or unreliable after installation; each said this led them to demand proof from every later vendor. One negative case stood out: the laboratory director of a stand-alone laboratory accepted the AI claim largely on the manufacturer's international reputation and reported being satisfied after purchase, an instance of characteristic-based trust standing in for verification.

"I know the manufacturer. If they say it works, I am prepared to trust that." (B11, laboratory director, stand-alone laboratory, Lagos)

The documents revealed a structural reason why AI claims had limited power. AI features had prominent space in all four sales brochures. None of the three tender documents in this corpus scored AI-related features as a criterion; two required demonstrated compatibility with existing laboratory information systems, and all three weighted servicing and delivery terms. Thus, even if a claim persuaded a laboratory scientist, the reviewed tender criteria provided no formal route for that claim to affect the documented award scoring. This pattern is termed here claim–criteria decoupling.

### *4.4 Theme 3: The Gravity of the Incumbent*

Existing wet analyzers, supply arrangements and infrastructure pulled buyers towards the familiar, yet the same conditions made the dry format attractive at some sites (RQ3). Vendors named power supply, service coverage, financing and the installed base of wet analyzers as the main constraints (nine, nine, eight and seven of ten, respectively). They responded by stressing that the cartridge format needs no cold chain, by offering demonstration units and, in four cases, by arranging staged payment through the distributor.

"Everybody has a wet analyzer already; with a reagent supplier they know. We are not competing with a machine. We are competing with a habit." (V09, distributor staff, Lagos)

Buyers ranked the constraints differently. Servicing and spare-parts availability were decisive for ten of the eleven buyers who discussed constraints. Financing was decisive for the four private-facility participants who commented on it, whereas public-facility participants emphasized tender procedures and budget cycles, neither of which featured among the main constraints named by vendors. Seven buyers described existing reagent supply arrangements and staff training as switching costs. Public and private facilities differed mainly in their decision pathway: public tertiary participants described multi-stage approval, whereas private participants described a shorter route through a director.

"Even if the committee likes it, it must pass through budget and tender. By then the person who liked it may have been transferred." (B04, procurement officer, public tertiary facility, Abuja)

In several accounts, however, the constraints increased the appeal of the dry format. Six buyers, five of them from private facilities or stand-alone laboratories, said that room-temperature storage and low maintenance would suit sites with unreliable power or limited technical staff. Two buyers worried that dependence on a single proprietary cartridge supplier would create a new lock-in. Contextual constraints therefore weakened the value proposition at some sites and strengthened it at others.

"We lose reagents when the power goes. Something that sits on a shelf at room temperature, that is not a small thing for us." (B10, laboratory scientist, stand-alone laboratory, Lagos)

### *4.5 Theme 4: Borrowed Trust*

Because buyers could not readily assess AI performance independently, demonstrations, peer experience and visible local service served as practical evidence and trust proxies in their accounts (RQ1, RQ3). Vendors described using live demonstrations (ten of ten), evaluation placements (six), peer references (eight), training (seven) and service commitments (nine). Published validation did not feature among the mechanisms they described. They judged evaluation placements the most effective, because buyers could test the analyzer on their own samples, but also the costliest and the hardest to get approved internally.

"Once it is in their lab for two weeks, the conversation changes. But getting the placement agreed can take longer than the sale." (V05, sales and marketing manager, Lagos)

Ten of twelve buyers said they would not consider the analyzer at all without a demonstration or evaluation on their own samples (a precondition for consideration, broader than the own-sample evidence nine cited for the AI claim itself; Section 4.3), and nine named peer experience as influential in their overall purchase deliberations, a broader category than the peer results cited as evidence for the AI claim. Trust attached less to the manufacturer than to the local distributor and the individual representative: seven buyers said they would judge the analyzer by whether the local team would respond when something failed.

"I trust the people who will come when it breaks. The brochure does not come when it breaks." (B12, consultant pathologist, stand-alone laboratory, Abuja)

Both demonstration protocols provided for testing the analyzer on the facility's own patient samples alongside its existing analyzer; only one described step for reviewing and overriding AI-generated morphology flags, and neither specified who was accountable for an erroneous automated result. In signalling terms, an evaluation placement or a credible service commitment may function as a costly signal because it requires vendor resources and may be difficult for a firm with an inferior offering to imitate [12]. Peer references are a separate, third-party signal. Two distinct conversion mechanisms are visible. Participants treated own-sample demonstrations and placements as experience-based evidence; this study terms their role in the purchase process verification substitution. These trials should not be equated with independent clinical validation. Peer references and local service commitments transfer trust from people and relationships to the product, which this study terms borrowed trust.

### *4.6 Theme 5: Two Languages of Value and the Accountability Question*

Across the first four themes, vendors and buyers spoke different languages of value (sub-theme 5.1). Seven vendors and eight buyers made remarks that illustrated this: vendors described the analyzer in terms of technology and capability, buyers in terms of operations and risk.

"I talk about what the machine can do. They ask what happens on a bad day." (V07, sales and marketing manager, Abuja)

The clearest expression of this gap was the question "who checks it?" (B05), captured in sub-theme 5.2, accountability for AI error. For vendors, AI meant less manual review and therefore relief from scarce skilled staff. For some buyers, the same feature raised the question of who would be accountable if the system erred. A claim intended as reassurance was heard as a transfer of risk. This emergent buying criterion is termed here accountability allocation: the demand that an AI-enabled offering specify who reviews, who can override and who answers for an automated result.

### *4.7 Cross-Case Patterns and Disconfirming Cases*

Decision outcomes varied across the nine facilities, but city, ownership and decision pathway cannot be disentangled in this small sample. All four purchasing facilities were in Lagos and were private or stand-alone laboratories; no facility in Abuja had purchased the analyzer. Participants in private facilities and stand-alone laboratories described shorter decision pathways and greater openness to the dry format, while public tertiary participants described tender procedures and peer evidence as important. Lagos participants, vendor-side and buyer-side combined, more often mentioned competing suppliers and price pressure (seven of 13), whereas Abuja participants more often mentioned procurement rules and approval chains (five of nine). These site and facility context patterns are reported here rather than as a separate sub-theme. All four purchasing facilities had experienced an on-site demonstration or placement, so the study cannot separate the role of demonstrations from the characteristics of the purchasing sites.

Three accounts did not fit the main patterns and were retained in the analysis. B11 accepted the AI claim on the strength of the manufacturer's reputation (Section 4.3). One distributor (V08) argued that AI was the decisive selling point for younger laboratory staff, which no buyer confirmed. A public-facility laboratory scientist (B02) was keen to adopt but had no budget route, which qualifies the link between enthusiasm and purchase. Table 5 compares vendor-side and buyer-side perspectives, and Table 6 maps buying-centre roles to the evaluation of AI claims.

**Table 5. Vendor-side and buyer-side perspectives compared**

| Dimension | Vendor-side view | Buyer-side view | Point of divergence |
|---|---|---|---|
| How the AI component is described | Supporting evidence for an operational case; relief from scarce skilled staff | Secondary or unclear at first presentation; often heard as a reason for caution | Vendors intend reassurance; buyers hear risk |
| Weight of AI relative to non-AI criteria | Price per test, servicing and financing decide; scientists most receptive to AI | Servicing, cost per test and spares first; AI considered afterwards | Broadly aligned; buyers more emphatic |
| Wet-to-dry technology shift | Sold as convenience: room-temperature storage, no liquid reagent handling | Easy to grasp; concerns about clinician acceptance (3) and cartridge-supplier dependence (2) | Buyers raise acceptance and lock-in; vendors did not |
| Evidence needed for credibility | Live demonstrations, placements, peer references, training, service commitments | Own-sample demonstration (9), peer results (7), published validation (4) | Some buyers seek published validation; no vendor described offering it |
| Main barriers in the Nigerian context | Power, service coverage, financing, installed base | Service and spares; tender procedure and budget cycles (public); switching costs | Tender procedure and budget cycles absent from the constraints vendors named |

**Table 6.** ***Buying-centre roles and the evaluation of AI-related claims***

| Buying-centre role | Participants | How AI claims are evaluated | Main concerns | Evidence (n) |
|---|---|---|---|---|
| Users | Laboratory scientists | Open to AI if results can be reviewed and overridden; test on own samples | Accountability for errors; workflow disruption | 4 |
| Influencers | Biomedical engineers, consultant pathologists | Judge technical credibility and validation | Servicing, validation, single-supplier risk | 3 |
| Buyers | Procurement officers | Treat AI as secondary to servicing and cost per test | Contract terms, budget, tender rules | 3 |
| Deciders | Medical and laboratory directors | Defer largely to scientists; interested if turnaround improves | Turnaround, reputation, risk | 2 |
| Gatekeepers | Tender committees and budget offices (described, not interviewed) | Screen on documented criteria in which AI is not scored | Compliance with tender rules | 0 (3 tender documents) |

## 5. Discussion

### *5.1 A Model of Credence-Claim Conversion*

The findings suggest that AI functioned less as a selling point than as a claim that buyers required vendors to earn. Figure 3 integrates them into a model of credence-claim conversion. The model starts from the premise, developed in Section 2.2, that the performance of an AI-based diagnostic function is a credence attribute: buyers cannot verify it before purchase and may struggle to do so after it. An unconverted AI claim therefore carries little weight in a purchase decision, and may even raise perceived risk. Vendors make the claim purchasable through three conversion mechanisms.

Attribute translation reframes the credence claim into search and experience attributes that buyers can observe or readily imagine, such as no reagent handling, less dependence on scarce staff and faster turnaround (Theme 1). Nine of ten vendors reported adopting this approach after AI-first pitches failed. Verification substitution describes how own-sample demonstrations and evaluation placements gave buyers experience of the system and served as practical evidence in purchase deliberations (Themes 2 and 4). The protocols reviewed, however, did not establish that these trials validated diagnostic accuracy. Borrowed trust transfers trust from people, relationships and peers to the product, so that a buyer who cannot judge the algorithm can judge the team that will service it (Theme 4).

Two conditions appeared to shape whether converted claims were associated with a purchase in this case. The first is the decision pathway. In accounts from private facilities and stand-alone laboratories, which described shorter pathways often involving a director, converted claims were more closely linked to purchase decisions. Where the pathway ran through multi-stage committees and tenders, the claims met claim–criteria decoupling: formal criteria, codified in tender documents, registered servicing and delivery terms but not AI, so persuasion at the user level had no formal route to the award. The second is infrastructure fit. Unreliable power and thin technical staffing raised switching costs for some buyers, but for others they made the room-temperature, low-maintenance format especially valuable (Theme 3). Finally, any interpretation of conversion is bounded by accountability allocation: unless the vendor specifies who reviews, overrides and answers for an AI result, the AI claim can increase rather than reduce perceived risk (Theme 5).

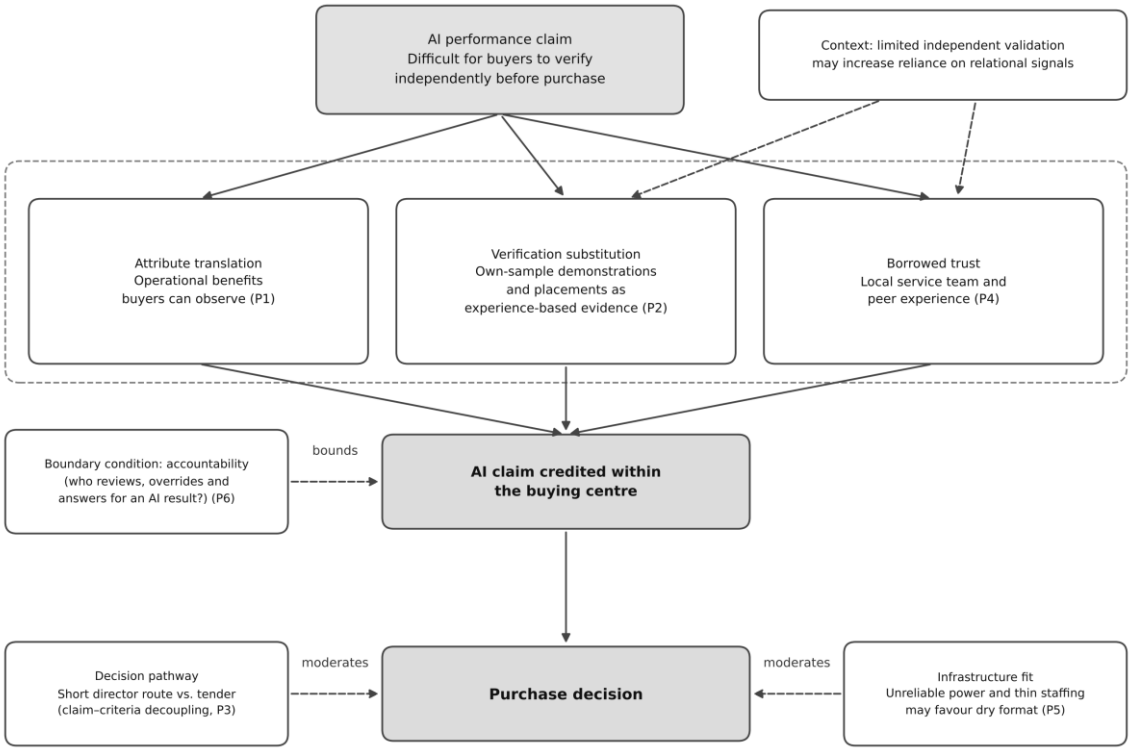



**Figure 3.** A model of credence-claim conversion in the sale of AI-enabled diagnostic equipment.

The model also clarifies the three sensitizing propositions. Proposition (a) was supported and refined: vendors did adapt AI claims to the listener, but the adaptation was systematic, demoting AI behind observable benefits for almost all audiences. Proposition (b) was strongly supported, and the documents revealed a mechanism behind it: AI was subordinated not only in buyers' minds but in the formal criteria that govern public awards. Proposition (c) was supported in an unexpected direction: Nigerian conditions did not simply impede AI-enabled equipment, but changed which part of the offering carried its value, shifting the appeal from the AI to the format.

### *5.2 Theoretical Contributions*

*Value-Based Selling for Opaque Offerings.* Value-based selling assumes that suppliers can quantify and document the value they create [5], [6], [7]. The present findings suggest that, for AI-enabled offerings whose performance is difficult to assess independently, a prior step may be required: the vendor must first convert an opaque, credence-type claim into something the buyer can verify, and only then can value be quantified in the buyer's own terms. Credence-claim conversion thus extends value-based selling to offerings whose core performance claims are difficult for buyers to observe and assess independently. It also helps explain why AI-first communication can backfire, consistent with evidence of algorithm aversion and resistance to medical AI [27], [28]: an unconverted AI claim invites scrutiny that the vendor cannot yet satisfy.

*Buying-Centre Theory and the AI Offering.* Buying-centre research stresses that purchasing is distributed across roles with different criteria [31], [32]. The study adds two refinements. First, claim–criteria decoupling shows that a claim can be persuasive to users and influencers while being invisible to the buyers and gatekeepers whose formal criteria govern the award. Tender documents acted as non-human gatekeepers whose criteria vendors had to address directly. Second, accountability allocation appears as an emergent buying criterion specific to AI-enabled offerings. Unlike conventional criteria such as price or service, it concerns the distribution of responsibility between the machine, its users and the vendor, echoing research showing that trust in AI depends on transparency and the possibility of human control [29].

*Signalling in Institutional Voids.* Experimental B2B research shows that certification and risk-based value-proposition signals can raise purchase intentions [13]. In the present setting, where local validation and independent testing were scarce, buyers relied instead on process-based and relational signals, such as own-sample trials, peer experience and the visible responsiveness of the local team. In Zucker's [35] terms, process-based trust substituted for weak institution-based trust; in the language of emerging-market strategy, relational signals filled an institutional void [14], [15]. Only four buyers mentioned published validation, and no vendor described offering it. This suggests that the signal repertoire for AI-enabled offerings is context-dependent, and that the scarcity of institutional signals raises the value of costly relational ones.

*Disruption Without the Headline Technology.* The case supports a disciplined reading of disruptive innovation [37]. Purchases in this sample were concentrated in private and stand-alone laboratories, whose participants described unreliable power, limited staffing or shorter approval routes. This pattern is consistent with a possible foothold in settings poorly served by incumbent formats, but the case cannot establish a disruptive market trajectory. Participants attributed the dry format's appeal mainly to its simplicity and fit with infrastructure constraints, rather than to AI features, consistent with work emphasizing simplification and frugal robustness in health care and emerging markets [39], [41]. The concern of two buyers about dependence on a single cartridge supplier also shows that a disruptive format can reproduce the lock-in it is meant to displace.

### *5.3 Propositions for Future Research*

The model yields six propositions for testing in other markets and product categories:

- **P1.** The less verifiable an AI claim is before purchase; the more vendors will subordinate it to observable operational attributes (attribute translation).
- **P2.** Own-sample demonstrations and evaluation placements increase the likelihood that buyers credit AI claims; this effect is stronger among users and influencers than among buyers and gatekeepers.
- **P3.** Where formal procurement criteria do not register AI-related features, user-level persuasion about AI will have a weaker effect on award decisions (claim–criteria decoupling).
- **P4.** The weaker the institutional infrastructure for verifying AI performance, the more buyers rely on relational and local-service signals (borrowed trust).
- **P5.** AI-enabled diagnostic offerings gain early adoption where short decision pathways coincide with poor infrastructural fit of incumbent technologies.
- **P6.** AI claims that specify human review, override and accountability arrangements are more credible to buying centers than claims that emphasize automation alone.

### *5.4 Comparison with Prior Research*

The findings are consistent with Nigerian surveys reporting favourable attitudes to AI among health professionals [18], [21], but show that favourable attitudes in principle do not translate directly into purchase priority. Procurement involves buyers and gatekeepers who apply criteria different from those of clinicians. The concerns clinicians raise about guidelines, misdiagnosis and infrastructure [21], [47] reappear here as the question of who checks the AI and as the demand for local service. Iheme's [49] study of Nigerian healthcare leaders who implemented AI-based devices identified financing and infrastructure as central; the buyer-side findings agree, and the vendor-side data show how the same barriers shape what vendors say and in what order, and why a buyer willing to implement may still not buy. If concerns about unverified vendor performance claims for deployed health AI in Nigeria are warranted [30], buyers' insistence on own-sample verification is a rational response rather than simple conservatism. Finally, the findings are consistent with research showing that limited infrastructure and human resources shape AI deployment in Nigeria [19], [48], while adding a nuance absent from the clinical literature: the same conditions can increase the appeal of a low-maintenance format at particular sites.

### *5.5 Rival Explanations*

Three alternative readings were considered. First, the difference between purchasing and declining facilities may reflect exposure to demonstrations as much as facility characteristics, because all four purchasers had experienced one; the design cannot separate the two. Second, all four purchasing facilities were in Lagos, while none of the

four Abuja facilities had purchased the analyzer. With nine facilities, the study cannot separate city from ownership, decision pathway, infrastructure fit or exposure to demonstrations. Third, the insider position may have encouraged vendor-side participants to present a coherent, adaptive narrative of their selling practice; the convergence between vendor and buyer accounts on the subordinate role of AI, and the retention of disconfirming cases, partly mitigate this concern. The negative cases (the director who relied on the manufacturer's reputation, the distributor who believed AI mattered most to younger staff, and the scientist with no budget route) show that the main pattern is a tendency rather than a rule.

### *5.6 Managerial Implications*

For vendors of AI-enabled diagnostic equipment, the conversion model suggests a selling sequence different from the AI-first pitch that many vendors reported initially using (Table 7). Lead with the operational case, such as storage, maintenance and staffing, and introduce AI as supporting evidence. Prepare a clear accountability script that explains who reviews and can override an automated result. Fund and fast-track own-sample demonstrations and evaluation placements, and streamline the internal approvals they require, because buyers repeatedly described these as important preconditions for considering AI-related claims. Make local service visible through response-time commitments and stocked spares. Train sales staff and distributors by buying-centre role. Consider private facilities and stand-alone laboratories as potential early adopters. Where procurement rules permit, engage public institutions transparently before tenders are issued to support evidence-based specifications, including criteria for independently verifiable AI performance. Address concerns about dependence on a single cartridge supplier through supply assurances, and invest in locally generated validation evidence, which no vendor reported offering.

**Table 7.** ***Managerial implications by conversion mechanism***

| Mechanism | Recommended action | Supporting evidence |
|---|---|---|
| Attribute translation | Lead with storage, maintenance and staffing benefits; introduce AI as supporting evidence | 9 of 10 vendors abandoned AI-first openings; 10 of 12 buyers recalled AI as secondary or unclear |
| Accountability allocation | Prepare an accountability script: who reviews, who overrides and who answers for an AI result | The question "who checks it?" (B05); scientists required review and override |
| Verification substitution | Fund and fast-track own-sample demonstrations and evaluation placements | 10 of 12 buyers required own-sample evidence; all four purchasing facilities had one |
| Borrowed trust | Make local service visible: response-time commitments, stocked spares, named local contacts | 7 buyers judged the analyzer by the local team's responsiveness |
| Role-specific selling | Train sales and distributor staff by buying-centre role | Evaluation criteria differed by role (Table 6) |
| Claim–criteria decoupling | Prioritise private and stand-alone laboratories; engage public institutions early in tender specification | No tender scored AI; all purchasers were private or stand-alone |
| Supply and evidence assurance | Offer cartridge supply assurances; generate local validation evidence | 2 buyers feared new lock-in; 4 buyers sought published validation |

### *5.7 Policy Implications*

None of the three tender documents reviewed contained scored AI-specific criteria. This small documentary sample cannot establish a general procurement gap, but it supports consideration of whether public tenders for diagnostic equipment should specify proportionate, verifiable evidence for AI-related performance claims, including local validation requirements and human-review arrangements. Such criteria would protect buyers from unsubstantiated claims and give vendors with validated offerings a legitimate route to differentiate.

## 6. Limitations and Future Research

Several limitations qualify these conclusions. First, this is a single case involving one product, one manufacturer and two cities, and the findings are not statistically generalizable. For confidentiality, the analyzer and manufacturer are anonymized, which limits readers' ability to assess product-specific claims; the findings concern reported selling and purchasing processes, not clinical accuracy, regulatory compliance or product effectiveness.

Second, the researcher's employment by the focal manufacturer creates potential for role conflict, social desirability and interpretive bias; the safeguards in Section 3.2 reduce but cannot eliminate these risks, and the manufacturer's publication permission may have influenced what is reported. Third, tender committees and budget offices were described by participants but not interviewed, and all four purchasing facilities were private or stand-alone, so conclusions about public procurement rest on accounts from facilities that had not purchased. Fourth, the data are self-reported and retrospective; sales encounters and committee deliberations were not observed, and nine documents cannot establish how written criteria are applied in practice.

Fifth, the design identifies patterns but cannot establish causal effects; in particular, it cannot separate the influence of demonstrations from the characteristics of the facilities that received them. Sixth, the demonstration protocols did not report independent reference standards or diagnostic accuracy metrics. The study therefore examines how buyers interpreted demonstrations, not whether those demonstrations validated AI performance. Seventh, the findings describe a particular period and may change as regulation, pricing and competing offerings evolve.

These limitations point to a research agenda. Comparative multiple-case studies of other manufacturers, product categories (such as imaging and other in vitro diagnostics) and African and Asian markets could test whether credence-claim conversion transfers beyond this case. Scenario experiments or surveys of procurement officers, laboratory scientists and directors could test Propositions P1 to P6, in particular whether demonstration, peer and service signals differ in influence by buying-centre role and institutional context. Longitudinal and observational studies could follow purchases over time, observe demonstrations and committee meetings directly, and compare post-purchase performance with the claims made during selling. Future studies should also include voices not heard here, such as tender committees, budget offices and the clinicians who receive results from dry systems. Finally, research on how human-review and override features affect trust in AI diagnostics would address the accountability question that buyers raised.

## 7. Conclusion

This study examined how vendors constructed and communicated AI-related value propositions in the sale of an AI-enabled dry haematology analyzer to hospital and laboratory buying centers in Lagos and Abuja, and how participants said these claims entered their decisions. AI functioned as a claim that buyers expected vendors to substantiate. Vendors reported translating AI claims into operational benefits, and most buyers said they required evidence before crediting them. None of the three tender documents reviewed scored AI-specific features. Participants described own-sample demonstrations, peer experience and visible local service as trust proxies. They attributed the format's appeal more to its operational fit than to its AI features. The concept of credence-claim conversion captures these dynamics and offers B2B marketing a way to theorize the selling of AI-enabled offerings whose core performance buyers cannot readily assess independently. As AI becomes embedded in ever more industrial products, the question for vendors is not only what their AI can do, but how buyers can come to believe it.

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