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Developing the IRAM Model for Organisational Big Data Transformation in Agri-Food Supply Chains: Instrument Development and Initial Content Validation

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Developing the IRAM Model for Organisational Big Data Transformation in Agri-Food Supply Chains: Instrument Development and Initial Content Validation.

Abstract:

Research on Big Data adoption, maturity, analytics capabilities and value creation often remains fragmented, limiting their articulation within a common organisational assessment. This study develops an integrated conceptual model "the Integrated Readiness-Adoption-Maturity (IRAM) model", distinguishing Readiness, Adoption, Maturity and Value Creation. It aims to assess the relevance, clarity and representativeness of its measurement items and the coherence of its conceptual architecture.

The French V1 instrument, comprising 49 items across 14 measurement domains, was reviewed by nine academic and professional experts, with a view to application in agri-food supply chains in Souss-Massa, Morocco. Items were rated on four-point scales; eight experts also assessed the conceptual architecture. Content validity indices were interpreted alongside qualitative comments.

S-CVI/Ave values reached 0.980 for relevance, 0.968 for clarity and 0.980 for representativeness. Universal agreement was lower for clarity (S-CVI/UA = 0.776). The distinction between Readiness, Adoption and Maturity received the lowest global mean score (3.375/4), identifying a conceptual boundary requiring further examination. All 49 items were provisionally retained, with wording revisions.

The study provides initial content validity evidence and proposes a measurement architecture connecting four distinct components of organisational Big Data transformation. Cognitive pretesting, pilot testing and psychometric validation remain necessary before diagnostic or benchmarking use.

Keywords: Big data; Digital transformation; Organisational readiness; Maturity; Adoption; Agri-food supply chains.
JEL Classification: M15; O33; C83; Q13.
Paper type: Instrument development and initial content validation study

Résumé :

Les recherches sur l'adoption du Big Data, la maturité, les capacités analytiques et la création de valeur restent souvent fragmentées, limitant leur articulation dans une évaluation organisationnelle commune. Cette étude développe un nouveau modèle conceptuel intégré (IRAM), distinguant préparation, adoption, maturité et création de valeur. Elle évalue la pertinence, la clarté et la représentativité des items et la cohérence de l'architecture conceptuelle.

La version française V1, comprenant 49 items répartis en 14 domaines, a été évaluée par neuf experts académiques et professionnels, en vue d'une application aux chaînes logistiques agroalimentaires de Souss-Massa, au Maroc. Les items ont été notés sur des échelles en quatre points ; huit experts ont également évalué l'architecture conceptuelle. Les indices de validité de contenu ont été interprétés conjointement avec les commentaires qualitatifs.

Les S-CVI/Ave atteignent 0,980 pour la pertinence, 0,968 pour la clarté et 0,980 pour la représentativité. L'accord universel est plus faible pour la clarté (S-CVI/UA = 0,776). La distinction entre préparation, adoption et maturité obtient la moyenne globale la plus faible (3,375/4), signalant une frontière conceptuelle à approfondir. Les 49 items ont été conservés provisoirement, avec des révisions de formulation.

L'étude apporte des éléments initiaux de validité de contenu et propose une architecture de mesure articulant quatre composantes distinctes de la transformation organisationnelle par le Big Data. Un prétest cognitif, une étude pilote et une validation psychométrique restent nécessaires avant toute utilisation diagnostique ou comparative.

Mots-clés : Big Data ; Transformation numérique ; Préparation organisationnelle ; Maturité ; Adoption ; Chaînes logistiques agroalimentaires.
Classification JEL : M15 ; O33 ; C83 ; Q13.
Type du papier : Étude de développement et de validation initiale du contenu d'un instrument de mesure.

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1. Introduction

Digital technologies expand organisations' ability to collect, exchange and analyse data, but their availability does not ensure sustained use or organisational value. Big Data transformation requires technological resources to be combined with human and managerial capabilities (Gupta & George, 2016; Wamba et al., 2017). Recent synthesis also identifies organisational readiness, governance maturity and analytical capabilities as conditions shaping value creation in operations and supply chains (Adaba et al., 2026). Assessing transformation therefore requires attention to enabling conditions, actual use, institutionalised capabilities and outcomes, while keeping these phenomena conceptually distinguishable.

These distinctions matter in agri-food supply chains, where perishability, seasonal production and traceability requirements increase the importance of timely, reliable and interoperable information. Production, quality, storage and transport data must be coordinated across actors whose resources and decision-making arrangements differ considerably. Large integrated businesses coexist with smaller producers, cooperatives, processors and logistics providers. Rejeb et al. (2021) identify opportunities for Big Data in resource management and traceability, alongside challenges involving data integration, skills and access to technology. The Food and Agriculture Organization of the United Nations (FAO, 2022) likewise identifies infrastructure, digital literacy and financial constraints as barriers to inclusive agricultural automation. These conditions motivate a common assessment architecture that remains attentive to organisational heterogeneity.

Morocco provides a relevant context for developing such an assessment. In 2024, agriculture, forestry and fishing accounted for 26.3% of total employment (Haut-Commissariat au Plan [HCP], 2025). Regional accounts report that agriculture and fishing contributed 10.7% of national GDP and 17.1% of GDP in Souss-Massa in the same year (HCP, 2026). These statistics concern primary activities rather than the entire agri-food economy. Génération Green 2020–2030 supports agricultural modernisation and digitalisation (Pôle Digital de l'Agriculture, de la Forêt et Observatoire de la Sécheresse, n.d.), while Digital Morocco 2030 establishes a broader national framework for digital development (Ministry of Digital Transition and Administration Reform, 2024). This setting motivates the intended application of IRAM, with subsequent organisational testing envisaged in Souss-Massa.

Established research already connects several elements of this transformation. Zhu et al. (2006) link technological, organisational and environmental conditions to initiation, adoption and routinisation in an integrative model of e-business assimilation. Industry 4.0 maturity research examines technical and organisational assessment domains and their suitability for smaller firms (Mittal et al., 2018). Big Data capability research links analytical resources to competitive performance through dynamic and operational capabilities (Mikalef et al., 2020). These studies establish the relevance of integrative perspectives and provide foundations for IRAM.

Published reviews identify a more specific assessment challenge. Al-Sai et al. (2023) report limitations in the documentation of Big Data maturity dimensions and validation procedures. Langer's (2025) systematic review of 38 data and analytics maturity models documents differences in architectures, maturity levels and domains. Adaba et al. (2026) show that analytics value depends on complementary organisational conditions and capabilities. Taken together, these findings motivate explicit measurement boundaries between enabling conditions, realised use, developed capabilities and associated outcomes. The present study builds on these reviews and established frameworks to provide a targeted synthesis intended for the development of instruments.

Recent agricultural frameworks further specify IRAM's positioning. Siewe et al. (2026) use the Unified Theory of Acceptance and Use of Technology (UTAUT) to analyse systemic barriers and propose four iterative implementation phases stratified across five digital-maturity levels.

Ahoa et al. (2026) develop a capability maturity model for digital integration in smart farming and examine it through three farms in the Netherlands. IRAM addresses a complementary assessment task: translating the integration of Big Data readiness, actual adoption, multidimensional maturity and value creation into a common organisational measurement instrument. Its originality lies in the explicit articulation and operationalisation of these four components, whose empirical distinctness and relationships remain to be tested.

The Integrated Readiness-Adoption-Maturity (IRAM) model defines Readiness as enabling technological, organisational and environmental conditions; Adoption as actual implementation and use; Maturity as the formalisation and integration of data and analytics capabilities; and Value Creation as outcomes associated with their use. This ordering provides a conceptual orientation for subsequent testing, rather than an established causal sequence or mandatory progression through numbered stages. The instrument draws on generic organisational theories and is intended for application in agri-food supply chain organisations. Its sectoral relevance concerns the information coordination needs and organisational diversity described above, rather than constructs or items exclusive to agri-food activities.

The central research question is: to what extent do experts judge the content of an instrument integrating Readiness, Adoption, Maturity and Value Creation to be adequate for assessing organisational Big Data transformation in agri-food supply chains? Three sub-questions guide the assessment: (1) Are the proposed items relevant, clear and representative of their assigned domains? (2) Do experts consider the four-component architecture coherent and its conceptual boundaries sufficiently distinguishable? (3) What revisions do their comments suggest to improve comprehensibility and intended organisational and sectoral applicability? The objectives are to specify these boundaries, operationalise them through a common instrument and obtain initial content-validity evidence. Nine academic and professional experts assessed the French V1 instrument, comprising 49 items across 14 measurement domains; eight also evaluated its conceptual architecture.

The study makes a conceptual contribution by articulating established perspectives within a four-component assessment architecture. Its methodological contribution consists of documented instrument development and preliminary content-validity evidence combining quantitative expert ratings and qualitative comments. Its contextual contribution is the expert assessment of an instrument intended for heterogeneous agri-food organisations, with subsequent testing envisaged in Souss-Massa. After further validation, its potential managerial contribution would be to help distinguish insufficient readiness, limited use, weak institutionalisation and outcomes not yet demonstrated. Expert perceived distinctions do not establish empirical discriminant validity; reliability, dimensionality, structural relationships and comparability across organisational types require subsequent assessment.

The remainder of the article is organised as follows. Section 2 presents the theoretical foundations and development of the IRAM instrument. Section 3 describes the expert consultation and content validation procedures. Section 4 reports the results. Section 5 discusses the contributions and implications, Section 6 addresses limitations and further validation requirements, and Section 7 concludes the article.

2. Literature Review and Development of the IRAM Instrument

2.1. Literature Gaps and the Basis of the IRAM Model

IRAM was developed from a focused synthesis of four complementary bodies of literature: organisational readiness and technology adoption, Big Data maturity, analytics capabilities, and value creation. Rather than treating these perspectives as equivalent, the model places them at different points in the transformation process. Table 1 summarises their contributions, the assessment issues relevant here and the response proposed by IRAM.

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The aim was not to replace established theories, but to connect their complementary insights in a common assessment architecture. The literature provides strong explanations of adoption conditions, capability development and performance, but gives less attention to their coordinated measurement as distinguishable components. IRAM addresses this measurement task through its four-component structure.

Organisational assimilation research already connects contextual conditions, adoption and post-adoption use (Cooper & Zmud, 1990; Zmud & Apple, 1992; Zhu et al., 2006). Agricultural frameworks also integrate adoption barriers, implementation and digital maturity (Siewe et al., 2026), or technical and organisational smart-farming capabilities (Ahoa et al., 2026). IRAM offers a complementary instrument-development synthesis: enabling conditions, actual use, institutionalised capabilities and outcomes are operationalised separately within one organisational instrument. This positioning draws on established reviews and frameworks rather than a new exhaustive systematic review.

Table 1 Literature gaps that motivated the development of the IRAM model.

Literature stream	Main focus	Assessment issue relevant to IRAM	IRAM response
TOE and adoption research (Gangwar et al., 2015; Maroufkhani et al., 2020)	Conditions and factors that influence adoption and use.	TOE classifies contextual factors; the distinction between conditions and realised use needs explicit operationalisation.	Separates Readiness from Adoption and makes actual use a distinct component.
Assimilation research (Cooper & Zmud, 1990; Zmud & Apple, 1992; Zhu et al., 2006)	Adoption, routinisation and fuller incorporation of technology.	Process integration predates IRAM; its operational translation must be specified for Big Data.	Distinguishes actual use from formalised and recurrent organisational integration.
Big Data maturity models (Comuzzi & Patel, 2016; Al-Sai et al., 2023; Langer, 2025)	Development, formalisation and scaling of data and analytics practices.	Assessment architectures and validation vary; fixed stages may imply a normative development path.	Assesses six complementary maturity domains without mandatory numbered stages.
Analytics-capability research (Gupta & George, 2016; Mikalef et al., 2020)	Data, technology, skills and managerial capabilities linked to organisational performance.	Capabilities and enabling conditions require distinct definitions when integrated in one instrument.	Treats developed and institutionalised capabilities as dimensions of Maturity.
Value-creation research (Akter et al., 2016; Wamba et al., 2017)	Operational, decision, innovation and competitive outcomes of Big Data use.	Capability–performance links are established, but outcomes should not be used to define maturity.	Keeps Value Creation as a distinct outcome component of the model.
Agri-food digitalisation (Rejeb et al., 2021, 2022; Siewe et al., 2026; Ahoa et al., 2026)	Digital applications, implementation and integration across heterogeneous actors.	Existing integrated frameworks serve different assessment tasks; cross-actor comparability remains to be established.	Proposes a common four-component Big Data instrument for subsequent sectoral testing.

Source: Authors

For the instrument, Big Data concerns data whose scale, heterogeneity, production rate or variability creates processing requirements calling for scalable storage, integration or analytical architectures (Chang & Grady, 2019). A single characteristic or product label is insufficient. ERP, BI and traceability systems may contribute to qualifying applications; their presence alone neither proves nor excludes adoption. Advanced analytics refers to methods such as prediction and optimisation, while artificial intelligence includes machine-based inference techniques; neither is synonymous with Big Data (Siddique et al., 2025). This clarification guides subsequent organisational testing; the expert ratings remain attached to French V1.

2.2. Big Data Readiness

Big Data Readiness is the extent to which an organisation possesses the technological, organisational and environmental conditions required to initiate and sustain adoption. The Technology-Organisation-Environment framework distinguishes technological resources and characteristics, organisational resources and managerial support, and external influences such as partners, providers and institutions (Tornatzky & Fleischer, 1990; Baker, 2012). In IRAM, readiness therefore covers infrastructure, data availability and quality, compatibility and security; management support, resources, skills and openness to change; and external support, competitive pressure and partner conditions. These attributes represent organisational potential and do not imply that big data solutions have already been deployed.

TOE is used here as a classificatory framework, not as a causal theory. Gangwar et al. (2015) concern cloud computing; their measures require contextual adaptation rather than direct transfer to Big Data. Readiness refers to resources available or mobilisable at the time of assessment and can coexist with adoption. Basic skills, management support and safeguards indicate enabling potential; they do not by themselves establish the coordinated, routinely applied practices assessed under Maturity.

2.3. Big Data Adoption

Big Data Adoption refers to effective organisational implementation and use of data-intensive technologies and analytical applications. It differs from adoption intention and from maturity: a solution may be operational in one function without being governed, recurrently embedded or scaled across the organisation. Organisational adoption is therefore treated as observable implementation and use rather than technological sophistication. This distinction is consistent with innovation-diffusion and technology-use perspectives, which separate antecedent conditions and intentions from realised adoption behaviour (Rogers, 2003; Venkatesh et al., 2003), and with organisational studies showing that digital maturity can influence technology acceptance without being equivalent to it (Dobrinić & Vrček, 2023).

Venkatesh et al. (2003) address individual acceptance and use, so their contribution is conceptual rather than direct evidence for an organisational scale. Assimilation research provides the organisational distinction: an adoption decision, actual use, routinisation and infusion are not equivalent (Cooper & Zmud, 1990; Zmud & Apple, 1992; Zhu et al., 2006). IRAM therefore separates use of analytical outputs for certain activities (BDA4) from formalised integration into recurring processes (POI1). Their V1 wording remains close, and the V2 clarification still requires cognitive and discriminant-validity assessment.

2.4. Big Data Maturity

Big Data Maturity represents the degree to which data and analytics practices and capabilities have been developed, formalised and integrated into organisational operations and strategy. Existing maturity models assess multiple organisational domains and levels of progression (Halper & Krishnan, 2013; Comuzzi & Patel, 2016; Al-Sai et al., 2023). From a dynamic-capability perspective, maturity also reflects the routinisation and coordination of capabilities that allow organisations to reconfigure resources and respond to change (Teece, 2007; Mikalef et al., 2020). Research on digital capability similarly treats maturity as a multidimensional organisational assessment problem linked to strategic and operational improvement (Draganić, 2023). IRAM does not assign organisations mechanically to numbered stages; its proposed domain scores describe the presence of maturity attributes across six domains:

- technology and architecture;
- data management and governance;
- analytics capabilities and deployment;
- people, skills and data culture;

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- processes and organisational integration;
- leadership and strategic alignment.

The institutionalisation criterion differentiates Maturity from Readiness: shared architecture in operation rather than infrastructure merely available; routinely applied governance rather than basic rules; coordinated deployment of skills rather than their availability; and implemented strategic coordination rather than support alone. These distinctions guide interpretation but do not establish empirical separation between the items.

Maturity models can imply a normative ideal and a linear path even when organisations develop unevenly across domains. Reviews document heterogeneous architectures and validation practices, while smaller organisations may face assessment criteria designed for larger firms (Wendler, 2012; Mittal et al., 2018; Al-Sai et al., 2023; Langer, 2025). IRAM retains separate domain profiles rather than imposing an obligatory ladder. The proposed scores and their comparability across actors remain to be validated.

2.5. Value Creation

Value Creation refers to organisational outcomes associated with the exploitation of data and analytics. The resource-based view argues that technological resources generate advantage only when they are combined with complementary organisational resources and capabilities (Barney, 1991; Gupta & George, 2016), while dynamic-capability research explains how such resources can be reconfigured into operational, innovative and competitive outcomes (Teece, 2007; Mikalef et al., 2019, 2020). IRAM therefore separates operational performance, decision-making performance, innovation performance and competitive performance from Maturity itself. This prevents maturity from being inferred merely from outcomes and enables later empirical testing of whether institutionalised capabilities are associated with value creation.

In agri-food settings, analytical opportunities in traceability, resource management and food quality coexist with difficulties in data sharing, ownership, trust and unequal access (Rejeb et al., 2021; Sullivan et al., 2024; Siddique et al., 2025). Amar et al. (2026) further question how the benefits and control of agricultural data are distributed. Thus, technical maturity cannot stand as a proxy for benefits to every supply-chain actor. IRAM assesses focal organisational outcomes; it does not establish equitable value distribution across the chain.

Table 2 summarises the boundaries used to interpret the four components. Their reference is the current organisation: Readiness concerns enabling potential, Adoption observable use, Maturity the level of institutionalisation, and Value Creation outcomes. In revised V2, outcomes refer to the last 12 months, or the period since use began when shorter.

Table 2. Component definitions and inclusion and exclusion criteria.

Component	Definition and inclusion criteria	Exclude as sufficient evidence	Discriminating illustration
Readiness	Available or mobilisable technological, organisational and environmental conditions; can precede and coexist with use.	Installed applications, institutionalisation or outcomes inferred merely from resource availability.	Basic skills/resources available (OR4/TR1), rather than recurrent coordinated deployment (PSC/MTA).
Adoption	Actual implementation and use within a defined organisational perimeter; scope, frequency and use of outputs.	Intention or purchase alone; maturity inferred solely from frequent use.	Using outputs for some decisions (BDA4), rather than their formal recurrent process integration (POI1).
Maturity	Formalisation, coordination and sustained deployment of practices across six complementary domains.	Resources merely available; isolated pilot or one-off individual practice.	Applied shared governance and common procedures (DMG/POI), rather than basic rules or willingness (OR).
Value Creation	Reported operational, decision, innovation and competitive outcomes associated with use.	Technology presence, maturity level or expected benefits treated as achieved results.	Improved efficiency (OP1), rather than the availability or sophistication of analytical tools.

Source: Authors

2.6. From the IRAM Model to the Measurement Instrument

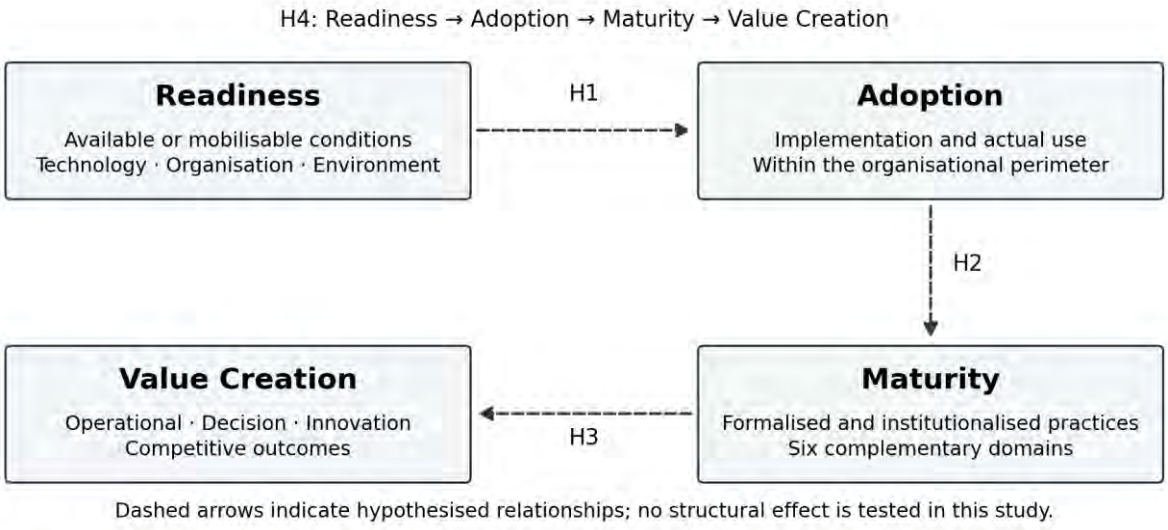
2.6.1. Research Model and Hypotheses

IRAM is a multidimensional measurement framework with a hypothesised relational structure. Its lifecycle orientation expresses a theoretical ordering, not mandatory organisational stages or a validated causal trajectory. The research model retains four hypotheses for later organisational testing:

H1. *Big Data Readiness positively influences Big Data Adoption.*
H2*. Big Data Adoption positively influences Big Data Maturity.*
H3. *Big Data Maturity positively influences Value Creation.*
H4. *Big Data Adoption and Big Data Maturity sequentially mediate the relationship between Big Data Readiness and Value Creation.*

H1 follows the contextual adoption perspective; ***H2*** extends it through assimilation and institutionalisation; ***H3*** draws on capability–performance research; ***H4*** states the integrative sequential mechanism to be tested (Zhu et al., 2006; Comuzzi & Patel, 2016; Wamba et al., 2017; Mikalef et al., 2020). These hypotheses do not imply that preparation guarantees adoption or that value is impossible at low maturity. A formal adoption decision is not required when identifiable use exists; without qualifying use, Big Data maturity and associated outcomes are not assessed. Feedback and direct Adoption–Value paths are possible extensions, but are not added as core hypotheses. A later mediation analysis must specify any direct paths before interpreting mediation as total or partial. None of these relationships is tested by expert content ratings.

Figure 1. IRAM research model.



Source: Authors

H1–H3 are direct hypotheses; H4 concerns the sequential indirect path. The arrows indicate proposed relationships rather than measured effects or obligatory stages.

2.6.2. Measurement Instrument

After the four components of IRAM had been defined, the model was converted into measurable domains and items. Readiness items were mainly based on the Technology-Organisation-Environment (TOE) framework and organisational readiness research. Adoption items drew on innovation diffusion, technology use and organisational implementation research. Maturity items were based on Big Data maturity models, analytics capability research and dynamic capability theory. Value Creation items were based on the resource-based view, dynamic capability research and empirical studies of Big Data performance. Each proposed

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item was linked to a predefined IRAM domain and to one or more theoretical or empirical sources before expert consultation.

The documented French V1 comprises 49 items. Earlier candidate formulations were synthesised and adapted to an organisational unit of analysis; the available record does not reconstruct the complete pre-consolidation count or merger history. Table 3 summarises the theoretical and measurement structure, while Supplementary Appendix A reports the item-level theoretical sources for all 49 items.

The measurement specification distinguishes items from higher-order dimensions (Jarvis et al., 2003; Sarstedt et al., 2019). The three Readiness domains are formative composites: infrastructure, compatibility, data quality, safeguards, support and external conditions are complementary ingredients, not interchangeable effects. These three domains jointly form higher-order Readiness. Adoption is specified as a first-order reflective construct: its four items are intended as manifestations of realised implementation and use, with their coherence to be examined empirically.

The six Maturity domains and four Value Creation domains are specified reflectively at first order: their three items are intended to express attainment or outcomes within each defined domain. At higher order, the domains form Maturity and Value Creation respectively, because technological, governance, human and process development, or different outcome types, cannot substitute for one another. This reflective–formative architecture preserves domain profiles and does not imply a single overall IRAM score. Reflective specification is a theoretical choice to be checked against item meaning, cognitive evidence and subsequent measurement results; it is not established by content-validity indices.

Table 3. Theoretical and measurement architecture of the initial IRAM instrument.

IRAM component	Measurement domain	Theoretical anchor	Principal sources	Items and first order mode
Readiness	Technological readiness	TOE technological context; BDA resource readiness	Tornatzky & Fleischer (1990); Baker (2012); Gangwar et al. (2015); Gupta & George (2016)	5; formative
Readiness	Organisational readiness	TOE organisational context; resource and capability readiness	Tornatzky & Fleischer (1990); Baker (2012); Gupta & George (2016); Babalghaith & Aljarallah (2024)	6; formative
Readiness	Environmental readiness	TOE environmental context; inter-organisational readiness	Tornatzky & Fleischer (1990); Baker (2012); Gangwar et al. (2015); Babalghaith & Aljarallah (2024)	4; formative
Adoption	Organisational Big Data adoption	Innovation diffusion and actual technology use	Rogers (2003); Venkatesh et al. (2003); Gangwar et al. (2015); Wamba et al. (2017)	4; reflective
Maturity	Technology and architecture	Big Data/digital maturity models	Comuzzi & Patel (2016); Al-Sai et al. (2019, 2023); Draganić (2023)	3; reflective
Maturity	Data management and governance	Data-management capability and governance maturity	Gupta & George (2016); Shamim et al. (2019); Al-Sai et al. (2023)	3; reflective
Maturity	Analytics capabilities and deployment	BDA capability; dynamic capabilities	Gupta & George (2016); Akter et al. (2016); Mikalef et al. (2020)	3; reflective
Maturity	People, skills and data culture	Human BDA capability and organisational capability	Gupta & George (2016); Akter et al. (2016); Mikalef et al. (2020)	3; reflective
Maturity	Processes and organisational integration	Institutionalisation, scaling and process maturity	Comuzzi & Patel (2016); Mikalef et al. (2020); Al-Sai et al. (2023)	3; reflective
Maturity	Leadership and strategic alignment	Strategic alignment and maturity governance	Akter et al. (2016); Comuzzi & Patel (2016); Al-Sai et al. (2023)	3; reflective
Value	Operational	RBV/dynamic capabilities;	Barney (1991); Akter et al. (2016);	3; reflective

Creation	performance	BDA performance	Wamba et al. (2017)	
Value Creation	Decision-making performance	BDA decision-making capability	Akter et al. (2016); Shamim et al. (2019); Wamba et al. (2017)	3; reflective
Value Creation	Innovation performance	Dynamic capabilities and BDA-enabled innovation	Mikalef et al. (2019, 2020); Wamba et al. (2017)	3; reflective
Value Creation	Competitive performance	RBV/dynamic capabilities; competitive outcomes	Gupta & George (2016); Mikalef et al. (2020); Wamba et al. (2017)	3; reflective

Source: Authors

For formative readiness measures, content validity primarily safeguards domain coverage, and low inter-item correlations alone do not justify deletion. Reflective domains additionally require assessment of loadings, reliability, convergent and discriminant validity. Higher-order composites require assessment of collinearity, weights and external or nomological validity; a two-stage approach may be used in later PLS-SEM analysis (Diamantopoulos & Winklhofer, 2001; Sarstedt et al., 2019). EFA/CFA and internal-consistency criteria should therefore not be applied indiscriminately to all 49 items. No such psychometric or structural test is reported at this stage.

The adaptation criteria are an organisational referent, one defined perimeter, and a distinction between resources, actual practices and outcomes. A future key informant must know the systems and activities assessed; complementary technical and managerial informants may be needed. Their responses should not be averaged without examining agreement and ensuring that they concern the same unit (Kumar et al., 1993). For consolidation, formulations addressing the same substantive facet should be compared while retaining distinct content. These criteria make the revision auditable; they do not replace a missing historical record of item-by-item mergers.

Table 4. Illustrative V1 items and conceptual supporting sources.

Measurement domain	Code	Exact French V1 wording evaluated by experts	Principal sources
Technological readiness	TR1	Notre organisation dispose d'une infrastructure de calcul, de stockage et de traitement suffisante pour prendre en charge les applications Big Data.	Tornatzky & Fleischer (1990); Baker (2012); Gangwar et al. (2015); Gupta & George (2016)
Organisational readiness	OR3	Notre organisation peut allouer des ressources financières et autres suffisantes aux initiatives Big Data.	Gangwar et al. (2015); Gupta & George (2016)
Environmental readiness	ER4	Nos principaux partenaires sont suffisamment disposés et techniquement capables de participer à des initiatives fondées sur les données.	Wamba et al. (2017); Rejeb et al. (2021, 2022)
Organisational Big Data adoption	BDA2	Les technologies Big Data sont effectivement utilisées dans une ou plusieurs fonctions de notre organisation.	Rogers (2003); Wamba et al. (2017)
Organisational Big Data adoption	BDA4	Notre organisation utilise activement les résultats issus des systèmes Big Data pour soutenir ses activités opérationnelles ou managériales.	Akter et al. (2016); Wamba et al. (2017)
Technology and architecture	MTA1	Notre architecture de données et d'analytique est intégrée, évolutive et réutilisable à l'échelle de l'organisation.	Comuzzi & Patel (2016); Al-Sai et al. (2023); Draganić (2023)
Data management and governance	DMG1	La gouvernance des données est institutionnalisée dans les différentes fonctions de notre organisation.	Shamim et al. (2019); Al-Sai et al. (2023)
Analytics capabilities and deployment	ACD1	Notre organisation est capable d'appliquer des techniques analytiques afin de produire des connaissances utiles à partir du Big Data.	Gupta & George (2016); Akter et al. (2016)
People, skills and data culture	PSC1	Les rôles liés aux données et à l'analytique sont formellement définis et coordonnés au sein de l'organisation.	Gupta & George (2016); Al-Sai et al. (2023)
Processes and organisational integration	POI1	L'analytique est intégrée dans les processus opérationnels et managériaux récurrents.	Comuzzi & Patel (2016); Al-Sai et al. (2023)

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Leadership and strategic alignment	LSA2	Les investissements en Big Data et en analytique suivent une feuille de route coordonnée et alignée sur les objectifs de l'organisation.	Akter et al. (2016); Comuzzi & Patel (2016); Al-Sai et al. (2023)
Operational performance	OP1	L'utilisation du Big Data a amélioré l'efficacité de nos opérations.	Barney (1991); Akter et al. (2016); Wamba et al. (2017)
Decision-making performance	DQ1	L'analytique Big Data permet aux responsables de prendre des décisions plus précises et davantage fondées sur des données probantes.	Akter et al. (2016); Shamim et al. (2019); Wamba et al. (2017)
Innovation performance	INN1	L'analytique Big Data soutient le développement de produits ou services nouveaux ou améliorés.	Mikalef et al. (2019, 2020); Wamba et al. (2017)
Competitive performance	CPER 1	Les capacités Big Data aident notre organisation à se différencier de ses concurrents.	Barney (1991); Gupta & George (2016); Mikalef et al. (2020)

Source: Authors

Table 4 provides one example per domain and an additional Adoption item illustrating the BDA4–POI1 boundary. Sources are conceptual anchors, not claims of verbatim borrowing from validated scales. Appendix A gives the complete V1 source mapping; Appendix B reports V1 ratings; Appendix C preserves the revised 49-item V2, with 35 revised and 14 unchanged formulations. These versions are not conflated: V1 indices do not validate V2.

Future respondents will receive the Big Data definition, a concrete use-case prompt and contrasting examples. A cold-chain application integrating frequent sensor streams and operational records through scalable processing may qualify; a spreadsheet of a few delivery temperatures does not qualify solely because it supports traceability. Ambiguous cases require technical clarification rather than forced classification. These instructions will be proposed for cognitive pretesting, separately from the expert-assessed material. The instrument has generic organisational foundations; sectoral relevance concerns its intended agri-food application, and transferability across organisational types remains to be tested.

3. Methodology

3.1. Research Design

This study reports the initial development and content validation of the French IRAM instrument. The design draws on established measure-development guidance (Hinkin, 1998; MacKenzie et al., 2011). The completed stages comprised construct definition, literature-based item generation and theoretical mapping, screening for conceptual overlap, and expert assessment of French V1. Quantitative ratings and qualitative comments informed the revision to V2. A separate Q-sort was not conducted before expert consultation. Experts evaluated items within their assigned domains rather than classifying them independently. A future item-sorting exercise could help examine whether the distinction between Adoption and Maturity is sufficiently clear. Cognitive pretesting, pilot testing and psychometric validation remain subsequent stages.

The expert consultation used the French V1 instrument. Sections 2.1 and 2.6 clarify the Big Data scope for subsequent organisational assessment: relevant data characteristics must create processing requirements calling for scalable storage, integration or analytical architectures. ERP, BI and traceability systems may contribute to such applications, but their presence alone is not evidence of adoption.

3.2. Expert Panel and Consultation Procedure

A purposive expert-selection approach was used to constitute a multidisciplinary panel covering the principal conceptual and contextual domains of the IRAM instrument. Experts were selected based on their academic or professional experience and demonstrated expertise in one or more of the following areas: Big Data and analytics, information systems, artificial intelligence,

technology adoption, digital transformation, organisational management, supply-chain management and the agri-food sector. The selection sought complementary rather than identical profiles. Recruitment relied on institutional and professional networks, including colleagues from the same university and engineering-school alumni or their professional contacts. Academic experts assessed the theoretical coherence of the instrument, the boundaries between the IRAM constructs and the correspondence between items and measurement domains. Professional experts examined managerial clarity, practical applicability and compatibility with organisational and supply-chain practices. Since no individual expert was expected to cover every domain, the panel was constituted collectively to provide technological, organisational, methodological and sectoral coverage (Grant and Davis, 1997 & Rubio et al., 2003). Ten experts were contacted between 24 August and 4 September 2026; nine returned completed forms by 17 September 2026 (90 per cent response). Each expert received a consultation document defining the constructs and a separate Excel evaluation form covering profile information, item ratings and global assessment. The invitation explained the purpose of the study, the voluntary nature of participation and the intended use of responses for doctoral research. Experts indicated their willingness to participate by completing and returning the evaluation form. Their assessments are reported anonymously. The final panel comprised nine experts: three academics specializing in data, information systems and artificial intelligence; two academic or academic-practitioner experts in management, digital transformation and supply chains; one professional specializing in digital transformation, ERP and business intelligence; and three professionals with experience in operations and agri-food supply chains. All nine experts completed the item-level assessment separately. An anonymized summary of the panel categories and selection criteria is presented in Table 5.

Table 5. Anonymised summary of panel categories and selection criteria.

Expert category	Main area of expertise	No. of experts	Expected contribution
Academic / Data, information systems and AI	Big Data, data science, information systems and artificial intelligence	3	Assessment of technological readiness, data architecture, analytics capabilities and technical terminology
Academic / academic-practitioner / Management and digital transformation	Organisational management, technology adoption, digital transformation and supply-chain research	2	Assessment of theoretical coherence, construct boundaries and organisational dimensions
Professional / Digital transformation, ERP and business intelligence	Implementation of digital systems, ERP, BI and organisational transformation	1	Assessment of implementation feasibility, adoption and managerial interpretation
Professional / Operations and agri-food supply chain	Operational management, supply-chain management and agri-food organisational practices	3	Assessment of sectoral applicability, operational relevance and respondent comprehension
Total	Complementary academic and professional expertise	9	Combined technological, organisational, methodological and contextual coverage

Source: Authors

3.3. Expert Assessment Procedure

All nine experts independently rated each of the 49 French V1 items for relevance (correspondence with the intended construct), clarity (comprehensibility and lack of ambiguity), and representativeness (coverage of the assigned domain), using four-point scales. Ratings of 3 or 4 counted as favourable for the indices, but a rating of 3 allowed minor revision. Experts could separately recommend retaining, revising or removing items and provide comments or alternative wording. Seven global questions addressed IRAM's architecture and sectoral relevance and were summarised separately from eight responses.

Only French V1 received expert ratings. Table 4 provides exact French V1 wording for one

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item per domain, together with an additional Adoption item illustrating the Adoption-Maturity boundary; Supplementary Appendix A gives the full inventory. English wording used to communicate item content serves reporting purposes; an English administration version has not been shown to be equivalent. Before administering such a version, independent forward translations, reconciliation, back-translation, expert review and cognitive pretesting are proposed, followed by evaluation of measurement properties in the intended population (Beaton et al., 2000).

3.4. Content-Validity Analysis

Following Polit and Beck (2006) and Polit et al. (2007), item-level indices were calculated as the proportion of ratings of 3 or 4. For relevance, at least seven favourable ratings out of nine were required (7/9 = 0.778, rounded to 0.78), consistent with the rounded benchmark discussed by Polit et al. (2007). This screening rule allows two ratings below 3 while requiring substantial support before considering retention; comments and domain coverage were also considered. The same count was used for clarity and representativeness as an operational rule. Scale-level indices were calculated by averaging across items and by counting items with universal agreement. Modified kappa was restricted to relevance, the criterion addressed by the cited CVI procedure (Polit et al., 2007). It adjusts item-level favourable ratings for chance under the stated model and does not measure agreement across all four ordinal categories.

$$I\text{-}CVI_i = \frac{A_i}{N_i} \quad (1)$$

$$S\text{-}CVI/Ave = \frac{1}{k}\sum_{i=1}^{k} I\text{-}CVI_i \quad (2)$$

$$S\text{-}CVI/UA = \frac{1}{k}\sum_{i=1}^{k} U_i \quad (3)$$

$$P_c = \frac{N!}{A!(N-A)!} \times (0.5)^N \quad (4)$$

$$K^* = \frac{I\text{-}CVI - P_c}{1-P_c} \quad (5)$$

For item i and a given criterion, A_i counts favourable ratings, N_i counts valid ratings, and U_i equals 1 if all nine experts gave favourable ratings and 0 otherwise. Both sums run over the k = 49 items. In equations (4) and (5), A and N refer to relevance ratings, C(N, A) is the binomial coefficient, and P_c is the probability of exactly A favourable ratings under the equal-chance model. With seven favourable relevance ratings out of nine, I-CVI = 7/9 = 0.778, P_c = 36/512 = 0.0703 and K* = 0.761, calculated before rounding.

Decisions took into account the ratings, written recommendations and coverage of each domain. Items with adequate relevance and no substantive concern were retained. Acceptable relevance with low clarity or convergent suggestions prompted revision. Weak content evidence or substantial overlap prompted reconsideration, including possible removal. Reported reasons for revision included more than one idea in an item, difficult technical terminology, overlap between constructs, and wording whose meaning depended on organisational context. These are descriptive reasons; frequencies from formal qualitative coding are not reported. Appendices B and C report the item-level indices and the revised V2, respectively.

A sensitivity analysis counted only ratings of 4 as favourable and recalculated S-CVI/Ave and universal agreement. These results supplement the primary analysis based on ratings of 3 or 4; they do not replace the original screening rule.

4. Results

4.1. Characteristics of the Expert Panel

Nine experts completed the item assessment. The panel included three academics specialising in data, information systems and artificial intelligence; two academic or academic-practitioner

experts in management, digital transformation and supply chains; one professional in digital transformation, ERP and business intelligence; and three professionals in operations and agri-food supply chains. Eight experts also completed the seven global questions. This composition supported technological, organisational, methodological and contextual appraisal while preserving independent item ratings.

In an exploratory comparison, the five academic or mixed profile experts gave favourable ratings (3 or 4) in 240/245 cases for relevance (98.0%), 237/245 for clarity (96.7%) and 238/245 for representativeness (97.1%). The corresponding figures for the four professionals were 192/196 (98.0%), 190/196 (96.9%) and 194/196 (99.0%). The denominators count ratings, not independent observations. The comparison describes this panel only; no inferential tests were performed.

4.2. Scale-Level Content Validity

The nine experts generated 441 ratings for each assessment criterion, corresponding to 49 items multiplied by nine experts.

Table 6. Scale-level content validity results

Criterion	Favourable ratings	S-CVI/Ave	S-CVI/UA
Relevance	432/441	0.980	0.857
Clarity	427/441	0.968	0.776
Representativeness	432/441	0.980	0.857

Source: Expert ratings of French V1; Supplementary Appendix B.

Table 6 shows high average proportions of favourable ratings: 0.980 for relevance and representativeness and 0.968 for clarity. Universal agreement was lower: 42 of 49 items for relevance and representativeness (0.857 each) and 38 of 49 for clarity (0.776). Thus, seven of the 49 items lacked unanimity for relevance, and 11 lacked unanimity for clarity. The clarity result was below the 0.80 reference point discussed for relevance-based applications (Polit & Beck, 2006); the comparison is descriptive, not a validated cutoff for clarity. The averages and the universal agreement index describe different features of the same ratings. When only ratings of 4 were counted, S-CVI/Ave fell to 0.930 for relevance (410/441), 0.796 for clarity (351/441) and 0.834 for representativeness (368/441). Unanimous ratings of 4 were recorded for 28, 14 and 14 of the 49 items, respectively.

4.3. Item-Level Content Validity

For relevance, 42 items obtained unanimous agreement, five obtained an I-CVI of 0.889, and two obtained an I-CVI of 0.778. For representativeness, 42 items obtained unanimous agreement, five obtained an I-CVI of 0.889, and two obtained an I-CVI of 0.778. Clarity showed slightly greater variability. Thirty-eight items obtained unanimous agreement, nine obtained an I-CVI of 0.889, DMG2 obtained an I-CVI of 0.778, and TR5 obtained an I-CVI of 0.667. The modified kappas for relevance, reconstructed from the reported favourable counts, were 1.000 for 42 items, 0.887 for five items and 0.761 for two items.

Table 7. Priority items identified through item-level content-validity analysis.

Item	Criterion	Favourable ratings	I-CVI	Decision
TR5	Clarity	6/9	0.667	Priority revision
OR6	Relevance	7/9	0.778	Retain and revise
ER4	Relevance	7/9	0.778	Retain and clarify
ER4	Representativeness	7/9	0.778	Retain and contextualise
DMG2	Clarity	7/9	0.778	Retain and simplify
BDA4	Representativeness	7/9	0.778	Retain provisionally and test for overlap

Source: Expert ratings

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The decision labels in Table 7 describe the type of revision. Retain and revise changes a formulation or narrows its content while keeping its place in the domain. Clarify or simplify reduces ambiguity or wording load; contextualise makes the actors or practice more explicit. Provisional retention with overlap testing preserves coverage while deferring a decision about redundancy. TR5 received nine favourable relevance ratings but only six favourable clarity ratings. Its V2 wording describes protection of data and restriction of access in a single statement (Table 10). This reduces wording load, but respondents may still distinguish protection from access restriction; cognitive interviews should test whether both ideas can be answered consistently and whether the confidentiality content remains adequately represented.

4.4. Global Assessment of the IRAM Structure

Eight of the nine experts answered the global questions. One expert inadvertently omitted the entire global section; no ratings were imputed. Table 8 reports response distributions and descriptive dispersion calculated from the eight available sets of ratings.

Table 8. Global assessment of the IRAM structure.

Code	Assessed aspect	Counts: 1 / 2 / 3 / 4	Favourable ratings	Mean score	SD
G1	Coverage of Big Data Readiness	0 / 0 / 1 / 7	8/8	3.875	***0.354***
G2	Distinction between Adoption, Readiness, and Maturity	0 / 1 / 3 / 4	7/8	3.375	***0.744***
G3	Integration of capabilities within Maturity	0 / 0 / 0 / 8	8/8	4.000	***0.000***
G4	Coverage of the six Maturity dimensions	0 / 0 / 3 / 5	8/8	3.625	***0.518***
G5	Coverage of the four Value Creation dimensions	0 / 0 / 2 / 6	8/8	3.750	***0.463***
G6	Overall coherence and distinctiveness of the constructs	0 / 0 / 3 / 5	8/8	3.625	***0.518***
G7	Relevance to the agri-food supply chain	0 / 0 / 4 / 4	8/8	3.500	***0.535***

SD is the sample standard deviation; counts describe the distribution on the four-point scale.

Source: Consolidated global expert ratings.

G3 received eight ratings of 4. G2, which addresses the joint distinction between Readiness, Adoption and Maturity, received the lowest mean (3.375): one rating of 2, three of 3 and four of 4. This makes the boundary a priority for further testing. The global rating does not identify a particular pair of constructs; the documented BDA4–POI1 concern provides a more specific item-level indication.

4.5. Domain Patterns and Documented Revisions

To complement the overall indices, Table 9 summarises the content-validity results by measurement domain and reports the number of item formulations revised in V2. It presents average relevance, clarity and representativeness indices, together with the number of items receiving unanimous favourable clarity ratings. This overview helps identify domains requiring particular attention during cognitive pretesting. The indices refer to French V1; the revision counts describe the subsequent wording changes and do not constitute validation evidence for V2.

Table 9. French V1 ratings and number of V2 revisions by domain

Domain	Items	Mean relevance	Mean clarity	Mean represent.	Unanimous clarity agreement	Revised
Technological readiness	5	1.000	0.911	0.978	3/5	3
Organisational readiness	6	0.963	0.963	1.000	4/6	5
Environmental readiness	4	0.889	0.944	0.889	2/4	3
Organisational Big Data adoption	4	0.972	0.972	0.944	3/4	4
Technology and architecture	3	1.000	0.963	1.000	2/3	3
Data management and governance	3	0.963	0.926	0.963	2/3	3
Analytics capabilities and deployment	3	1.000	0.963	0.963	2/3	1
People, skills and data culture	3	1.000	0.963	1.000	2/3	3
Processes and organisational integration	3	1.000	1.000	1.000	3/3	3
Leadership and strategic alignment	3	0.963	1.000	1.000	3/3	2
Operational performance	3	1.000	1.000	1.000	3/3	2
Decision-making performance	3	1.000	1.000	1.000	3/3	0
Innovation performance	3	1.000	1.000	1.000	3/3	2
Competitive performance	3	1.000	1.000	1.000	3/3	1

Mean indices refer to French V1. Unanimous clarity agreement indicates the number of items receiving favourable clarity ratings from all nine experts, divided by the number of items in the domain. Revision counts refer to V2.

Source: Authors.

Table 10. Examples of French wording before and after revision

Item	French V1	French V2	Primary revision
TR5	Notre organisation dispose de mesures adéquates pour assurer la sécurité, la confidentialité et le contrôle d'accès aux données utilisées dans les initiatives Big Data.	Notre organisation protège les données utilisées dans ses initiatives Big Data et en limite l'accès aux personnes autorisées.	Simplification of security and access wording
OR6	Notre organisation a défini les responsabilités et les règles de base relatives à la gestion et à la gouvernance des données.	Notre organisation a défini des règles et des responsabilités de base pour la gestion des données avant le déploiement d'initiatives Big Data.	Basic pre-adoption governance only
ER4	Nos principaux partenaires sont suffisamment disposés et techniquement capables de participer à des initiatives fondées sur les données.	Nos principaux partenaires, notamment les fournisseurs, clients ou prestataires logistiques, peuvent partager des données exploitables dans le cadre d'initiatives communes.	Named partners and observable data-sharing capacity
BDA4	Notre organisation utilise activement les résultats issus des systèmes Big Data pour soutenir ses activités opérationnelles ou managériales.	Notre organisation utilise les résultats produits par ses solutions Big Data ou analytiques pour soutenir certaines décisions ou activités.	Occasional use separated from recurrent process integration
ACD1	Notre organisation est capable d'appliquer des techniques analytiques afin de produire des connaissances utiles à partir du Big Data.	Notre organisation applique régulièrement des techniques analytiques pour produire des connaissances utiles à partir de ses données.	Actual practice rather than potential capability
POI1	L'analytique est intégrée dans les processus opérationnels et managériaux récurrents.	L'utilisation des résultats analytiques est formalisée et intégrée dans les processus opérationnels ou managériaux récurrents.	Formal recurrent integration separated from Adoption
OP2	L'utilisation du Big Data a réduit les coûts d'exploitation, le gaspillage de ressources ou les inefficacités évitables.	L'utilisation du Big Data a réduit les pertes ou le gaspillage de ressources dans nos opérations.	Specific operational outcome

Source: Authors' selection from Supplementary Appendices A and C. The examples are item formulations.

Of the 49 items, 35 (71.4%) were revised and 14 retained their wording. A retrospective grouping of the primary revision recorded in Appendix C assigned one category to each revised

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item: separating concepts or domains (9), simplifying or narrowing wording (11), and making practices, actors or outcomes observable in context (15). This counts revision decisions, not individual comments or the number of experts raising a concern. Table 10 gives exact French wording before and after revision.

5. Discussion

5.1. Content-Validity Evidence for the IRAM Instrument

The high S-CVI/Ave values show that favourable responses predominated, but they do not imply that the items were ready for administration. The scoring rule classifies both 3 and 4 as favourable even though 3 permits minor revision. This creates a ceiling in the dichotomised index and can conceal differences between those two ratings. The lower universal agreement for clarity and the revision of 35 items show why the quantitative indices were interpreted alongside the reasons for revision. Under the stricter rule, the largest decline was for clarity (0.968 to 0.796). This identifies wording clarity as the criterion most sensitive to the scoring rule. The 4-only results supplement the primary CVIs; they do not replace the original decision rule.

5.2. Originality and Theoretical Contribution of the IRAM Model

The main conceptual contribution of this study is the integration of Readiness, Adoption, Maturity and Value Creation within a common organisational measurement framework. The individual concepts are not new; IRAM's contribution lies in their explicit articulation while preserving their different meanings. Readiness concerns enabling conditions available to support implementation and use. Adoption concerns actual implementation and use. Maturity concerns the formalisation, coordination and integration of data and analytics capabilities into recurrent organisational practices. Value Creation concerns the outcomes associated with their use. This ordering provides a theoretical orientation rather than mandatory organisational stages or an established causal sequence. These distinctions help avoid equating readiness with adoption, technology use with maturity, or performance with evidence of maturity.

IRAM builds on research connecting analytics resources, organisational capabilities and performance (Gupta & George, 2016; Wamba et al., 2017). Its integrative emphasis connects the conditions supporting adoption with realised use, the institutionalisation of capabilities and associated outcomes. Technological, governance, analytics, people, process and leadership capabilities are situated within Maturity insofar as they are developed and embedded in formal, recurrent practices. Separating Value Creation from Maturity allows subsequent research to examine whether more developed capabilities are associated with better outcomes, without assuming that this relationship necessarily holds. The 49-item instrument provides an initial operationalisation of this architecture, with item-level theoretical sources reported in Supplementary Appendix A.

The contribution also differs in scope from the approaches used in the selected studies. Gupta and George (2016) operationalise resources that combine into an analytics capability, whereas Comuzzi and Patel (2016) evaluate a Big Data maturity model qualitatively with practitioners and apply it in three organisations. IRAM's expert assessment contributes preliminary evidence at the instrument-development stage, before organisational field testing. These studies do not provide directly comparable relevance, clarity and representativeness indices obtained under the same panel and scoring conditions. The present CVIs therefore cannot establish that IRAM is superior to these instruments or that its measurement architecture has been empirically validated.

The Adoption–Maturity boundary remains a particular concern. BDA4 addresses the use of analytical outputs, whereas POI1 addresses their formal and recurrent integration into

organisational processes. The V2 revisions seek to clarify this distinction, but their effectiveness remains to be examined. Other candidate overlaps include BDA3–ACD1, ACD3–POI1 and BDA2–POI2. Cognitive interviews should investigate whether respondents distinguish these items through concrete examples of organisational practice. Further reformulation, merging or removal should depend on the evidence obtained and the need to preserve domain coverage. The expert assessment identifies boundaries requiring further examination; it does not establish empirical discriminant validity.

5.3. Relevance to Agri-Food Information Systems Transformation

Agri-food organisations differ in their data access, decision structures and roles in the chain. Those differences matter when respondents interpret use, integration and value (Ahoa et al., 2026; Candraningrat et al., 2026). G7 provides an overall assessment of relevance: four experts selected 3 and four selected 4. It does not demonstrate that the instrument works equally well for producers, cooperatives, processors, logistics providers and integrated groups.

5.4. Practical Implications and Next Validation Stage

The intended users are managers responsible for data, operations or supply-chain coordination in agri-food organisations, including cooperatives. The present instrument can guide questions for pretesting and consultation. Diagnostic thresholds, rankings and comparisons for public decision-making require field evidence on the meaning and comparability of scores. The initial reporting design is a profile by component and domain; no overall IRAM score, cross-component weighting scheme or diagnostic threshold is proposed at this stage. Any future composite score would require a justified weighting rule, explicit treatment of missing or inapplicable domains, and sensitivity analysis.

6. Limitations and Future Research

This study drew on a small purposive panel: nine experts rated the items and eight answered the global questions. The four-point scale and dichotomisation of ratings of 3 or 4 limit sensitivity at the favourable end. Recruitment through institutional and professional networks may have introduced selection bias and limits the diversity of perspectives represented in the panel. The small profile groups limit interpretation of the descriptive comparison. The regional focus on Souss-Massa limits conclusions about transfer to other regions and actors. French V1 was assessed; neither revised V2 wording nor an English administration version has equivalent evidence. No second expert round is reported. The reflective and formative specifications in Section 2.6 are theoretical proposals; the factor structure of the reflective blocks, composite properties, measurement invariance and structural relationships remain untested.

A proposed next step is targeted expert reassessment of substantially revised V2 items, followed by two rounds of cognitive interviews with approximately 8-12 intended respondents in total. Purposive recruitment should cover different organisation sizes and chain positions, including cooperatives or producers, processors and logistics or integrated operators. Think-aloud and targeted probes should assess interpretation, retrieval of evidence and choice of response, particularly for the adoption filter and the candidate item overlaps (Willis, 2005). A subsequent feasibility pilot of approximately 30–50 organisational units should check completion time, branching, missingness and response distributions. The 49 items are provisional: interview evidence, burden and redundancy should inform shortening while preserving domain coverage. The pilot is not intended to establish the full factor structure.

For the main study, recruitment should be stratified by chain position and organisation size where the sampling frame permits. The target size should be determined by a power or simulation analysis of the specified structural paths, expected response and missingness, and planned comparisons. Multiple informants from one organisation should not be counted as

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independent units; aggregation requires evidence of within-organisation agreement. Reflective blocks should be assessed with ordinal exploratory factor analysis where needed and confirmatory assessment on independent data or a held-out sample when feasible. The Adoption block and reflective Maturity domains should be checked for discriminant validity using HTMT with bootstrap intervals (Henseler et al., 2015). For formative blocks, assess content coverage, collinearity, weights and external relationships; HTMT is not a test for these composites. A suitable composite modelling approach, such as PLS-SEM, can then examine H1-H4. Measurement invariance should precede comparisons between adequately represented chain actors, using an approach suited to the specification (e.g., MICOM for composites; Henseler et al., 2016).

The nomological tests should examine the specified links from Readiness to Adoption, Adoption to Maturity and Maturity to Value Creation, alongside the proposed sequential indirect relationship. Maturity and Value Creation follow the adoption filter: skipped items should not be scored as zero. If the filter also prevents non-adopters from answering the Adoption block, the observed adoption status can be analysed for all eligible organisations, separately from analyses using Adoption scores among adopters. An indirect association from a cross-sectional design cannot establish temporal or causal ordering.

7. Conclusion

This study translates the IRAM framework into an initial instrument for assessing organisational Big Data transformation in agri-food supply chains. Its contribution lies in connecting perspectives often examined separately within a common measurement architecture. By distinguishing enabling conditions, realised use, institutionalised capabilities and associated outcomes, IRAM provides a basis for examining different organisational situations without reducing transformation to technology deployment or imposing a uniform progression. Its value at this stage is therefore conceptual and methodological: it makes the proposed distinctions explicit and open to subsequent empirical examination.

The expert assessment provided preliminary content-validity evidence and informed revisions to the French instrument. A central lesson is that favourable aggregate ratings can coexist with wording difficulties and uncertain conceptual boundaries. Qualitative comments were consequently essential to interpreting the numerical results and guiding revision decisions. The resulting V2 should be regarded as a candidate instrument requiring further assessment, particularly concerning the Adoption–Maturity distinction. The study establishes a foundation for continued development rather than demonstrating a validated organisational diagnostic tool.

The next research stage is to determine whether intended respondents can interpret the proposed distinctions consistently and provide meaningful organisational evidence for their answers. Testing in Souss-Massa will help assess the instrument's relevance across heterogeneous agri-food actors; its transferability beyond this setting remains an empirical question. If subsequent validation supports the measures, IRAM could help managers identify where organisational efforts need to be directed. This potential depends on establishing that the resulting profiles are interpretable and comparable, rather than assuming that a common instrument necessarily produces equivalent assessments across organisations.

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Appendix A: Item-Level Theoretical Traceability of the Initial IRAM Instrument

This matrix preserves the exact V1 French wording assessed by the expert panel and makes the theoretical basis of each item explicit. Theoretical anchors identify the conceptual lens used to justify item placement; supporting sources document derivation or conceptual adaptation rather than verbatim reproduction. Content-validity indices reported in the study therefore apply to these V1 formulations.

IRAM component / domain	Code	Initial French wording V1	Theoretical anchor	Principal supporting sources
Readiness - Technological readiness	TR1	Notre organisation dispose d'une infrastructure de calcul, de stockage et de traitement suffisante pour prendre en charge les applications Big Data.	TOE technological context; tangible BDA resources	Tornatzky & Fleischer (1990); Baker (2012); Gangwar et al. (2015); Gupta & George (2016)
Readiness - Technological readiness	TR2	Les technologies Big Data sont compatibles avec nos systèmes d'information et nos technologies opérationnelles existants.	TOE/innovation compatibility	Rogers (2003); Gangwar et al. (2015)
Readiness - Technological readiness	TR3	Les données disponibles dans notre organisation sont suffisamment exactes, complètes et à jour pour les analyses Big Data.	Technological readiness; data-resource quality	Gupta & George (2016); Babalghaith & Aljarallah (2024)
Readiness - Technological readiness	TR4	Notre organisation est capable d'intégrer les données pertinentes provenant de différentes sources internes et externes.	Technological readiness; BDA integration capability	Gupta & George (2016); Wamba et al. (2017)
Readiness - Technological readiness	TR5	Notre organisation dispose de mesures adéquates pour assurer la sécurité, la confidentialité et le contrôle d'accès aux données utilisées dans les initiatives Big Data.	TOE technological context; technology risk/readiness	Gangwar et al. (2015); Babalghaith & Aljarallah (2024)
Readiness - Organisational readiness	OR1	La direction soutient activement la mise en œuvre et l'utilisation du Big Data dans notre organisation.	TOE organisational context	Tornatzky & Fleischer (1990); Baker (2012); Gangwar et al. (2015); Babalghaith & Aljarallah (2024)
Readiness - Organisational readiness	OR2	Notre organisation dispose d'une stratégie Big Data claire et alignée sur ses objectifs organisationnels.	Organisational readiness; strategic alignment	Gupta & George (2016); Akter et al. (2016)
Readiness - Organisational readiness	OR3	Notre organisation peut allouer des ressources financières et autres suffisantes aux initiatives Big Data.	TOE organisational context; resource readiness	Gangwar et al. (2015); Gupta & George (2016)
Readiness - Organisational readiness	OR4	Notre organisation dispose de collaborateurs possédant les compétences nécessaires pour travailler efficacement avec les données et les outils analytiques.	Human-resource readiness	Gupta & George (2016); Akter et al. (2016)
Readiness - Organisational readiness	OR5	La culture de notre organisation encourage l'utilisation des données et des analyses factuelles dans la prise de décision.	Organisational readiness; BDA capability antecedents	Gupta & George (2016); Babalghaith & Aljarallah (2024)
Readiness - Organisational readiness	OR6	Notre organisation a défini les responsabilités et les règles de base relatives à la gestion et à la gouvernance des données.	Pre-adoption governance readiness	Shamim et al. (2019); Al-Sai et al. (2023)
Readiness - Environmental readiness	ER1	La pression concurrentielle encourage notre organisation à adopter et à utiliser l'analytique Big Data.	TOE environmental context	Tornatzky & Fleischer (1990); Baker (2012); Gangwar et al. (2015); Babalghaith & Aljarallah (2024)
Readiness - Environmental readiness	ER2	L'environnement réglementaire et les politiques publiques offrent un soutien et une clarté suffisants pour une utilisation responsable du Big Data.	TOE environmental context	Tornatzky & Fleischer (1990); Baker (2012); Babalghaith & Aljarallah (2024)
Readiness - Environmental readiness	ER3	Des fournisseurs technologiques qualifiés sont disponibles pour accompagner la mise en œuvre et le développement du Big Data dans notre organisation.	TOE environmental context; vendor support	Gangwar et al. (2015); Babalghaith & Aljarallah (2024)
Readiness - Environmental readiness	ER4	Nos principaux partenaires sont suffisamment disposés et techniquement capables de participer à des initiatives fondées sur les données.	Inter-organisational readiness	Wamba et al. (2017); Rejeb et al. (2021, 2022)

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IRAM component / domain	Code	Initial French wording V1	Theoretical anchor	Principal supporting sources
Adoption - Organisational Big Data adoption	BDA1	Notre organisation a mis en œuvre des technologies Big Data pour soutenir ses activités.	Innovation adoption and implementation	Rogers (2003); Gangwar et al. (2015); Wamba et al. (2017)
Adoption - Organisational Big Data adoption	BDA2	Les technologies Big Data sont effectivement utilisées dans une ou plusieurs fonctions de notre organisation.	Organisational technology use	Rogers (2003); Wamba et al. (2017)
Adoption - Organisational Big Data adoption	BDA3	Les collaborateurs concernés utilisent régulièrement des technologies Big Data ou des applications analytiques dans leur travail.	Use behaviour / post-adoption usage	Venkatesh et al. (2003); Wamba et al. (2017)
Adoption - Organisational Big Data adoption	BDA4	Notre organisation utilise activement les résultats issus des systèmes Big Data pour soutenir ses activités opérationnelles ou managériales.	Post-adoption use and assimilation	Akter et al. (2016); Wamba et al. (2017)
Maturity - Technology and architecture	MTA 1	Notre architecture de données et d'analytique est intégrée, évolutive et réutilisable à l'échelle de l'organisation.	Big Data maturity - technology architecture	Comuzzi & Patel (2016); Al-Sai et al. (2023); Draganić (2023)
Maturity - Technology and architecture	MTA 2	Des plateformes partagées permettent un accès gouverné aux données et aux services analytiques à l'échelle de l'organisation.	Big Data maturity - shared infrastructure	Al-Sai et al. (2023); Draganić (2023)
Maturity - Technology and architecture	MTA 3	Nos flux de données et nos environnements analytiques sont suffisamment automatisés et fiables pour une utilisation à l'échelle de l'organisation.	Big Data maturity - automation	Comuzzi & Patel (2016); Al-Sai et al. (2023)
Maturity - Data management and governance	DMG 1	La gouvernance des données est institutionnalisée dans les différentes fonctions de notre organisation.	Data-management capability; governance maturity	Shamim et al. (2019); Al-Sai et al. (2023)
Maturity - Data management and governance	DMG 2	Des définitions, normes, règles de propriété et mécanismes de responsabilité communs en matière de données sont appliqués de manière cohérente.	Data governance and institutionalisation	Shamim et al. (2019); Al-Sai et al. (2023)
Maturity - Data management and governance	DMG 3	Notre organisation gère de manière systématique la qualité, l'accessibilité et le cycle de vie de volumes importants et variés de données.	Data-management capability	Gupta & George (2016); Akter et al. (2016); Shamim et al. (2019)
Maturity - Analytics capabilities and deployment	ACD1	Notre organisation est capable d'appliquer des techniques analytiques afin de produire des connaissances utiles à partir du Big Data.	BDA analytics capability	Gupta & George (2016); Akter et al. (2016)
Maturity - Analytics capabilities and deployment	ACD2	Les analyses prédictives ou avancées sont utilisées au-delà de projets pilotes isolés pour soutenir les décisions organisationnelles.	Analytics deployment maturity	Gupta & George (2016); Mikalef et al. (2020); Al-Sai et al. (2023)
Maturity - Analytics capabilities and deployment	ACD3	Les modèles analytiques et les connaissances qui en résultent sont régulièrement intégrés dans les processus de travail concernés.	Analytics institutionalisation	Comuzzi & Patel (2016); Al-Sai et al. (2023)
Maturity - People, skills and data culture	PSC1	Les rôles liés aux données et à l'analytique sont formellement définis et coordonnés au sein de l'organisation.	Human BDA capability; maturity	Gupta & George (2016); Al-Sai et al. (2023)
Maturity - People, skills and data culture	PSC2	Les collaborateurs des fonctions concernées disposent du niveau de culture des données et des compétences analytiques requis pour leurs responsabilités.	Human BDA capability	Gupta & George (2016); Akter et al. (2016)
Maturity - People, skills and data culture	PSC3	Les collaborateurs des métiers et les spécialistes techniques collaborent efficacement et utilisent régulièrement des analyses factuelles dans la prise de décision.	Managerial/human BDA capability	Gupta & George (2016); Mikalef et al. (2020)
Maturity - Processes and organisational integration	POI1	L'analytique est intégrée dans les processus opérationnels et managériaux récurrents.	Process institutionalisation / maturity	Comuzzi & Patel (2016); Al-Sai et al. (2023)
Maturity - Processes and organisational integration	POI2	Notre organisation est capable de déployer les solutions Big Data à plus grande échelle dans plusieurs fonctions et processus.	Scaling and organisational maturity	Gupta & George (2016); Mikalef et al. (2020)
Maturity - Processes and organisational integration	POI3	Les pratiques Big Data sont standardisées, coordonnées et améliorées en continu dans les unités organisationnelles concernées.	Process standardisation / maturity	Comuzzi & Patel (2016); Al-Sai et al. (2023)

IRAM component / domain	Code	Initial French wording V1	Theoretical anchor	Principal supporting sources
Maturity - Leadership and strategic alignment	LSA1	La direction considère les données et l'analytique comme une priorité stratégique à l'échelle de l'organisation.	Strategic leadership and maturity	Comuzzi & Patel (2016); Al-Sai et al. (2023)
Maturity - Leadership and strategic alignment	LSA2	Les investissements en Big Data et en analytique suivent une feuille de route coordonnée et alignée sur les objectifs de l'organisation.	Strategic alignment	Akter et al. (2016); Comuzzi & Patel (2016); Al-Sai et al. (2023)
Maturity - Leadership and strategic alignment	LSA3	La direction évalue régulièrement les progrès en matière de maturité Big Data et ajuste les priorités et les ressources en conséquence.	Maturity governance and leadership	Comuzzi & Patel (2016); Al-Sai et al. (2023)
Value Creation - Operational performance	OP1	L'utilisation du Big Data a amélioré l'efficacité de nos opérations.	RBV/dynamic capabilities; BDA performance	Barney (1991); Akter et al. (2016); Wamba et al. (2017)
Value Creation - Operational performance	OP2	L'utilisation du Big Data a réduit les coûts d'exploitation, le gaspillage de ressources ou les inefficacités évitables.	BDA operational performance	Akter et al. (2016); Wamba et al. (2017)
Value Creation - Operational performance	OP3	L'utilisation du Big Data a amélioré la rapidité et la fiabilité de nos processus organisationnels.	BDA operational performance	Akter et al. (2016); Wamba et al. (2017)
Value Creation - Decision-making performance	DQ1	L'analytique Big Data permet aux responsables de prendre des décisions plus précises et davantage fondées sur des données probantes.	BDA decision-making capability	Akter et al. (2016); Shamim et al. (2019); Wamba et al. (2017)
Value Creation - Decision-making performance	DQ2	L'analytique Big Data permet de réagir plus rapidement aux problèmes et aux opportunités émergentes.	Dynamic/operational capability; decision performance	Wamba et al. (2017); Mikalef et al. (2020)
Value Creation - Decision-making performance	DQ3	L'analytique Big Data améliore notre capacité à évaluer différentes options avant de prendre une décision.	BDA decision quality	Shamim et al. (2019); Akter et al. (2016)
Value Creation - Innovation performance	INN1	L'analytique Big Data soutient le développement de produits ou services nouveaux ou améliorés.	Dynamic capabilities; BDA-enabled innovation	Mikalef et al. (2019, 2020); Wamba et al. (2017)
Value Creation - Innovation performance	INN2	L'analytique Big Data permet de développer des processus, des pratiques ou des modèles d'affaires nouveaux ou améliorés.	Dynamic capabilities; BDA-enabled innovation	Mikalef et al. (2019, 2020); Wamba et al. (2017)
Value Creation - Innovation performance	INN3	L'analytique Big Data renforce notre capacité à identifier et à exploiter des opportunités d'innovation.	Dynamic capabilities	Mikalef et al. (2019, 2020); Wamba et al. (2017)
Value Creation - Competitive performance	CPER 1	Les capacités Big Data aident notre organisation à se différencier de ses concurrents.	RBV and competitive advantage	Barney (1991); Gupta & George (2016); Mikalef et al. (2020)
Value Creation - Competitive performance	CPER 2	Les capacités Big Data permettent à notre organisation de réagir plus efficacement que ses concurrents.	Dynamic capabilities; competitive responsiveness	Mikalef et al. (2020); Wamba et al. (2017)
Value Creation - Competitive performance	CPER 3	Les capacités Big Data ont renforcé la position concurrentielle ou la position de marché globale de notre organisation.	RBV/dynamic capabilities; competitive performance	Mikalef et al. (2020); Wamba et al. (2017)

Note:
Full bibliographic details are provided in the reference list of the main manuscript.
The V1 wording is reproduced because it is the version rated by the nine experts; revised V2 wording is reported separately in Supplementary Appendix C.

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Appendix B: Complete content-validity results

Favourable ratings are scores of 3 or 4. I-CVI is the favourable count divided by nine. Modified kappa is reported for relevance and adjusts the I-CVI for chance agreement. These indices describe the initial V1 wording. The decision column summarises the authors' retention and revision choices; it does not reproduce individual expert comments. Checks proposed for cognitive pretesting are identified separately.

Code	Relevance	K*	Clarity	Representativeness	Decision based on quantitative and qualitative evidence
TR1	9/9 (1.000)	1.000	8/9 (0.889)	9/9 (1.000)	Formulation simplifiée pour exprimer la disponibilité des ressources. Prétest : compréhension des ressources techniques.
TR2	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Formulation V1 conservée. Prétest : compréhension et capacité d'un répondant connaissant les systèmes à répondre.
TR3	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Périmètre des données précisé ; qualité distinguée de l'intégration des sources.
TR4	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Formulation V1 conservée. Prétest : compréhension de l'intégration des sources.
TR5	9/9 (1.000)	1.000	6/9 (0.667)	8/9 (0.889)	Item conservé provisoirement et formulation simplifiée autour de la protection et des accès. Prétest : compréhension et couverture de la confidentialité.
OR1	9/9 (1.000)	1.000	8/9 (0.889)	9/9 (1.000)	Soutien de la direction reformulé comme condition de préparation, distincte du leadership stratégique avancé.
OR2	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Objectifs préparatoires explicités, distincts de la feuille de route mise en œuvre en LSA2.
OR3	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Ressources financières, humaines et matérielles explicitement nommées.
OR4	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Possibilité de mobiliser des compétences de base explicitée.
OR5	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Formulation V1 conservée. Prétest : compréhension et distinction avec la culture et les pratiques institutionnalisées.
OR6	7/9 (0.778)	0.761	8/9 (0.889)	9/9 (1.000)	Règles et responsabilités de base reformulées comme préparation au déploiement. Prétest : interprétation temporelle par les organisations déjà adoptantes.
ER1	8/9 (0.889)	0.887	9/9 (1.000)	9/9 (1.000)	Pression externe reformulée sans présumer une adoption effective.
ER2	8/9 (0.889)	0.887	8/9 (0.889)	8/9 (0.889)	Item recentré sur la clarté du cadre réglementaire ; aucun item supplémentaire sur le soutien public ajouté.
ER3	9/9 (1.000)	1.000	9/9 (1.000)	8/9 (0.889)	Formulation V1 conservée. Prétest : compréhension et capacité à identifier les fournisseurs pertinents.
ER4	7/9 (0.778)	0.761	8/9 (0.889)	7/9 (0.778)	Partenaires nommés et capacité de partage de données exploitables explicitée.
BDA1	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Formulation harmonisée pour mesurer la mise en œuvre effective d'au moins une solution. Prétest : conformité au périmètre Big Data défini.
BDA2	8/9 (0.889)	0.887	9/9 (1.000)	9/9 (1.000)	Utilisation effective dans au moins une fonction explicitée, distincte de la fréquence mesurée en BDA3.
BDA3	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Fréquence d'utilisation et référent organisationnel explicités.
BDA4	9/9 (1.000)	1.000	8/9 (0.889)	7/9 (0.778)	Usage des résultats conservé provisoirement et reformulé. Prétest : distinction avec BDA3 et l'intégration récurrente mesurée par la maturité.
MTA1	9/9 (1.000)	1.000	8/9 (0.889)	9/9 (1.000)	Architecture reformulée en termes d'usage observable. Prétest : compréhension de l'architecture et capacité à répondre.
MTA2	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Plateformes partagées et règles d'accès décrites dans un langage plus accessible.
MTA3	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Item recentré sur l'automatisation ; gestion de la qualité maintenue dans DMG3.
DMG1	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Gouvernance reformulée comme pratique formalisée effective, distincte de la disponibilité de règles de base.
DMG2	8/9 (0.889)	0.887	7/9 (0.778)	8/9 (0.889)	Définitions, normes et responsabilités communes simplifiées. Prétest : distinction avec OR6.
DMG3	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Gestion systématique recentrée sur les données utilisées pour l'analytique.
ACD1	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Capacité potentielle remplacée par une pratique effectivement déployée.
ACD2	9/9 (1.000)	1.000	8/9 (0.889)	8/9 (0.889)	Formulation V1 conservée. Prétest : compréhension et capacité à documenter le déploiement au-delà des pilotes.
ACD3	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Formulation V1 conservée. Prétest : compréhension et distinction avec l'intégration des processus en POI1.
PSC1	9/9 (1.000)	1.000	8/9 (0.889)	9/9 (1.000)	Rôles des personnes explicités, distincts des responsabilités de gestion des données en DMG2.
PSC2	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Mobilisation régulière des compétences mise en avant ; aucune dimension juridique supplémentaire ajoutée.

Code	Relevance	K*	Clarity	Representativeness	Decision based on quantitative and qualitative evidence
PSC3	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Item recentré sur la collaboration entre métiers et spécialistes techniques.
POI1	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Intégration formalisée et récurrente explicitée, distincte de l'utilisation des résultats en BDA4.
POI2	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Capacité potentielle remplacée par un déploiement effectif dans plusieurs fonctions ou processus.
POI3	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Item recentré sur les procédures communes, sans ajout d'item. Prétest : couverture de l'amélioration continue.
LSA1	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Formulation V1 conservée. Prétest : compréhension et distinction avec le soutien préparatoire de la direction.
LSA2	8/9 (0.889)	0.887	9/9 (1.000)	9/9 (1.000)	Coordination d'une feuille de route effective explicitée.
LSA3	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Suivi des résultats et ajustement des priorités explicités, sans présumer un score de maturité.
OP1	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Formulation V1 conservée ; période de référence commune précisée dans les consignes.
OP2	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Item recentré sur les pertes ou le gaspillage, distinct de l'efficacité générale mesurée par OP1.
OP3	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Item recentré sur la fiabilité des processus.
DQ1	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Formulation V1 conservée. Prétest : compréhension de la précision et de l'appui sur les données.
DQ2	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Formulation V1 conservée ; aucune extension automatique de Value Creation.
DQ3	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Formulation V1 conservée. Prétest : compréhension et exemples de comparaison des options.
INN1	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Formulation V1 conservée. Prétest : compréhension et exemples d'innovations de produits ou de services.
INN2	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Item recentré sur l'innovation de processus ; aucun item supplémentaire sur les modèles d'affaires ajouté.
INN3	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Transformation des opportunités en innovations mises en œuvre explicitée.
CPER1	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Formulation V1 conservée. Prétest : compréhension et capacité à apprécier la différenciation.
CPER2	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Comparaison directe aux concurrents remplacée par la réactivité face aux évolutions du marché.
CPER3	9/9 (1.000)	1.000	9/9 (1.000)	9/9 (1.000)	Formulation V1 conservée ; période de référence commune précisée dans les consignes.

Priority cases: TR5 clarity = 6/9 (0.667); OR6 relevance = 7/9 (0.778); ER4 relevance and representativeness = 7/9 (0.778); DMG2 clarity = 7/9 (0.778); BDA4 representativeness = 7/9 (0.778).

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Appendix C: Revised IRAM instrument for cognitive pretesting

This appendix presents the French-language V2 produced after integration of the quantitative indices and qualitative expert comments. The CVI values reported in Appendix B apply to the V1 wording. Thirty-five item formulations were revised and fourteen were unchanged. The revised formulations require cognitive pretesting and have not yet been independently revalidated. Understanding of technology-specific items and respondents' ability to answer them will be examined during cognitive pretesting. The common instructions below clarify the Big Data scope and specify a reference period for the Value Creation section; their suitability will also be assessed during cognitive pretesting.

The common instructions and proposed response options below are intended for cognitive pretesting and were not assessed by the expert panel. They clarify administration without changing the 49 V2 item formulations or the count of revised items.

Consigne commune : Dans ce questionnaire, le Big Data renvoie à des usages de données dont l'ampleur, l'hétérogénéité, la rapidité de production ou la variabilité créent des exigences de stockage, d'intégration ou de traitement nécessitant des architectures évolutives, internes ou externalisées. La seule présence d'un ERP, d'un outil de reporting, de business intelligence, de traçabilité ou d'une fonction d'intelligence artificielle ne suffit pas à établir une adoption du Big Data ; référez-vous aux usages correspondant à cette définition.

Périmètre de réponse : Répondez pour une seule organisation ou unité décisionnelle clairement identifiée. Pour un groupe multi-sites, précisez les établissements et fonctions couverts. Les réponses portent sur les pratiques de cette unité, et non sur vos préférences personnelles.

Modalités proposées pour le prétest cognitif : Pour chaque affirmation, indiquez votre degré d'accord : 1= Pas du tout d'accord ; 2 = Plutôt pas d'accord ; 3 = Ni d'accord ni en désaccord ; 4 = Plutôt d'accord ; 5 = Tout à fait d'accord. Si vous ne disposez pas de l'information, sélectionnez « Ne sait pas » . Cette réponse est distincte du point médian et ne reçoit pas de score numérique. Ces modalités seront examinées au prétest ; elles diffèrent des échelles à quatre points utilisées par les experts.

Repérage des usages et parcours proposés : Avant les items d'Adoption, identifiez une application effectivement utilisée dans l'unité et vérifiez qu'elle correspond à la définition ci-dessus. En l'absence d'usage correspondant, complétez la partie Readiness et renseignez l'absence d'adoption ; ne renseignez pas les parties Maturity et Value Creation. Les réponses ainsi omises ne doivent pas être remplacées par une note minimale. En cas d'incertitude sur l'usage, demandez une précision à une personne compétente. Ce parcours reste à tester au prétest cognitif.

Consigne pour la section Value Creation : Pour les items OP1 à CPER3, répondez en vous référant aux résultats observés dans votre organisation au cours des 12 derniers mois. Si l'utilisation du Big Data a commencé il y a moins de 12 mois, considérez la période écoulée depuis le début de cette utilisation.

Code	Revised French wording V2	Status	Primary revision
TR1	Notre organisation dispose des ressources de calcul, de stockage et de traitement nécessaires pour soutenir ses premières initiatives Big Data.	Revised	Simplification of multiple technical capacities
TR2	Les technologies Big Data sont compatibles avec nos systèmes d'information et nos technologies opérationnelles existants.	Unchanged	V1 wording retained for cognitive pretesting
TR3	Les données nécessaires aux analyses Big Data sont suffisamment exactes, complètes et à jour.	Revised	Separation of data quality from source integration
TR4	Notre organisation est capable d'intégrer les données pertinentes provenant de différentes sources internes et externes.	Unchanged	V1 wording retained for cognitive pretesting
TR5	Notre organisation protège les données utilisées dans ses initiatives Big Data et en limite l'accès aux personnes autorisées.	Revised	Simplification of security and access wording
OR1	La direction est disposée à soutenir le lancement et la mise en œuvre d'initiatives Big Data.	Revised	Clearer readiness-stage managerial support
OR2	Notre organisation a défini des objectifs préparatoires clairs pour ses initiatives Big Data.	Revised	Separation from the maturity road map
OR3	Notre organisation peut mobiliser les ressources financières, humaines et matérielles nécessaires aux initiatives Big Data.	Revised	Explicit resource categories
OR4	Notre organisation peut mobiliser des collaborateurs possédant les compétences de base nécessaires pour travailler avec les données et les outils analytiques.	Revised	Mobilisable basic skills before implementation
OR5	La culture de notre organisation encourage l'utilisation des données et des analyses factuelles dans la prise de décision.	Unchanged	V1 wording retained for cognitive pretesting
OR6	Notre organisation a défini des règles et des responsabilités de base pour la gestion des données avant le déploiement d'initiatives Big Data.	Revised	Basic pre-adoption governance only

Code	Revised French wording V2	Status	Primary revision
ER1	La pression concurrentielle incite notre organisation à envisager l'adoption de solutions Big Data.	Revised	External pressure without assuming adoption
ER2	Le cadre réglementaire applicable à l'utilisation des données et du Big Data est suffisamment clair pour notre organisation.	Revised	Focus on regulatory clarity
ER3	Des fournisseurs technologiques qualifiés sont disponibles pour accompagner la mise en œuvre et le développement du Big Data dans notre organisation.	Unchanged	V1 wording retained for cognitive pretesting
ER4	Nos principaux partenaires, notamment les fournisseurs, clients ou prestataires logistiques, peuvent partager des données exploitables dans le cadre d'initiatives communes.	Revised	Named partners and observable data-sharing capacity
BDA1	Notre organisation a effectivement mis en œuvre au moins une solution de données avancées ou d'analytique Big Data.	Revised	Observable implementation of at least one solution
BDA2	Au moins une fonction de notre organisation utilise effectivement une solution Big Data ou analytique.	Revised	Use in at least one function
BDA3	Les collaborateurs concernés utilisent régulièrement les solutions Big Data ou analytiques mises en œuvre par notre organisation.	Revised	Explicit regular use
BDA4	Notre organisation utilise les résultats produits par ses solutions Big Data ou analytiques pour soutenir certaines décisions ou activités.	Revised	Occasional use separated from recurrent process integration
MTA1	Notre organisation utilise une architecture de données et d'analytique intégrée et évolutive à l'échelle de plusieurs fonctions.	Revised	Observable integrated and scalable architecture
MTA2	Des plateformes partagées permettent aux fonctions autorisées d'accéder aux données et aux services analytiques selon des règles définies.	Revised	Accessible description of shared platforms
MTA3	Les flux de données et les traitements analytiques récurrents sont automatisés à l'échelle des fonctions concernées.	Revised	Focus on automation
DMG1	La gouvernance des données est appliquée de manière formalisée dans les différentes fonctions concernées de notre organisation.	Revised	Effective institutionalised governance practice
DMG2	Des définitions, normes et responsabilités communes relatives aux données sont appliquées de manière cohérente dans l'organisation.	Revised	Simplified shared rules and responsibilities
DMG3	Notre organisation gère systématiquement la qualité, l'accessibilité et le cycle de vie des données utilisées pour l'analytique.	Revised	Systematic management of analytics data
ACD1	Notre organisation applique régulièrement des techniques analytiques pour produire des connaissances utiles à partir de ses données.	Revised	Actual practice rather than potential capability
ACD2	Les analyses prédictives ou avancées sont utilisées au-delà de projets pilotes isolés pour soutenir les décisions organisationnelles.	Unchanged	V1 wording retained for cognitive pretesting
ACD3	Les modèles analytiques et les connaissances qui en résultent sont régulièrement intégrés dans les processus de travail concernés.	Unchanged	V1 wording retained for cognitive pretesting
PSC1	Les rôles des personnes chargées des données et de l'analytique sont formellement définis et coordonnés dans l'organisation.	Revised	People roles separated from data ownership
PSC2	Les collaborateurs concernés mobilisent régulièrement les compétences analytiques correspondant à leurs responsabilités.	Revised	Regular mobilisation of skills
PSC3	Les collaborateurs des métiers et les spécialistes techniques collaborent régulièrement sur les projets fondés sur les données.	Revised	Focus on cross-functional collaboration
POI1	L'utilisation des résultats analytiques est formalisée et intégrée dans les processus opérationnels ou managériaux récurrents.	Revised	Formal recurrent integration separated from Adoption
POI2	Les solutions Big Data sont effectivement déployées dans plusieurs fonctions ou processus de notre organisation.	Revised	Effective multi-function deployment
POI3	Des procédures communes encadrent les pratiques Big Data dans les unités organisationnelles concernées.	Revised	Common procedures; one observable focus
LSA1	La direction considère les données et l'analytique comme une priorité stratégique à l'échelle de l'organisation.	Unchanged	V1 wording retained for cognitive pretesting
LSA2	Les investissements en Big Data et en analytique sont coordonnés au moyen d'une feuille de route effectivement mise en œuvre.	Revised	Effective coordinated road map

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Code	Revised French wording V2	Status	Primary revision
LSA3	La direction suit régulièrement les résultats des initiatives Big Data et ajuste les priorités ou les ressources en conséquence.	Revised	Outcome monitoring without presuming a maturity score
OP1	L'utilisation du Big Data a amélioré l'efficacité de nos opérations.	Unchanged	V1 wording retained for cognitive pretesting
OP2	L'utilisation du Big Data a réduit les pertes ou le gaspillage de ressources dans nos opérations.	Revised	Specific operational outcome
OP3	L'utilisation du Big Data a amélioré la fiabilité de nos processus organisationnels.	Revised	Reliability separated from decision speed
DQ1	L'analytique Big Data permet aux responsables de prendre des décisions plus précises et davantage fondées sur des données probantes.	Unchanged	V1 wording retained for cognitive pretesting
DQ2	L'analytique Big Data permet de réagir plus rapidement aux problèmes et aux opportunités émergentes.	Unchanged	V1 wording retained for cognitive pretesting
DQ3	L'analytique Big Data améliore notre capacité à évaluer différentes options avant de prendre une décision.	Unchanged	V1 wording retained for cognitive pretesting
INN1	L'analytique Big Data soutient le développement de produits ou services nouveaux ou améliorés.	Unchanged	V1 wording retained for cognitive pretesting
INN2	L'analytique Big Data soutient le développement de processus organisationnels nouveaux ou améliorés.	Revised	Single innovation outcome
INN3	L'analytique Big Data aide notre organisation à transformer des opportunités identifiées en innovations mises en œuvre.	Revised	Implemented innovation outcome
CPER1	Les capacités Big Data aident notre organisation à se différencier de ses concurrents.	Unchanged	V1 wording retained for cognitive pretesting
CPER2	Les capacités Big Data améliorent la réactivité de notre organisation face aux évolutions du marché.	Revised	Observable market responsiveness
CPER3	Les capacités Big Data ont renforcé la position concurrentielle ou la position de marché globale de notre organisation.	Unchanged	V1 wording retained; common section instructions clarified for cognitive pretesting