RECONCEPTUALIZING AGRICULTURAL EXTENSION AS AN AI-ENABLED KNOWLEDGE ECOSYSTEM: A THEORY-INFORMED IASEE FRAMEWORK

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Abstract

Agricultural advice now circulates through heterogeneous data infrastructures, AI systems and plural knowledge networks. This article asks how extension can be theorised as a governed knowledge ecosystem in which algorithmic intelligence becomes contextual advice and accountable human decisions. The Integrated AI-Driven Smart Agricultural Extension Ecosystem (IASEE) V1.0 is developed through purposive theory synthesis and conceptual model building. Pluralistic advisory services, agricultural innovation systems, socio-technical governance, knowledge creation, decision support and resilience scholarship are compared according to their explanatory roles and boundaries. This is not a systematic literature review or an empirical evaluation. Eight constructs—agricultural data ecosystem, AI-enabled intelligence, knowledge integration, contextual agricultural knowledge, intelligent agricultural extension, adaptive decision support, human–AI collaboration and agribusiness resilience—are organised into four conceptual domains and eight contestable propositions. Governance and feedback condition the proposed transitions. IASEE specifies three distinct transitions: from digital inference to defensible knowledge, from contextual knowledge to facilitated decisions, and from feasible human action to potential resilience. Its claimed contribution lies in these mediating mechanisms and explicit boundary conditions, not in the first use of AI, governance or human-in-the-loop design in extension. Practical implications and limitations: The model gives researchers and extension organisations a way to examine provenance, knowledge disagreement, decision authority and implementation feasibility. Illustrative maize and cocoa situations in Bolaang Mongondow are conceptual thought experiments. No software deployment, field evaluation or resilience effect is claimed; systematic evidence synthesis and empirical testing are reserved for subsequent research.

Keywords: *Agricultural Extension; Artificial Intelligence; Socio-Technical Systems; Adaptive Decision Support; Agribusiness Resilience.*

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1. Introduction

Agricultural extension is expected to help farmers navigate simultaneous changes in weather variability, market access, production technologies, institutional arrangements and the availability of agronomic information. Its operating environment now includes remotely sensed observations, weather forecasts, farm records, scientific publications, market signals, mobile communications and machine-generated predictions. The multiplication of information channels expands the reach of advice, yet the consequences for agricultural decisions depend on how information is interpreted and embedded in local practice. Agricultural knowledge and advice networks are therefore better understood as relations among farmers, advisers, institutions and technologies than as a one-way communication channel (Fielke et al., 2020).

Agricultural digitalisation does not constitute an exclusively technical transformation. Analyses of digital agriculture identify altered work practices, data ownership, organisational power and changes in agricultural knowledge and innovation systems as central concerns (Klerkx et al., 2019). Big Data infrastructures additionally reconfigure control over information and the conditions of its use (Wolfert et al., 2017). These insights challenge technological determinism: the presence of data and AI does not by itself establish reliable knowledge, equitable access or a decision that farmers can implement.

Existing scholarship also warns against conflating agricultural decision-support functionality with effective advice. Rose et al. (2016) show that the design and delivery of agricultural decision-support tools depend on their usability, relevance and fit with decision processes. Pluralistic advisory-service frameworks likewise foreground different governance, capacity, management and delivery arrangements (Birner et al., 2009). These works illuminate complementary elements, although neither a technically reliable algorithm nor a well-organised extension service alone specifies the full transition from heterogeneous data through validated knowledge and human judgement towards adaptive action.

The frontier of agricultural AI makes differentiation particularly important. Kpodo and Nejadhashemi (2025) developed an advanced conceptual account of smart agricultural extension platforms that already incorporates multimodal data processing, neurosymbolic AI, human-in-the-loop processes and governance. Their subsequent examination of data sourcing and conversion further develops the data-to-decision platform agenda (Kpodo & Nejadhashemi, 2026). Separately, High et al. (2026) show through a study of AI-supported smallholder advisory practice that greater access and personalisation can coexist with relatively one-directional learning. Accordingly, a new framework cannot legitimately claim novelty merely because it combines AI, agriculture, human oversight and governance.

The unresolved theoretical problem examined here concerns the processes that turn computationally generated information into jointly interpretable, context-sensitive and accountable agricultural knowledge and then into decisions under material constraints. This requires a distinction among the epistemic status of data, algorithmic inference, agronomic explanation, extension-mediated advice and farmer action. It also requires a conditional rather than automatic relationship with resilience: an informed

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farmer may still be unable to adapt because of unavailable water, labour, credit, land rights or market opportunities.

The distinction matters for extension scholarship. A digital advisory platform is frequently analysed by its information-processing capability or the range of functions offered to its users. An extension knowledge ecosystem, by contrast, must explain who recognises an agricultural problem, whose knowledge is considered legitimate, how disagreements are resolved, how options are negotiated and who carries the responsibility for a decision. These are questions about advisory relations and knowledge brokerage. The potential value of AI is therefore contingent on how computational inference enters a human and institutional learning process, not merely on how much content the system generates (Fielke et al., 2020; High et al., 2026).

The framework is designed for broader theoretical relevance while remaining sensitive to situated agricultural decisions. Illustrative decision episodes concerning maize water management and cocoa planting-material management in Bolaang Mongondow, North Sulawesi, Indonesia, are used to test the clarity and transferability of conceptual distinctions. They are not presented as sampled observations, implementation results or evidence of IASEE effectiveness. The article proceeds from theoretical foundations and methodological logic to the framework, propositions, comparison with prior approaches, implications and limitations.

2. Literature Review

Extension theory has progressed beyond a uniform research–extension–farmer sequence. Advisory provision may involve public agencies, private firms, farmers' organisations, universities, cooperatives and informal knowledge brokers, with different incentives and accountability structures. Birner et al. (2009) therefore recommend examining the fit between advisory design and its institutional circumstances. In the IASEE argument, the multiplicity of actors is analytically significant because advice derives its authority from different sources: scientific verification, contextual experience, legal mandates, collective learning and market relationships.

An agricultural innovation systems perspective adds attention to interactions, institutional constraints and the processes through which stakeholders negotiate agricultural problems. Digitalisation changes the density and speed of these interactions, but increased connectivity can alter dependencies and create new informational asymmetries (Fielke et al., 2020; Klerkx et al., 2019). Consequently, IASEE treats extension as a mediating practice. The extension worker may translate, challenge, corroborate or defer AI-supported advice, rather than merely forward a model output.

This distinction offers an explicit alternative to technology-centred accounts. A system that distributes accurate recommendations may nonetheless fail when farmers question their legitimacy or cannot relate them to farm conditions. Conversely, extension relationships can function effectively with limited technology where skilled advisers and trusted peer networks already provide satisfactory problem-solving. An AI-enabled ecosystem should therefore be justified by additional knowledge-processing and coordination capabilities, not by the assumption that digital mediation is intrinsically superior.

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Socio-technical reasoning considers the joint configuration of technical capabilities, human practices, institutions and decision rights. AI systems are produced through data selection, modelling assumptions and organisational choices, which makes their operation inseparable from human arrangements. Reviews of smart farming highlight data rights, privacy, security and asymmetries between data providers and technology companies (Wolfert et al., 2017). These issues become even more consequential where farmers contribute data but possess limited control over access, correction or onward use. IASEE accordingly regards governance as constitutive of system behaviour, rather than an external checklist. Data provenance determines whether advice can be traced to its underlying evidence; accountability determines who may approve or stop a risky recommendation; and participation determines whose agronomic experience enters the knowledge base. A conceptual model that omits these arrangements risks treating an apparently neutral prediction as self-authorising. Governance in this paper is a cross-cutting design condition rather than a ninth core construct, a distinction that can be revisited through systematic evidence synthesis.

Knowledge creation scholarship distinguishes formal representations from experience-dependent understanding. Nonaka (1994) described the dynamic interaction of tacit and explicit knowledge within organisations. In agriculture, this distinction is useful but requires careful adaptation: farmers' practice-based knowledge is not simply a deficient version of codified expertise, and farmers are not employees within a unified hierarchy. Advisory encounters often involve different perceptions of authority, risk and relevant evidence. Studies of agronomist–farmer exchange demonstrate that knowledge is negotiated through particular interactions rather than transmitted unchanged (Ingram, 2008).

For IASEE, an AI recommendation is an inferential product whose reliability depends on training data, assumptions, model limits and the conditions of application. Scientific evidence, extension knowledge, farmer observations, local ecological history, market information and algorithmic inference should enter a process of provenance checking consistency assessment, contextual interpretation and—in cases of disagreement—documented reconciliation. Evidence that is relevant at a regional or seasonal scale may not be valid for a particular plot and decision date. Knowledge integration thus names an epistemic operation, whereas contextual agricultural knowledge names its potentially usable product.

Work on agricultural multi-stakeholder platforms shows that co-creation may support practical outcomes, although findings are heterogeneous and evidence of unsuccessful initiatives is less frequently reported (van Ewijk & Ros-Tonen, 2021). The theoretical implication is that collaborative knowledge creation is neither guaranteed nor value-free. IASEE requires mechanisms to resolve conflicting evidence, protect the legitimacy of local expertise and allow users to contest recommendations. These qualities are propositions about a desirable knowledge ecosystem rather than established effects of the proposed framework.

Knowledge integration is an institutional achievement rather than a neutral aggregation of documents. Farmer knowledge may be shaped by locally repeated observations, scientific recommendations by controlled conditions, and AI outputs by

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training data and model assumptions. When these sources disagree, an advisory system must make the disagreement visible and specify legitimate procedures for reconciliation. The systematic review by Tumwebaze et al. (2025) identifies the dispersed and context-sensitive character of agricultural knowledge management; van Ewijk and Ros-Tonen (2021) further caution that evidence of outcomes from multi-stakeholder knowledge co-creation is mixed and that failures are underreported. IASEE consequently assigns epistemic responsibilities to actors rather than assuming a common repository is sufficient.

A human-centred design must also ask whose knowledge becomes reusable digital content and under what permission. Farmers may contribute observations that improve an advisory model yet have limited control over subsequent use, while extension agencies and private providers may have unequal access to data infrastructures. Work on responsible smart farming highlights these socio-ethical conditions as part of technology development (Eastwood et al., 2019). For IASEE, knowledge governance therefore concerns source attribution, contestation, permission to reuse farmer-originated knowledge and procedures to correct an unsuitable recommendation. These governance requirements can conflict with efficiency, and that tension is a boundary condition to be studied rather than a problem solved by the conceptual diagram.

Agricultural decisions occur under uncertainty, time constraints and uneven access to assets. Decision-support research highlights the need to fit tools to users' workflows, decision horizons and preferences (Rose et al., 2016). Human judgement enters when alternative actions are weighed against local constraints; even an accurate probability estimate is insufficient if the suggested intervention is unaffordable or unavailable. IASEE therefore separates adaptive decision support from subsequent agricultural action and avoids treating a recommendation as a behavioural outcome.

Farming-system resilience encompasses robustness, adaptability and transformability, and its assessment must take account of the functions, shocks and institutional context of the system being studied (Meuwissen et al., 2019). The outcome is more demanding than knowledge gain or a successful one-time intervention. Porciello et al. (2022) identified comparatively little measured evidence on climate resilience outcomes in their scoping review of digital agricultural services in low- and middle-income countries. This finding supports caution when extending AI-related claims from information access to system-level resilience.

IASEE uses resilience as a theoretically specified distal domain, potentially reflected in anticipatory capacity, disturbance absorption, adaptive adjustment, recovery and longer-term transformation. These are not presumed to rise together, and some adaptation decisions may impose costs on other actors or future production periods. The framework therefore proposes a mediated and conditional pathway: data and intelligence may contribute to knowledge; extension and decision support may improve choices; implemented choices may, under identifiable conditions, affect resilience capacities. Alternative causes and temporal lags remain integral to the explanation.

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3. Research Method

Research methods consist of framework theory (framework) used. This study adopts a conceptual theory-synthesis and model-building design. Conceptual research derives contributions from explicit treatment of theories and their relationships, rather than from an empirical dataset or a numerical aggregation of studies. Jaakkola (2020) distinguishes theory synthesis and model development as legitimate approaches when theoretical selection and analytical operations are made transparent. Jabareen (2009) similarly regards a conceptual framework as a system of related concepts shaped by ontological and epistemological assumptions. IASEE combines these perspectives to construct an explanatory model of agricultural extension as knowledge orchestration.

The starting phenomenon was defined as a decision episode linking a recognised agricultural problem to advice, an accountable decision, implementable action and subsequent feedback. Seven disciplinary streams were used as sensitising perspectives: agricultural extension; innovation systems; agricultural digitalisation; knowledge management; decision support; socio-technical governance; and farming-system resilience. The selected theoretical works are purposive and illustrative rather than the outcome of an exhaustive database search. For that reason no database search totals, inclusion rates, PRISMA flow or comprehensive evidence-ranking claims are made for V1.0.

Conceptual development proceeded through five analytical operations. First, theories were compared by primary unit of analysis and type of explanation, separating institutional interactions from information-processing functions and agricultural outcomes. Second, candidate concepts were retained only where they explained a distinct transition within a decision episode. Third, constructs were defined by input, mechanism, output, actor and scale to reduce semantic overlap. Fourth, relational propositions were derived together with boundary conditions and plausible rival explanations. Fifth, the resulting model was assessed against published alternatives and illustrative maize and cocoa decision situations for conceptual coherence.

The purpose of selecting a source was explanatory coverage, not bibliometric representativeness. Candidate works were examined for (i) their relevance to agricultural extension or a construct-level explanatory mechanism, (ii) their explicit treatment of decision actors or institutional context, (iii) the possibility of translating their concepts into defined inputs, operations or outcomes and (iv) the presence of acknowledged limitations useful for a rival explanation. Seminal methodological or knowledge-creation papers were retained when they supplied concepts not replaceable by recent summaries. More recent agricultural scholarship was preferred for describing digitalisation, AI-enabled advisory provision and resilience. This is a transparent rationale for an interpretive synthesis, but it should not be confused with a replicable search protocol or an unbiased census of the literature.

Theoretical triangulation was used as a discipline of criticism rather than a claim of independent empirical validation. Socio-technical scholarship was used to challenge AI-centric explanations; knowledge-creation theory to challenge information-transfer assumptions; and resilience theory to challenge immediate-outcome measures. Specific counterfactual questions were posed: Could good advice arise without AI? Could accurate

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intelligence fail to become knowledge? Could a sound decision fail to become action? Could adaptation in one season fail to improve longer-term resilience? A framework unable to accommodate such possibilities would be insufficiently discriminating.

To strengthen internal validity at the conceptual level, each proposed transition was evaluated against three questions: is its explanandum distinct from that of the preceding construct; is an alternative mechanism plausible; and could an observable case challenge the proposition? This produces negative-case tests in place of invented empirical support. For example, the observation that a locally trusted human adviser produces an equally appropriate decision without AI would question AI-related incremental value but would not necessarily undermine the role of knowledge brokerage. Likewise, the absence of irrigation infrastructure could prevent action despite excellent advice; such a case would indicate failure at the feasibility boundary rather than at the prediction boundary. The analytical distinctions are recorded in Tables 2 and 3.

The outputs of this procedure are eight core constructs, four architectural domains, cross-cutting governance principles and eight propositions. The analysis does not claim that no other publication has already proposed related components. Indeed, Kpodo and Nejadhashemi (2025, 2026) offer closely related platform-level approaches. The proposed contribution is assessed at the level of explanatory architecture: an explicit decomposition of epistemic mediation, extension interaction, decision authority and resilience-oriented feedback. The study provides a theory-informed baseline for a later systematic review and empirical design; neither is retroactively described as a completed V1.0 method.

Table 1. Theoretical lenses, explanatory tasks and implications for IASEE V1.0 (analytical synthesis).

Theoretical lens	Primary explanatory task	IASEE implication
Pluralistic advisory services (Birner et al., 2009)	Why provision, management and advice vary across institutions	Extension and governance cannot be reduced to a digital interface
Innovation/advisory networks (Fielke et al., 2020)	How knowledge flows and network relations change	Model multi-actor mediation, legitimacy and feedback
Data and socio-technical transitions (Wolfert et al., 2017; Klerkx et al., 2019)	How infrastructures and institutions shape access and power	Embed provenance, access rules and accountability
Knowledge creation (Nonaka, 1994; Ingram, 2008)	How explicit, tacit and experiential knowledge meet	Separate AI-derived inference from contextual knowledge
Decision support (Rose et al., 2016)	How evidence becomes usable choice alternatives	Distinguish advisory, human decision and action
Resilience (Meuwissen et al., 2019)	How farming systems maintain and change functions under stress	Treat resilience as conditional, distal and multidimensional

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4. Result

The resultof this theory-informed synthesis derived from selected scholarship and analytical contrasts. The literature selection is purposive, without a fully reproducible database search or formal study-quality assessment; comprehensiveness and uniqueness cannot therefore be established. Some constructs are deliberately broad and require operational differentiation to avoid measurement overlap. The proposed process also spans multiple levels and temporal horizons, making simple cross-sectional tests insufficient for several links.

The Bolaang Mongondow illustrations are hypothetical applications grounded in plausible maize and cocoa decision domains, not original field evidence. No pilot software, AI model, farmer survey, expert Delphi exercise or observed resilience effect is reported here. The architecture may be less suitable where digital infrastructure, institutional authority or actionable knowledge is severely constrained, and attention to AI may distract from more urgent investments in water, transport or advisory staffing. These limitations are substantive boundaries on the claims rather than procedural weaknesses to be hidden.

5. Discussion

The framework is a theory-informed synthesis derived from selected scholarship and analytical contrasts. The literature selection is purposive, without a fully reproducible database search or formal study-quality assessment; comprehensiveness and uniqueness cannot therefore be established. Some constructs are deliberately broad and require operational differentiation to avoid measurement overlap. The proposed process also spans multiple levels and temporal horizons, making simple cross-sectional tests insufficient for several links.

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6. Conclusion

This article proposes IASEE V1.0 as a theory-informed conceptual framework that reconceptualises agricultural extension as an AI-enabled knowledge ecosystem. Eight bounded constructs are linked through four architectural domains and a decision-episode logic: heterogeneous data inform computational intelligence, intelligence is reconciled with plural knowledge, extension mediates situational interpretation, and accountable human decisions may lead to adaptive actions and learning. Governance, human–AI collaboration and trustworthy feedback are integral to the explanation.

The theoretical contribution lies in specifying the intermediate social and epistemic mechanisms that stand between AI capability and agricultural outcomes. Eight

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propositions identify testable expectations, rival explanations and boundary conditions. The framework neither claims priority over existing AI-enabled extension platforms nor assumes that intelligent advice has already improved agribusiness resilience. Systematic evidence synthesis and subsequent empirical design are required to assess whether the proposed architecture adds explanatory and practical value across farming contexts

References

Birner, R., Davis, K., Pender, J., Nkonya, E., Anandajayasekeram, P., Ekboir, J., Mbabu, A., Spielman, D. J., Horna, D., Benin, S., & Cohen, M. (2009). From best practice to best fit: A framework for designing and analyzing pluralistic agricultural advisory services worldwide. The Journal of Agricultural Education and Extension, 15(4), 341–355. https://doi.org/10.1080/13892240903309595

Eastwood, C., Klerkx, L., Ayre, M., & Dela Rue, B. (2019). Managing socio-ethical challenges in the development of smart farming: From a fragmented to a comprehensive approach for responsible research and innovation. Journal of Agricultural and Environmental Ethics, 32, 741–768. https://doi.org/10.1007/s10806-017-9704-5

Fielke, S., Taylor, B., & Jakku, E. (2020). Digitalisation of agricultural knowledge and advice networks: A state-of-the-art review. Agricultural Systems, 180, 102763. https://doi.org/10.1016/j.agsy.2019.102763

High, C., Singh, N., & Nemes, G. (2026). Artificial intelligence for agricultural extension: Supporting transformative learning among smallholder farmers. Journal of Development Policy and Practice, 11(1), 61–80. https://doi.org/10.1177/24551333251345224

Ingram, J. (2008). Agronomist–farmer knowledge encounters: An analysis of knowledge exchange in the context of best management practices in England. Agriculture and Human Values, 25(3), 405–418. https://doi.org/10.1007/s10460-008-9134-0

Jaakkola, E. (2020). Designing conceptual articles: Four approaches. AMS Review, 10, 18–26. https://doi.org/10.1007/s13162-020-00161-0

Jabareen, Y. (2009). Building a conceptual framework: Philosophy, definitions, and procedure. International Journal of Qualitative Methods, 8(4), 49–62. https://doi.org/10.1177/160940690900800406

Jellason, N. P., Salite, D., Conway, J. S., & Ogbaga, C. C. (2022). A systematic review of smallholder farmers' climate change adaptation and enabling conditions for knowledge integration in Sub-Saharan African (SSA) drylands. Environmental Development, 43, 100733. https://doi.org/10.1016/j.envdev.2022.100733

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Klerkx, L., Jakku, E., & Labarthe, P. (2019). A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. NJAS: Wageningen Journal of Life Sciences, 90–91, 100315. https://doi.org/10.1016/j.njas.2019.100315

Kpodo, J., & Nejadhashemi, A. P. (2025). Navigating challenges/opportunities in developing smart agricultural extension platforms: Multi-media data mining techniques. Artificial Intelligence in Agriculture, 15(3), 426–448. https://doi.org/10.1016/j.aiia.2025.04.001

Kpodo, J., & Nejadhashemi, A. P. (2026). Navigating challenges/opportunities in developing smart agricultural extension platforms: Data source, compilation, and conversion. Information Processing in Agriculture. Advance online publication. https://doi.org/10.1016/j.inpa.2026.06.004

Meuwissen, M. P. M., Feindt, P. H., Spiegel, A., Termeer, C. J. A. M., Mathijs, E., de Mey, Y., Finger, R., Balmann, A., Wauters, E., Urquhart, J., Vigani, M., Zawalińska, K., Herrera, H., Nicholas-Davies, P., Hansson, H., Paas, W., Slijper, T., Coopmans, I., Vroege, W., ... Reidsma, P. (2019). A framework to assess the resilience of farming systems. Agricultural Systems, 176, 102656. https://doi.org/10.1016/j.agsy.2019.102656

Nonaka, I. (1994). A dynamic theory of organizational knowledge creation. Organization Science, 5(1), 14–37. https://doi.org/10.1287/orsc.5.1.14

Porciello, J., Coggins, S., Mabaya, E., & Otunba-Payne, G. (2022). Digital agriculture services in low- and middle-income countries: A systematic scoping review. Global Food Security, 34, 100640. https://doi.org/10.1016/j.gfs.2022.100640

Rose, D. C., Sutherland, W. J., Parker, C., Lobley, M., Winter, M., Morris, C., Twining, S., Ffoulkes, C., Amano, T., & Dicks, L. V. (2016). Decision support tools for agriculture: Towards effective design and delivery. Agricultural Systems, 149, 165–174. https://doi.org/10.1016/j.agsy.2016.09.009

Tumwebaze, R. P., Walsh, J. N., & Lannon, J. (2025). Knowledge management in the agriculture sector: A systematic literature review. Knowledge Management Research & Practice, 23(2), 131–148. https://doi.org/10.1080/14778238.2024.2359419

van Ewijk, E., & Ros-Tonen, M. A. F. (2021). The fruits of knowledge co-creation in agriculture and food-related multi-stakeholder platforms in sub-Saharan Africa – A systematic literature review. Agricultural Systems, 186, 102949. https://doi.org/10.1016/j.agsy.2020.102949

Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M.-J. (2017). Big Data in Smart Farming – A review. Agricultural Systems, 153, 69–80. https://doi.org/10.1016/j.agsy.2017.01.023

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