IAOS Conference 12-14 May 2026, Vilnius, Lithuania. Navigating the Data Revolution: Innovations and Impact in Modern Statistics

From Standards to Practice: AI as a Communication Partner for Guided Problem Solving & Guided Learning

Mogens Grosen Nielsen
Nielsen Statistics Consulting, Copenhagen, Denmark.
mogensgrosen@gmail.com
Lars Thygesen
Thygesen Statistics Consulting, Copenhagen, Denmark.
Lthygesen@gmail.com

annex

Abstract

Official statistics organizations have no shortage of standards and frameworks—UN NQAF, ESS QAF, GSBPM/GAMSO, statistical legislation and a lot of domain specific standards —but they often struggle to convert them into day-to-day decisions, work instructions, and change plans. We present a practical approach called AI-CATCH for Statistics (see ai-catch.com) that treats AI not as an "answer engine," but as guided practice that helps staff learn standards and apply them to real problems with traceability.

The approach turns standards and frameworks into structured interaction patterns tailored to five recurring "persona" contexts: Solo Explorer, Workshop Participant, Reviewer, Decision Maker and Platform Operator.

AI-CATCH uses standard-linked prompts to: (1) ask about missing context, (2) map issues in relation to relevant framework principles/requirements, (3) generate comparable options, and (4) produce outputs designed for hand-over (briefs, checklists, review notes) with explicit assumptions and risks.

The guided practice is supported by a large, curated document archive that combines standards with practical best-practice examples, templates, and prior project materials, so users can retrieve and reuse proven patterns.

The paper demonstrates two end-to-end workflows: a learning workflow (understanding a framework element by applying it to a local process) and a problem-solving workflow (moving from an operational quality issue to structured options and a decision brief). The contribution is a repeatable, persona-driven method for turning "framework knowledge" into usable practice while strengthening staff capability and accountability.

1.Introduction

The IAOS 2026 theme, “Navigating the Data Revolution: Innovations and Impact in Modern Statistics”, fits a practical question facing many statistical organisations: how can new technologies help staff use existing guidance in real work, without weakening responsibility, quality or trust? Recent publications on AI in official statistics show that the discussion has moved beyond experiments with new tools. The main issues are now readiness, governance, quality, skills, metadata, privacy, trust and responsible use in daily work (UNECE / HLG-MOS, 2025; PARIS21, 2025; Committee for the Coordination of Statistical Activities (CCSA), 2026).

UNECE’s recent work on generative AI is especially relevant because it uses GSBPM and GAMSO models to locate AI use cases across the statistical production process. This is useful for showing where AI may support or automate tasks such as coding, processing, analysis, dissemination and communication (UNECE / HLG-MOS, 2025). MacFeely adds an important warning: AI may help official statistics move faster, but it may also create risks for quality, accuracy, trust and professional judgement if organisations become too dependent on automated outputs (MacFeely, 2026). This warning is also reflected in recent AI-readiness work (e.g. PARIS21, 2025), which stresses that AI adoption requires governance, skills, ethical safeguards and institutional capacity, not only technical tools.

This paper presents AI-CATCH as a new approach. Indirectly it can be seen as a practical answer to challenges mentioned above. The aim is not to use AI as an “answer engine” or to replace review and approval. The aim is to use AI as guided support for staff: to clarify problems, compare options, expose assumptions and prepare reviewable work products before decisions are made. AI-CATCH should help organisations move from standards and frameworks to usable practice, while keeping responsibility with the organisation.

AI-CATCH is also grounded in a newer approach to organisational change, drawing on insights from sociology and modern systems theory. This theoretical background is briefly explained in Annex A and in insight blog post: https://nielsenstatistics.com/insights-better-faster-decisions It is for readers who want to understand the theoretical foundation, but it is not needed for following the practical argument of the article.

2. The practical gap: standards do not apply themselves

A standard is useful only when it changes what people can do next. A long framework document may say what good practice looks like, but it rarely tells a production team exactly how to handle a late source delivery, a possible quality break, a new administrative data source, an unclear disclosure risk or an AI proposal from another unit.

In day-to-day work, decisions are shaped by deadlines, inherited routines, local knowledge, available staff, IT constraints, user expectations and previous agreements. That is why a formal framework may be known but still remain outside the real work. It may be cited in reports but not used in meetings, handovers or approvals.

The risk is stronger when AI is added. AI can produce convincing text very quickly. But convincing text is not the same as a checked decision. If an AI output hides assumptions, ignores legal limits, or skips review, it may speed up mistakes instead of improving practice.

AI-CATCH is designed to close this gap by converting broad guidance into practical work products: a clearer issue statement, a checklist, a comparison of options, a reviewer note, a decision brief, a draft work instruction or an escalation point.

3. How AI-CATCH work #1 From first concern to comparable options to draft premisses for next step

The starting point is simple: the first description of a problem is never complete. “Our data source is unstable”, or “we have a quality issue” may be true, but each statement already points attention in one direction and away from others.

A better method is to ask what practical problem must be solved before choosing a solution. One team may see the problem as accuracy. Another may see timeliness. Legal colleagues may see authority and confidentiality. IT may see architecture and security. Communication staff may see public trust. Each view leads to different possible responses.

AI-CATCH therefore begins with restatement, clarification and comparison. It asks: What is the issue? What is missing? Which standards are relevant? What could be overlooked? What are two or three different ways to respond, and what would each of them make easier or harder?

This turns AI from a shortcut into a disciplined helper. The stronger result is not a perfect answer; it is a better prepared question, a fair comparison of options and a draft that can be challenged before it becomes the basis for action.

4. How AI-CATCH works #2: Connecting a chain of work-situations

Figure 1 below shows a familiar chain of work situations.

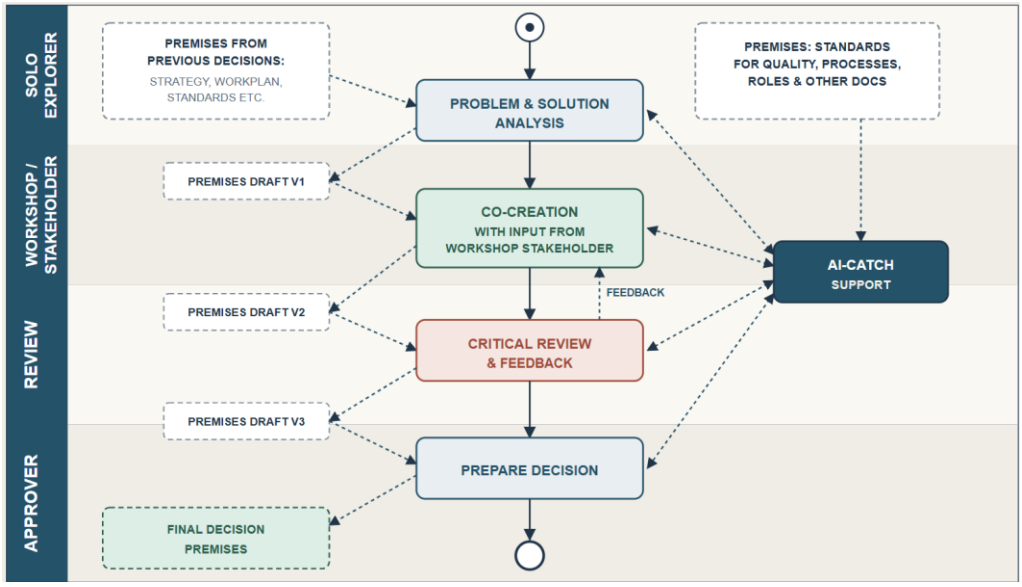

Figure 1. Chain of work-situations

Someone starts with a problem, idea, or quality concern and prepares a first draft. The draft is not the final answer, but it gives others something concrete to react to. It can then be used in a stakeholder dialogue, workshop, or team discussion, where different perspectives are added. After this, the material is reviewed: assumptions are tested, weak evidence is identified, and risks are made visible. Only then can the organisation prepare clearer premises for a decision. Drafts are handovers between work situations. AI-CATCH supports this chain by helping staff dive into large amounts of text, retrieve relevant standards and examples, and turn them into usable drafts, review notes, and decision briefs.

The public AI-CATCH description emphasises a combination of structured problem-solving, AI insight and human collaboration. It also presents five practical skills: structured change work, AI as an exploratory partner, translating generic guidance into local knowledge, co-creation with stakeholders, and sustaining change through organisational memory.

These ideas are implemented through standard-linked prompts and a curated document archive. The archive can include UN NQAF, ESS QAF, GSBPM, GAMSO, legislation, templates, good examples and earlier project material. The point is not only to retrieve text. The point is to retrieve patterns that help staff prepare usable outputs.

5. Two workflows for conference demonstration

WORKFLOW A: MOVING FROM AN OPERATIONAL ISSUE TO A DECISION BRIEF

In the problem-solving workflow, the user starts with a concrete issue. AI-CATCH restates it, asks for missing context, checks the issue against relevant standards, compares three possible responses and prepares a reviewable output.

A typical output might include: the issue, why it matters, affected roles, relevant standards, three options, main benefits, main trade-offs, what must be checked first, the recommended direction, open questions and a single concrete next step.

This is useful because it does not ask a reviewer or manager to start from zero. The next person can see the reasoning, challenge weak parts, add missing evidence and decide what can move forward.

WORKFLOW B: PREPARE A STANDARD-BASED QUALITY REPORT

In the learning workflow, staff prepare a standard-based quality report for a statistical product or process. The report follows the Eurostat SIMS logic: it uses common quality and metadata concepts so that the result can be understood, compared and reused across the European Statistical System.

6. How to improve trust - what makes a decision defensible?

For official statistics, a decision is defensible when the reasons behind it can be seen, checked and challenged by the right people. It is not enough that the decision is technically clever. The link to the relevant context must be described: resources and costs, law and confidentiality, political mandate and independence, scientific method, technical architecture, and public communication.

These links become practical only when they are written as clear working premises: what is assumed, which standard is used, which evidence is accepted, which role must review the case, which risks stop the process, and which conditions must be met before the next step. A decision brief should therefore show not only the recommendation, but also the premises that make the recommendation acceptable.

Those premises must be made public to the relevant parties. Public does not always mean open to everyone; confidentiality and internal deliberation still matter. It means that the people who must review, approve, use, explain or challenge the decision can see the issue, the options considered, the standards used, the rejected alternatives, the remaining risks and the review responsibilities.

This must be handled throughout the whole AI-CATCH path: Solo Explorer, workshop, reviewer and Decision Maker. AI can help especially in the critical test of a recommended solution by checking whether the premises are explicit, whether the relevant contexts have

been covered, and whether a legal, methodological, technical or communication review is needed before operational use.

7. What AI should and should not do

AI can help produce variation: better drafts, clearer questions, alternative framings, comparison tables, summaries and first versions of briefs. This can reduce search time and make meetings more focused.

AI should not decide what is approved. It should not silently turn a draft into a rule. It should not replace methodological, legal, security or management review. The organisation remains responsible for deciding what counts as accepted practice.

This limit is not a weakness. It is the condition for responsible use. The value of AI-CATCH is that it speeds up preparation while keeping responsibility, review and approval in human and organisational hands.

8. Expected benefits

First, AI-CATCH can reduce the distance between standards and daily work. Staff receive guided help in turning broad requirements into local questions, options and draft products.

Second, it can improve handover. A problem analysis, workshop note or decision brief can travel between production, methodology, IT, legal, communication and management without losing the main assumptions and risks.

Third, it can support capability building. Staff learn standards by using them on real cases. This is more likely to stick than one-off training or a generic chatbot answer.

Fourth, it can improve accountability. A documented path from issue to options to review makes it easier to explain why one option was chosen, what was rejected and what conditions remain.

9. Critical test

The strongest objection is that AI-CATCH could become one more framework in organisations already overloaded with frameworks. That objection is valid. AI-CATCH is justified only if it reduces search time, improves handover, makes assumptions clearer and produces outputs that are reused in real work.

A second objection is that staff may treat AI output as more reliable than it is. The answer is not more warnings in general. The answer is built-in review: source visibility, explicit assumptions, comparison of alternatives, named review roles, escalation points and clear limits for high-risk topics.

A third objection is that public trust cannot be created by a tool. This is also correct. Trust depends on conduct over time. AI-CATCH can only help by making the preparation of

decisions more transparent to the people who must review, approve, explain or challenge them.

10. Next step: pilot, collaboration and shared AI-CATCH apps

AI-CATCH is still under construction, but its apps are already being used by Lars Thygesen and Mogens Grosen Nielsen when helping national statistical organisations. The next step should be collaborative pilots with interested NSOs.

The practical problem is clear: statistical organisations have many standards, frameworks and guidelines, but these do not automatically become useful in daily production, quality work, AI governance, architecture design or app development. Staff still have to clarify problems, compare options, document assumptions and prepare decisions that can be reviewed.

AI-CATCH can support this at three levels. At the **individual level**, staff learn by applying standards to real cases. At the **group level**, teams use AI-CATCH in workshops to compare perspectives and prepare reviewable notes. At the **organisational level**, repeated outputs can become decision briefs, checklists, work instructions, architecture drafts, app specifications and organisational memory.

Pilots should test whether AI-CATCH helps NSOs move from unclear problems to reviewable outputs and clearer decision premises. Relevant areas include quality reporting, operational quality issues, AI review procedures, administrative data, metadata, stakeholder communication, architecture work and app development in the GSBPM design and build phases. The claim is not that AI-CATCH has already solved this problem, but that it provides a testable model for doing so.

A useful next project would be further integration of PARIS21, UN and UNECE material into AI-CATCH, so their ideas appear in concrete interactions such as problem clarification, option comparison, reviewer notes and decision briefs, but also in concrete architecture drafts and apps prepared by AI-CATCH in the GSBPM design and build phases.

A shared AI-CATCH knowledge base could also be developed for official statistics, including international standards, domain guidance, examples, templates and tested prompts. In this way, AI-CATCH could become an interaction layer between complex standards and daily statistical practice, without replacing the standards themselves.

10. Conclusion

The main challenge for official statistics is not a lack of standards, frameworks or AI tools. The harder problem is organisational: how can guidance become useful in concrete work situations where staff must clarify problems, compare options, review risks, design solutions and prepare decisions?

AI-CATCH addresses this by treating AI not as an answer engine, but as a communication partner for guided learning, structured problem solving and practical development work. It helps users move from unclear concerns to reviewable outputs: issue descriptions, checklists, option comparisons, reviewer notes, decision briefs, work instructions, architecture drafts and app specifications.

This distinction matters. AI can produce text quickly, but speed does not create quality, legitimacy or trust. In official statistics, a proposal becomes useful only when assumptions are visible, links to standards are clear, risks can be challenged and relevant people can review the consequences. AI-CATCH therefore supports the preparation of decisions and solutions, not the authorisation of decisions.

The practical value appears at three levels. At the individual level, staff can learn standards by applying them to real problems. At the group level, teams can use AI-CATCH to structure workshops, compare perspectives and prepare reviewable notes. At the organisational level, repeated outputs can become decision premises, checklists, work instructions, architecture patterns, app drafts and organisational memory.

The next step is collaborative pilots with interested national statistical organisations. These pilots should test AI-CATCH in concrete work situations, such as quality reporting, operational quality issues, AI review procedures, administrative data problems, metadata improvement, stakeholder communication, architecture work and app development in the GSBPM design and build phases. The claim is not that AI-CATCH has already solved this problem, but that it provides a testable model for doing so.

A further proposal is to combine AI-CATCH more systematically with UN, UNECE and PARIS21 guidance. Their material on quality, production, AI readiness and responsible use is valuable, but must still be translated into local questions, review points, decision premises, architecture drafts and practical app designs. AI-CATCH can support this translation through structured interactions such as problem clarification, option comparison, reviewer notes, decision briefs and development-oriented drafts.

In this way, AI-CATCH could become an interaction layer between complex standards and daily statistical practice. It would not replace standards. Instead, it would help statistical organisations use them more effectively in learning, collaboration, decision preparation, architecture design and app development.

References

UNECE / HLG-MOS. (2025). *Generative AI for Official Statistics*. United Nations Economic Commission for Europe. https://unece.org/sites/default/files/2025-09/Generative%20AI%20for%20Official%20Statistics%20HLG-MOS%20Report.pdf

MacFeely, S. (2026). *The role of AI in Official Statistics: Black hole or worm hole? Statistical Journal of the IAOS, 42*(1). https://journals.sagepub.com/doi/10.1177/18747655251410711

PARIS21. (2025). *Towards AI-Ready National Statistical Offices: A Framework for Strengthening NSO Capacity in Low- and Middle-Income Countries*. PARIS21. https://www.paris21.org/sites/default/files/media/document/2025-12/ai-readiness-nso-framework.pdf

Committee for the Coordination of Statistical Activities (CCSA). (2026). *AI-Ready Official Statistics: Opportunities, Challenges, and Strategic Priorities*.Background document for the 57th session of the United Nations Statistical Commission. https://unstats.un.org/UNSDWebsite/statcom/session_57/documents/BG-5h-CCSA_AI_Readiness_Official_Statistics_v2-E.pdf

Eurostat. *Quality reporting: Single Integrated Metadata Structure (SIMS)*. European Commission.

UNECE. (2019a). *Generic Activity Model for Statistical Organisations (GAMSO), version 1.2*. United Nations Economic Commission for Europe.

UNECE. (2019b). *Generic Statistical Business Process Model (GSBPM), version 5.1*. United Nations Economic Commission for Europe.

United Nations. (2019). *United Nations National Quality Assurance Frameworks Manual for Official Statistics*. United Nations.

Nielsen, M. G. (2024). *A new approach to organisational change using social systems theory and generative AI*. Paper presented as Luhmann conference, Dubrovnik, Croatia.

Nielsen, M. G. (2025). *Making Programs Work: Applying Luhmann's Social SystemsTheory to Quality Management and AI in Statistical Organizations*. Paper presented as Luhmann conference, Cambridgee. https://www.researchgate.net/publication/398987433_Making_Programs_Work_Applying_Luhmann's_Social_Systems_Theory_to_Quality_Management_and_AI_in_Statistical_Organizations#fullTextFileContent

Nielsen, M. G. (2026). *Generative AI in Organisations: Better and Faster Decision Processes?*. Paper presented at Wolfson College, Cambridge. https://nielsenstatistics.com/insights-better-faster-decisions

Annex A: Theoretical background

AI-CATCH is based on a practical translation Niklas Luhmann's theory of organisations, knowledge and decision-making. The core idea is that standards, expert knowledge and AI outputs do not change practice by themselves. They become useful only when they are translated into reviewable work products that can shape later decisions: problem descriptions, quality reports, checklists, review notes, decision briefs and work instructions.

The approach draws on four theoretical ideas.

First, organisations are understood as chains of decisions, so AI-CATCH focuses on preparing material that can be reviewed and used in later decisions, not on producing final answers.

Second, knowledge is not treated as a direct mirror of reality: the same issue may be framed as a quality, legal, IT, resource, user-trust or management problem. AI-CATCH therefore starts with restatement, problem reconstruction and blind-spot analysis.

Third, the functional method asks what problem a proposal is meant to solve, which alternatives could solve the same problem, and what side effects each alternative creates.

Fourth, standards and management tools are treated as resources for decision-making, not as automatic solutions. This draws on Knudsen's work on standards as possible decision premises and Scheytt's work on management accounting, which shows that management tools do not neutrally depict organisational reality but shape what becomes visible, comparable and actionable.

For official statistics, the practical implication is that a decision is more defensible when two conditions are met.

First, the relevant links to the decision context must be described: legal requirements, scientific and methodological quality, political mandate, resources, IT architecture, users, media and public trust.

Second, the premises for the decision must be visible to the relevant parties: what was considered, which standards were used, which alternatives were rejected, who reviewed the proposal, what remains uncertain and what conditions apply.

AI can help prepare this through critical tests, comparison tables and decision briefs, but it cannot itself authorise the decision. Responsibility remains with the organisation.

This theoretical foundation has been developed through papers and discussions at Luhmann conferences, a workshop in Aarhus on AI and organisations, and the Cambridge Wolfson Tool Factory workshop on generative AI in organisations. The practical conclusion is simple: AI may support problem reconstruction, option comparison and critical testing, but the organisation must remain in the steering seat.

Besio, C., & Pronzini, A. (2010). Inside organizations and out: Methodological tenets for empirical research inspired by systems theory. *Forum Qualitative Sozialforschung / Forum: Qualitative Social Research, 11*(3), Article 16.

Knudsen, M. (2007). Structural couplings between organizations and function systems: Looking at standards in health care. *Cybernetics & Human Knowing, 14*(2–3), 111–131.

Luhmann, N. (1990). Cognition as construction. In H.-G. Moeller (Trans.), *Cognition as construction*.

Luhmann, N. (2012). *Theory of society: Volume 1* (R. Barrett, Trans.). Stanford University Press.

Luhmann, N. (2013). *Theory of society: Volume 2* (R. Barrett, Trans.). Stanford University Press.

Luhmann, N. (2018). *Organization and decision* (R. Barrett, Trans.). Cambridge University Press.

Nielsen, M. G. (2024). *A new approach to organisational change using social systems theory and generative AI*. Paper presented as Luhmann conference, Dubrovnik, Croatia.

Nielsen, M. G. (2025). *Making Programs Work: Applying Luhmann's Social SystemsTheory to Quality Management and AI in Statistical Organizations*. Paper presented as Luhmann conference, Cambridgee. https://www.researchgate.net/publication/398987433_Making_Programs_Work_Applying_Luhmann's_Social_Systems_Theory_to_Quality_Management_and_AI_in_Statistical_Organizations#fullTextFileContent

Nielsen, M. G. (2026). *Generative AI in Organisations: Better and Faster Decision Processes?*. Paper presented at Wolfson College, Cambridge. https://nielsenstatistics.com/insights-better-faster-decisions

Ocampo, S. P. (2025). Artificial Legitimacy? Possibilities, paradoxes, and ironies of the relationship between digital communication and legitimation through procedures.

Roth, S., & Sales, A. (2025). Multifunctional organisation: A systems-theoretical concept and its practical implications. *Journal article proof/manuscript*.

Scheytt, T. (2005). Management accounting from a systems-theoretical perspective. In D. Seidl & K. H. Becker (Eds.), *Niklas Luhmann and organization studies* (pp. 386–406). Copenhagen Business School Press.

Seidl, D., & Mormann, H. (2015). Niklas Luhmann as organization theorist. In P. S. Adler, P. du Gay, G. Morgan, & M. Reed (Eds.), *The Oxford handbook of sociology, social theory, and organization studies: Contemporary currents* (pp. 125–157). Oxford University Press.

Van Assche, K., & Verschraegen, G. (2008). The limits of planning: Niklas Luhmann's social systems theory and the analysis of planning and planning ambitions. *Planning Theory, 7*(3), 263–283.