



Navigating subjectivity in causal context: a non-deterministic approach for information behaviour research

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Abstract

Introduction. Information behaviour research often asks causal questions with tools that describe associations. Conventional, regression-based models struggle when constructs are subjective, context-bound, and difficult to estimate. The academic setting is one example where behaviour is often self-directed, cues are fragmentary, social constructs are latent, and perceptions vary across roles and disciplines. Under these conditions, deterministic causes rarely occur and purely probabilistic models can miss how context shapes action.

Method. This paper proposes a hybrid causal procedure—the fuzzy subjective structure model—designed to handle the nuance of human perception. It integrates sufficiency paths (what usually works) from PLS-SEM, bottlenecks (what constrains action) from necessary condition analysis, and the decision-oriented visualization of combined importance–performance map analysis. To address the specific challenges of information behaviour, the model adds two adjustments: it uses entropy weighting to account for how differently people interpret survey questions, and inverse probability weighting to ensure that comparisons between groups (e.g., disciplines) are fair and balanced.

Analysis. The fuzzy subjective structure model formalizes four distinct, non-deterministic causal claims: typical sufficiency ('if X , then typically Y '), typical necessity ('if not X , then typically not Y '), probabilistic sufficiency ('if X , then probably Y '), and probabilistic necessity ('if not X , then probably not Y '). This four-claim structure addresses a noted gap in causal analysis for the social sciences by separating 'works for most cases' statements from probability-scale, counterfactual-style contrasts.

Results. The fuzzy subjective structure model reorients causal analysis in information research from behaviour-driven explanations to a perception-first assessment with visual aids. It positions latent institutional factors like culture and management as the primary drivers that shape individual behaviour through subjectively perceived affordances and constraints.

Conclusion(s). The approach supports quantitative inference by identifying conditions that usually enable behaviours and conditions whose absence makes their individual perception unlikely, while keeping latent constructs and small samples in mind.

Introduction

Causal inference has advanced many social sciences by moving beyond correlation to estimate the effects of causes (Morgan & Winship, 2014). Frameworks such as the Rubin Causal Model (Imbens & Rubin, 2015; Rubin, 1974) and Pearl's Structural Causal Models (Pearl, 2000) formalize counterfactual reasoning. Yet information behaviour research often relies on conventional regression or structural equation modelling. These methods describe associations well, but without strong—and often unrealistic—design assumptions they cannot support the causal claims that many information-behaviour questions implicitly demand (Pearl, 2010). This creates a recurring impasse: researchers estimate relationships between self-assessed variables (e.g., perceived information literacy and empowerment) but report them in causal terms, implying that improving information literacy or acceptance of information behaviour increases empowerment in a population of interest. For individuals, however, this reading is fragile. Are these perceptions causally linked, or are they joint outcomes of deeper, unobserved conditions such as institutional culture or information management? This paper argues that causal logic, already productive in social science research (Morgan, 2013), can also advance information behaviour research. The field is distinctive because information itself drives change in what people know, feel able to do, and ultimately do—yet key conditions (culture, management quality, literacy, policy) are typically measured as subjective perceptions of the culture in observational designs. That combination leaves a gap between 'context' and 'behaviour' that association models do not fully bridge. To keep the causal question concrete, consider one academic deciding whether to share data. They may have the skills but still refrain if the repository is perceived as a barrier, procedures are unclear, incentives misalign, or local norms discourage openness. The design-aware question is whether strengthening trust, clarity, and supportive information management would shift the likelihood that this person shares—rather than treating 'culture' as a downstream correlate of what they already do.

A statistical model of causal links may be useful for policymakers seeking general solutions because it estimates average effects for a population, often through latent variables derived from theory-driven measurement models. Real individuals, however, are rarely 'average'; they act in specific contexts. Regression models therefore indicate what tends to work on average, not what will work for a given person in a given setting. Understanding and influencing behaviour requires attention to upstream drivers that shape subjective interpretation—information culture, information management, and enabling technologies. In information research, this shifts attention to the inherently fuzzy perception of information need that motivates behaviour, whether observed or self-reported. Cole and Wilson's synthesis reinforce this context-first orientation (Cole & Wilson, 2024). Wilson's model treats information seeking as stimulated by needs (physiological, affective, cognitive) and filtered by social roles and performance, as well as socio-cultural, politico-economic, and physical environments (Wilson, 1981, 2022). Cole's primary-need perspective similarly treats information need as a basic human need linking external data to internal knowledge, with the individual transforming data into information in context (Cole, 2018). Taken together, these arguments imply a context-first causal direction: environments and conditions give rise to subjectively interpreted behaviours. The modelling stance therefore reverses the common regression habit of treating perceptions as explanators of other perceptions, reducible to latent constructs that merely 'explain variance'. Instead, context can be modelled as the cause of subjectively interpreted behaviour—e.g., behaviour is enabled within information management because perceived needs and available information culture support it—rather than claiming that 'acceptance' follows from behaviour and then 'explains' culture and makes practices effective.

Information is defined here in a strictly causal sense, as a change in a knowledge structure. Following Cole and Wilson (2024), a knowledge state can be represented as $K[S]$. When dynamic information ΔI is introduced, the result is a modified state $K[S + \Delta S]$. In this formulation, ΔI denotes information insofar as it produces an effect or change. Interpreted this way, organizational and

cultural conditions are not passive background factors; they function as sources of ΔI that shift knowledge states and enable action. The implication for causal modelling is that information should be treated not as a static object but as an intervention whose impact is observable as structural cognitive change.

Consequently, information need is not fixed in advance; it evolves through iterative movement between what is already known and what the environment allows (Bates, 1989; Taylor, 1968). This is exactly why causal questions belong in information behaviour research. If information is defined by the change it produces, then asking ‘what causes people to seek, accept, trust, or use information’ is not an optional philosophical add-on—it is the core question. For individuals, the practical implication is: which conditions make it more likely that information becomes a real input to thinking or acting (a change in understanding, confidence, or next action), rather than just random noise that gets ignored in regression model? In universities, those conditions are often institutional: the usability and legitimacy of a massive open online course systems, the clarity of rules, and the trust embedded in local culture (Deja & Wójcik, 2021).

Another issue in information research and in academic settings is that constructs like information literacy, self-efficacy, and empowerment are latent for people. They are estimated for the general population so they will be interpreted differently across roles and disciplines (Deja et al., 2021; Hatlevik et al., 2018). Behaviour in these contexts is often governed by non-compensatory constraints, or bottlenecks; without a minimal level of a certain condition, high levels of an outcome seldom occur (Dul, 2016, 2024). In such environments, universal laws of sufficiency or pure probability are rare, but patterns of typical outcomes or necessity conditions are common (Wagner, 2020).

Navigating causal context

The conceptual roots of this interpretation of cause lie in two lines of work. First, causal inference distinguishes associational regularities from the effects of hypothetical interventions (Pearl & Mackenzie, 2018). Its strength is that it makes causal questions explicit as counterfactual queries and states identification conditions for those queries, for example via the *do*-operator and backdoor reasoning (Pearl, 2010). A more traditional approach, conditional process analysis, uses related probabilistic logic but focuses on observed variables (often composites rather than latent constructs) and linear paths. It offers accessible models of mediation and moderation, yet commonly leaves latent measurement and non-compensatory constraints outside the model (Hayes et al., 2017; Hayes & Rockwood, 2020). Both approaches aim at generalisable claims, but both face limits in information behaviour settings where constructs are subjective, vary across roles and contexts, and are measured through indicators intended to capture meaning rather than direct treatments. Conventional structural equation modelling addresses latent structure but typically assumes compensatory sufficiency; without explicit design or identification arguments, it cannot resolve causal direction from association alone (Hair et al., 2022; Tarka, 2018).

Second, necessity and typicality supply an alternative logic for institutional context. Necessary condition analysis formalises ‘if not X, then (typically) not Y’ through non-compensatory thresholds and limited, theory-justified exceptions (Dul, 2016, 2024). Typicality refers to properties that hold for almost all cases in a set; it relies on high cardinality rather than probability mass and tolerates structured exceptions (Wagner, 2020; Wilhelm, 2022). This middle ground avoids the rigidity of deterministic claims found in set-theoretic approaches and the looseness of purely probabilistic sufficiency.

The combined importance–performance map analysis demonstrates how necessity can be embedded alongside sufficiency paths in PLS-SEM to support decision-oriented interpretation (Hauff et al., 2024). However, combined importance–performance map analysis inherits two common limitations of institutional survey research. First, it can understate how differently

respondents interpret indicators across disciplines, roles, and cultures, even when measurement quality appears acceptable. Second, it does not itself address confounding in observational comparisons: differences attributed to culture or management may partly reflect differences in who is exposed to those conditions (e.g., discipline, seniority, gender). These limitations matter because they shape how one should read familiar outputs such as path coefficients, scaled 'performance' means, or necessary condition analysis effect sizes. In information behaviour research, the same numerical result can imply different practical meanings depending on whether a factor typically enables outcomes when present or mainly constrains outcomes when missing.

To address these issues, a fuzzy subjective structure model is proposed: a hybrid, non-deterministic procedure integrating PLS-SEM and necessary condition analysis within the combined importance–performance map analysis framework, with two adjustments tailored to information behaviour. Entropy weighting treats dispersion in item responses as informative about subjective interpretation, up-weighting indicators whose response patterns carry more discriminating information (Song, 2025). Inverse probability weighting rebalances observed covariates across exposure groups, creating a pseudo-population in which comparisons more closely approximate an intervention contrast under stated assumptions (Hogan & Coote, 2014; Huber, 2014).

Within fuzzy subjective structure model, standard tools first set the quantitative baseline. PLS-SEM summarizes how conditions tend to operate 'on average' through sufficiency-type paths, whereas necessary condition analysis asks whether a minimal level of a condition functions as a practical prerequisite for high outcomes, even when other drivers are strong (Dul, 2016, 2024). Combined importance–performance map analysis then makes this dual reading easier to communicate and compare across settings by showing—within one visual paradigm—both what appears to matter and where bottlenecks may block success, while keeping inference contingent on explicit estimands and diagnostics (Hauff et al., 2024; Hair et al., 2022). The added value of fuzzy subjective structure model is interpretive: the same PLS-SEM paths, combined importance–performance map analysis 'importance/performance', and necessary condition analysis bottlenecks can all be re-read through a person-in-context necessity lens by reducing each summary back to person-by-person membership under fuzzy perception (who clears a threshold, who does not, and who becomes an exception). In this reading, coefficients stop being 'one rule for everyone' and become counts and probabilities about how often an enabling pattern holds—and how rarely high outcomes occur when a condition is missing.

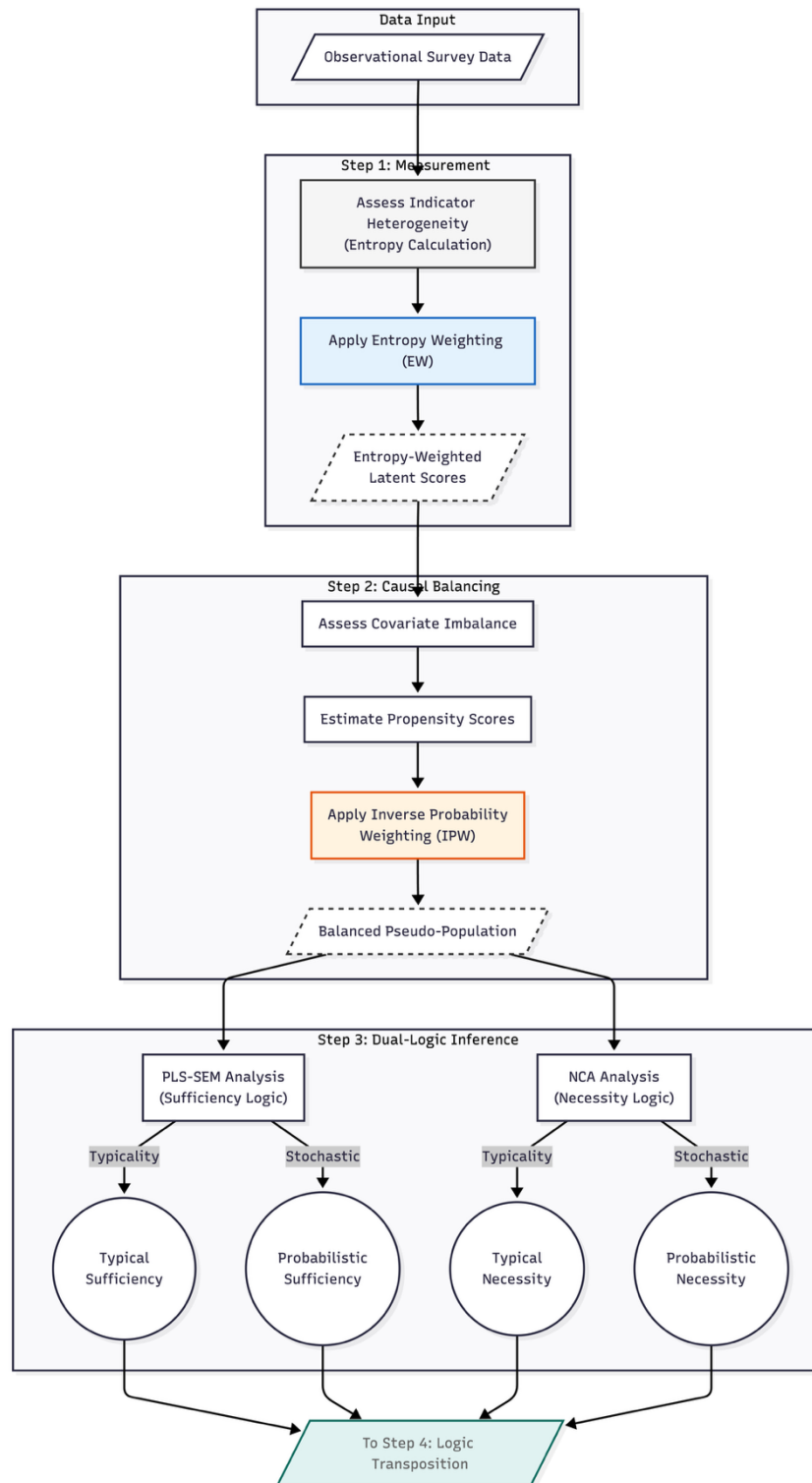


Figure 1. The fuzzy subjective structure model methodological workflow: filtering subjective perception and confounding before dual-logic inference

This combined view changes how the usual statistics are read: path coefficients and combined importance–performance map analysis ‘importance’ are treated as sufficiency evidence, and ‘performance’ is interpreted alongside necessity evidence to separate factors that mainly amplify outcomes from factors that mainly constrain them. Switching across the four fuzzy subjective

structure model claims—typical sufficiency, typical necessity, probabilistic sufficiency, and probabilistic necessity—adds a simple check: a factor that looks strong in a sufficiency model but has no bottleneck behaves like an amplifier, while a factor with a clear bottleneck but modest average effect behaves like a gatekeeper that matters most when missing (Dul, 2016, 2024). Because all claims are expressed on latent scores, results remain population-level and design-contingent, yet individual cases can still be located relative to enabling regions and bottlenecks for person-in-context interpretation without implying ‘one-size-fits-all’ causation (Morgan & Winship, 2014; Pearl, 2010).

Causal logic for information behaviour

Academic information work often fits a context-first logic. Policies on open access, data sharing, or digital transformation rarely produce compliance directly; what matters is whether systems feel legitimate, usable, and trustworthy in everyday work (Deja & Wójcik, 2021; Kim & Adler, 2015; Virkus & Salman, 2020). Likewise, information literacy supports action through intermediate steps—competence tends to build self-efficacy, self-efficacy supports empowerment, and empowerment supports collaboration and data stewardship (Sparks et al., 2016; Hatlevik et al., 2018; Ahmad et al., 2020). Cultural norms—openness, trust, rule clarity—often act as floors: below certain levels, strong outcomes are rare regardless of gains elsewhere (Choo, 2013; Deja & Wójcik, 2021). The task is therefore to identify what usually helps (sufficiency patterns) and what is hard to compensate for when missing (necessity constraints). Combined importance–performance map analysis supports organizational planning by showing what is important and how well it is realised; fuzzy subjective structure model keeps that visual logic but treats subjectivity and confounding as central to explaining why an action is (or is not) likely for a given person in a given context.

Theory: Probabilistic, typical, and necessary claims

David Hume’s two descriptions of causality—constant conjunction and counterfactual denial—motivate why fuzzy subjective structure model treats causation in information behaviour as non-deterministic: in real information environments, causes rarely guarantee behaviour, but they can still enable it for most people or block it when missing (Dul, 2024; Hume, 1758). Applied models in the field often default to probabilistic sufficiency (‘if X increases, higher Y becomes more likely’), consistent with structural equation modelling -style interpretations when identification is credible. necessary condition analysis adds a complementary constraint logic: typical necessity (‘without X , very high Y is uncommon’), expressed via bottlenecks and rare exceptions (Dul, 2016; Vis & Dul, 2018). Dul (2024) argues that two further claims are often left implicit: typical sufficiency (‘with meaningful X , Y occurs in most cases’, allowing limited exceptions) (Wagner, 2020; Wilhelm, 2022) and probabilistic necessity (‘if X is missing, Y becomes unlikely’), which turns bottlenecks into an explicitly probabilistic, counterfactual-style risk statement. fuzzy subjective structure model keeps these four meanings distinct and uses them as cross-checks, assessing sufficiency after measurement adjustment and covariate balancing, and assessing necessity both as exception patterns and as low success probabilities under sub-threshold conditions in the balanced pseudo-population (Figure 1).

Measurement under subjective fuzzy perception

Indicators of latent constructs carry different amounts of subjective perception because respondents read items through disciplinary, role-based, and cultural lenses. Entropy weighting accounts for this heterogeneity. Formally, each indicator X_i is assigned a weight w_i derived from normalized entropy. While the mathematical expression calculates dispersion, the underlying logic is intuitive. In self-reported survey data, indicators vary in how consistently and clearly they are interpreted by respondents. Entropy weighting functions as a filtering mechanism: indicators exhibiting clear, discriminating response patterns (high information content) receive greater weight, whereas indicators characterized by diffuse or random responses (noise) receive less. As a

result, the latent constructs emphasize the most meaningful components of participants' subjective perceptions.

$$w_j = \frac{1 - \left(-\frac{1}{\ln(m)} \sum_{i=1}^m p_{ij} \ln(p_{ij}) \right)}{\sum_{j=1}^n \left[1 - \left(-\frac{1}{\ln(m)} \sum_{i=1}^m p_{ij} \ln(p_{ij}) \right) \right]}, \quad \text{where } p_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}}$$

The basic idea is simple: items that show clearer, more discriminating response patterns across people carry more information and therefore receive more weight, while items that look closer to noise receive less weight (Song, 2025). Low entropy indicates more informative variation. These weights can be incorporated in how latent scores are constructed so that the inner model reflects the most informative parts of subjective measurement, rather than treating all indicators as equally interpretable (Hair Jr. et al., 2021). Low entropy indicates more informative variation. We incorporate these weights when constructing latent scores, so the inner model reflects the most informative parts of subjective measurement rather than treating all indicators as equally interpretable (Hair Jr. et al., 2021). This does not remove subjectivity; it makes it visible and accountable. Substantively, it matters because all four causal claims are evaluated on the resulting latent-score scale: who counts as 'high' or 'low' on X^* (and therefore who falls above a sufficiency cut-point or below a bottleneck) can shift once measurement is reweighted. Typical sufficiency still requires bottleneck-based reasoning to check whether 'having enough of X ' is commonly associated with 'having high Y ', while allowing that some cases will differ.

Counterfactual balance under observational data

Survey-based information behaviour research is observational, so group differences can reflect confounding. For example, an apparent relationship between general perception of information culture and general level of empowerment may partly reflect discipline, seniority, or other structural differences. Inverse probability weighting addresses this by constructing a pseudo-population in which exposure to a condition is statistically independent of observed covariates, simulating a randomized experiment (Hogan & Coote, 2014).

$$w_i = \frac{T_i}{e(Z_i)} + \frac{1 - T_i}{1 - e(Z_i)}, \quad \text{where } e(Z_i) = P(T_i = 1 | Z_i)$$

To account for confounding in causal estimation, inverse probability weighting (w_i) is employed. Here, the propensity score $e(Z_i)$ denotes the estimated probability that an individual i to declare association with certain category, conditional on confounder Z_i where $T_i \in 0,1$ indicates whether the category is observed. These weights re-balance the sample so that the distribution of confounders like gender, experience etc. is independent of potential treatment status, simulating a pseudo-randomized condition. The practical goal is to create a pseudo-population where measured confounders are less tied to exposure, so conditional probabilities can be interpreted as approximations to intervention contrasts under stated assumptions (Morgan & Winship, 2014; Pearl, 2010). In fuzzy subjective structure model, inverse probability weighting supports the probabilistic claims, while necessary condition analysis contributes evidence about bottlenecks and the rarity of exceptions. Together, they allow necessity statements to be expressed in a probabilistic form ('when X is weak, high Y is unlikely'), while still retaining the constraint logic (Dul, 2024) that is central to institutional information behaviour.

Formalising fuzzy subjective structure model

The integration of entropy weighting for subjective measurement and inverse probability weighting for causal balance allows us to formalize four distinct, non-deterministic causal claims, addressing the gap noted by Dul (2024). These claims separate typicality (high-cardinality statements about what holds for most cases in a reference class) from probability (stochastic

statements about outcome likelihood, interpreted on a counterfactually balanced pseudo-population). The distinctive move of fuzzy subjective structure model is interpretive: the familiar numerical outputs of PLS-SEM, necessary condition analysis, and combined importance-performance map analysis are treated as a starting point, and then re-read in person-in-context terms by reducing each summary back to weighted, case-level membership on a latent-score scale (who clears a threshold, who does not, and who becomes an exception). In other words, the ‘causal claim’ is not the coefficient itself, but the pattern of weighted cases it implies—how often an enabling configuration holds and how rarely high outcomes appear when a condition is missing.

To operationalize these claims, we can first define our core components. Let X_i^* and Y_i^* be the entropy-weighted latent variable scores for a condition (X) and an outcome (Y) for individual i , scaled to a 0–100 range consistent with combined importance-performance map analysis’s performance metric. Also, for analytical clarity, we can define a normalized level for each case as $L_X(i) := X_i^*/100 \in [0,1]$, which directly links the case-level score to the overall combined importance-performance map analysis performance metric via the weighted mean

$$\text{Perf}_X = 100 \times \sum_{i \in \mathcal{R}} \tilde{w}_i L_X(i)$$

where $\mathcal{R}$ is the analytic reference set (e.g., all non-missing cases after filtering) and $\tilde{w}_i = w_i / \sum_{j \in \mathcal{R}} w_j$ are the weights normalized to sum to 1. The unnormalized weights w_i are case weights constructed for causal balance (inverse probability weighting) and may include survey design weights if applicable.

Let w_i be the case-level weight for individual i , derived from inverse probability weighting to ensure causal balance, i.e., used when averaging across people responses. For our analysis, these weights are normalized such that $\sum_{i \in \mathcal{R}} w_i = 1$. The threshold for context variable being condition, T_X , is not arbitrary; it is derived directly from the necessary condition analysis bottleneck that corresponds to a meaningful target outcome level, T_Y .

From necessary condition analysis, a bottleneck (or ‘ceiling-line’) function $b_X(y)$ maps any outcome level y to the minimal level of X^* that is required to make y attainable without violating the ceiling. With a contextually meaningful ‘high’ outcome threshold T_Y (on 0–100), the necessary condition analysis-implied necessity threshold is:

$$T_X := b_X(T_Y)$$

For typical/probabilistic sufficiency, a ‘sufficient’ region may be defined by theory or a practical cut-point (e.g., a high quantile), even if it is not identical to the necessary condition analysis bottleneck.

If $b_X(T_Y)$ is the minimum required level of X^* to achieve T_Y , then we can set $T_X := b_X(T_Y)$. Also, for analytical clarity, we can define a normalized level for each case as $L_X(i) := X_i^*/100 \in [0,1]$, which directly links the case-level score to the overall combined importance-performance map analysis performance metric via the weighted mean $\text{Perf}_X = 100 \times \sum_i \tilde{w}_i L_X(i)$. This setup ensures our causal tests are grounded in the same empirical scale as the combined importance-performance map analysis visualization, with all subsequent analysis performed on the pseudo-population balanced by inverse probability weights (w_i). With this foundation, we can articulate the four causal logics. Because all four estimands are computed as weighted counts over meaningful regions of X_i^* and Y_i^* (above/below thresholds or bottlenecks), the same latent-variable model can support both population summaries and person-in-context interpretations without implying a single deterministic rule for everyone.

Typical sufficiency

The claim ‘if X , then typically Y ’ is a high-cardinality statement about co-occurrence in the balanced reference class. In plain terms: once we compare like with like using weights, a sufficient level of X is almost always accompanied by a high level of Y , with a small number of exceptions permitted. Typical sufficiency is quantified as:

$$\hat{\alpha}_X = \frac{\sum_{i \in \mathcal{R}} w_i \cdot \mathbf{1}\{Y_i^* \geq T_Y, X_i^* \geq T_X\}}{\sum_{i \in \mathcal{R}} w_i \cdot \mathbf{1}\{X_i^* \geq T_X\}}$$

The indicator $\mathbf{1}\{\cdot\}$ equals 1 when the condition in braces is true and 0 otherwise. The numerator counts weighted cases with both sufficient X and high Y ; the denominator counts all weighted cases with sufficient X . The claim is supported when $\hat{\alpha}_X$ meets a high threshold, conventionally 0.85. Substantively, $\hat{\alpha}_X$ answers a concrete question: among respondents who report enough of a condition—enough perceived information culture, enough literacy and self-efficacy, enough system legitimacy—how often do we also observe a high outcome such as empowerment, collaboration, or data stewardship? This resembles how survey models are commonly interpreted in information behaviour research, for instance when claiming that information literacy influences self-efficacy and empowerment (Deja et al., 2021). The difference is that the claim is now explicitly framed as a for-most-people regularity rather than an implied universal lever, and the comparison is made on a pseudo-population where observed confounders are less entangled with exposure.

Typical necessity

The claim ‘if not X , then typically not Y ’ follows Dul’s cardinal logic and focuses on the rarity of exceptions—cases that reach high Y without meeting the necessary condition analysis-implied requirement for X at their observed outcome level. This is quantified as the weighted exception share:

$$\hat{\varepsilon}_X = \frac{\sum_{i \in \mathcal{R}} w_i \cdot \mathbf{1}\{Y_i^* \geq T_Y, X_i^* < b_X(Y_i^*)\}}{\sum_{i \in \mathcal{R}} w_i \cdot \mathbf{1}\{Y_i^* \geq T_Y\}}$$

An exception is a case that achieves a high outcome despite falling below the bottleneck requirement for its observed Y . The claim is supported when three conditions are jointly met: the necessary condition analysis effect size is meaningful (conventionally $d \geq 0.10$), the necessary condition analysis permutation test is significant ($p \leq 0.05$), and the weighted exception share is small ($\hat{\varepsilon}_X \leq 0.05$). Intuitively, among all high- Y cases, only a very small fraction manages this without the required X .

The estimator $\hat{\varepsilon}_X$ captures what institutional information studies often describe qualitatively as non-compensatory conditions: factors that people can occasionally work around but that are difficult to bypass in practice. Information culture is positioned as a condition shaping downstream information practices and outcomes (e.g., information culture $\rightarrow$ information use). A *typical-necessity* test would treat information culture as X and information use as Y , derive T_X from the information culture bottleneck for a high information use target, and then ask: among those with very high information use, how rare are cases that fall below the information culture requirement given by $b_X(Y_i^*)$?

Probabilistic sufficiency

The claim ‘if X , then probably Y ’ shifts from cardinality to probability. This is the conditional probability of high Y given sufficient X , computed on the inverse probability weighting-balanced pseudo-population:

$$\hat{P}(Y^* \geq T_Y \mid X^* \geq T_X)$$

Uncertainty for $\hat{P}(\cdot)$ and related probability-scale summaries is obtained with a nonparametric case bootstrap (resampling respondents with replacement). In each bootstrap replicate we recompute the latent scores (including entropy weighting if used), re-estimate the propensity model and stabilized inverse probability weighting weights, and then recompute $\hat{P}(\cdot)$ under the same threshold rules. Thresholds can be held fixed (theory-anchored or necessary condition analysis-derived in the main sample) or re-estimated within each replicate as a sensitivity check. Percentile or bias-corrected and accelerated bootstrap intervals are then reported for all probability and uplift quantities.

To clarify practical meaning—especially compared to standardised path coefficients—fuzzy subjective structure model also reports a probability-scale contrast, or uplift:

$$\hat{\Delta}_X = \hat{P}(Y^* \geq T_Y \mid X^* \geq T_X) - \hat{P}(Y^* \geq T_Y \mid X^* < T_X)$$

The uplift $\hat{\Delta}_X$ states directly how much outcome likelihood changes across the threshold, after balancing observed covariates. This shifts attention from hypothesis-testing framing toward an estimand that states what often matters in applied research: how much does the probability of success differ when the condition is present at a meaningful level versus when it is not?

Using the structure in Deja et al. (2021) as an example, let X = high information literacy and Y = high information empowerment (IE). Then $\hat{P}(Y^* \geq T_Y \mid X^* \geq T_X)$ reads plainly as: in a covariate-balanced comparison, what is the probability of high empowerment among academics who have high literacy? The uplift $\hat{\Delta}_X$ adds: how many percentage points higher is that probability compared to otherwise similar academics who are not in the ‘high IL’ region? To do so, the approach is to estimate uncertainty by repeatedly re-running the full analysis on many ‘resampled’ versions of the survey (drawing respondents again with replacement) and using the spread of results to form confidence intervals for the probabilities and uplift.

Probabilistic necessity

The claim ‘if not X , then probably not Y ’ shifts from counting exceptions to estimating risk. The central question becomes: if the condition is absent, how likely is success? This is quantified as:

$$\hat{\beta}_X = \frac{\sum_{i \in \mathcal{R}} w_i \cdot \mathbf{1}\{Y_i^* \geq T_Y, X_i^* < T_X\}}{\sum_{i \in \mathcal{R}} w_i \cdot \mathbf{1}\{X_i^* < T_X\}}, \text{ with } \Pr(Y \geq T_Y \mid \text{do}(X < T_X)) \approx \hat{\beta}_X$$

Framed in interventional terms using Pearl's do-operator, this approximates $\Pr(Y \geq T_Y \mid \text{do}(X < T_X))$ under the identifying assumptions sustained by the weighting. Empirically, $\hat{\beta}_X$ is the weighted proportion of cases in the balanced pseudo-population that attain a high outcome despite being below the necessity threshold for X . The claim is supported when this proportion is small—conventionally $\hat{\beta}_X \leq 0.20$ —indicating that success in the absence of the condition is a rare exception rather than a viable pathway.

For information behaviour research, $\hat{\beta}_X$ can be read as a risk-style statement: when the enabling condition falls below a workable minimum, the chance of achieving a very strong outcome is low, though not zero. If information culture is treated as the enabling condition and high information use as the outcome, then $\hat{\beta}_X$ answers a plain question: after balancing by role, discipline, and similar covariates, how likely is very high information use when culture is below the bottleneck level required for that outcome? This is the ‘unlikely when missing’ claim expressed as a probability, not merely as a small-exceptions count.

Fuzzy subjective structure model’s probabilistic sufficiency and probabilistic necessity are effects-of-causes summaries: they describe how likely high Y is under ‘high enough X ’ versus ‘too low X ’ in a balanced pseudo-population. Li and Pearl's probability of sufficiency and probability of necessity

(2024), by contrast, are causes-of-effects quantities defined at the individual level conditional on what was observed—for instance, for someone who did experience Y , was X necessary for that particular person? Fuzzy subjective structure model asks ‘how likely is a high outcome in comparable contexts when X is (or is not) present at a meaningful level?’ while PN/PS asks ‘for this person, would changing X have changed Y ?’ The concepts are aligned in spirit—both are counterfactual—but the estimands differ. In information behaviour research, fuzzy subjective structure model’s version may be the more natural starting point because context conditions such as culture, management, and policy climate are measured as graded latent scores rather than as discrete treatments. The bottleneck logic then serves as a structured way to express information need as constraint: when enabling conditions fall below a workable minimum, high outcomes become unlikely even if not impossible.

Fuzzy membership

The crisp threshold formulation treats membership as binary: a case either meets the condition or does not. This discretisation, while analytically convenient, discards information about degree—how far above or below a threshold a case falls. For constructs measured on continuous latent scales, fuzzy logic provides a more faithful representation by replacing 0/1 indicators with graded membership values in $[0,1]$. Rather than classifying each case i as simply ‘in’ or ‘out’ of a category, fuzzy membership assigns each case a continuous value $\mu(i) \in [0,1]$ representing its degree of belonging. A case with $\mu(i) = 1$ fully belongs to the category; a case with $\mu(i) = 0$ fully does not belong; and intermediate values indicate partial membership. For instance, if the bottleneck requires $X^* \geq 60$ for high outcomes, a case with $X^* = 60$ has $\mu_X^S(i) = 0$ (just at the boundary), a case with $X^* = 80$ has $\mu_X^S(i) = 0.5$ (halfway to the ceiling), and a case with $X^* = 100$ has $\mu_X^S(i) = 1$ (full membership). These case-level membership values are then aggregated across the sample: rather than counting cases (as in crisp formulations), we sum weighted membership degrees to compute population-level estimands.

For sufficiency-type membership, the function $\mu_X^S(i)$ measures the degree to which case i has enough of condition X to enable a high outcome, anchored at the fixed bottleneck $b_X(T_Y)$:

$$\mu_X^S(i) = \max \left\{ 0, \min \left\{ 1, \frac{X_i^* - b_X(T_Y)}{U_X - b_X(T_Y)} \right\} \right\}$$

where U_X is the upper bound of the scale. Cases at or below the bottleneck have $\mu_X^S(i) = 0$; cases at the scale ceiling have $\mu_X^S(i) = 1$. The complement $\mu_X^{-S}(i) = 1 - \mu_X^S(i)$ measures the degree of insufficiency.

For necessity-type membership, the function $\mu_X^N(i)$ measures the degree to which case i meets the X requirement for its own observed outcome level, anchored at the case-specific bottleneck $b_X(Y_i^*)$:

$$\mu_X^N(i) = \max \left\{ 0, \min \left\{ 1, \frac{X_i^* - L_X}{b_X(Y_i^*) - L_X} \right\} \right\}$$

where L_X is the lower bound of the X scale. Cases that meet or exceed their required bottleneck have $\mu_X^N(i) = 1$; cases at the scale floor have $\mu_X^N(i) = 0$.

For outcome membership, the function $\mu_Y(i)$ measures the degree to which case i achieves a high outcome:

$$\mu_Y(i) = \max \left\{ 0, \min \left\{ 1, \frac{Y_i^* - L_Y}{T_Y - L_Y} \right\} \right\}$$

Cases at or above T_Y have $\mu_Y(i) = 1$; cases at or below L_Y have $\mu_Y(i) = 0$.

The parallel fuzzy formulations of all four causal claims—fuzzy typical sufficiency ($\tilde{\alpha}_x$), fuzzy typical necessity ($\tilde{\eta}_x$ and $\tilde{\varepsilon}_x$), fuzzy probabilistic sufficiency ($\tilde{\Delta}_x$), and fuzzy probabilistic necessity ($\tilde{\beta}_x$)—are detailed in the supplementary materials (OSF: <https://osf.io/b8maq/>). This two-stage logic preserves the person-in-context interpretability of fuzzy subjective structure model: we can examine any individual case's membership profile to understand why they contribute (or fail to contribute) to a population-level pattern, while the causal claims themselves remain statements about regularities across the reference class.

Design and identification

As an example of how these causal ideas can be implemented with survey-based information behaviour data, the causal story is specified as a context-first chain in which information management (M) shapes information culture (C); culture shapes information literacy self-efficacy (S); self-efficacy supports empowerment (E); and empowerment encourages collaboration (B): $M \rightarrow C \rightarrow S \rightarrow E \rightarrow B$. Culture is also allowed to have direct upstream effects on S, E, and B. Each arrow is treated as its own causal question rather than as a single 'global model claim', so the estimand and the identification argument are stated for each exposure–outcome contrast. This stepwise structure matters because the meaning of 'cause' differs across the four fuzzy subjective structure model claims: some arrows are more naturally read as typical enablers (sufficiency-type) and others as constraints that block success when missing (necessity-type). Crucially, the framework does not assume that PLS-SEM paths or probability contrasts are causal by default; causal interpretation requires temporal ordering arguments, a justified adjustment set (e.g., via a Direct Acyclic Graph), overlap diagnostics, etc.

Interpreted in information-behaviour terms, these four claims answer different practical questions even when they are computed on the same weighted latent constructs: typical sufficiency means 'if the information policy is there, most people acknowledge the need and act'; typical necessity means 'if the support is missing, very strong acceptance of behaviour is rare, with only a few exceptions'; probabilistic sufficiency means 'raising the support increases the chance of information behaviour'; and probabilistic necessity means 'lacking the policy makes behaviour unlikely.' In this sense, sufficiency claims tell us what to strengthen to raise outcomes, whereas necessity claims tell you what must not fall below a workable level or the system stalls; typical claims emphasize 'for most cases', while probabilistic claims emphasize 'how likely, or how much the odds change'.

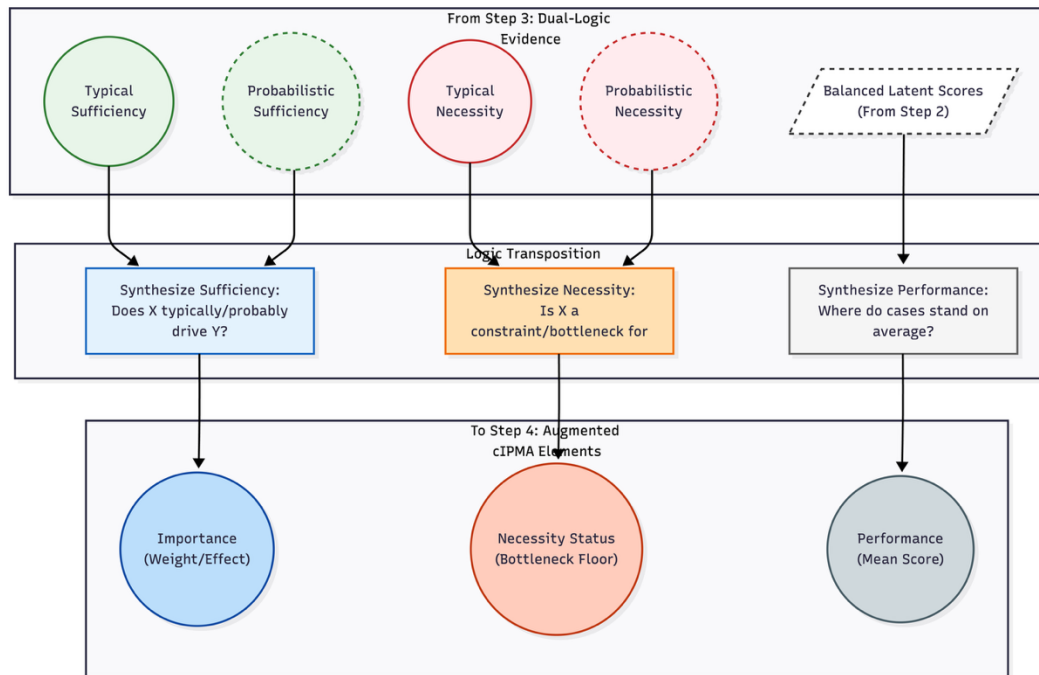


Figure 2. Mapping typical/probabilistic sufficiency and necessity to importance, necessity status, and performance

As shown in Figure 2, all four causal claims are evaluated on latent scores (Step 2) constructed from entropy-weighted measures: once X_i^* and Y_i^* are entropy-weighted, who counts as ‘high’ or ‘low’ on a construct can shift in a principled way. These balanced scores feed the dual-logic evidence (Step 3): typical and probabilistic sufficiency (α and the probability/uplift summaries) are synthesized as importance (effect), while typical and probabilistic necessity (ε and β) are synthesized as necessity (bottleneck) using the necessary condition analysis boundary $b_X(Y_i^*)$. In parallel, the same balanced latent scores are summarized as Performance (normalized mean score), so the combined importance–performance map analysis view (Figure 3, Step 4) reports—on one consistent scale—what tends to drive outcomes (importance), what can block outcomes when too low (necessity status), and where the context currently sits on average (performance) (Hauff et al., 2024).

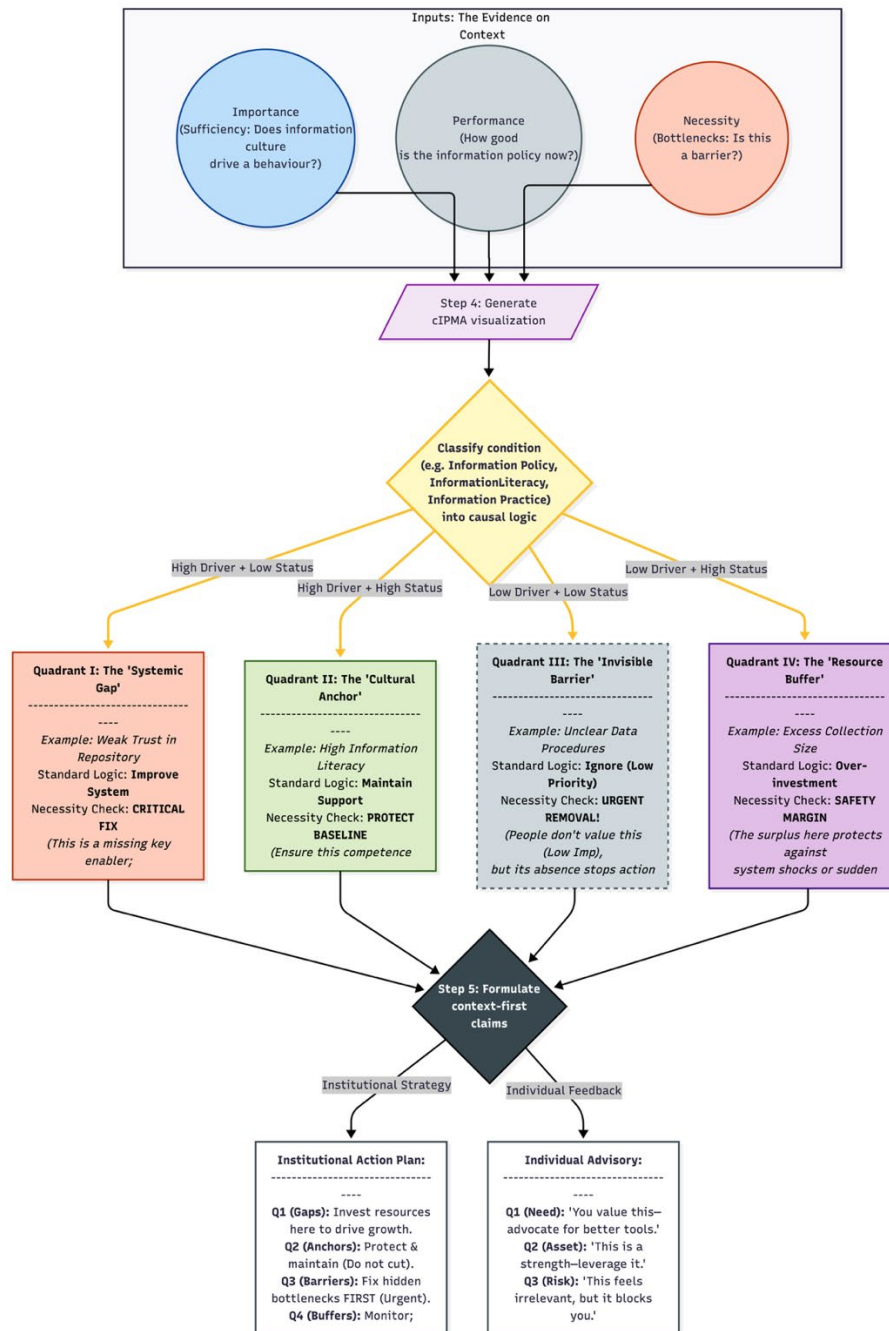


Figure 3. Augmented combined importance–performance map analysis interpretation workflow

Discussion

Many empirical models in information research put individual behaviour on the left-hand side and treat culture or management as downstream correlates. This direction is at odds with the everyday reality of universities, where perceived norms, governance, and system quality enable or constrain what people can do. Compliance with open access or data policies is not an effect of ‘compliance behaviour’ but a response to institutional affordances such as trust in repositories, fit with incentives, and procedural clarity (Deja, 2024; Kim & Adler, 2015). Fuzzy subjective structure model replaces the usual regression-based default by treating information culture and information management as upstream conditions and by estimating both their sufficiency paths and their necessity bottlenecks for self-efficacy, empowerment, and behaviour. In this framing, higher

literacy typically co-occurs with greater self-efficacy; higher self-efficacy typically co-occurs with greater empowerment; but without culture or management at (at least) their bottleneck levels, very high empowerment or collaboration should be rare. Figure 2 clarifies how these statements map onto distinct estimands rather than being left as implicit ‘causal-sounding’ interpretations of associations, while Figure 3 shows how the same evidence can support institutional planning without collapsing everything into a single coefficient narrative.

Potential areas for implementation of fuzzy subjective structure model

Information literacy remains the foundational competence for academic work, understood as the ability to locate, evaluate, and use information effectively, ethically, and reflectively (Kurbanoglu et al., 2006; Sparks et al., 2016). Because respondents read items through disciplinary and role-based lenses, subjectivity in measurement is accommodated. In the present implementation, indicator heterogeneity is treated through entropy-based reweighting as a robustness device to probe whether the main findings are sensitive to differences in response dispersion; the core structural conclusions do not rest on reweighting alone. With this measurement stance, sufficiency paths from literacy to self-efficacy tend to pass typicality criteria, consistent with prior evidence on the literacy-confidence link (Hatlevik et al., 2018; Kultawanich et al., 2015). Empowerment—understood as the capacity to shape one’s information environment—typically follows from self-efficacy and supportive culture (Ahmad et al., 2020; Choo, 2007, 2013). Necessity is evaluated by asking whether high empowerment is uncommon when culture is below its necessary condition analysis-derived bottleneck T_X . When the inverse probability weighting-balanced probability of high empowerment under sub-threshold culture (β) is small (e.g., $\beta \leq 0.20$), the result supports a probabilistic-necessity reading that aligns with institutional experience: without minimal cultural support, success is unlikely even if not impossible.

Methodological implications

Fuzzy subjective structure model remains anchored in combined importance-performance map analysis as a decision-oriented way to summarise what matters and how well it is currently realised, but it changes what those summaries mean for information behaviour research. By adding indicator-level entropy weighting and case-level balancing, and by allowing the analyst to switch between sufficiency- and necessity-oriented readings depending on the substantive theory of information need, the procedure becomes usable across a wider range of information-behaviour questions than a single regression-style interpretation. It still addresses the general need-behaviour relation—how environments shape whether perceived needs translate into action—but it does so in a way that is closer to person-in-context reasoning. Instead of treating coefficients and average scores as if they imply the same mechanism for everyone, fuzzy subjective structure model asks how often enabling patterns are observed among comparable individuals (typical sufficiency), and how rarely high outcomes occur when key conditions are weak (probabilistic necessity). That shift makes the interpretation more ‘causal in intent’ even when the data are surveys and constructs are continuous latent estimates because the claims are expressed as counterfactual-style contrasts and cross-checked against bottlenecks and exception patterns, while remaining explicitly contingent on research design and identification assumptions.

Limits and scope conditions

No statistical procedure substitutes for research design. Identification requires a design-level account of confounding and temporal ordering, ideally formalized with a directed acyclic graph that justifies the conditioning set for each exposure-outcome contrast (Morgan & Winship, 2014; Pearl, 2010). Inverse probability weighting hinges on measured-confounder sufficiency, positivity (overlap), and correct specification of the propensity model; weights should be stabilized and diagnostics reported to guard against extreme values. Because necessary condition analysis permutation tests are implemented without design weights, unweighted necessary condition analysis evidence on bottlenecks is paired with weighted exception rates and probabilities for causal interpretation, and any discrepancy is treated as a signal for sensitivity analysis rather than

as a contradiction. To avoid circularity, necessity thresholds might be learned from training data or theory and evaluated out-of-sample; sufficiency thresholds can also be defined independently (e.g., high quantiles) rather than reusing necessity cut-points. Finally, PLS-SEM paths remain associational unless the design and identification argument license a causal reading; balancing and bottleneck checks reduce but do not eliminate ambiguity. Entropy reweighting can also shift construct meaning by emphasizing certain response patterns; therefore, reporting both weighted and unweighted results, and where possible subgroup checks, is part of responsible interpretation.

Conclusion

Within academic settings, culture and management function as upstream enabling conditions rather than mere correlates of behaviour: openness and trust tend to foster sharing, while rule-centric climates may secure compliance yet dampen initiative unless complemented by other enablers (Choo, 2002; Deja, 2024; Deja & Wójcik, 2021; Detlor, 2010). Fuzzy subjective structure model renders these expectations testable as causal hypothesis. Hence, a causal claim in information behaviour must be design-contingent. Fuzzy subjective structure model should therefore be read as a principled workflow rather than as a turnkey identifier: it combines PLS-SEM for sufficiency paths, necessary condition analysis for necessity bottlenecks and exceptions, and combined importance–performance map analysis for decision-oriented visualization, with inverse probability weighting-based balancing and measurement sensitivity checks to align statistical estimands with counterfactual questions when the assumptions required for such alignment are explicitly defended. When enabling conditions exceed their thresholds, desirable outcomes usually appear; when they remain below, success is unlikely. These claims are most credible when thresholds are theory-anchored, identification is justified with explicit design assumptions, and results are validated through out-of-sample evaluation, diagnostics, and sensitivity analysis.

About the author

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References

- Ahmad, F., Widén, G., & Huvila, I. (2020). The impact of workplace information literacy on organizational innovation: An empirical study. *International Journal of Information Management*, 51, 102041. <https://doi.org/10.1016/j.ijinfomgt.2019.102041>
- Bates, M. J. (1989). The design of browsing and berrypicking techniques for the online search interface. *Online Review*, 13(5), 407–424. <https://doi.org/10.1108/eb024320>
- Choo, C. W. (2002). Sensemaking, Knowledge Creation, and Decision Making: Organizational Knowing as Emergent Strategy. In C. W. Choo & N. Bontis (Eds), *The Strategic Management of Intellectual Capital and Organizational Knowledge* (pp. 79–88). Oxford University Press New York, NY. <https://doi.org/10.1093/oso/9780195138665.003.0005>.
- Choo, C. W. (2007). Information seeking in organizations: Epistemic contexts and contests. *Information Research*, 12(2), paper 298.
- Choo, C. W. (2013). Information culture and organizational effectiveness. *International Journal of Information Management*, 33(5), 775–779.
- Cole, C. (2018). *The consciousness' drive: Information need and the search for meaning*. Springer International Publishing. <https://doi.org/10.1007/978-3-319-92457-1>
- Cole, C., & Wilson, T. D. (2024). Information need: What is it? In P. Heisig (Ed.), *Handbook On Information Sciences* (pp. 73–97). Edward Elgar Publishing. <https://doi.org/10.4337/9781035343706.00013>
- Deja, M. (2024). Information culture of university administration: Making personnel bureaucracy a professional bureaucracy. *Journal of Librarianship and Information Science*, 56(2), 379–396. <https://doi.org/10.1177/09610006221145931>
- Deja, M., Rak, D., & Bell, B. (2021). Digital transformation readiness: Perspectives on academia and library outcomes in information literacy. *The Journal of Academic Librarianship*, 47(5), 102403. <https://doi.org/10.1016/j.acalib.2021.102403>
- Deja, M., & Wójcik, M. (2021). Information culture and academic empowerment: Developing a collective mindfulness strategy for embedded librarianship. *Journal of Academic Librarianship*, 102276. <https://doi.org/10.1016/j.acalib.2020.102276>
- Detlor, B. (2010). Information management. *International Journal of Information Management*, 30(2), 103–108. <https://doi.org/10.1016/j.ijinfomgt.2009.12.001>
- Dul, J. (2016). Necessary Condition Analysis (NCA): Logic and Methodology of “Necessary but Not Sufficient” Causality. *Organizational Research Methods*, 19(1), 10–52. <https://doi.org/10.1177/1094428115584005>
- Dul, J. (2024). A different causal perspective with necessary condition analysis. *Journal of Business Research*, 177, 114618. <https://doi.org/10.1016/j.jbusres.2024.114618>
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd edition). SAGE.
- Hair Jr., J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer Nature.

- Hatlevik, O. E., Throndsen, I., Loi, M., & Gudmundsdottir, G. B. (2018). Students' ICT self-efficacy and computer and information literacy: Determinants and relationships. *Computers & Education*, 118, 107–119. <https://doi.org/10.1016/j.compedu.2017.11.011>
- Hauff, S., Richter, N. F., Sarstedt, M., & Ringle, C. M. (2024). Importance and performance in PLS-SEM and NCA: Introducing the combined importance-performance map analysis (cIPMA). *Journal of Retailing and Consumer Services*, 78, 103723. <https://doi.org/10.1016/j.jretconser.2024.103723>
- Hayes, A. F., Montoya, A. K., & Rockwood, N. J. (2017). The analysis of mechanisms and their contingencies: PROCESS versus structural equation modeling. *Australasian Marketing Journal*, 25(1), 76–81. <https://doi.org/10.1016/j.ausmj.2017.02.001>
- Hayes, A. F., & Rockwood, N. J. (2020). Conditional process analysis: Concepts, computation, and advances in the modeling of the contingencies of mechanisms. *American Behavioral Scientist*, 64(1), 19–54. <https://doi.org/10.1177/0002764219859633>
- Hogan, S. J., & Coote, L. V. (2014). Organizational culture, innovation, and performance: A test of Schein's model. *Journal of Business Research*, 67(8), 1609–1621. <http://dx.doi.org/10.1016/j.jbusres.2013.09.007>
- Huber, M. (2014). Identifying causal mechanisms (primarily) based on inverse probability weighting: Identifying causal mechanisms. *Journal of Applied Econometrics*, 29(6), 920–943. <https://doi.org/10.1002/jae.2341>
- Hume, D. (1758). *Essays and treatises on several subjects*. A. Millar; and A. Kincaid and A. Donaldson, at Edinburgh.
- Imbens, G. W., & Rubin, D. B. (2015). *Causal inference in statistics, social, and biomedical sciences*. Cambridge university press.
- Kim, Y., & Adler, M. (2015). Social scientists' data sharing behaviors: Investigating the roles of individual motivations, institutional pressures, and data repositories. *International Journal of Information Management*, 35(4), 408–418. <https://doi.org/10.1016/j.ijinfomgt.2015.04.007>
- Kultawanich, K., Koraneekij, P., & Na-Songkhla, J. (2015). A Proposed Model of Connectivism Learning Using Cloud-based Virtual Classroom to Enhance Information Literacy and Information Literacy Self-efficacy for Undergraduate Students. *Procedia - Social and Behavioral Sciences*, 191, 87–92. <https://doi.org/10.1016/j.sbspro.2015.04.394>
- Kurbanoglu, S., Akkoyunlu, B., & Umay, A. (2006). Developing the information literacy self-efficacy scale. *Journal of Documentation*, 62(6), 730–743. <https://doi.org/10.1108/00220410610714949>
- Li, A., & Pearl, J. (2024). Probabilities of causation with nonbinary treatment and effect. *Proceedings of the AAAI Conference on Artificial Intelligence*, 38(18), 2465–2472. <https://doi.org/10.1609/aaai.v38i18.30030>
- Morgan, S. L. (Ed.). (2013). *Handbook of causal analysis for social research*. Springer Netherlands. <https://doi.org/10.1007/978-94-007-6094-3>
- Morgan, S. L., & Winship, C. (2014). *Counterfactuals and causal inference: Methods and principles for social research*. Cambridge University Press.

- Pearl, J. (2000). *Causality: Models, reasoning, and inference*. (pp. xvi, 384). Cambridge University Press.
- Pearl, J. (2010). Causal Inference. *Proceedings of Workshop on Causality: Objectives and Assessment at NIPS 2008*, 39–58. <https://proceedings.mlr.press/v6/pearl10a.html>
- Pearl, J., & Mackenzie, D. (2018). *The book of why: The new science of cause and effect*. Basic books.
- Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology*, 66(5), 688.
- Song, Y. (2025). Fuzzy evaluation of teaching quality in ‘smart classroom’ with application of entropy weight coupled TOPSIS. *International Journal of Advanced Computer Science and Applications (IJACSA)*, 16(2), Article 2. <https://doi.org/10.14569/IJACSA.2025.0160236>
- Sparks, J. R., Katz, I. R., & Beile, P. M. (2016). Assessing digital information literacy in higher education: A review of existing frameworks and assessments with recommendations for next-generation assessment. *ETS Research Report Series*, 2016(2), 1–33. <https://doi.org/10.1002/ets2.12118>
- Tarka, P. (2018). An overview of structural equation modeling: Its beginnings, historical development, usefulness and controversies in the social sciences. *Quality & Quantity*, 52(1), 313–354. <https://doi.org/10.1007/s11135-017-0469-8>
- Taylor, R. S. (1968). Question-negotiation and information seeking in libraries. *College & Research Libraries*, 29(3), 178–194. https://doi.org/10.5860/crl_29_03_178
- Virkus, S., & Salman, A. (2020). Effective leadership behaviours and information culture in the higher education institution. *Global Knowledge, Memory and Communication*, 70(4–5), 418–441. <https://doi.org/10.1108/GKMC-08-2020-0106>
- Vis, B., & Dul, J. (2018). Analyzing Relationships of Necessity Not Just in Kind But Also in Degree: Complementing fsQCA With NCA. *Sociological Methods & Research*, 47(4), 872–899. <https://doi.org/10.1177/0049124115626179>
- Wagner, G. (2020). Typicality and minutis rectis laws: From physics to sociology. *Journal for General Philosophy of Science*, 51(3), 447–458. <https://doi.org/10.1007/s10838-020-09505-7>
- Wilhelm, I. (2022). Typical: A theory of typicality and typicality explanation. *The British Journal for the Philosophy of Science*, 73(2), 561–581. <https://doi.org/10.1093/bjps/axz016>
- Wilson, T. D. (1981). On user studies and information needs. *Journal of Documentation*, 37(1), 3–15. <https://doi.org/10.1108/eb026702>
- Wilson, T. D. (2022). *Exploring information behaviour: an introduction*. Eiconics Ltd.

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