

Amplifying Insights: How Logarithmic Bayesianism Can Validate Causation in Participatory Policymaking Methods

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Abstract

Creative, community-based methods are recognised for their ability to challenge top-down approaches and uncover alternative policy solutions. Despite their value, such methods often face criticism for lacking rigour. This paper addresses this concern by integrating participatory research with Bayesian Causal Process Tracing (CPT) to enhance methodological robustness, triangulate findings and provide actionable policy insights. Using a case study on female entrepreneurs in North Yorkshire, England, we adopt a multi-stage approach—combining interviews, focus groups, and problem trees—to identify key challenges female entrepreneurs face. Bayesian CPT is applied, a method that systematically traces causal mechanisms through diverse evidence sources. By moving beyond descriptive analysis, CPT weighs evidence, compares hypotheses, and strengthens causal inferences. Rather than simply identifying correlations, CPT reveals how and why a hypothesis affects an outcome by revealing the underlying mechanisms that shape causal relationships. In offering an empirical example, the logarithmic scale in Bayesian CPT (Fairfield & Charman, 2022) estimates the “loudness” of evidence. This provides a structured, interpretable way to assess causal strength. This approach offers a powerful tool for balancing community-driven insights with empirical rigour, strengthening the link between research and practical policy solutions. Beyond policymaking, triangulation and validation of participatory research, future research should look to incorporate and maximise the potential of Bayesian CPT, which is yet empirically underutilised.

Keywords

Causal process tracing, Bayesianism, Participatory research, Policymaking, Female entrepreneurship

Introduction

Established policymaking norms traditionally rely on technical expertise and democratic accountability, adopting a structured, evidence-driven approach that prioritises technical rigour. Critics argue that creative methods lack the systematic rigour of these established processes (Lewis et al., 2020), yet there is growing recognition that creative, community-focused methods, far from undermining policy foundations, enhance rigour by supporting place-based insights and seek alternative policy responses that may otherwise be unknown to policymakers and missed by top-down approaches (Considine, 2012; Ison & Straw, 2020; Rodriguez & Komendantova, 2022). While creative methods incorporate robust analytical steps, this study demonstrates how its methodological rigour can be intensified through systematic triangulation. This research

employs Bayesian causal process tracing (CPT) to validate qualitative findings derived from participatory workshops with female entrepreneurs in North Yorkshire, England. This approach exemplifies how creative methods can maintain innovation while strengthening empirical foundations through causal analysis.

CPT systematically examines evidence to trace causal chains in social and political phenomena, addressing limitations of descriptive and statistical analyses by illuminating underlying causal mechanisms and give insight into

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how something occurred (Crasnow, 2017), often called causal process observations (CPOs) (Podesta, 2023). CPT enables researchers to incorporate diverse evidence sources (Gonzalez-Ocantos & LaPorte, 2021), conduct within-case analysis (Green et al., 2022), examine evidence in a temporal sequence (Collier et al., 2010) and engage in both theory-testing and theory-building (Hall, 2006; Mahoney, 2015; Schimmelfennig, 2014). While CPT is popularly underpinned by Van Evera's (1997) four tests (see also Collier, 2011; Mahoney, 2012) this paper adopts Bayesian CPT. As outlined by Fairfield and Charman (2022), Bayesian CPT provides an intuitive framework for assessing the strength of hypotheses by expressing their plausibility in decibels, indicating whether a hypothesis is 'loud' (strongly supported) or barely audible (weakly supported). This approach is particularly valuable when triangulating data from participatory and creative methods, integrating multiple data sources and evaluating underlying mechanisms of causality. By linking descriptive evidence to relevant policy outcomes, this approach helps bridge the gap between empirical analysis and practical application (Bijak et al., 2021).

This paper proceeds as follows: The participatory research methods and data analysis employed are first described before qualitative validation techniques and rigour are discussed. CPT is offered as a method to strengthen rigour of participatory data, demonstrated through its empirical application of the logarithmic approach of our case study.

Methodology

Qualitative research allows for the development of causal processes and mechanisms that inform hypotheses and relationships, which includes collaborative methods such as participatory action research (Kopeć, 2023), offering an effective basis to combine participatory methods with CPT.

Participatory research methods are particularly well-suited for our study on the challenges faced by female entrepreneurs. Creative and participatory approaches emphasise more active, open and inclusive policymaking processes (Broadley & Dixon, 2022; Considine, 2012) and highlight the value of local knowledge in assembling processes that bring together people, ideas, and spaces to co-create policy and generate knowledge (Braye & McDonnell, 2013; Escobar, 2013). By engaging local people in the research process, we gain a deeper understanding of the specific challenges they face.

This research adopts a multi-stage approach that incorporates qualitative data from five focus groups (4 in-person and 1 online, n = 32) and a small number of purposefully sampled interviews (n = 4) to ensure inclusion of intersectional identities and characteristics. This formed the exploratory work ahead of hosting a participatory workshop. Access to participants was made possible due to the collaborative nature

of this research between the researcher and the Federation of Small Businesses.

The leading researcher is a woman and sharing the gender identity of participants may have fostered a sense of trust and rapport, potentially encouraging openness and richer data sharing. This might have helped participants feel comfortable discussing challenges unique to female entrepreneurs. However, the researcher's position as an outsider to the entrepreneurial community could also affect interpretation, and the nuances captured. The presence of other 'insider' members from the research collaboration provided valuable contextual understanding and facilitated the emergence of relevant, community-grounded insights.

Thematic analysis of transcripts from the focus groups and IDIs, conducted using NVivo software, identified key themes or challenges for exploration during the workshop. The transcripts underwent open coding through an inductive, iterative process before axial coding to form categories based on interlinkages between the identified codes. Continued familiarisation with the data facilitated further iterative coding. Engagement with collaborative research partners aided a critical reflection on the emerging categories. This external perspective helped to challenge assumptions and enhance the credibility and trustworthiness of the analysis. Subsequently, these categories were organised into thematic groups. Throughout the coding process, reflexive and iterative coding, alongside discussions of key themes with the collaborative research group, helped guard against subjective bias. Additionally, the researcher's familiarity with the data from collection necessitated careful attention to minimise selective memory from impacting the coding process. To address this, the researcher engaged in ongoing reflexive practices, critically examining assumptions and interpretations.

While the workshop had seven key challenges, each derived from thematic areas generated, this paper focuses on the issue of customer acquisition and retention, as illustrated in Figure 1. Other themes included lack of confidence, balancing work-life and access to finance/funding.

Approximately 35 female entrepreneurs from the region participated in a workshop focused on several problem and solution trees (PASTs). Popular in development studies, the problem tree is a useful tool for communities to order their cause-effect relationship (Chevalier & Buckles, 2013; Hinds, 2013), circumnavigating the restrictions of linear problem-solving approaches (Salinas, 2022). Subsequently, to provide corrective actions, evidence on a problem tree can be followed by converting the causes and effects into means and ends through a solution tree (see Sapkota et al., 2024).

Participants began by reflecting on the key challenge identified in their problem tree and used sticky notes to record what they believed to be the root causes of that challenge. Next, they considered the consequences that this

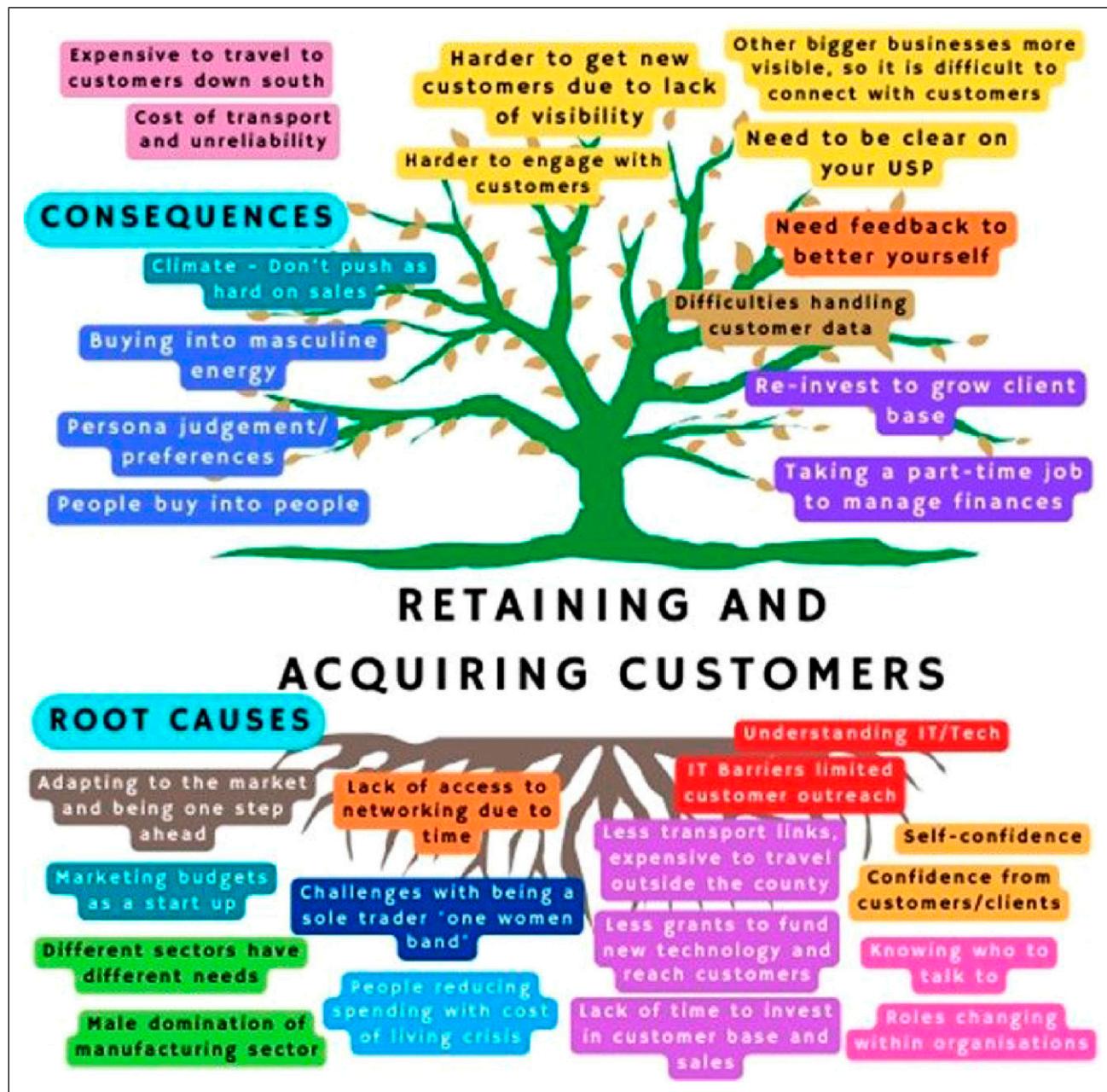


Figure 1. Problem Tree on Retaining and Acquiring Customers

challenge has on their daily lives and entrepreneurial aspirations, writing these reflections on the leaves of the tree. In the final step, participants grouped their responses into broad themes, creating colour-coded clusters for both root causes and consequences to visually represent related ideas on the problem tree. These identified causal relationships will be validated to ensure that resulting policy recommendations are well-targeted and evidence-based.

Participants reframed their reflections into actionable solutions using star-shaped sticky notes beside the thematic clusters of sticky notes developed at the workshop. Actionable solutions are interventions that can

be implemented through policy or changes to address the root causes and consequences identified in the problem tree. This step aimed to generate feasible policy responses that directly target the underlying issues and their effects. Validation of cause-effect relationships identified through the problem tree can inform subsequent workshopped solutions.

Qualitative Validation and Rigour

Although design-led or human-centred approaches such as design thinking are popular (Lewis et al., 2020), such

methods are not without drawbacks as a lack of policy-focused research can lead to unactionable generalised recommendations.¹ Strengthening policy impact requires the use of robust qualitative validation frameworks and subjecting data to rigorous standards, including credibility (such as ethical conduct, credible sources, and appropriate research design), contextualisation, and iterative processes like coding. Rigour is further ensured through transferability, dependability (e.g., audit trails or reflexive journals), and confirmability via triangulation by cross-checking findings across sources, combining methods, or involving multiple researchers or analysts.

Building on these standards, evaluation studies have introduced innovative approaches to strengthen causal inference and impact assessment. Contribution Analysis (CA), for example, is discussed by [Mayne \(2012, p.270\)](#) as an “approach to confirming that an invention is a contributing cause”. He notes that CA is valuable because it constructs a case for an intervention’s contribution within a theory of change. An empirical example is offered by [Delahais and Toulemonde \(2017\)](#) who applied CA to assess whether programmes led by the Centre for International Forestry Research (CIFOR) contributed to sustainable forest management in the Congo Basin. Also enhancing qualitative evaluation, [Remnant et al. \(2024\)](#) highlight the Qualitative Impact Protocol (QuIP), which collects narrative causal statements from those affected by an intervention through ‘double-blindfolded’ interviews, where neither party knows the intervention details. [Copestake \(2025\)](#) discusses QuIP’s value in complex contexts and its push for more systematic, transparent qualitative evaluation. While QuIP is a standalone method, it can complement approaches like process tracing.

Building on this, this paper offers logarithmic Bayesianism as another validation technique that can aid in enhancing qualitative rigour and evaluation methods.

Causal Process Tracing (CPT)

Whilst CPT does not have one singular definition (see [Trampusch & Palier, 2016](#)), it is a qualitative research method generally understood as a within-case analysis like detective work where the researcher builds upon suspects (or theories) and clues (evidence) ([Bennett, 2023](#)). [Maxwell \(2004\)](#) contends that quantitative methods favour a variable-oriented approach, treating causation as an unobservable process and focusing solely on systematic relationships between inputs (X) and outputs (Y). Maxwell stresses that the link between X and Y is not fixed but context-dependent, shaped by the mechanisms at work. [Gerring \(2010, p. 1500\)](#) builds on this, arguing that a focus on causal mechanisms offers an alternative to positivist notions of causality, which often reduce causation to a mere “probabilistic association between X and Y.” Instead, Gerring underscores the importance of examining

generative components, i.e., the actual processes through which X influences Y.

A key strength of CPT is that it uses mechanisms to describe the unobservable physical, social, political and psychological phenomena to illuminate and evaluate causal claims by opening the ‘black box’ of underlying causal mechanisms ([Beach, 2016; Collier, 2011; Kay & Baker, 2015; Trampusch & Palier, 2016](#)). Unlike variables, mechanisms are theoretical constructs that explain recurring relationships and clarify why X causes Y ([Hall, 2013](#)), such that:

$$X \rightarrow M \rightarrow Y$$

i.e., where X is treated as the cause, M the mechanism and Y the outcome ([Mahoney, 2015](#)). They differ from intervening variables by requiring ontological reflection, as outcomes are context-dependent rather than fixed ([Falleti & Lynch, 2009](#)).

A key advantage of CPT is the ability to collect a range of evidence to incorporate into analysis to determine the strength of hypotheses, and to enable the researcher to establish the weight of causation or the likelihood of one hypothesis over another. The researcher goes through a ‘soak and poke’ open-ended research to immerse themselves in a case ([Bennett, 2023; Gonzalez-Ocantos & LaPorte, 2021](#)) and provide thick description ([Byrne et al., 2009](#)).

From a policy perspective, it is often more important to know what effect a treatment has on an outcome than why it has that effect ([Gerring, 2010](#)). However, adequately addressing complex issues requires dismantling the messy and complex underbelly of social interventions ([Byrne et al., 2009](#)) to adequately understand the complex issue in the first place, to then appropriately develop a policy response. For example, solely focusing on the effect of a sugar tax in reducing confectionary consumption, overlooks the underlying mechanisms behind this outcome, which could include tougher family finances, more awareness of healthy eating, etc. CPT is useful for dealing with complex systems that do not have sharp boundaries and should be understood as a series of flows that can transform over time ([Byrne, 2024](#)). It is also useful in this context to demonstrate the relative strength of competing hypotheses on an outcome.

Bayesianism

Advances in CPT and its links to Bayesianism has prompted some scholars to go so far as to say that Bayesianism is the only sound approach for causal analysis within qualitative data as it provides a clear framework for scrutinising inferences and pinpointing sources of disagreement ([Fairfield & Charman, 2022](#)). While Bayesianism can be used in comparative analysis, generally with typical and deviant cases, small-N comparisons or

Table 1. Qualitative to Quantitative Correspondence (dB): (Fairfield & Charman, 2022, p. 133)

dB	Acoustic perception	Plain language description	Equivalent Odds or Likelihood ratio
3	Smallest meaningful difference	Very weak	2:1
6	Clearly noticeable difference	Weak	4:1
10	Twice as loud	Moderate	10:1
20	Four times louder	Strong	100:1
30	Eight times louder	Very strong	1,000:1

within-case studies are more useful for assessing causal theories as the researcher can investigate causal processes in detail (Hall, 2003). While there is some disagreement over the use of deductive and/or inductive characteristics of CPT (see Checkel, 2021), it is an iterative process where inductive investigation can alter our hypotheses and the values ascribed to competing hypotheses.

The first step of Bayesianism is in clarifying the research question and hypotheses. The researcher must develop a well-defined theoretical framework and theorise the causal pathways leading to an outcome (Ulriksen & Dadalauri, 2016), requiring careful consideration of factors such as the mutually exhaustive and exclusive nature of chosen hypotheses. Typically, Bayesian scholars advocate for the assessment of rival hypotheses to determine which hypothesis has a greater probable impact on the outcome. However, this research assesses a hypothesis H_1 against its logical negation \bar{H}_1 to triangulate the validity of H_1 in determining the outcome, as the focus is on testing the strength of the causal relationships identified through participants' reflections.

After clarifying the research question and hypotheses, priors are identified, i.e., theoretical and verifiable expectations (Ulriksen & Dadalauri, 2016). This is the initial view on the plausibility of a hypothesis (Fairfield & Charman, 2022). Generalist knowledge informs arguments about a plausible prior probability, but this informal step can be formalised by relying on a structured evidence synthesis (Behrens & Rohlfing, 2025). How prior probabilities are assigned differs depending on the model of Bayesianism employed. In heuristic Bayesianism, a fraction of 1 is assigned to each hypothesis. For example, in the case of two rival hypotheses, equal priors of 0.5 may be assigned to each hypothesis, or, if prior knowledge favours one hypothesis over the other, priors such as 0.7 and 0.3 can reflect this preference. The researcher must clarify why there is a preference. This is represented through Bayes' rule where:

$$P(H_1|I)$$

P (probability), H_1 (hypothesis 1), I (information).

However, when using Fairfield and Charman's (2022) explicit Bayesianism, a logarithmic measure of the ratio of sound levels relative to human hearing thresholds is adopted. It may be difficult to discern the difference between an ascribed value of 0.7 to 0.8 and different

researchers will have different interpretations of the meaning behind these numbers. However, using a logarithmic scale, the strength or likelihood of a hypothesis is discussed in a different way to demonstrate how 'loud' a hypothesis is by inhabiting the world of the hypothesis. This approach offers an innovative alternative. While some subjectivity and interpretation remain, workshopping evidence is facilitated by the provision of clear reference points for assessing the 'loudness' or significance of each piece of evidence. This contextualisation supports decision-making and offers a more intuitive framework for interpreting evidence than heuristic Bayesianism. There is clearer meaning to numbers, or in this case, decibels, that show how strong the researcher has deemed the evidence to be (Table 1).

In acoustics, the minimal noticeable difference that a typical person can detect is around 3 dB in real-world environments, but this is insubstantial. Where a change of 5 dB is clearly noticeable, an increase of 10 dB is twice as loud and so on. In qualitative research, 30 db is considered very loud. Reference sound levels, as shown in Table 2, provide useful context. For example, a change of 30 dB is likened to the difference between a quiet bedroom and a typical conversation. Thus, evidence favouring a hypothesis by 30 dB is speaking clearly and highly compelling.

Table 2. Typical Sound Levels (dB): (Fairfield & Charman, 2022, p. 134)

dB	Reference Sounds
0	Human hearing threshold (healthy child)
10	Adult hearing threshold, pin-drop
20	Whisper
30	Quiet bedroom or library
45	Sufficient to wake a sleeping person
50	Moderate rainstorm
60	Typical conversation
70	Noisy restaurant
80	Busy curbside, alarm clock
90	Passing motorcycle
100	Dance club, construction site
115	Rock concert, screaming baby
125	Pile driver

After assigning a dB level to the prior probability, the next step is to incorporate the likelihood ratio or the weight of evidence (WoE). Documenting different aspects of the causal story often requires evidence from different sources (Collier, 2011). For example, where national economic statistics may authenticate a key step in a causal chain, it might also be necessary to conduct interviews with policy makers to account for the mechanisms that led to the particular state of affairs (Gonzalez-Ocantos & LaPorte, 2021). Bayesian process tracing prefers unstructured evidence because it has a greater exploratory potential and a higher probability of generating observations for alternative hypotheses (Kreuzer, 2016). In Bayes' rule, the likelihood ratio is represented as:

$$P(E|H_1I)$$

i.e., the probability of observing the evidence (E) under hypothesis 1, taking the background information (I) into account.

The total WoE can be decomposed into separate calculations per each evidence such that:

$$WoE_0(H_1|E_0) = dB$$

$$WoE_1(H_1|E_0E_1) = dB$$

$$WoE_N(H_1|E_0E_1\dots E_N) = dB$$

The researcher evaluates each piece of evidence individually, assigns a dB value, and then calculates a total sum that considers all the evidence. Each piece of evidence can add dBs, take away, or have no effect where the evidence neither strengthens nor weakens the hypothesis. A dB value is assigned after inhabiting the world of the hypothesis and asking how expected (high probability) or surprised (low probability) the evidence would be (Fairfield & Charman, 2022).

Finally, we move to the posterior probability:

$$P(H_1|EI)$$

i.e., the probability of the hypothesis taking the evidence and information into account. Bayesian logic traditionally depicts its equation with one hypothesis relative to another rival hypothesis as follows:

Posterior odds = prior odds x likelihood ratio

$$\frac{P(H_1|EI)}{P(H_2|EI)} = \frac{P(H_1|I)}{P(H_2|I)} \times \frac{P(E|H_1I)}{P(E|H_2I)}$$

However, this research instead refers to the logical negation of the hypothesis, as the objective is not to test the relative strength of one hypothesis against another but rather to use Bayesianism as a triangulation and validation tool. Testing a hypothesis in isolation increases the risk of researcher bias, where only supporting evidence is sought. By evaluating the logical negation, evidence for and against the hypothesis is collected. In Bayes' rule, the equation of logical negation is:

$$\frac{P(H_1|EI)}{P(\bar{H}_1|EI)} = \frac{P(H_1|I)}{P(\bar{H}_1|I)} \times \frac{P(E|H_1I)}{P(E|\bar{H}_1I)}$$

However, given that a logarithmic scale is adopted, the execution of the equation looks slightly different as the odds of H_1 to \bar{H}_1 are directly compared at each stage of the process. This approach allows the prior and WoE to be summed to gain the posterior probability, such that:

$$P(H_1 : \bar{H}_1|EI) = P(H_1 : \bar{H}_1|I) + P(E|H_1 : \bar{H}_1I)$$

Table 3 outlines this process in a step-by-step guide.

Table 3. Step-by-step Guide

Step	How-to
1. Research question	• Define research question
2. Define hypotheses (X), mechanisms (M) and outcomes (Y)	• Develop hypotheses that reflect the causal relationships under investigation • Decide whether to test rival hypotheses for comparison or use logical negation for validation • Identify mechanisms that explain how and why your hypothesis leads to the outcome, considering social, political, and psychological contexts
3. Assign a prior probability score	• Assign a prior probability to each hypothesis, using generalist knowledge to judge its likelihood relative to its rival or logical negation • Using the logarithmic score, assign a dB level based upon your assessment of how likely or unlikely the hypothesis is
4. Collate and define evidence	• Collect and analyse a diverse range of data sources, carefully assessing the relevance of each piece of evidence • Use sources as evidence to evaluate the weight of evidence of one hypothesis against another
5. Assess and assign the weight of evidence (WoE)	• Inhabit the hypothesis and assess how surprising or expected the evidence is under each hypothesis • Assign a dB value based upon how loud the evidence is in favour of the hypothesis under study
6. Add up the WoE	• Sum the total WoE from each piece of evidence
7. Add the prior and the WoE to get the posterior odds	• The posterior odds equal the sum of the prior odds and the weight of evidence. This is the total probability of a hypothesis relative to its rival or logical negation

Discussion

The research question is: What challenges do female entrepreneurs face in acquiring and attaining customers?

As part of the participatory workshop and born out of thematic analysis of key challenges highlighted in preliminary data collection and analysis, a problem tree is included which focuses on acquiring and attaining customers. Hypotheses, mechanisms, and outcomes are developed based on the causal relationships mapped by participants in the problem tree (Table 4), linking hypotheses (X) to outcomes (Y). Mechanisms are developed by reflecting on questions of how and why between X and Y, informed by the understanding of M as social, political and psychological contexts. There may be multiple M at work simultaneously and interacting, but the goal in opening the black box of causality is to understand the underlying mechanisms. Therefore, the analysis remains valid for assessing whether these mechanisms are influencing the relationship between X and Y.

For illustrative purposes and to manage the breadth of available evidence, this paper applies logarithmic Bayesianism CPT to the first hypothesis and its logical negation ($H_1: \bar{H}_1$).

A limitation of this study is that decibel assignments were made by a single researcher. However, the process was iterative, involving individual assessment of each source contributing to a piece of evidence, followed by a review of all sources for that evidence. Later, the relative strength of each evidence was reconsidered in the context of other evidence (e.g., vs. E0, E1, E2, etc.) to ensure balanced scoring. This approach, combined with a range of primary and secondary data, enhanced the robustness and validity of the scoring. Peer-reviewed articles are included among the secondary sources, increasing the credibility of the evidence base and supporting triangulation, as emphasised by [Delahais and Toulemonde \(2017\)](#), who highlight the

importance of authoritative sources in strengthening evaluation credibility. Triangulation is further enhanced by drawing on independent sources, to reduce bias and provide a more comprehensive evaluation.

Assigning Priors

Prior probabilities are assigned using the logarithmic scale *prior* to further evidence collection and analysis. As per Table 5, H_1 has a high prior probability relative to \bar{H}_1 , represented by a rating of 20 dB in favour of H_1 . This is a strong difference between the hypotheses that is likened to the difference between a quiet bedroom and a moderate rainstorm. Generalist knowledge indicates that networking is critical for creating opportunities and fostering business development. Social connections play a pivotal role in opening doors for entrepreneurs. Networking is important for gaining access to information on the market, acquiring advise and building diverse networks. Additionally, networking facilitates referrals, which contribute to business growth. In contrast, prior information for \bar{H}_1 does not favour this hypothesis however, one could argue that referrals or collaborations are not required for greater customer exposure as there may be an organic flow of customers to the entrepreneur (Table 5).

The Weight of Evidence (WoE)

Throughout the evidence gathering and analysis, this study seeks to open the ‘black box’ of causality by identifying and explaining the mechanisms that produce observed outcomes by analysing evidence from primary and secondary sources.

Secondary sources consistently highlight the gender-specific challenges female entrepreneurs face, including societal perceptions, self-confidence barriers, and household

Table 4. Hypotheses, Mechanisms and Outcomes

Hypotheses	Mechanisms, questions of ‘why’ and ‘how’	Outcomes
$X \Rightarrow$	$M \Rightarrow$	Y
H_1 Visibility and access to new and existing customers is reduced due to lack of networking	Lack of networking \Rightarrow limited exposure to potential clients and collaborators \Rightarrow fewer referrals and collaborations \Rightarrow reduced visibility in the market	Difficulty acquiring new customers and retaining existing ones
H_2 Visibility and access to new and existing customers is reduced due to gender biases	Gender biases \Rightarrow perceived lack of competence or credibility \Rightarrow fewer opportunities for engagement \Rightarrow reduced visibility and trust	Difficulty acquiring new customers and retaining existing ones
H_3 Visibility and access to new and existing customers is reduced due to costs and the unreliability associated with public transport to physically access new and existing customers	Transport barriers \Rightarrow missed opportunities for in-person engagement \Rightarrow reduced visibility	Difficulty acquiring new customers and retaining existing ones
H_4 Visibility and access to new and existing customers is reduced due to inability to have comparable marketing budgets and IT knowledge to connect with customers compared to bigger companies	Limited budgets \Rightarrow inability to compete in digital marketing \Rightarrow poor online presence \Rightarrow reduced visibility	Difficulty acquiring new customers and retaining existing ones

Table 5. Prior Probabilities

Hypotheses X	Prior probability ($H_1: \bar{H}_1$)
H_1 visibility and access to new and existing customers is reduced due to lack of networking	20 dB
\bar{H}_1 visibility and access to new and existing customers is <i>not</i> reduced due to lack of networking	

responsibilities as structural biases. However, there is relatively limited literature focusing explicitly on female entrepreneurs' access to new customers as limited due to lack of networking. This gap became evident through systematic

searches of peer-reviewed literature, where limited relevant results necessitated both methodological refinements and careful inclusion of international studies with directly applicable findings (see [Appendix A](#)). The discussion reviews each piece of evidence and its supporting evidence sources in turn. The remainder of the discussion will focus on E0-E3 with inclusion of E4-E7 in [Appendix B](#).

The likelihood ratios are demonstrated in [Table 6](#).

E0: Needing to Travel to Nearby Cities for Networking and Not Knowing Where to Access Networks

$$WoE_0(H_1|\bar{H}_1) = 6dB$$

Primary research reveals that female entrepreneurs in non-urban areas face significant challenges in accessing

Table 6. The Weight of Evidence

H_1 Visibility and access to new and existing customers is reduced due to lack of networking	
\bar{H}_1 Visibility and access to new and existing customers is <i>not</i> reduced due to lack of networking	

Evidence	Source	WoE ($H_1: \bar{H}_1$)
E0 Access Networks remain inaccessible, some entrepreneurs must travel to cities, while others lack knowledge on where to access networks	Primary evidence Focus groups, IDIs	6 dB
E1 Information sharing Limited networking restricts information sharing, hindering business growth and customer retention strategies	Primary evidence Focus groups, IDIs Secondary evidence: (Bozkurt et al., 2022 ; Nevi et al., 2024 ; The Alison Rose Report, 2019)	20 dB
E2 Collaboration Access to networks is necessary to facilitate introductions and connections to help scale businesses Incubators, accelerators, and co-working spaces specifically for female entrepreneurs in male-dominated contexts can foster collaboration and mentoring	Secondary evidence: (GEM, 2024 ; HSBC, 2019 ; Ozkazanc-Pan & Clark Muntean, 2018 ; Treanor & Marlow, 2025)	15 dB
E3 Support Having a larger social and supporting network size is likely to lead to an improvement in product and service quality as well as an increase in customer attraction and retention	Primary evidence: Focus groups, IDIs Secondary evidence: (O'donnell, 2014 ; Ozkazanc-Pan & Clark Muntean, 2018 ; HSBC, 2019 ; George & Dhaliwal, 2024 ; John, 2024 ; Ricciardi et al., 2025)	3 dB
E4 Direct engagement to customers B2B – selling to other businesses means that attending sector networking is a direct link to customers	Primary evidence: Focus groups, IDIs Secondary evidence: (Brahem & Boussema, 2023 ; Foster & Brindley, 2018 ; Nevi et al., 2024 ; Popovic-Pantic et al., 2023)	10 dB
E5 Reputation and referrals Networking is important for positive word of mouth	Primary evidence Focus groups, IDIs Secondary evidence: (O'donnell, 2014 ; Hodges et al., 2015 ; Vagoner, 2021 ; Gopalan, 2023)	3 dB
E6 Industry standards Guides from business websites that advocate on the importance of networking for client leads	Secondary evidence: (Business Advice, 2025 ; Businessforum.uk, 2023 ; Soni, 2023)	5 dB
E7 Networking events are not effective Cons of networking can include an inefficient use of time, skills/business mismatch at events and social pressures	Primary evidence Focus groups, IDIs Secondary evidence: (Bozkurt et al., 2022 ; Tagent, 2025 ; Waters, 2024)	-3 dB
Total		59 dB

professional networks, largely due to inadequate public transport and limited knowledge of where to find networking opportunities. This issue is particularly pronounced in rural regions. One interviewee expressed the dilemma succinctly: “It’s a choice, yes, fine, live rurally, but it’s how you access the bigger places … I feel disadvantaged because of that. Particularly for my type of career.” These transportation difficulties directly impact access to valuable networking opportunities, which are often concentrated in urban centres. As one entrepreneur noted, “I really miss out on the networking opportunities because they are fabulous in Leeds. They really are. You could go out every night and network with people that obviously bring about opportunity, and we just haven’t got that here.”

[Delahais and Toulemonde \(2017\)](#) note data credibility and reliability when the same themes emerge within different stages of the primary data collection. Indeed, this is true of the focus groups and IDIs where the same themes around rurality and transport as barriers to accessing networks emerged. These accounts highlight several interconnected challenges faced by non-urban female entrepreneurs, including the time and resource investment required to travel to nearby cities, the limited availability of local networking options, especially for those outside dominant regional sectors, and reduced visibility to potential customers. The evidence strongly suggests that rural and coastal entrepreneurs face distinct disadvantages compared to their urban counterparts, where networking opportunities are more plentiful and accessible.

However, this primary evidence, drawn from the rural and coastal sample, indicates that refining the hypothesis to focus specifically on non-urban participants would likely increase the strength of this assessment. Such refinement underscores the importance of geographic context in understanding the networking challenges faced by female entrepreneurs outside urban centres.

Considering that the sample holds both urban and non-urban participants, if one inhabits the worlds of the two hypotheses, i.e., the hypothesis and its logical negation to determine the strength of the causal relationship between networking and customers as developed through the causal-linear pathways in the PASTs, the evidence is in favour of H_1 by 6 dB, indicating a 4:1 likelihood ratio and a clearly noticeable difference. This score reflects the combination of urban and rural components within the sample, and it is likely that the score would increase in a sample comprised solely of non-urban participants.

By examining these issues in depth, the analysis opens the ‘black box’ of causality, revealing the underlying mechanisms, such as geographic isolation and transport barriers, that explain how networking challenges reduce customer acquisition for non-urban female entrepreneurs.

E1: Information Sharing Is Limited, and This Means that It Is Harder to Grow Business

$$WoE_1(H_1|\overline{H}_1) = 200B$$

Research underscores the multifaceted value of networking for female entrepreneurs. [Bozkurt et al. \(2022\)](#) in their study of a female entrepreneur operating a circular business, acknowledge that while some view networking as a ritualistic exercise, it nonetheless provides substantial benefits, particularly in facilitating knowledge-sharing. Similarly, [Nevi et al. \(2024\)](#) emphasise the role of networks in developing human capital, reinforcing the idea that access to diverse connections is instrumental for entrepreneurial growth. This is echoed in primary accounts from female entrepreneurs, who describe the tangible consequences of limited networking: “information-sharing is limited. It means I don’t get to know what’s going on out there. Those are the challenges that I have face, that I keep facing, and I hear a lot of other female entrepreneurs talk about.” Another participant elaborates:

That’s where it’s a real challenge if you don’t have that network and you just focus on one thing, and you don’t have the flexibility to go out and meet other people, then you’ll never grow, well, it’ll be a challenge to grow. It’ll be really tough. That’s one way of really expanding knowledge.

Beyond simply acquiring knowledge, entrepreneurs also recognise the strategic value of building networks that extend their own expertise. As one participant explained, “I want to create a good network that I can refer to if my expertise doesn’t cover that client.” This perspective highlights that effective networking is not only about personal gain, but also about being able to connect clients or collaborators with the right expertise within a broader network.

The importance of networks is further highlighted in [The Alison Rose Report \(2019\)](#), which advocates for centralised, government-led information initiatives designed to create a first-stop information shop for entrepreneurs. The report notes that improving access to information is critical for both men and women but also observes that “women are more likely than men to identify networks as an important source of business help” and that networks function as “loose umbrellas of connections that allow like-minded individuals to meet, compare notes and seek informal advice” ([The Alison Rose Report, 2019](#), p. 68).

Limited access to networking not only restricts information sharing but also reduces visibility and access to key resources such as funding, training, and mentorship. Exclusion from these circles makes it more difficult to stay abreast of industry developments and to understand evolving customer needs. Primary data shows consistency with findings in secondary sources, raising the likelihood ratio to a level comparable to the difference between a quiet bedroom and a moderate rainstorm as the findings are both supported by triangulation of

multiple data sources and authoritative data source types. Evidence shows the substantial impact that restricted networking has on the opportunities and growth potential of female entrepreneurs.

E2: Networking Facilitates Collaboration

$$WoE_2(H_1|\bar{H}_1) = 150B$$

HSBC's 2019 report, *She's the Business*, while primarily focused on investment and securing capital, also highlights the importance of supporting female trailblazers and emphasises the role of banks in facilitating introductions to collaborators with other organisations. Similarly, the Global Entrepreneurship Monitor (GEM) (2024, p. 67) notes that "incubators, accelerators, and co-working spaces specifically for women entrepreneurs in male-dominated contexts can foster collaboration, mentoring, and access to resources". GEM (2024, p. 69) further argues that "collaboration between startups and established businesses can accelerate innovation", and stresses the critical role of networks in education, mentorship, and market access. Ozkazanc-Pan and Clark Muntean (2018) also highlight that incubators help female entrepreneurs to access customers and potential partners, underscoring the importance of such environments in facilitating collaboration and business growth.

The impact of network access on business growth leaves a clear "signature" or "fingerprint" in the evidence, as discussed by Delahais and Toulemonde (2017). This is evident in the experiences of entrepreneurs who become well-networked, consistently reporting increased opportunities and visibility. As one participant described, "we just became essentially well-networked. Because of that, a lot of opportunities came our way. So if there was any funding or any events to be put on, our names were always at the top of the list." This recurring pattern where greater network access consistently leads to enhanced visibility and more opportunities serves as a fingerprint of the causal relationship between networking and the ability to scale a business.

However, networking opportunities and their collaborative benefits are not equally accessible to all entrepreneurs. Treanor and Marlow (2025) highlight that females are underrepresented in sectors such as STEM and in business incubators, where support structures often reflect a gendered landscape. They argue that gender, as a social construct, shapes power dynamics within networks, affecting females' confidence and ability to engage effectively in networking activities that lead to collaboration and investment readiness. Ozkazanc-Pan and Clark Muntean (2018) further explain that females often lack access to informal social networks, such as the "old boys club," which limits their ability to build and leverage social capital. Their research also suggests that females tend to approach networking through relationship-building and mutual support rather than transactional exchanges, fostering collaborative environments that encourage learning

and shared growth. This indicates that females may be less likely to benefit from the transactional aspects of networking in the same way as male entrepreneurs. This context helps to explain concerns raised by Treanor and Marlow (2025), who note that female mentors often encourage female entrepreneurs to adopt more 'masculine' qualities when networking.

Many networking groups remain exclusionary, with one participant describing them as "men-only clubs" and another recounting an experience where a male counterpart dismissed her business expertise during a networking event:

One of the things, challenges, there was this networking event I attended a couple of months back, and there was this guy, when everyone's pitching, and this guy sounded really interesting. So I thought, I'll have a chat with him, see what we can do together. So I went to speak with him and instantly he decided to teach me about my business.

Despite some negative experiences of networking for collaboration, there is a general consensus of its value in fostering business growth and support when expanding a clientele base. The evidence shows the importance of fostering introductions and collaboration with other entrepreneurs. Not only does this expand the network of the entrepreneur and facilitate knowledge sharing, but it also gives way to collaboration, which in turn can open a new customer base. Collaboration can enable entrepreneurs to scale their businesses and encourage high growth. Evidence also highlights the role of gender bias in networking opportunities and points out that female entrepreneurs are comparatively less likely to experience such benefits in contrast to their male counterparts. There is a moderate confidence reflecting recognition of challenges but consistent evidence of positive collaborative outcomes. The evidence is in favour of H_1 , at least that between a quiet bedroom and what is sufficient to wake a sleeping person, i.e., it is noticeable and enough to provoke a reaction.

E3: Networking Provides Support for Female Entrepreneurs, which Leads to Increase in Business

$$WoE_3(H_1|\bar{H}_1) = 30B$$

While networking provides female entrepreneurs with valuable support, such as mentoring, confidence-building, and collaborative brainstorming (Ricciardi et al., 2025), its direct impact on business growth remains tenuous. Access to networks is often framed as essential for entrepreneurial success, yet many face a lack of peers and mentors, limiting their growth potential (HSBC, 2019). Evidence suggests that networks often foster solidarity (e.g., female-led "communities" rather than transactional exchanges) and emotional resilience, but their translation into concrete commercial outcomes such as customer acquisition or retention, is weakly correlated.

This aligns with Ozkazanc-Pan and Clark Muntean's (2018) observation that women approach networking in a less transactional and more supportive manner, as reflected in the primary data: "I think there is more networking, but there is less network ... It's very much women helping other women ... I think if you changed the word 'network' to 'community', then I think that's what I find."

Moreover, while familial support in culturally specific contexts (George & Dhaliwal, 2024) aids entrepreneurs through financial and informational resources, such dynamics operate independently of formal networking structures. This further underscores the limited causality between networking and commercial success. Additionally, George and Dhaliwal (2024) note that networking fails to mitigate structural barriers, such as sexism from male-dominated customer bases, demonstrating that support systems rarely override systemic constraints. Even when women do gain access to networks, these connections, while valuable for personal encouragement and motivation (O'donnell, 2014), often lack the strategic influence or industry leverage needed to drive significant growth.

Some research suggests that networking can indirectly contribute to business growth by expanding support circles and improving SME performance. John (2024), for instance, argues that entrepreneurial networks, social, business, and supportive, enhance learning, product quality, and customer attraction. However, these findings are context-dependent, emerging from studies in informal economies like Tanzania, and may not be generalisable.

Even where social and business networks improve SME performance metrics (e.g., customer retention strategies), the link between networking and tangible business growth remains weak. While support networks may boost confidence and provide mentorship, access to customers is a secondary benefit rather than a direct outcome. As one entrepreneur notes:

I think it's so short-sighted of businesses not to work together if you're in the same field, or in any field. I'd be happy to help anybody out if I could. I was more than happy, I think, to tell you I don't see you as competition. Obviously, we're in the same field. There's lots of business to go around.

This sentiment highlights networking's emphasis on collaboration over competition, reinforcing its role in community-building rather than direct commercial gain.

This analysis unpacks the underlying causal mechanisms shaping networking for female entrepreneurs, emphasising emotional and social support while revealing why these benefits often fall short of driving direct business growth. By opening the 'black box' of causality, the study moves beyond surface correlations to illuminate the nuanced roles networks play in fostering entrepreneurial resilience and growth constraints. Indeed, evidence shows that networking's benefit for female entrepreneurs lies in non-transactional support rather than in measurable business expansion and this is evidenced in

both primary and secondary data collected, which triangulate to support the probability of H_1 over \bar{H}_1 . Networking can support visibility and access to customers, however, in a small meaningful difference. The causal pathway from networking to concrete growth outcomes remains weak. This supports a 3 dB assessment in favour of H_1 .

E4: Networking Provides Direct Access to Customers

$$WoE_4(H_1|\bar{H}_1) = 10dB$$

E5: Reputation and Referral are Important to Access Customers

$$WoE_5(H_1|\bar{H}_1) = 3dB$$

E6: Networking Is Widely Accepted as Beneficial for Business Growth

$$WoE_6(H_1|\bar{H}_1) = 5dB$$

E7: Networking Events can be an Inefficient Use of Time

$$WoE_7(H_1|\bar{H}_1) = -3dB$$

This results in a total of 59 dB in favour of the hypothesis over its logical negation:

$$WoE(H_1|\bar{H}_1) = 59dB$$

Posterior Probabilities

Finally, turning to the posterior probability, i.e., the total probability of a hypothesis taking the prior probability and the WoE into account to determine the probability of H_1 to \bar{H}_1 :

$$\text{Posterior odds} = \text{prior odds} + \text{weight of evidence}$$

$$\text{Posterior odds} = 20dB + 59dB$$

$$= 79dB$$

There is overwhelming evidence in favour of H_1 relative to \bar{H}_1 , thus clearly offering a validation of this cause-effect relationship between lack of networking and visibility and access to existing and prospective customers. The evidence is likened to hearing a busy curbside or an alarm clock. Importantly, this opens the black box of causality to observe and assess mechanisms at work. While the strength of doing so is apparent through the ability to answer how and why questions, it also clearly offers the ability to understand the complex context at play and more appropriately inform intervention strategies or policy development. For example, limited networking (X) reduces visibility and access to customers, making it harder to acquire and retain them (Y). This reveals causal mechanisms such as transport barriers,

poor information flow, and weak social support, which can guide targeted interventions. This method highlights not only the ability to validate, ground and contextualise findings from creative methods but offers a validity tool to explore policy responses.

Conclusion

This paper demonstrates the application of explicit Bayesian analysis using a logarithmic scale to validate qualitative data. The method allows researchers to transparently assess the strength of causal relationships in hypotheses, considering the mechanisms between hypotheses and outcomes. While not providing definitive judgments (Fairfield & Charman, 2022), it offers an approach to grounding and contextualising hypothesis strength. The method incorporates various sources to demonstrate hypothesis volume and can be used to compare hypotheses or validate a single hypothesis against its negation. In this case, overwhelming evidence supports H_1 relative to \overline{H}_1 , validating the cause-effect relationship identified through participatory methods. This approach also reveals how opening the black box of causality can prove useful for assessing intervention strategies as well as effective policy development which reflects the end-user experience.

CPT while useful for articulating the volume of a hypothesis, has some limitations. It can be a time-consuming process and resource constraints may necessitate prioritising hypotheses that are uncertain or warrant further investigation. Researchers must balance data quality and quantity, using discretion to determine an appropriate stopping point. This decision-making process is like those encountered in field research and literature reviews, where researchers must weigh the trade-offs between thoroughness and resource availability. A challenge of solely relying upon CPT is that policy initiatives are often developed on the assumption that strategic action can be understood through analysis of simple cause-and-effect mechanisms (De Smedt & Borch, 2022). Therefore, CPT should be grounded in its environment in a more holistic way.

Inevitably, researcher positionality and potential bias can be called into question when applying decibel scores. Positionality was addressed through researcher reflection and noting that no males participated. While the primary research shouted loudly in favour of a hypothesis, a very loud decibel score above 20 db was not awarded both to reflect the data collected, and to correct for any researcher bias. This method could be furthered strengthened by a larger research team that independently assess pieces of evidence to ensure consistency of dB application. To offer a detailed rationale for dB ratings within the context of the research topic, it is recommended that greater narrative analysis of the evidence be conducted, particularly in relation to policy formation or theory-testing/building, to provide more detail and validate the dB awarded.

Beyond using Bayesian CPT to offer validation to creative and/or participatory methods, the method, yet relatively underutilised, could be incorporated into policy feedback literature where mechanisms remain unknown (Campbell, 2012; SoRelle & Michener, 2022), further aiding with the problem of

feedback effect directions. CPT can also be incorporated into evaluation studies (Podesta, 2023; Rothgang & Lageman, 2021) and is also an ideal method to understand institutional change (Skarbek, 2020). Ultimately, this paper presents an empirical application of logarithmic Bayesian CPT, marking only the beginning of its potential applications.

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Ethical Considerations

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The author declares no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Supplemental Material

Supplemental material is available online.

Note

1. See Saguin and Cashore (2022) for their discussion on the trade-offs between design-led policy or whether we should design for policy.

References

Beach, D. (2016). 'It's all about mechanisms – What process-tracing case studies should be tracing. *New Political Economy*, 21(5), 463–472. Available at: <https://doi.org/10.1080/13563467.2015.1134466>

Behrens, L., & Rohlfing, I. (2025). The integration of Bayesian regression analysis and Bayesian process tracing in mixed-methods research. *Sociological Methods & Research*, 00491241241295336. Available at: <https://doi.org/10.1177/00491241241295336>

Bennett, A. (2023). Causal inference and policy evaluation from case studies using bayesian process tracing. In *Causality in policy studies* (pp. 187–215): Springer International Publishing AG.

Bijak, J., Martin, H., & Sarah, N. (2021). Bayesian model-based approach: Impact on science and policy. In J. Bijak (Ed.), *Towards bayesian model-based demography* (pp. 155–174). Springer.

Bozkurt, Ö., Xheneti, M., & Vicky. (2022). On the front line of the circular economy: The entrepreneurial, identity and institutional work of a female entrepreneur towards the circular transition. *Work, Employment & Society*, 36(1), 156–166. Available at: <https://doi.org/10.1177/09500170211043005>

Brahem, M., & Boussema, S. (2023). Social media entrepreneurship as an opportunity for women: The case of Facebook-commerce. *The International Journal of Entrepreneurship and Innovation*, 24(3), 191–201. Available at: <https://doi.org/10.1177/14657503211066010>

Braye, S., & McDonnell, L. (2013). Balancing powers: University researchers thinking critically about participatory research with young fathers. *Qualitative Research*, 13(3), 265–284. Available at: <https://doi.org/10.1177/1468794112451012>

Broadley, C., & Dixon, B. (2022). Participatory design for democratic innovation: Participation requests and community empowerment in Scotland. *Policy Design and Practice*, 5(4), 444–465. Available at: <https://doi.org/10.1080/25741292.2022.2157195>

Business Advice. (2025). The power of networking: Building meaningful business connections in 2025, business advice. Available at: <https://businessadvice.co.uk/business-advice/the-power-of-networking-building-meaningful-business-connections-in-2025/> (Accessed 26 February 2025).

Businessforum.uk. (2023). Importance of networking for business success in the UK. Available at: <https://www.businessforum.uk/blog/the-importance-of-networking-for-business-success-in-the-uk/1934> (Accessed 26 February 2025).

Byrne, D. (2024). Causation in complex systems where human agency is in play. *International Journal of Social Research Methodology*, 27(3), 357–367. Available at: <https://doi.org/10.1080/13645579.2023.2173845>

Byrne, D., Wendy, O., & Sandra, D. (2009). Causality and interpretation in qualitative policy-related research. In *The Sage handbook of case-based methods* (pp. 511–521). Sage Publications Ltd. Available at: <https://doi.org/10.4135/9781446249413>

Campbell, A. L. (2012). Policy makes mass politics. *Annual Review of Political Science*, 15(1), 333–351. Available at: <https://doi.org/10.1146/annurev-polisci-012610-135202>

Checkel, J. , T. (2021). Process tracing - Towards a new research agenda. In *Annual convention of the: American Political Science Association*.

Chevalier, J., & Buckles, D. (2013). *Participatory action research: Theory and methods for engaged inquiry*. Taylor & Francis Group.

Collier, D. (2011). Understanding process tracing. *PS: Political Science & Politics*, 44(4), 823–830. Available at: <https://doi.org/10.1017/S1049096511001429>

Collier, D., Brady, H., & Seawright, J. (2010). Causal inference: Old dilemmas, new tools. In H. Brady & D. Collier (Eds.), *Rethinking social inquiry: Diverse tools, shared* (pp. 114–116). Rowman & Littlefield. Available at: <https://r2.vlereader.com/EpubReader?ean=1781442203457> (Accessed: 19 July 2023).

Considine, M. (2012). Thinking outside the box? Applying design theory to public policy. *Politics & Policy*, 40(4), 704–724. Available at: <https://doi.org/10.1111/j.1747-1346.2012.00372.x>

Copestake, J. (2025). Evaluating social and development interventions using the qualitative impact protocol (QuIP). Available at: <https://www.bath.ac.uk/projects/evaluating-social-and-development-interventions-using-the-qualitative-impact-protocol-quip/> (Accessed 10 July 2025).

Crasnow, S. (2017). Process tracing in political science: What's the story? *Studies in history and philosophy of science*, 62, 6–13. Available at: <https://doi.org/10.1016/j.shpsa.2017.03.002>

Delahais, T., & Toulemonde, J. (2017). Making rigorous causal claims in a real-life context: Has research contributed to sustainable forest management? *Evaluation*, 23(4), 370–388. Available at: <https://doi.org/10.1177/1356389017733211>

De Smedt, P., & Borch, K. (2022). Participatory policy design in system innovation. *Policy Design and Practice*, 5(1), 51–65. Available at: <https://doi.org/10.1080/25741292.2021.1887592>

Escobar, O. (2013). Commentary: Public engagers and the political craft of participatory policy making. *Public Administration Review*, 73(1), 36–37. Available at: <https://doi.org/10.1111/puar.12008>

Fairfield, T., & Charman, A. E. (2022). *Social inquiry and bayesian inference*: Cambridge University Press.

Falleti, T. G., & Lynch, J. F. (2009). Context and causal mechanisms in political analysis. *Comparative Political Studies*, 42(9), 1143–1166. Available at: <https://doi.org/10.1177/0010414009331724>

Foster, C., & Brindley, C. (2018). Female entrepreneurial networking in the marketing services sector. *Qualitative Market Research: An International Journal*, 21(2), 182–201. Available at: <https://doi.org/10.1108/QMR-11-2016-0106>

GEM. (2024). GEM report highlights 25 years of progress in women's entrepreneurship. *GEM Global Entrepreneurship Monitor*. Available at: <https://www.gemconsortium.org/reports/womens-entrepreneurship> (Accessed: 14 February 2025).

George, R., & Dhaliwal, S. (2024). Navigating uncertainty: Challenges faced by Bangladeshi female entrepreneurs in East London, UK. *Journal of Entrepreneurship*, 33(4), 839–861. Available at: <https://doi.org/10.1177/09713557241309481>

Gerring, J. (2010). Causal mechanisms: Yes, but. *Comparative Political Studies*, 43(11), 1499–1526. Available at: <https://doi.org/10.1177/0010414010376911>

Gonzalez-Ocantos, E., & LaPorte, J. (2021). Process tracing and the problem of missing data. *Sociological Methods & Research*, 50(3), 1407–1435. Available at: <https://doi.org/10.1177/0049124119826153>

Gopalan, G. (2023). The power of networking for women entrepreneurs: Building connections for success, women on business. Available at: <https://www.womenonbusiness.com/the-power-of-networking-for-women-entrepreneurs-building-connections-for-success/> (Accessed 27 February 2025).

Green, J., Benjamin, H., & Mark, P. (2022). Case study research and causal inference. *BMC Medical Research Methodology*, 22(307). Available at: <https://doi.org/10.1186/s12874-022-01790-8> (Accessed: 28 January 2025).

Hall, P. A. (2003). Aligning ontology and methodology in comparative research. In J. Mahoney & D. Rueschemeyer (Eds.), *Comparative historical analysis in the social sciences* (1st ed.,

pp. 373–404). Cambridge University Press. Available at: <https://doi.org/10.1017/CBO9780511803963.012>

Hall, P. A. (2006). Systematic process analysis: When and how to use it. *European Management Review*, 3(1), 24–31. Available at: <https://doi.org/10.1057/palgrave.emr.1500050>

Hall, P. A. (2013). Tracing the progress of process tracing. *European Political Science*, 12(1), 20–30. Available at: <https://doi.org/10.1057/eps.2012.6>

Hinds, R. (2013). Tools for participatory analysis of poverty, social exclusion and vulnerability. Available at: <https://assets.publishing.service.gov.uk/media/57a08a00ed915d3cf00052e/hdq959.pdf> (Accessed 17 June 2024).

Hodges, N., Jennifer, Y., Kittichai, W., Karpova, E., Marcketti, S., Hegland, J., Yan, R. N., & Childs, M. (2015). Women and apparel entrepreneurship: An exploration of small business challenges and strategies in three countries. *International Journal of Gender and Entrepreneurship*, 7(2), 191–213. Available at: <https://doi.org/10.1108/IJGE-07-2014-0021>

HSBC. (2019). *She's the business*. HSBC. Available at: <https://www.privatebanking.hsbc.com/content/dam/privatebanking/gpb/discover/women-and-wealth/allbright/2019/AllBright/partnership/-/September/2019-Shes/the/business/report.pdf> (Accessed: 14 February 2025).

Ison, R., & Straw, E. (2020). *The hidden power of systems thinking: Governance in a climate emergency*: Routledge.

John, E. (2024). ‘Show me your networks and i’ll tell you your future: Entrepreneurial networks and SME performance. *Cogent Business & Management*, 11(1), 2363433. Available at: <https://doi.org/10.1080/23311975.2024.2363433>

Kay, A., & Baker, P. (2015). What can causal process tracing offer to policy studies? A review of the literature. *Policy Studies Journal*, 43(1), 1–21. Available at: <https://doi.org/10.1111/psj.12092>

Kopec, A. (2023). Policy feedback & research Methods: How qualitative Research designs with marginalized groups inform theory. *International Journal of Qualitative Methods*, 22, 16094069231217915. Available at: <https://doi.org/10.1177/16094069231217915>

Kreuzer, M. (2016). Assessing causal inference problems with Bayesian process tracing: The economic effects of proportional representation and the problem of endogeneity. *New Political Economy*, 21(5), 473–483. Available at: <https://doi.org/10.1080/13563467.2015.1134467>

Lewis, J. M., McGann, M., & Blomkamp, E. (2020). When design meets power: Design thinking, public sector innovation and the politics of policymaking. *Policy & Politics*, 48(1), 111–130. Available at: <https://doi.org/10.1332/030557319X15579230420081>

Mahoney, J. (2012). The logic of process tracing tests in the social sciences. *Sociological Methods & Research*, 41(4), 570–597. Available at: <https://doi.org/10.1177/0049124112437709>

Mahoney, J. (2015). Process tracing and historical explanation. *Security Studies*, 24(2), 200–218. Available at: <https://doi.org/10.1080/09636412.2015.1036610>

Maxwell, J. A. (2004). Causal explanation, qualitative research, and scientific inquiry in education. *Educational Researcher*, 33(2), 3–11. <https://doi.org/10.3102/0013189x033002003>

Mayne, J. (2012). Contribution analysis: Coming of age? *Evaluation*, 18(3), 270–280. Available at: <https://doi.org/10.1177/1356389012451663>

Nevi, G., Rosa, P., Chiara, A., & Palladino, R. (2024). Investigating female entrepreneurship: A micro-perspective of drivers and barriers for aspiring and experienced women entrepreneurs. *The International Entrepreneurship and Management Journal*, 21(1), 11. Available at: <https://doi.org/10.1007/s11365-024-01012-1>

O’donnell, A. (2014). The contribution of networking to small firm marketing. *Journal of Small Business Management*, 52(1), 164–187. Available at: <https://doi.org/10.1111/jsbm.12038>

Ozkazanc-Pan, B., & Clark Muntean, S. (2018). Networking towards (in)equality: Women entrepreneurs in technology. *Gender, Work and Organization*, 25(4), 379–400. Available at: <https://doi.org/10.1111/gwao.12225>

Popovic-Pantic, S., Kirin, S., & Vucetic, I. (2023). The sustainability analysis of women-owned businesses examined through the impact of selected variables on dimensions of innovation capacity. *JWEE*, 128–145. Available at: <https://doi.org/10.28934/jwee23.pp128-145>

Podestà, F. (2023). Combining process tracing and synthetic control method: Bridging two ways of making causal inference in evaluation research. *Evaluation*, 29(1), 50–66. Available at: <https://doi.org/10.1177/13563890221139511>

Remnant, F., James, C., & Rebekah, A. (2024). Qualitative impact protocol | Better Evaluation, qualitative impact protocol. Available at: <https://www.betterevaluation.org/methods-approaches/approaches/qualitative-impact-protocol> (Accessed 10 July 2025).

Ricciardi, A., Cerrato, D., & Antoldi, F. (2025). How micro-firms innovate: A qualitative study on the role of networks. *Journal of Small Business Management*, 63(2), 620–652. Available at: <https://doi.org/10.1080/00472778.2024.2336471>

Rodriguez, F. S., & Komendantova, N. (2022). *Approaches to participatory policymaking processes: Technical report*. United Nations Industrial Development Organization.

Rothgang, M., & Lageman, B. (2021). The unused potential of process tracing as evaluation approach: The case of cluster policy evaluation. *Evaluation*, 27(4), 527–543. Available at: <https://doi.org/10.1177/13563890211041676>

Sagquin, K., & Cashore, B. (2022). Two logics of participation in policy design. *Policy Design and Practice*, 5(1), 1–11. Available at: <https://doi.org/10.1080/25741292.2022.2038978>

Salinas, L. (2022). Designing for local policy: Exploring preferable futures in the UK. *Policy Design and Practice*, 5(4), 516–528. Available at: <https://doi.org/10.1080/25741292.2022.2144808>

Sapkota, S., Simon, R., Madhusudan, S., Subedi, M., Balen, J., Gautam, S., Adhikary, P., Simkhada, P., Wasti, S. P., Karki, J. K., Panday, S., Karki, A., Rijal, B., Joshi, S., Basnet, S., & Marahatta, S. B. (2024). Participatory policy analysis in health policy and systems research: Reflections from a study in Nepal. *Health Research Policy and Systems*, 22(1), 7. Available at: <https://doi.org/10.1186/s12961-023-01092-5>

Schimmelfennig, F. (2014). Efficient process tracing. Analysing the causal mechanisms of European integration. In A. Bennett & J. T. Checkel (Eds.), *Process tracing. From metaphor to analytic tool* (pp. 98–125): Cambridge University Press.

Skarbek, D. (2020). Qualitative research methods for institutional analysis. *Journal of Institutional Economics*, 16(4), 409–422. Available at: <https://doi.org/10.1017/S174413741900078X>

Soni, R. (2023). Council post: The art of networking: Five ways to build connections that matter. *Forbes*. Available at: <https://www.forbes.com/councils/forbesbusinesscouncil/2023/08/10/the-art-of-networking-five-ways-to-build-connections-that-matter/> (Accessed 26 February 2025).

SoRelle, M., & Michener, J. (2022). Methods for applying policy feedback theory. In C. M. Weible & S. Workman (Eds.), *Methods of the policy process*: Routledge. Available at: <https://www.taylorfrancis.com.libproxy.york.ac.uk/reader/download/fa5686a9-8d75-40d8-a60c-60617e8ad11b/chapter/pdf?context=ubx> (Accessed 13 March 2025).

Tagent, P. (2025) The pros and cons of networking events: A balanced perspective, Bath marketing consultancy. Available at: <https://bathmarketingconsultancy.co.uk/business-networking/> (Accessed: 26 February 2025).

The Alison Rose Report. (2019). The alison rose review of female entrepreneurship, GOV.UK. Available at: <https://www.gov.uk/government/publications/the-alison-rose-review-of-female-entrepreneurship> (Accessed 6 December 2023).

Trampusch, C., & Palier, B. (2016). Between X and Y: How process tracing contributes to opening the Black box of causality. *New Political Economy*, 21(5), 437–454. Available at: <https://doi.org/10.1080/13563467.2015.1134465>

Treanor, L., & Marlow, S. (2025). A nudge in the right direction? gender-Informed support by female business-incubation managers for female STEM-Entrepreneurs. *Entrepreneurship & Regional Development*, 37(1–2), 92–112. Available at: <https://doi.org/10.1080/08985626.2024.2362838>

Ulriksen, M. S., & Dadalauri, N. (2016). Single case studies and theory-testing: The knots and dots of the process-tracing method. *International Journal of Social Research Methodology*, 19(2), 223–239. Available at: <https://doi.org/10.1080/13645579.2014.979718>

Van Evera, S. (1997). *Guide to methods for students of political science*: Cornell University Press.

Wagoner. (2021). This is why word-of-mouth referrals should be your number one metric of success | entrepreneur. Available at: <https://www.entrepreneur.com/growing-a-business/this-is-why-word-of-mouth-referrals-should-be-your-number/379274> (Accessed 27 February 2025).

Waters, J. (2024). Business networking pros and cons: What you need to know. *Waters Business Consulting*. 26 September. Available at: <https://watersbusinessconsulting.com/2024/09/26/business-networking-pros-and-cons-what-you-need-to-know/> (Accessed 26 February 2025).