International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 6.4 Website: https://ijarmt.com ISSN No.: 3048-9458

Measuring Technological Complexity Across Stone and Metal Technologies in Ancient Bengal: An Empirical Application of Petri Net–Based Complexity Metrics

Mayanka Kapoor
Research Scholar, Department of Fine Arts, Maharaja Agrasen Himalayan Garhwal University**Dr.**
Dr. Archana Tyagi
Assistant Professor, Department of Fine Arts, Maharaja Agrasen Himalayan Garhwal University

Abstract
Archaeological work in Bengal has produced rich descriptions of stone, ceramic and metal technologies from the Lower Palaeolithic to the Early Iron Age, yet these technologies are usually compared qualitatively rather than measured against a common scale of complexity. This paper adapts the Petri net–based technological complexity framework proposed by Fajardo, Kozowyk and Langejans (2023) to a set of reconstructed chaînes opératoires from Bengal and eastern India. Five representative workflows are modelled: core-and-flake handaxe production, Late Pleistocene microlithic bladelet production, Neolithic/Neo-Chalcolithic ground-stone axe manufacture, Chalcolithic copper ornament casting, and Early Iron Age bloomery iron smelting and forging. Each sequence is encoded as a Petri net and evaluated using three complexity dimensions defined by Fajardo et al.: structural complexity, behavioural complexity and information complexity. Results show a clear ordinal increase in technological complexity from early lithic reduction to iron smelting, with microliths and ground-stone axes occupying intermediate positions. Technologies associated with larger, more permanent settlements and stronger evidence for craft specialisation tend to exhibit higher complexity scores. The study demonstrates that Petri net–based metrics can be meaningfully applied to South Asian archaeological datasets, providing a quantitative basis for linking technological complexity with cognitive demands and socio-economic organisation in Bengal's long-term history.

Keywords: technological complexity; Petri nets; chaîne opératoire; ancient Bengal; iron smelting; microliths; craft specialisation

1. Introduction

1.1 Background

The idea that technological complexity is tied to cognition and social organisation has become increasingly prominent in archaeology and evolutionary anthropology. Complex technologies demand planning, coordination and the management of extended sequences of actions, and can therefore be used as indirect evidence for changes in cognitive capacities and social arrangements (Shennan, 2008; Stout, 2011). At the same time, technologies are embedded in social and economic systems: more complex production sequences often appear alongside larger, more settled communities, emerging craft specialisation and widening exchange networks (Richerson & Boyd, 2005; Killick & Fenn, 2012).

In South Asia, and particularly in Bengal and eastern India, the technological record is rich but unevenly quantified. Scholars have documented long sequences from core-and-flake Palaeolithic industries through Late Pleistocene microliths, mixed stone–metal Neolithic and Chalcolithic toolkits, and Early Iron Age bloomery smelting (Chakrabarti, 1993; Datta, 1981, 2010; Basak &

Srivastava, 2017; Ray & Mondal, 2013). These technologies are usually described in terms of raw materials, tool types and broad production stages. Terms such as "simple," "elaborate" or "advanced" are used freely, but there is rarely an explicit, comparative metric of complexity.

Recent methodological advances offer a way to move beyond impressionistic labels. Fajardo, Kozowyk and Langejans (2023) have proposed a formal way to measure technological complexity using Petri nets, a class of graphical models widely used in computer science to represent processes with states, transitions and flows. In their study of ancient adhesives and other technologies, Petri nets are used to encode production sequences, and complexity is quantified through three metrics: structural complexity (the size and connectivity of the network), behavioural complexity (the diversity and concurrency of possible execution paths), and information complexity (an information-theoretic measure of uncertainty in the process).

1.2 Research problem and aim

The archaeological literature on Bengal contains detailed qualitative reconstructions of different technological systems, but these have not been brought together using a common quantitative framework. As a result, it is hard to evaluate claims such as "iron technology is more complex than microlithic technology" in anything other than intuitive terms. The absence of such a framework limits our ability to test whether technological complexity actually tracks major socio-economic shifts, such as the move from mobile foraging to agriculture, or the emergence of more permanent settlements and craft specialists.

The aim of this paper is to make a first step toward filling this gap. It applies the Petri net-based technological complexity metrics developed by Fajardo et al. (2023) to a set of reconstructed chaînes opératoires representing key technologies in Bengal and adjacent eastern India. Rather than attempting exhaustive modelling, the study focuses on a small, carefully chosen sample of production sequences that span major chronological and technological thresholds.

1.3 Research questions and hypotheses

Two main research questions guide the analysis:

- **RQ1:** Does technological complexity, as measured through Petri net metrics, increase from Palaeolithic/Mesolithic stone technologies to Chalcolithic and Early Iron Age metal technologies in Bengal?
- **RQ2:** Is higher technological complexity associated with archaeological contexts that show stronger indications of settlement hierarchies and craft specialisation?

From these, two working hypotheses are derived:

- **H1:** Mean complexity scores will be lowest for core-and-flake lithic sequences, intermediate for microlithic bladelet production and ground-stone axes, and highest for bloomery iron smelting workflows.
- **H2:** Technologies used in contexts with larger, more permanent settlements and archaeometallurgical workshops will show higher complexity scores than those associated with small camps and low levels of specialisation.

The paper proceeds by outlining the Bengal dataset and modelling approach (Section 2), presenting the empirical results (Section 3), and discussing their implications for technology, cognition and socio-economic change (Section 4). The conclusion highlights methodological contributions and directions for further work.

International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 6.4 Website: https://ijarmt.com ISSN No.: 3048-9458

2. Materials and Methods

2.1 Selection of technologies and production sequences

To keep the exercise focussed yet representative, five technologies were selected that together span the main pre- and protohistoric phases discussed in the associated thesis:

1. **Core-and-flake handaxe production** in Lower Palaeolithic contexts on lateritic surfaces in Bankura, Midnapore and neighbouring districts (Ghosh, 1961, 1966; Chakrabarti & Chattopadhyay, 1984; Misra, 2001).
2. **Microlithic bladelet production** in Late Pleistocene contexts at Mahadebbera and Kana in Purulia, where stratified microlithic levels dated between c. 42–25 ka BP have been reported (Basak et al., 2014; Basak & Srivastava, 2017).
3. **Ground-stone axe production** in Neolithic/Neo-Chalcolithic contexts of eastern India, with particular reference to upland sites at the hill margins and in the lateritic belt, where ground axes and adzes appear alongside pottery and early agriculture (Datta & Sanyal, 2013).
4. **Copper ornament production** in Chalcolithic contexts, especially at Pandu Rajar Dhibi and related sites in the Ajay–Damodar valleys, where rings, bangles and other ornaments have been recovered with evidence for casting and finishing (Datta, 1981, 2004–2005; Ray, 1991).
5. **Bloomery iron smelting and forging** in Early Iron Age and early historic contexts in western West Bengal and the eastern fringes of the Chotanagpur plateau, documented through slag, furnace remains and iron tools (Chattopadhyay, 1991; Acharya, 2006; Datta, 2010; Ray & Mondal, 2013).

Each technology is represented by an idealised chaîne opératoire reconstructed from the thesis database and published descriptions, supplemented where needed by comparative experimental and ethnographic work (Hegde, 1991; Rice, 1987; Killick & Fenn, 2012). The goal is not to model every local variant, but to encode a plausible, internally consistent workflow for each class.

2.2 Data sources

For each technology, the reconstruction of production steps draws on a combination of:

- **Archaeological reports** describing artefact assemblages, production waste and features such as furnaces or working floors (e.g., Basak et al., 2014; Datta, 1981, 2010; Chattopadhyay, 1991).
- **Regional syntheses** for environmental and settlement context (Chakrabarti, 1993; Ghosh & Majumdar, 1991).
- **Methodological literature** on lithic, ceramic and metallurgical technologies, which provides generic sequences and technical constraints (Andrefsky, 2005; Rice, 1987; Killick & Fenn, 2012).

Production sequences are formulated at a “meso-scale”: individual actions such as “strike with hammerstone” are grouped into broader steps like “primary flaking” or “bladelet removal,” to keep Petri nets manageable and comparable across domains.

2.3 Petri net modelling and complexity metrics

Petri nets are bipartite directed graphs composed of **places** (circles), **transitions** (rectangles) and **arcs** connecting them (Fajardo et al., 2023). Places represent states, resources or intermediate products (e.g., "unworked ore," "charged furnace"), while transitions represent events or operations (e.g., "smelt," "hammer to shape"). Tokens move through the net according to firing rules, capturing the flow of materials and actions.

Following Fajardo et al. (2023), each reconstructed chaîne opératoire is translated into a Petri net by:

1. Identifying distinct states and sub-products (raw materials, intermediate forms, tools, waste).
2. Defining transitions corresponding to major processing steps.
3. Connecting places and transitions with arcs to represent the logical and material dependencies of the workflow.

Once the Petri net is specified, three complexity metrics are considered, closely following the definitions in Fajardo et al. (2023):

1. **Structural complexity**, which captures the size and connectivity of the network. It is operationalised through a combined index based on the number of places, number of transitions and normalised density of arcs. Larger, more densely connected nets are structurally more complex.
2. **Behavioural complexity**, which reflects the variety of possible execution paths and the presence of concurrency or alternative branches. This is approximated through counts of decision points, loops and parallel structures, following the behavioural analysis of Petri nets used in process mining (Fajardo et al., 2023).
3. **Information complexity**, which approximates the uncertainty and information load of the workflow. It is derived in an ordinal way from the number of alternative choices and the variety of inputs and outputs at each transition, inspired by the information-theoretic measure used by Fajardo et al. (2023).

Because the aim here is exploratory rather than strictly statistical, complexity values are interpreted as **ordinal categories** (low, medium, high) based on the relative positions of the five technologies once encoded, rather than as precise numerical scores. This keeps the analysis transparent and avoids over-interpreting a small sample of stylised models.

2.4 Coding procedure and reliability

Each chaîne opératoire was first drafted as a textual flowchart and then encoded as a Petri net diagram. To check consistency, the five workflows were independently coded twice at different times by the author, using the same written descriptions and criteria. Differences in the placement or grouping of steps were resolved by re-examining the archaeological and experimental sources until a single agreed version was reached.

Given the small number of technologies and the integrative nature of the modelling, a formal inter-coder reliability statistic such as Cohen's kappa was not calculated. Instead, reliability is addressed through transparency of assumptions and by reporting only broad ordinal categories of complexity.

International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 6.4 Website: https://ijarmt.com ISSN No.: 3048-9458

2.5 Contextual variables

To link technological complexity to broader socio-economic patterns, three contextual variables were assigned to each technology, based on the synthesis of settlement, craft and exchange evidence in the thesis and in published literature (Chakrabarti, 1993; Datta, 2010; Ray & Mondal, 2013):

- **Settlement scale**, scored qualitatively as 1 (small camp or temporary site), 2 (village-sized, semi-permanent settlement), or 3 (large village/proto-urban centre).
- **Craft specialisation**, scored as low, medium or high, depending on indications of dedicated production areas, standardisation and integration into wider exchange networks.
- **Exchange involvement**, scored as low, medium or high, based on evidence for imported raw materials or products, and connections to broader regional networks.

These scores are necessarily approximate, but they capture broad differences between highly mobile hunter-gatherer camps and more settled Chalcolithic or Early Iron Age communities with organised metallurgical production.

Table 1 summarises the technologies and associated analytical variables.

Table 1
Technologies and analytical variables used in the Petri net study

Code	Technology / sequence	Broad phase	Main context (site / region)	Settlement scale*	Craft specialisation	Exchange involvement
T1	Core-and-flake handaxe and cleaver production	Lower Palaeolithic	Lateritic surfaces, Bankura/Midnapore (eastern India)	1 (camp)	Low	Low
T2	Microlithic bladelet production	Late Pleistocene (microlithic)	Mahadebbera and Kana, Purulia	1–2	Low–medium	Low–medium
T3	Ground-stone axe (axe/adze) production	Neolithic/Neo-Chalcolithic	Eastern India hill margins and lateritic belt	2 (village)	Medium	Medium
T4	Copper ornament casting and finishing	Chalcolithic	Pandu Rajar Dhibi and related Ajay–Damodar valley sites	2–3	Medium–high	Medium–high
T5	Bloomery iron smelting and forging of tools	Early Iron Age/early historic	Western fringe of Bengal, Chotanagpur plateau edge	3 (proto-urban)	High	High

International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 6.4 Website: https://ijarmt.com ISSN No.: 3048-9458

*Scale: 1 = small camp, 2 = village, 3 = large village/proto-urban.

2.6 Data analysis

For each technology, the Petri net was examined to determine:

- The **relative structural complexity** (small/linear vs large/branched networks).
- The **relative behavioural complexity** (few vs many alternative paths and concurrent activities).
- The **relative information complexity** (few vs many decision points and distinct inputs/outputs).

These were then coded as low, medium or high for each dimension. Given the extremely small sample (five technologies), formal inferential statistics are not appropriate. Instead, the analysis looks for consistent **gradients** in complexity scores from T1 to T5, and for simple associations between higher complexity categories and higher contextual scores in settlement scale and craft specialisation.

3. Results

3.1 Descriptive patterns of technological complexity

Encoding the five chaînes opératoires as Petri nets confirmed substantial differences in their structure and behaviour. The Lower Palaeolithic core-and-flake sequence (T1) could be represented with a relatively small number of places and transitions arranged in a largely linear pattern: raw nodule selection, primary flaking, shaping, edge maintenance and discard. Feedback loops (e.g., re-sharpening) exist but are limited, and most actions occur sequentially with little concurrency.

In contrast, the iron smelting and forging workflow (T5) required many more places and transitions. Distinct stages involve ore procurement and preparation, charcoal production, furnace construction and maintenance, charging and smelting, bloom consolidation, primary forging and secondary tool finishing. Several of these stages can occur in parallel, and branching is present where different furnace charges or forging paths are possible (Hegde, 1991; Acharya, 2006; Datta, 2010).

Intermediate technologies fall between these extremes. Microlithic bladelet production (T2) shows a clear modular structure with repeated cycles of core preparation and bladelet removal, and a distinct stage for backing or shaping inserts (Basak et al., 2014). Ground-stone axe production (T3) introduces long grinding and polishing stages, which require sustained access to water and abrasive materials (Datta & Sanyal, 2013). Copper ornament production (T4) adds casting and finishing steps, including the preparation of moulds, control of melting and cooling, and post-casting working (Ray, 1991).

Table 2 summarises the resulting ordinal complexity scores.

Table 2

Relative technological complexity scores by technology class

Code	Technology / sequence	Structural complexity	Behavioural complexity	Information complexity
T1	Core-and-flake handaxe production	Low	Low	Low
T2	Microlithic bladelet	Medium	Medium	Medium

International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 6.4 Website: https://ijarmt.com ISSN No.: 3048-9458

	production			
T3	Ground-stone axe production	Medium	Medium	Medium
T4	Copper ornament casting and finishing	Medium–high	High	High
T5	Bloomery iron smelting and forging	High	High	High

In line with **H1**, there is a clear monotonic gradient: early lithic technology is consistently low in all three complexity dimensions, microlithic and ground-stone technologies occupy intermediate positions, and metal-working technologies, especially iron smelting, lie at the upper end.

It is notable that microlithic and ground-stone axe production share similar complexity categories. Although they work with different materials, both involve a greater number of structured steps and longer production sequences than early core-and-flake industries.

3.2 Complexity and contextual variables

A simple comparison between Table 1 and Table 2 suggests that higher technological complexity tends to align with higher scores for settlement scale and craft specialisation. T1, representing Lower Palaeolithic core-and-flake technology, is associated with small camps and little evidence for specialised production (Ghosh, 1961; Misra, 2001) and has uniformly low complexity scores.

T2 and T3, the microlithic and ground-stone technologies, are linked to camp-to-village situations with limited but emerging specialisation (Basak & Srivastava, 2017; Datta & Sanyal, 2013). Their complexity scores are consistently medium. By the time we reach copper ornament production at Pandu Rajar Dhibi (T4) and iron smelting (T5), settlement size and craft specialisation scores have increased, and so have all three complexity dimensions (Datta, 1981, 2010; Acharya, 2006; Ray & Mondal, 2013).

Although the sample size precludes formal statistical testing, the qualitative pattern supports **H2**: more complex technologies, as captured by the Petri net–derived indices, tend to occur in contexts where archaeological indicators of social and economic complexity are also stronger.

3.3 Visual contrast between simple and complex workflows

Comparing the Petri nets for T1 and T5 highlights the intuitive meaning of the complexity gradient. The core-and-flake net consists of a short sequence of places and transitions with one main line of flow and a few minor loops. In contrast, the iron smelting net includes multiple sub-networks: a charcoal-making loop, a furnace-building and drying circuit, branching paths for different ore batches, and sequential forging and finishing stages. Tokens move in parallel through some of these structures, and the number of points at which choices must be made is visibly higher.

This visual difference matches the ordinal complexity scores and helps to communicate the idea that complexity is not only a matter of more steps, but also of more interdependence, concurrency and decision-rich branching.

4. Discussion

4.1 Interpreting the complexity gradient

The ordinal gradient in Table 2 is consistent with long-standing expectations that metal technologies, especially bloomery iron smelting, are procedurally more complex than basic knapping. Iron smelting requires the coordination of more resources (ore, fuel, clay), more stages of preparation, and more precise control of invisible parameters such as furnace temperature and atmosphere (Killick & Fenn, 2012; Hegde, 1991). The Petri net models capture this through larger, more interconnected networks with more branching and parallelism.

From an evolutionary perspective, the gradient can be read as a history of increasing **planning depth** and **organisational demand**. Shennan (2008) argues that technologies can be seen as cultural traits that vary in complexity, cost and benefit, and that more complex traits require more robust systems of social learning to be maintained. The Petri net results are in line with this view: the move from simple core-and-flake sequences to iron smelting implies not only more steps, but also more dependencies between those steps, and thus more opportunities for failure if knowledge is not transmitted accurately.

At the same time, the results remind us that even “simple” technologies have non-trivial complexity. Microlithic and ground-stone axe production both register as medium complexity. Bladelet production at Mahadebbera and Kana, for example, involves structured sequences of core preparation, systematic blank removal and backing (Basak et al., 2014). Ground-stone axes require extended grinding and polishing, which in practice means repeated, labour-intensive cycles of work and targeted access to water and abrasives (Datta & Sanyal, 2013). These are not trivial procedures and would have required social mechanisms for teaching and apprenticeship.

4.2 Technology, cognition and practice

One of the motivations for using explicit complexity metrics is to connect archaeological technologies to debates about cognition and material engagement. Stout (2011) and Stout and Chaminade (2012) have shown that learning to produce Acheulean handaxes activates brain areas associated with motor control, planning and language, and that more complex knapping tasks involve more sustained cognitive control. Malafouris (2013) argues more broadly that tools and artefacts act as “thinking devices” that extend and structure cognitive processes.

In this light, the Bengal sequences modelled here can be seen as different forms of externalised cognitive scaffolding. A core-and-flake sequence with low complexity requires the maker to track fewer dependencies, but still demands a sense of stone properties and flaking angles. Microlithic bladelet production and ground-stone axes introduce more extended planning: cores must be organised for repeated removals, and grinding sequences stretch over long periods and involve managing effort and time.

Metal technologies, particularly bloomery iron smelting, increase the cognitive load further. Smelting requires operators to manage delayed feedback: the success or failure of the process may only become evident when the furnace is tapped or the bloom is retrieved. This demands reliance on indirect cues, such as colour, sound and airflow, and on shared procedural knowledge transmitted over generations (Hegde, 1991; Killick & Fenn, 2012). The high behavioural and information complexity scores in T4 and T5 reflect these demands.

The Petri net metrics do not measure cognition directly, but they provide a structured way of expressing the **minimum organisational complexity** that any cognitive system must handle to execute the workflow. This opens the door for more explicit dialogue between South Asian archaeologists and cognitive archaeology.

4.3 Technology and socio-economic change in Bengal

The alignment between higher technological complexity and archaeological indicators of settlement scale and craft specialisation supports long-standing arguments that technological and socio-economic changes in Bengal were intertwined. Datta (2010) has shown that the expansion of iron technology in eastern India was closely linked to agricultural intensification, forest clearance and the growth of early historic centres. Ray and Mondal (2013) emphasise that iron production in the region involved organised smelting sites, specialised labour and integration into wider networks of demand.

The Petri net-derived complexity scores strengthen this picture by providing a more formal representation of the procedural demands of iron technology. High complexity in T5 is not only an abstract property of the Petri net; it corresponds to historically significant features such as multi-stage procurement (ore, fuel, clay), workshop organisation and sequential forging. When these demands are placed next to evidence for larger, more permanent settlements and increasing social differentiation, it becomes easier to argue that the rise of iron technology was both a driver and a consequence of socio-economic transformation.

At the other end of the sequence, the fact that microlithic technologies register as medium complexity is consistent with interpretations of Late Pleistocene foragers in Purulia as cognitively sophisticated, landscape-savvy groups able to manage risk and seasonality through flexible toolkits (Basak & Srivastava, 2017). The Petri net framework makes it clear that "microlithic" does not mean "simple" in an organisational sense.

4.4 Comparison with other regions and methods

Fajardo et al. (2023) developed their Petri net approach in the context of European adhesive technologies and other complex tasks, showing that their metrics could distinguish between comparatively simple and elaborate Neanderthal and Homo sapiens workflows. The present study extends this approach to a different technological and geographical domain, indicating that Petri net-based metrics are sufficiently general to be applied across continents and material classes.

Other attempts to quantify technological complexity have used measures such as the number of distinct operations, the diversity of tools involved or subjective expert rankings (e.g., Tostevin, 2011; Lycett & Eren, 2013). Petri nets bring two advantages. First, they capture not just the number of steps but also their coordination and branching structure. Second, they provide an explicit model that can be inspected, critiqued and modified as new archaeological data become available.

At the same time, the current application has clear limitations. The Bengal workflows are reconstructed at a fairly coarse level, and some steps are collapsed for comparability. The complexity scores are therefore best seen as **relative indicators** rather than as precise measurements. A more ambitious programme would include multiple variants of each technology, model uncertainty explicitly and use dedicated Petri net analysis software to derive more detailed metrics.

International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 6.4 Website: https://ijarmt.com ISSN No.: 3048-9458

4.5 Methodological reflections and limitations

Several caveats are worth stating clearly. First, the small sample size and stylised nature of the workflows mean that the results cannot be generalised beyond the specific technologies and contexts modelled here. Second, the assignment of contextual scores for settlement and craft specialisation is somewhat subjective, relying on synthesised descriptions rather than site-by-site quantification.

Third, the use of ordinal categories for complexity, while appropriate for an exploratory study, hides some of the nuance that more fine-grained metrics could provide. Future work could, for example, distinguish between different kinds of behavioural complexity (e.g., alternative paths vs concurrency) or apply information-theoretic calculations more strictly, as in Fajardo et al. (2023).

Finally, the method shifts part of the interpretive burden from typological listing to model building. Constructing Petri nets requires assumptions about where one step ends and another begins. These assumptions need to be made explicit and opened to debate, rather than treated as hidden technicalities.

5. Conclusion

This paper has demonstrated that the Petri net–based technological complexity framework proposed by Fajardo et al. (2023) can be adapted to a South Asian archaeological dataset, in this case a set of five representative technologies from ancient Bengal and eastern India. By encoding core-and-flake handaxe production, microlithic bladelet production, ground-stone axe manufacture, copper ornament casting and bloomery iron smelting as Petri nets, and by evaluating them using three complexity dimensions, the study has produced several substantive and methodological insights.

Substantively, the results support a clear gradient in technological complexity from early lithic technologies to iron smelting, with microlithic and ground-stone technologies occupying intermediate positions. This gradient aligns with independent evidence for increasing settlement scale, craft specialisation and participation in wider exchange networks, supporting the hypothesis that technological and socio-economic change in Bengal were tightly linked (Chakrabarti, 1993; Datta, 2010; Ray & Mondal, 2013).

The analysis also highlights that microlithic and ground-stone technologies, often described in simple terms, are organisationally quite demanding. Their medium complexity scores suggest that Late Pleistocene and early agricultural communities in Bengal were managing multi-step, structured workflows that required stable traditions of technical knowledge and social learning (Basak & Srivastava, 2017; Datta & Sanyal, 2013).

Methodologically, the study illustrates how Petri nets can serve as a bridge between qualitative chaîne opératoire reconstructions and quantitative complexity metrics. By making assumptions explicit in model form, they invite transparent debate and cumulative refinement. Even with small samples, ordinal complexity scores can help organise comparative discussions and reveal patterns that might otherwise remain implicit.

Looking ahead, several extensions suggest themselves. Additional technologies, such as ceramic firing sequences, bead production and high-temperature glass or faience technologies, could be modelled in the same way, allowing a more comprehensive mapping of Bengal's technological landscape. More detailed modelling of variants within each class, combined with sensitivity analysis, would strengthen confidence in the metrics. Finally, closer integration with cognitive archaeology, including experimental replication and neuroarchaeological work, could deepen our understanding of how different levels of technological complexity were experienced and maintained by ancient craftspeople.

For now, the main contribution of this paper is to show that quantitative measures of technological complexity are feasible and informative for ancient Bengal. When combined with the rich contextual work already done by archaeologists in the region, such measures can help turn qualitative impressions of "simple" or "complex" technology into more explicit, testable claims about how people, materials and knowledge came together over the long term.

References

1. Acharya, D. (2006). A study of the ancient iron working in the eastern fringes of the Chhotanagpur Plateau, West Bengal. *Man and Environment, 31*, 29–43.
2. Andrefsky, W. (2005). *Lithics: Macroscopic approaches to analysis* (2nd ed.). Cambridge University Press.
3. Basak, B. (1998). Late Quaternary environment, palaeontology and culture of Tarafeni valley, Midnapur district, West Bengal: A preliminary study. *Journal of the Geological Society of India, 51*(6), 231–240.
4. Basak, B., & Srivastava, P. (2017). Earliest dates of microlithic industries (42–25 ka) from West Bengal, eastern India: New light on modern human occupation in the Indian subcontinent. *Asian Perspectives, 56*(2), 237–259.
5. Basak, B., Srivastava, P., Dasgupta, S., Kumar, A., & Rajaguru, S. N. (2014). Earliest dates and implications of microlithic industries of Late Pleistocene from Mahadebbera and Kana, Purulia District, West Bengal. *Current Science, 107*(7), 1167–1171.
6. Bhattacharya, B. (2007). An overview and perspective of Mesolithic research in India. *Man and Environment, 32*(2), 1–18.
7. Chakrabarti, D. K. (1993). *Archaeology of Eastern India: Chhotanagpur Plateau and West Bengal*. Munshiram Manoharlal.
8. Chakrabarti, D. K., & Chattopadhyay, R. K. (1984). Prehistoric stratigraphy in West Bengal: The evidence from Burdwan and Midnapur. *Man and Environment, 8*, 39–48.
9. Chattopadhyay, P. K. (1991). Ancient iron smelting technology in West Bengal. In A. Datta (Ed.), *Studies in archaeology* (pp. 175–192). Books and Books.
10. Datta, A. (1981). The problem of the Chalcolithic culture of West Bengal. *Puratattva, 10*, 44–54.
11. Datta, A. (2004–2005). The so-called Pandu Rajar Dhibi culture of West Bengal: An archaeological perspective. *Pratna Samiksha, 10–11*, 1–25.
12. Datta, A. (2010). Iron technology and socio-economic change in eastern India. *Man and Environment, 35*(1), 76–89.
13. Datta, A., & Sanyal, S. (2013). Neolithic and Neo-Chalcolithic cultures of eastern India: A fresh appraisal. *Man and Environment, 38*(1), 1–18.
14. Fajardo, S., Kozowyk, P. R. B., & Langejans, G. H. J. (2023). Measuring ancient technological complexity and its cognitive implications using Petri nets. *Scientific Reports, 13*, 14961.
15. Ghosh, A. K. (1961). Prehistoric studies in eastern India. *Science and Culture, 27*, 369–375.

16. Ghosh, A. K. (1966). Implementiferous laterite in eastern India. In D. Sen & A. K. Ghosh (Eds.), *Studies in prehistory: Robert Bruce Foote memorial volume* (pp. 149–162). Firma K. L. Mukhopadhyay.
17. Ghosh, R. N., & Majumdar, S. (1991). Geology and morphostratigraphy of West Bengal: A database for archaeological exploration. In A. Datta (Ed.), *Studies in archaeology* (pp. 7–40). Books and Books.
18. Hegde, K. T. M. (1991). *Ancient Indian iron metallurgy*. Indian Institute of Advanced Study.
19. Killick, D., & Fenn, T. (2012). Archaeometallurgy: The study of preindustrial mining and metallurgy. *Annual Review of Anthropology, 41*, 559–575.
20. Lemonnier, P. (1992). *Elements for an anthropology of technology*. Museum of Anthropology, University of Michigan.
21. Lycett, S. J., & Eren, M. I. (2013). Levallois lessons: The complexity of hominin tool-making, and the cognitive implications. In S. J. Lycett & P. R. Chauhan (Eds.), *The evolution of hominin behaviour during the later Pleistocene* (pp. 219–235). Springer.
22. Malafouris, L. (2013). *How things shape the mind: A theory of material engagement*. MIT Press.
23. Misra, V. N. (2001). Prehistoric human colonisation of India. *Journal of Biosciences, 26*(4), 491–531.
24. Ray, A. (1991). Chalcolithic culture of West Bengal. In A. Datta (Ed.), *Studies in archaeology* (pp. 109–133). Books and Books.
25. Ray, R., & Mondal, S. (2013). Archaeometallurgy in eastern India: An overview. In K. N. Dikshit (Ed.), *Neolithic–Chalcolithic cultures of eastern India* (pp. 201–220). Indian Archaeological Society.
26. Rice, P. M. (1987). *Pottery analysis: A sourcebook*. University of Chicago Press.
27. Richerson, P. J., & Boyd, R. (2005). *Not by genes alone: How culture transformed human evolution*. University of Chicago Press.
28. Shennan, S. (2008). Evolution in archaeology. *Annual Review of Anthropology, 37*, 75–91.
29. Stout, D. (2011). Stone tools, culture and cognition in human evolution. *Philosophical Transactions of the Royal Society B, 366*(1567), 1050–1059.
30. Stout, D., & Chaminade, T. (2012). Stone tools, language and the brain in human evolution. *Philosophical Transactions of the Royal Society B, 367*(1585), 75–87.
31. Torrence, R. (1989). *Time, energy and stone tools*. Cambridge University Press.
32. Tostevin, G. B. (2011). Levels of theory and social practice in the reduction sequence and chaîne opératoire methods of lithic analysis. *PaleoAnthropology, 2011*, 351–375.