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A TEK-Integrated Decision-Support Framework for Traditional Lift-Net Fisheries: System Design and Simulation-Based Feasibility Analysis

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Abstract

Deploying machine-learning decision support in traditional fishing is constrained less by predictive accuracy than by whether practitioners accept and appropriately use advice alongside their own tacit knowledge. This paper presents the design of a decision-support framework for traditional Chinese fishing-net (Cheena vala) operations in Kerala, India, that couples a Random Forest catch-suitability model with formalized Traditional Ecological Knowledge (TEK) while preserving fisher decision authority, together with a simulation-based feasibility analysis. The prediction component is evaluated on a 1,000-event environmental dataset emulating the study site: a Random Forest model attains a mean absolute error of 0.84 kg (R^2 = 0.22) for catch-weight prediction, outperforming Gradient Boosting, an LSTM, and a hybrid TEK-ML variant, with sonar fish-detection the dominant feature (34.7% importance). Fisher-adoption behaviour is examined in a transparent simulation testbed driven by an explicit stochastic behaviour model with stated parameters; it is intended to surface framework properties and to specify hypotheses for subsequent field validation, and does not constitute empirical evidence about real fisher behaviour. Under the stated model, overall simulated adherence is 74.9%, a smart-waiting policy reduces modelled operating cost through avoided low-suitability trips, and the hybrid model improves catch-weight error by 7-14% where TEK rules are active. We articulate design principles for decision support in traditional contexts and a proposed technology-acceptance model framed as testable hypotheses.

Keywords:- Decision Support Systems, Traditional Ecological Knowledge, Human-AI Collaboration, Smart Fisheries, Simulation Modelling, Technology Acceptance, Hybrid Intelligence.

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I. INTRODUCTION

Machine-learning systems deployed in traditional occupational contexts face challenges beyond technical performance. A model may achieve strong offline accuracy, yet its real-world value depends on human acceptance, appropriate reliance, and integration with knowledge and practices already in use [1]. This is acute in traditional industries such as fishing, where practitioners hold tacit, experiential knowledge accumulated over generations that automated systems cannot easily capture or replace [2]. Human-AI collaboration theory holds that the best outcomes arise when machine pattern-recognition is paired with human contextual judgement, with task allocation guided by comparative advantage [3]. Most empirical work, however, concerns knowledge-work settings with educated, technology-comfortable users [4]; manual and craft occupations remain comparatively underexplored.

Traditional Chinese fishing nets (Cheena vala) in Kerala are shore-operated lift-net structures dating back several centuries [5]. Each requires three to five workers operating a large horizontal net on a cantilever frame, and operators rely on experiential knowledge and direct observation of tide, time, weather, and water condition to decide when to lower the net. Advances in Internet-of-Things (IoT) sensing and machine learning offer support through real-time monitoring and prediction [6], [7], yet prior technology interventions in small-scale fisheries have frequently failed for social rather than technical reasons: perceived threat to expertise, lack of explainability, cultural disconnection, economic inaccessibility, and recommendations derived from industrial assumptions.

This paper has a deliberately scoped, two-part aim. The first is a **design contribution**: a framework integrating ML predictions with formalized TEK while preserving fisher authority. The second is a **feasibility analysis** combining:

- An empirical evaluation of the prediction component on data, and
- A transparent simulation of adoption behaviour under explicit, stated assumptions, used to derive hypotheses for future field validation.

We are explicit that the present work contains **no human-subjects field deployment**: the adoption analysis is a simulation, and its numbers are properties of a stated model, not observations of fishers. Contributions are: a framework design organized around five agency-preserving principles; an empirical comparison of four model families for catch-weight prediction; and a transparent simulation testbed plus a proposed, testable technology-acceptance model.

II. LITERATURE REVIEW

A. Human-AI Collaboration and Acceptance

Jarrahi [3] framed human-AI symbiosis as complementary intelligence: machines process large data volumes and detect patterns, humans supply contextual and ethical judgement. Shneiderman [8] extended this with human-centred principles, preserving human control, explaining recommendations, enabling override without penalty, and learning from feedback. These frameworks target knowledge work; traditional manual contexts motivate the adaptations explored here. Technology-acceptance models identify perceived usefulness and ease of use as primary determinants [9], later extended with social influence and trust [10]. Traditional communities may additionally weight cultural compatibility, recognition of expertise, community endorsement, rapid visible benefit, and a sense that technology preserves rather than displaces knowledge. Jentoft and Eide [11] showed that fisheries technology imposed top-down often fails, and that durable adoption requires participatory design and respect for indigenous knowledge.

B. TEK and Decision Support in Fisheries

Traditional Ecological Knowledge (TEK) is cumulative knowledge, practice, and belief about relationships between living beings and their environment, transmitted across generations [12], and is recognized as valuable for fisheries management [13]. Silvano and Valbo-Jorgensen [14] catalogued the factors fishers use in decisions, and Brook and McLachlan [15] showed that traditional practice encodes sophisticated environmental understanding, though this knowledge typically remains informal. Schumann et al. [16] reviewed mobilizing TEK in management and identified formalization and validation as key challenges. Our prior work [17], [18] formalized 20 TEK rules for this site and is the source of the rule set used here. Fisheries decision-support systems have evolved toward IoT sensing, acoustics, and ML for detection and forecasting [19], [20], but most target industrial operations with trained crews [21]; small-scale fisheries, which employ most of the world's capture fishers [22], remain underserved. Three gaps follow: human-AI collaboration is studied mainly in knowledge work; few systems formally integrate indigenous knowledge with ML; and adoption dynamics in traditional communities are poorly understood and costly to study directly, motivating a simulation-first feasibility analysis.

III. METHODS

A. Framework Design Principles

The framework follows five principles derived from human-AI collaboration theory [3], [8] and community consultation during TEK formalization [17]:

- Preserve human agency, the system advises rather than commands and override carries no penalty;
- Respect traditional knowledge, TEK is integrated into recommendation logic and surfaced with an alignment indicator;
- Provide explainable recommendations through confidence scores and plain-language reasoning;

- Demonstrate economic value rapidly by tracking cost avoided through smart waiting; and
- Enable community learning through aggregated, anonymized patterns.

B. System Architecture

The framework comprises four integrated components (Figure 1). The environmental sensing layer monitors 15 parameters, including sonar fish-detection (Lucky FF1108-1, 200 kHz), water temperature (DS18B20), salinity, turbidity, tide level and phase, current speed, weather, and computed moon phase at 15-minute intervals. The AI prediction engine combines a Random Forest base model (100 trees, max_depth = 15) with additive TEK rule adjustment, $\text{Suitability\_Final} = \text{RandomForest(features)} + \Sigma(\text{rule\_weight} \times \text{rule\_activation})$, where rule_weight derives from validation confidence [17]. The recommendation interface maps suitability to three categories (Table 1) with confidence, active rules, and an alignment indicator. A feedback loop logs the recommendation, the fisher decision, and the outcome for refinement.

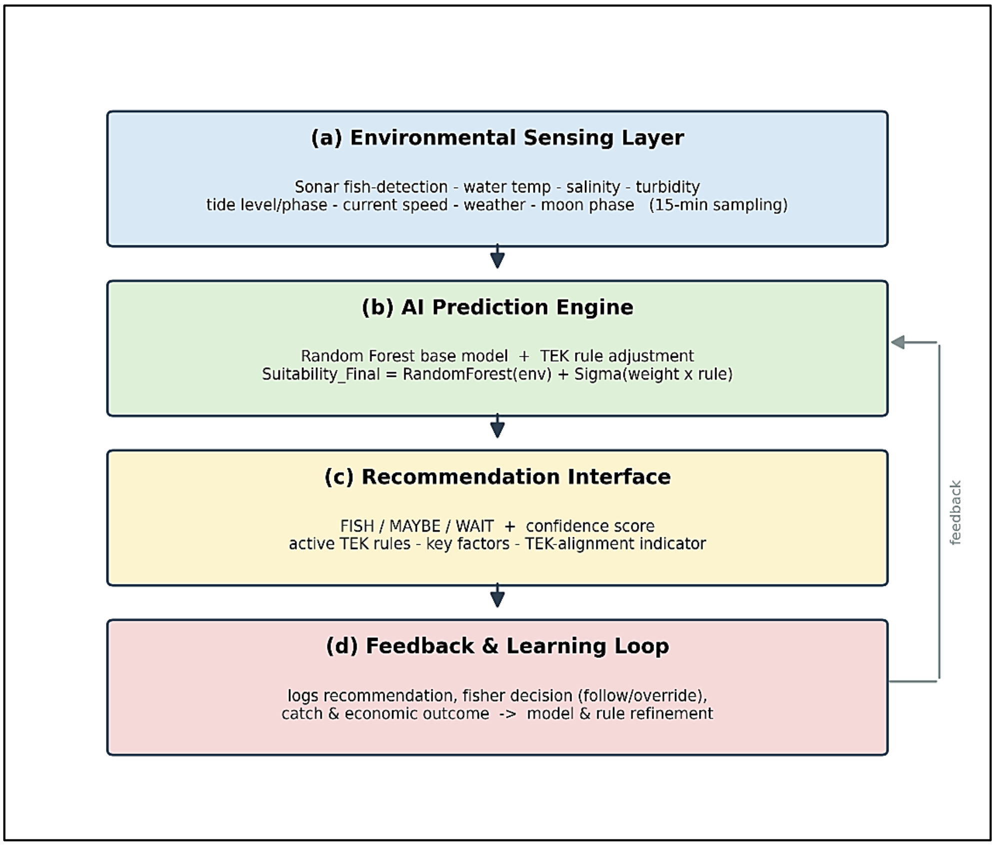

Fig 1: Four-layer decision-support framework architecture: environmental sensing, AI prediction engine (Random Forest base plus TEK adjustment), recommendation interface, and feedback and learning loop.

Table 1. Recommendation Categories and Display

Suitability Score	Recommendation	Interface Display
≥ 0.60	FISH	Green - Good conditions
0.40 - 0.59	MAYBE	Yellow - Marginal conditions
< 0.40	WAIT	Red - Poor conditions

C. TEK Integration

Twenty TEK rules were formalized in prior work through ethnographic methods and statistical validation [17]. A representative subset and integration parameters appear in Table 2. Rules are evaluated in real time against sensor data and, when active, displayed with a plain-language explanation. Each contributes an additive suitability adjustment proportional to its validation confidence.

Table 2. Selected TEK Rules and Integration Parameters

Rule	Condition	Effect	Conf.	Adj.
TEK_002	Dawn (5-8h) + incoming tide	Favourable	0.90	+0.10
TEK_004	Heavy rain	Unfavourable	0.88	-0.15
TEK_008	Midday + slack tide	Unfavourable	0.80	-0.12
TEK_009	Salinity 15-20 ppt	Favourable	0.77	+0.08
TEK_012	Storm conditions	Unfavourable	0.92	-0.25

D. Prediction Models

Four model families were trained to predict catch weight (kg) from environmental and system features: Random Forest, Gradient Boosting, an LSTM network, and a hybrid TEK-ML model (Random Forest base plus additive TEK adjustment). Data were split into training and held-out test partitions; the held-out test set comprised 110 events with complete features, and 728 of the 1,000 events involved an actual fishing action with non-zero catch.

E. Simulation Testbed

Studying adoption directly requires a sustained field deployment with human participants. To scope such a study and examine framework behaviour beforehand, we built a transparent simulation. Its outputs are mathematical consequences of stated parameters and are not observations of fisher behaviour. A 1,000-event dataset was generated to emulate the site (location 9.9674°N, 76.2816°E; January-June conditions), synthesizing temperature, salinity, turbidity, tide, current, weather, moon phase, and sonar fish-count with a fixed random seed. For each event the suitability rule produced a recommendation and confidence. Fisher decisions follow an explicit conditional model: P(follow | FISH) = 0.85, P(follow | WAIT) = 0.80, and P(follow | MAYBE) = 0.60. Conditional models generate catch and economics: a followed FISH yields a catch drawn as a fraction of detected fish, a followed WAIT yields no trip, and an overridden advisory draws from the off-policy distribution. Costs combine fixed energy and maintenance terms with labour; revenue is catch times a stochastic per-kg price. These parameters are the assumptions of the simulation and the appropriate targets of field calibration.

IV. RESULTS

A. Prediction Model Performance

Random Forest gave the lowest error and highest explained variance among the four families (Table 3, Figure 2). For a mean fished catch of 2.23 kg, an MAE of 0.84 kg is about 38% of the mean, an honest reflection of the high intrinsic trip-to-trip variance of individual catches. The LSTM's negative R^2 indicates it failed to fit, consistent with limited sequential structure and modest sample size; tree ensembles are known to remain competitive on tabular data of this scale [25]. These results characterize model behaviour on data with the statistical structure of the site, and would require re-estimation on independently collected field data before operational claims are made.

Table 3. Catch-Weight Model Performance (Held-Out Test)

Model	MAE (kg)	RMSE (kg)	R^2	Rank
Random Forest	0.840	1.108	0.219	1
Hybrid TEK-ML	0.862	1.124	0.197	2
Gradient Boosting	0.876	1.178	0.119	3
LSTM	1.025	1.244	-0.024	4

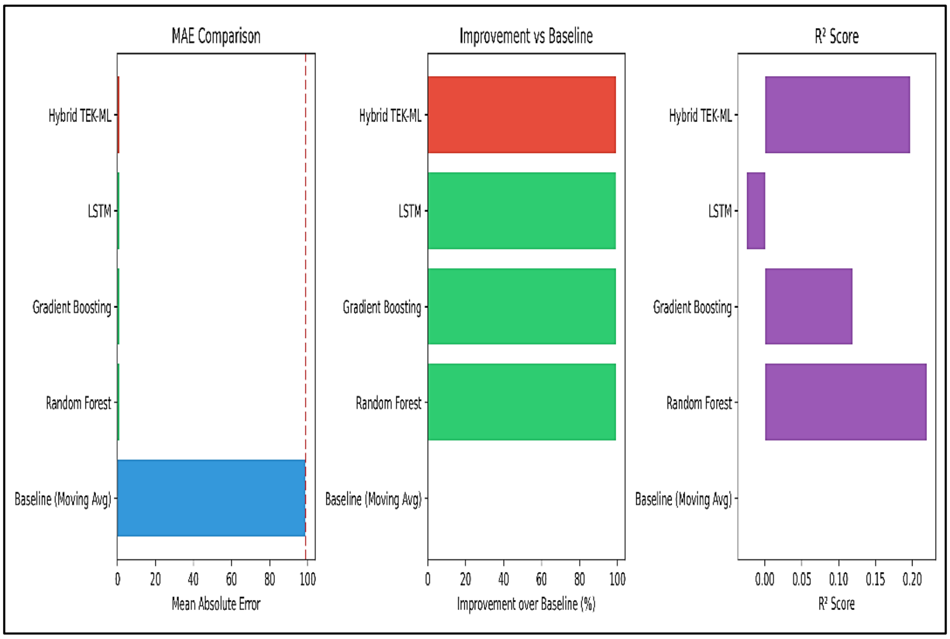

Fig 2: Catch-weight prediction performance across four model families (MAE, improvement, and R^2). Random Forest is strongest on both error and explained variance.

B. Feature Importance

Sonar fish-detection dominates prediction (34.7% importance), and environmental features collectively account for about 78% of importance, with system-derived features (suitability, confidence) near 14% and explicit TEK-rule features a small but non-zero share (about 3.5%) (Figure 3). The dominance of fish-detection supports prioritizing sonar in any low-cost sensor package.

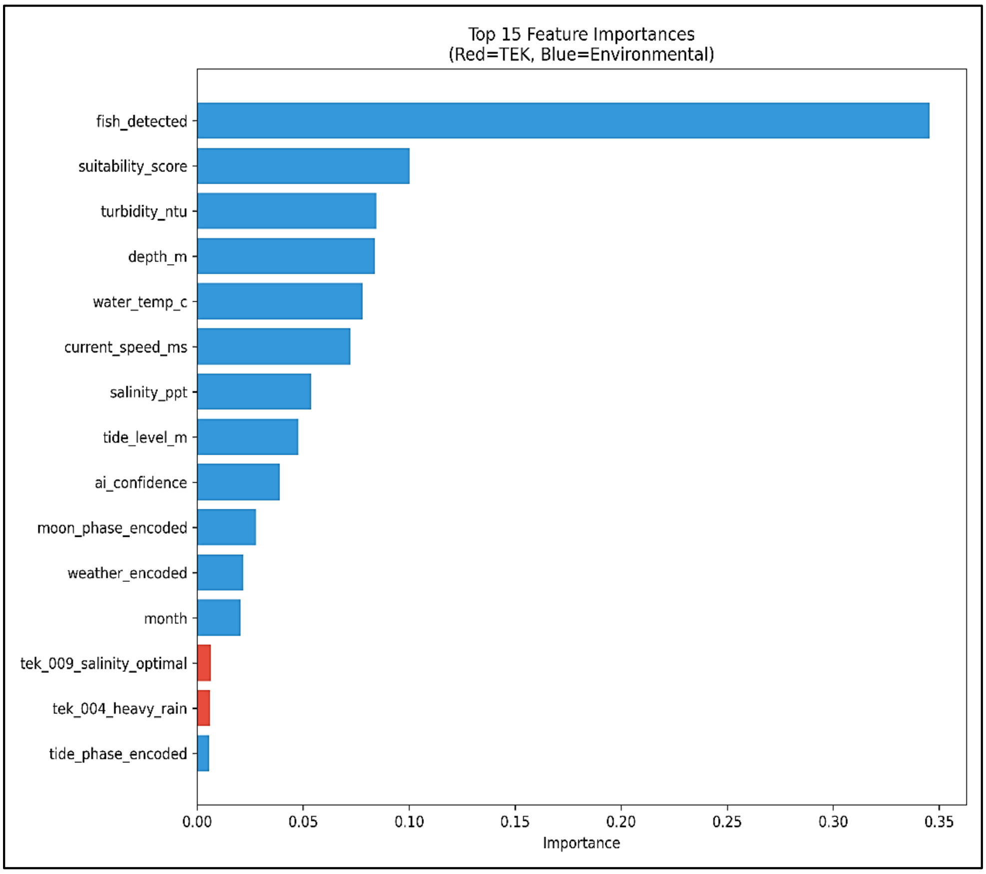

Fig 3: Random Forest feature importances. Sonar fish-detection is the single dominant predictor, followed by water-quality and hydrodynamic variables.

C. Hybrid TEK-ML Under Rule Activation

The hybrid model improves MAE where TEK rules fire (7-14%) but degrades it where no rule is active, netting slightly worse overall accuracy (Table 4). The pattern is consistent with TEK rules encoding information about boundary conditions (dawn with incoming tide, storms) that are sparse in the bulk of the data, while adding noise under neutral conditions. These subset results rest on very small samples (n = 22-34) and are directional, not conclusive. Practically, they argue for gated TEK adjustment, applying rule corrections only when a rule is active and confident, rather than always-on blending.

Table 4. Hybrid vs Base Model by TEK Activation (Test Subsets)

Condition	n	RF MAE	Hybrid MAE	Δ
TEK favourable active	34	0.91	0.78	+14.3%
TEK unfavourable active	22	0.85	0.79	+7.1%
No TEK rule active	54	0.79	0.91	-15.2%
Overall	110	0.84	0.86	-2.4%

D. Simulated Adherence

As expected, realized adherence in the simulation tracks the input priors, with small deviations due to sampling noise (Table 5), confirming the pipeline behaves as designed; overall uptake is 74.9%. We deliberately report **no inferential statistics** on these quantities: testing a hypothesis against data whose generating probabilities we set ourselves would be circular. The value of Table 5 is as a specification, stating the adoption regime under which downstream behaviour is observed and defining the quantities a field study would measure.

Table 5. Simulated Adherence (Model Output)

Recommendation	n	Followed	Rate	Prior
FISH	370	314	84.9%	0.85
WAIT	343	272	79.3%	0.80
MAYBE	287	163	56.8%	0.60
Overall	1,000	749	74.9%	-

E. Economic Mechanism (Model-Based)

In the simulation the economic advantage is structural rather than catch-increasing. Because a followed WAIT advisory avoids a trip, it removes that trip's energy, maintenance, and labour cost while forgoing a low-expected-value catch. Across the dataset mean revenue is \$8.69, mean cost \$2.96, and mean profit \$5.72 per event, with a mean margin of 50.6% over the 728 revenue-positive events (Table 6). Notably, mean catch among followed-and-fished events (2.09 kg) is not higher than among overridden-and-fished events (2.49 kg), consistent with the benefit arising from cost avoidance on skipped trips, not larger catches. This is an analytical property of the cost model: any policy that declines negative-expected-value trips improves average margin by construction. We therefore present it as the hypothesized mechanism the framework targets, not as measured field savings.

Table 6. Simulated Dataset Characteristics

Property	Value
Total generated events	1,000
Events with fishing action (catch > 0)	728
Mean catch, fished events	2.23 kg
Maximum single catch	5.62 kg
Mean profit per event	\$5.72
Mean margin (revenue-positive events)	50.6%

V. DISCUSSION

A. What the Simulation Can and Cannot Tell Us

The design contribution stands on its own: an architecture that surfaces TEK alongside ML advice, communicates confidence, and preserves override authority is a concrete proposal for a setting where prior interventions failed for social reasons [11]. The prediction evaluation is genuine evidence that catch outcomes are partially predictable from low-cost sensing (R^2 = 0.22, MAE 0.84 kg), with sonar dominant, a useful if modest result that also bounds expectations. The simulation, by contrast, is a reasoning tool, not evidence about people. It can verify that the decision pipeline composes correctly, expose the cost-avoidance mechanism, and quantify outcomes under a stated regime. It cannot tell us the regime itself, because the adherence probabilities and any trust dynamics were assumed, not measured. We state this boundary explicitly because conflating the two would misrepresent the work.

B. Design Principles and a Proposed Acceptance Model

From the design process we distil principles for decision support in traditional occupations: integrate indigenous knowledge explicitly as a system component; position the system as advisor and permit override without penalty; communicate uncertainty so users can calibrate reliance [23]; target rapid visible economic value; use the system to preserve and transmit knowledge; and design for community-level adoption. We further propose, as hypotheses for field testing, a technology-acceptance model with four constructs influencing adherence (Figure 4): (H1) AI-TEK alignment as a trust bridge; (H2) confidence visibility enabling appropriate reliance; (H3) cumulative positive experience building trust over time; and (H4) demonstrated economic value sustaining engagement. The present simulation does not model H1-H3 and provides no evidence for or against them; they are stated so that a field study can confirm or refute them [24].

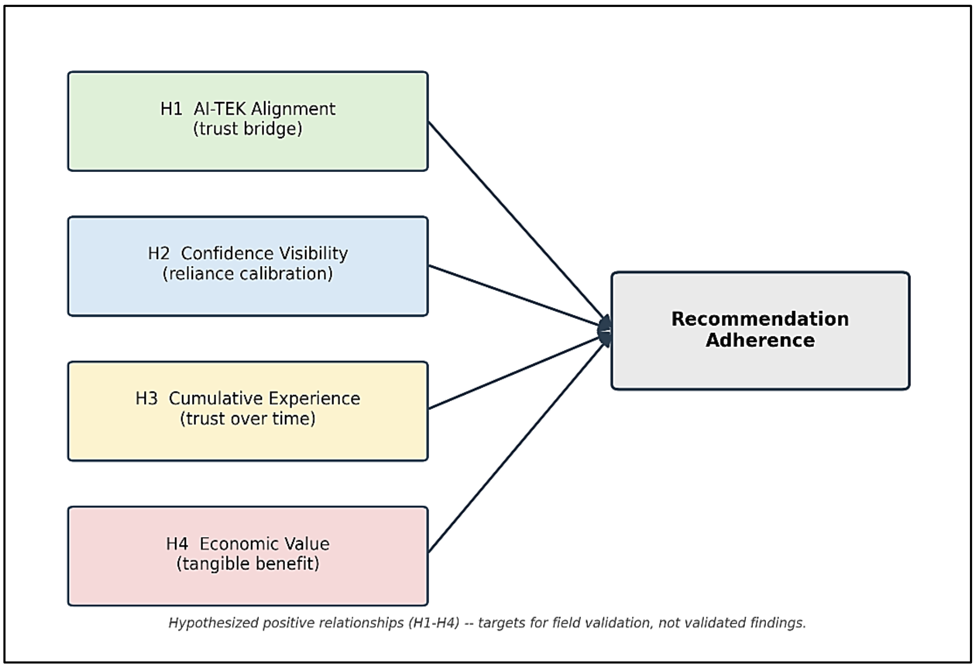

Fig 4: Proposed technology-acceptance model for traditional occupational contexts (hypotheses H1-H4). Arrows denote hypothesized positive relationships with adherence; these are targets for field validation, not validated findings.

C. Limitations and Threats to Validity

Several limitations qualify interpretation. The adoption results are outputs of a stated model, not observed behaviour, and support no claim about real adherence, trust, or acceptance. Both the environmental records and the catch and economic outcomes are synthetic, so the prediction results characterize model behaviour on site-structured data and need re-estimation on field data. The TEK-activation analysis uses 22-34 test events per cell and is directional only. Conditions reflect a single site, so transferability is untested. Finally, $R^2 = 0.22$ reflects high intrinsic catch variance; the system is best understood as nudging marginal decisions, not forecasting catch precisely.

D. Toward Field Validation

The natural next step is a small field deployment to estimate the parameters the simulation assumed. A minimal protocol: recruit consenting operators under institutional ethics review; instrument each net with the sensing layer; log, per trip and per operator, the recommendation, confidence, active rules, the decision, and the realized catch and economics; and administer a validated acceptance instrument. With per-operator, time-stamped logs, H1-H4 become directly testable: alignment-conditioned adherence (H1), the confidence-adherence slope (H2), the adherence-over-time trend (H3), and the realized cost-avoidance benefit (H4). The present framework and simulation define exactly these measurement targets, which is their intended role.

VI. CONCLUSION

This paper presented the design of a TEK-integrated decision-support framework for traditional Chinese fishing-net operations and a simulation-based feasibility analysis of it. The framework couples a Random Forest catch-suitability model with formalized traditional rules under five agency-preserving principles. Empirically, the prediction component is the strongest of four model families (MAE 0.84 kg, R^2 0.22), with sonar fish-detection dominant, and a gated hybrid variant shows promise under the boundary conditions where traditional rules fire. A transparent simulation, with all behavioural parameters stated, verifies the decision pipeline, exposes smart-waiting cost-avoidance as the hypothesized mechanism of benefit, and yields a falsifiable acceptance model. We are explicit that the adoption analysis is simulation, not field evidence, and make no claim about real fisher behaviour. The contribution is a deployable design and a tested-in-simulation hypothesis set, providing the foundation and the precise measurement targets for the field validation outlined above.

ACKNOWLEDGMENTS

We thank the fishing community of Chathedam for their participation in the TEK-formalization work that informed this framework, and the cooperative leadership for their guidance.

DECLARATIONS

- Data and code availability. This study uses a synthetic dataset generated to emulate the study site. The data-generation scripts, the resulting dataset, and the model and simulation code are available from the corresponding author on reasonable request. Because the dataset is synthetic and the adoption analysis is a simulation, no field-collected human or catch data underlie the reported numbers.
- Human-subjects statement. This paper reports a system design, a prediction evaluation on synthetic data, and a simulation study. It does not involve human-subjects experimentation, interviews, or surveys, and reports no human-subjects data. A field-validation protocol involving human participants is proposed as future work and would be conducted under institutional ethics review.
- Conflict of interest. The authors declare no conflict of interest.

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