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AI-Driven Decision Support for Global Knowledge-Sharing Interventions

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Abstract—**In global organizations, knowledge-sharing interventions — such as webinars, workshops, and targeted training sessions — are essential drivers of collaboration, skill development, and organizational learning. However, decisions about which type of intervention to conduct are typically made through intuition rather than systematic, data-driven analysis. This paper proposes an AI-driven Decision Support System (DSS) that analyzes organizational signals — including stakeholder feedback, attendance history, engagement metrics, survey responses, cultural factors, and Natural Language Processing (NLP)-derived behavioral patterns from meeting transcripts — to recommend the most suitable knowledge-sharing intervention. The system classifies meeting discussions into behavioral pattern categories such as Conceptual Knowledge Gap, Technical Failure, Governance Issue, and Exploration Mode, and maps each pattern to a targeted intervention strategy. A case study drawn from real meeting transcripts within a Microsoft Power Platform deployment context validates the model, demonstrating high classification confidence for conceptual gap identification. The proposed framework offers a replicable, data-informed approach that can improve decision quality, reduce ineffective sessions, and optimize organizational learning outcomes across culturally diverse global teams.**

Index Terms—**Decision support system, knowledge-sharing interventions, AI-driven recommendation, NLP, behavioral pattern classification, organizational learning, Power Platform, global teams.**

I. INTRODUCTION

The proliferation of global work environments has made knowledge sharing a strategic imperative. Organizations operating across multiple countries and cultures must deliver training, webinars, and collaborative workshops to sustain operational effectiveness. Yet the selection of which knowledge-sharing format to deploy — and when — remains largely intuitive, driven by managerial judgment rather than evidence from organizational data.

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A persistent challenge is that different regional contexts exhibit distinct engagement behaviors, stakeholder influence structures, and learning preferences. A webinar that achieves high participation in one region may yield minimal engagement in another. Similarly, a workshop that effectively addresses a conceptual knowledge gap in one team may be entirely unsuitable for a team facing a technical implementation barrier. Without a principled, data-informed selection mechanism, organizations waste resources and fail to achieve their learning objectives.

Recent advances in Artificial Intelligence (AI) — particularly in Natural Language Processing (NLP), machine learning (ML) classification, and decision support systems (DSS) — offer a pathway to systematic intervention selection. This paper presents an AI-driven Decision Support System that ingests organizational signals from multiple sources (meeting transcripts, engagement metrics, survey responses, and stakeholder feedback) and produces a recommended intervention strategy with a confidence level and execution plan.

The remainder of this paper is structured as follows: Section II reviews related work. Section III defines the problem formally. Section IV describes the proposed model and its components. Section V presents a case study. Section VI discusses results. Section VII outlines limitations and future work. Section VIII concludes.

II. RELATED WORK

Decision support systems have a long history in organizational management. Early DSS frameworks, as reviewed by Turban et al. [1], established the foundational components of data-driven organizational decision-making. However, these systems relied primarily on structured numerical data and rule-based logic, with limited capacity to handle unstructured inputs such as meeting discourse or free-text feedback.

The integration of machine learning into DSS — surveyed comprehensively by Sołtysik-Piorunkiewicz et al. [2] — has dramatically extended the range of analyzable inputs. ML-enhanced DSS can now incorporate classification models, clustering, and predictive analytics into recommendation pipelines. However, applications specifically targeting knowledge-sharing intervention selection remain scarce.

NLP has been applied extensively in organizational and educational contexts. Sentiment analysis, topic modelling, and intent classification from meeting transcripts have been demonstrated in enterprise communication platforms [3]. These techniques are directly applicable to the challenge of identifying knowledge gaps, confusion signals, and governance discussions from team meeting recordings.

AI applications in knowledge management are reviewed by Ansari et al. [4], who identify recommendation systems, expert-finding tools, and intelligent tutoring systems as key areas. The proposed system extends this line of work by focusing specifically on intervention-type recommendation from multi-modal organizational signals.

Cross-cultural considerations in knowledge management remain underexplored in computational systems. Hofstede's cultural dimensions [5] provide a theoretical basis for understanding regional variation in knowledge engagement, but their integration into automated recommendation systems has not been widely demonstrated. Our framework acknowledges cultural and regional factors as first-class inputs.

III. PROBLEM STATEMENT

Let O denote a global organization with teams distributed across R regions. Each team T_r ($r \in R$) participates in periodic knowledge-sharing events drawn from an intervention set I = {Webinar, Workshop, Targeted Session, No Immediate Action}.

At each decision point d, the organization collects a signal vector $S_d = \{F_d, E_d, A_d, Q_d, C_d\}$, where:

- F_d : stakeholder feedback (free-text and ratings)
- E_d : engagement metrics (attendance rates, interaction counts)
- A_d : attendance history over prior sessions
- Q_d : survey response data
- C_d : cultural and regional contextual factors

Additionally, for organizations that record meetings, a transcript T_d is available and processed through NLP to yield behavioral signals B_d = {Intent, Complexity, Urgency, Risk Type, Stakeholder Conflict, Discussion Type}.

The objective is to learn a mapping $f : (S_d, B_d) \rightarrow (i^*, P, X)$, where $i^* \in I$ is the recommended intervention, P is a confidence level, and X is an execution strategy (e.g., priority level, session format, timeline). The system must be robust to missing features, culturally variable engagement norms, and multi-lingual transcript inputs.

IV. PROPOSED MODEL

A. System Architecture

The proposed AI-driven DSS comprises five functional layers: (1) Data Ingestion, (2) Preprocessing and Feature Extraction, (3) NLP-Based Behavioral Signal Extraction, (4) Pattern Classification, and (5) Decision Output and Recommendation.

B.Data Ingestion Layer

Inputs are collected from four source types: (i) meeting transcripts exported from platforms such as Microsoft Teams, (ii) engagement dashboards, (iii) post-session survey forms, and (iv) HR and regional profile data. Transcripts may be multilingual; the case study data includes English and Finnish segments, illustrating the real-world code-switching that occurs in multinational teams.

C.NLP-Based Behavioral Signal Extraction

Meeting transcripts are processed through a pipeline that includes: language detection, sentence segmentation, keyword extraction, intent classification, and named entity recognition. The pipeline extracts the following behavioral parameters for each meeting:

- Intent: classified as {Learning/Understanding, Implementation, Problem-Solving, Governance, Exploration}
- Complexity: estimated as {Low, Medium, High} based on domain terminology density
- Urgency: derived from temporal language cues and explicit deadline mentions
- Risk Type: classified as {Capability Risk, Design Risk, Governance Risk, No Risk}
- Stakeholder Conflict: binary detection of disagreement markers
- Discussion Type: {Conceptual Clarification, Technical Troubleshooting, Planning, Retrospective}

D. Pattern Classification

The behavioral signal vector B_d is mapped to one of six pattern classes using a trained multi-class classifier (Random Forest with SHAP-based explainability):

- Conceptual Knowledge Gap Pattern — team lacks clarity on foundational concepts or decision criteria
- Technical Failure Pattern — active system or implementation error
- Usability Issue Pattern — friction with tooling or interface
- Implementation Need Pattern — team ready to build but requires guidance
- Exploration Mode Pattern — early-stage discovery or ideation
- Governance Discussion Pattern — policy, access, or process-level concerns

E. Intervention Recommendation Engine

Each detected pattern is associated with a recommended intervention through a rule-augmented lookup table, refined by confidence scores from the classification model. Confidence levels above 0.85 trigger direct recommendations; scores between 0.60 and 0.85 generate conditional recommendations with stated assumptions. Scores below 0.60 trigger a data collection request rather than a recommendation.

The output for each decision point includes: recommended intervention type, execution strategy, priority level (High/Medium/Low), session format (conceptual workshop, hands-on lab, targeted 1:1, asynchronous module), and a human-readable rationale derived from the top contributing features identified by SHAP.

V. CASE STUDY

F. Dataset

Seven meeting transcripts were collected from a Microsoft Power Platform deployment project involving a multinational consulting team (Finland-based consultants, Indian developers, and European client stakeholders). Participants included Lalit Dhuwe, Sari Da Conceicao, Markus Näkki, Tatu Seppälä, Visa Linkiö, Jari Niemi, Mihail Lefler, Jasmine Donovan, Olga Donkovtceva, and Manjinder Singh. Transcripts ranged from approximately 20 minutes to over 3 hours in duration.

G. Analyzed Meeting (Transcript 4)

The primary case study focuses on a one-hour team discussion concerning application design choices within Microsoft Power Platform. The meeting involved five participants (Lalit, Sari, Tatu, Visa, Jari) and centered on ensuring that developers understand the distinction between model-driven apps and canvas apps before commencing implementation.

The NLP pipeline extracted the following behavioral signals from Transcript 4:

TABLE I NLP BEHAVIORAL SIGNAL EXTRACTION — TRANSCRIPT 4

Parameter	Value
Intent	Learning / Understanding
Complexity	Medium
Urgency	Medium
Risk Type	Capability / Design Risk
Stakeholder Conflict	No
Discussion Type	Conceptual Clarification

Key extracted keywords confirming the conceptual gap pattern: "understand the difference", "what they should be choosing", and "just that they understand" (Transcript 4, 59:49–1:00:22).

H. Pattern Classification Result

The classifier assigned the Conceptual Knowledge Gap Pattern with High confidence, based on the combination of Learning/Understanding intent, absence of technical failure signals, and the prevalence of decision-criteria language. The behavioral signal table (Table II) confirms the absence of technical and usability failure signals.

TABLE II BEHAVIORAL SIGNAL CLASSIFICATION — TRANSCRIPT 4

Signal	Detected
Conceptual Confusion	YES
Technical Failure	NO
Usability Issue	NO
Implementation Need	NO
Exploration Mode	NO
Governance Discussion	NO
Personal Issue	NO

I. Decision Output

Based on the classification, the system produced the following recommendation:

Decision: Conceptual Training + Knowledge Alignment Session

Execution Strategy: Planned Learning Intervention

Priority: Medium

Intervention Type: Workshop (Conceptual, not technical)

The rationale generated by the system: The team demonstrates clear understanding intent without evidence of technical blockers. The discussion centers on decision-criteria clarity (model-driven vs. canvas apps). A conceptual workshop — not a coding lab — is the appropriate intervention to build shared understanding before implementation begins.

J. Cross-Transcript Analysis

Analysis across all seven transcripts revealed a diversity of meeting patterns. Transcript 7 (Lalit and Jasmine, 3h28m) involved knowledge transfer about SharePoint-based Copilot agents, classified as an Implementation Need Pattern with a recommended Hands-On Guided Session. Transcripts 2 and 6 (Markus, Mihail, Manjinder, Olga) showed Exploration Mode signals around Microsoft Fabric and Dynamics 365 Journeys, recommending a structured Discovery Workshop. Transcript 3 (Lalit, Sari) exhibited a mixed Governance/Personal signal around backlog prioritization and career development, classified as No Immediate Technical Intervention Required.

VI. DISCUSSION

The case study results demonstrate that NLP-based behavioral signal extraction from meeting transcripts provides a reliable basis for knowledge-sharing intervention classification. The framework successfully distinguishes between meetings that require conceptual alignment (workshops), implementation guidance (hands-on sessions), and exploratory discovery (open-format sessions).

A notable observation is the multilingual nature of the transcripts. Participants frequently code-switched between English and Finnish, reflecting real-world global team dynamics. The NLP pipeline must therefore incorporate language detection at the utterance level rather than the document level, and should weight English-language utterances more heavily in intent classification given their higher proportion of task-relevant content in the observed dataset.

The absence of stakeholder conflict signals across most transcripts suggests that this organization has relatively aligned team dynamics, which may reduce classification ambiguity. In organizations with higher internal conflict, the Governance Discussion Pattern and Personal Issue Pattern would require more discriminative features.

The SHAP-based explainability component proved valuable for validating recommendations. Decision-makers consistently found the natural language rationale (generated from SHAP feature contributions) more useful than raw confidence scores, suggesting that explainability is a first-class requirement for DSS adoption in organizational settings.

II. Limitations and Future Work

Several limitations apply to the current study. First, the dataset comprises seven transcripts from a single organizational context; generalizability requires validation across broader organizational types, sectors, and cultural contexts. Second, the behavioral pattern classification model was developed using domain expert labeling rather than a large labeled corpus; future work should

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develop a benchmark dataset for this classification task. Third, the current system does not model temporal dynamics — the evolution of knowledge gaps across multiple sessions — which may be important for longitudinal intervention planning.

Future work will extend the framework in three directions: (1) integration with real-time meeting analytics to enable in-session recommendations rather than post-hoc analysis; (2) incorporation of Hofstede cultural dimension scores as features to improve cross-regional recommendation accuracy; and (3) development of a feedback loop mechanism where post-intervention engagement data is used to retrain the recommendation model, enabling continuous improvement.

The synthetic transcript generation methodology developed alongside this work — producing realistic meeting transcripts across diverse scenarios and technology domains — will also be used to pre-train the NLP pipeline before fine-tuning on real organizational data, addressing the cold-start problem for new organizational deployments.

VII. CONCLUSION

This paper presented an AI-driven Decision Support System for recommending knowledge-sharing interventions in global organizations. By combining NLP-based behavioral signal extraction from meeting transcripts with organizational engagement data, the system classifies discussion patterns and maps them to targeted intervention strategies with explainable confidence scores. A case study across seven real meeting transcripts from a Microsoft Power Platform deployment project validated the framework, demonstrating high-confidence classification of a Conceptual Knowledge Gap Pattern and an actionable, human-readable intervention recommendation. The proposed system addresses a meaningful gap in the organizational learning literature: the absence of systematic, data-informed mechanisms for matching knowledge-sharing formats to team needs. By making this decision explicit, traceable, and continuously improvable, the framework offers organizations a practical path toward more effective global learning operations.

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