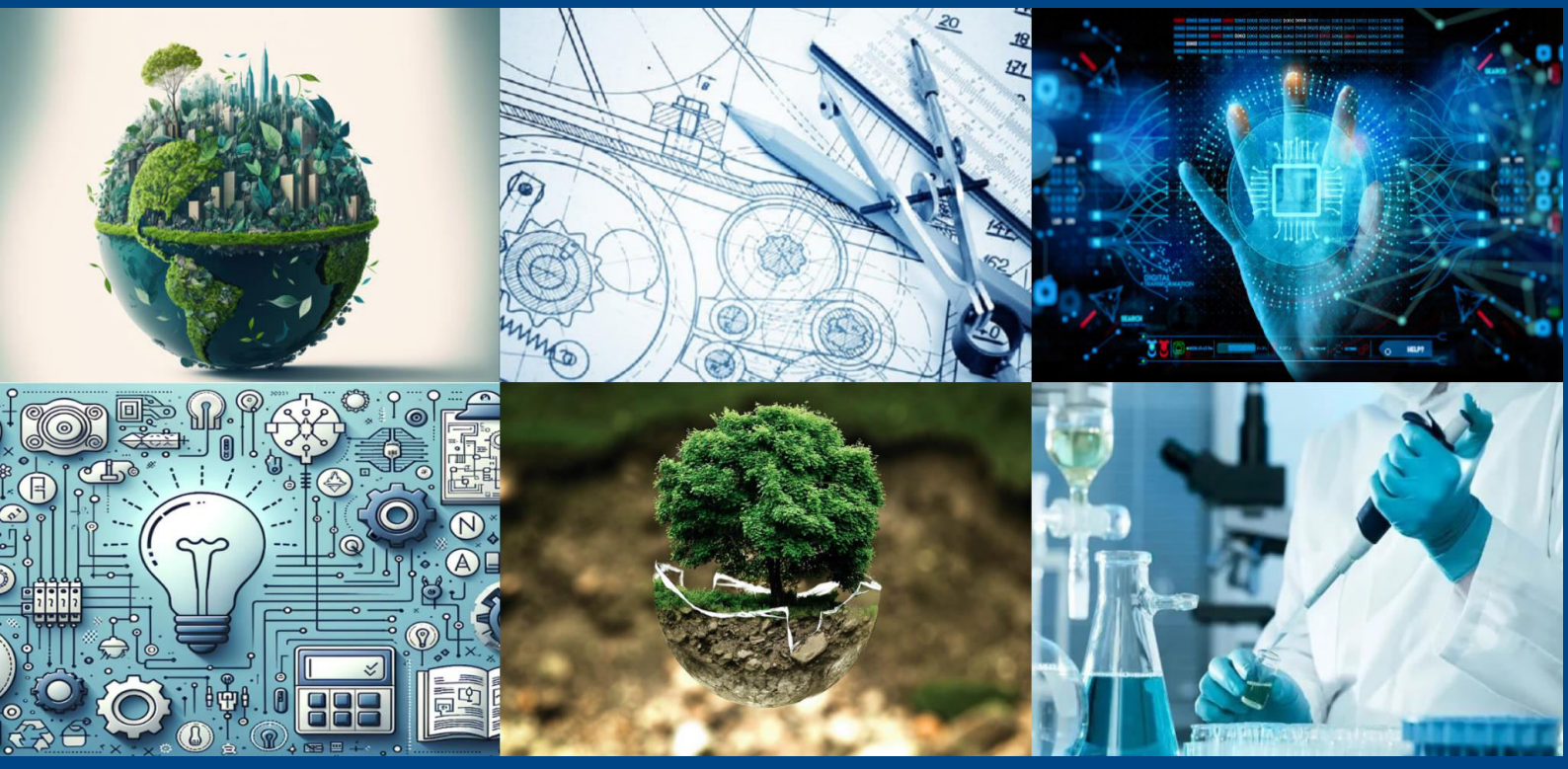
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A Graph-Theoretic Framework for Analyzing Human Skill Dynamics and Resilience in AI-Supported Work

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ABSTRACT: Artificial intelligence (AI) can improve task completion by supplying recommendations, explanations, generated content, and automated procedures. Yet a successful AI-assisted output does not establish that a person can reproduce the task independently. This paper develops a graph-theoretic framework for examining how AI use, cognitive offloading, independent practice, feedback, task complexity, and prior expertise relate to human skill retention and recovery. The framework represents these factors as vertices in a weighted, undirected association graph and uses degree, weighted degree (strength), betweenness centrality, and network density to describe structural importance and connectivity. A longitudinal four-condition study design is specified, with independent skill assessments at baseline, immediately after training, delayed follow-up, and after refresher practice. To demonstrate the analysis format without presenting fabricated observations as evidence, a clearly labelled synthetic dataset is supplied for 120 hypothetical participants, with 30 assigned to each condition. Illustrative group means show how skill trajectories may be compared, while a small worked network demonstrates graph measures. The proposed framework separates assisted output from unaided competence and provides a reproducible way to investigate whether practice pathways and human–AI interaction patterns are associated with resilience. The numerical examples are methodological demonstrations only; empirical conclusions require real participant data.

KEYWORDS: graph theory; human skill retention; skill deterioration; resilience; artificial intelligence; cognitive offloading; centrality; human–AI interaction.

I. INTRODUCTION

AI-enabled systems now participate in activities that once required people to retrieve knowledge, plan procedures, recognize patterns, and evaluate alternatives. Their use can reduce routine workload and increase the speed of producing an answer. However, the quality of an assisted result and the capability of the person who used the system are different outcomes. A user may complete a task successfully because the AI supplied key reasoning steps, while the user's ability to perform the same task without assistance remains uncertain.

Research on automation has documented automation bias and reduced monitoring when people rely heavily on automated recommendations [1]. Work on AI assistants has raised related questions about the possible weakening of practiced expertise when cognitive work is repeatedly delegated [2]. At the same time, AI can support learning when it provides explanations, feedback, and opportunities for deliberate practice. Thus, the effect of AI is unlikely to be uniform; it may depend on the design of assistance and the amount of independent effort retained [3].

Graph theory offers a useful language for representing this multi-factor setting. Rather than treating AI exposure, practice, feedback, confidence, and skill as isolated variables, a graph can encode their relationships. Network measures can then identify highly connected factors and possible intermediaries. This paper introduces such a model and links it to a repeated-measures study of independent performance.

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II. PROBLEM DEFINITION AND RESEARCH MOTIVATION

Many evaluations of AI adoption emphasize immediate productivity, completion time, or user satisfaction. These measures are important for operational efficiency but do not reveal whether users retain the knowledge and procedures needed when AI is unavailable. A second limitation is that the factors influencing skill change are interconnected: assistance can alter practice frequency; practice can affect retention; feedback can influence adaptation; and dependence can influence verification behavior.

The research problem is therefore twofold: (i) define a measurable representation of the relationships among AI-use factors and human skill outcomes, and (ii) distinguish short-term assisted performance from longer-term independent competence. The graph-theoretic component is intended to organize and analyze associations, not to claim that a network correlation alone proves causation.

III. OBJECTIVES AND RESEARCH QUESTIONS

1. To construct a graph representation of the factors associated with human skill deterioration, retention, adaptation, and resilience in AI-supported work.
2. To define graph measures that describe the structural importance of practice, assistance, feedback, dependence, and performance variables.
3. To specify a longitudinal evaluation design that measures independent skill at multiple time points.
4. To demonstrate the proposed reporting procedure using explicitly synthetic data rather than claiming empirical findings.

RQ1: How are the frequency and intensity of AI assistance associated with independent performance over time?
RQ2: Does independent practice change the relationship between AI assistance and delayed skill retention?
RQ3: Which factors occupy structurally important positions in the proposed skill-support network?
RQ4: Are guided assistance, feedback, and retrieval practice associated with stronger recovery after AI support is withdrawn?
RQ5: How closely do self-reported confidence and measured independent performance correspond?

IV. RESEARCH GAP AND CONTRIBUTION

Prior work provides foundations on automation bias, cognitive offloading, skill retention, and learning practice [1]–[6]. However, these strands are often considered separately. A study that measures only AI-supported task scores may overlook autonomous capability; a study that records only AI-use frequency may overlook the protective role of practice and feedback. The present proposal contributes an integrated representation in which the relevant factors and outcomes are connected in a graph, while repeated independent assessments provide the principal evidence of skill change.

The contribution is methodological: a graph-based factor model, a set of operational network measures, a longitudinal assessment plan, and a transparent synthetic demonstration. It does not claim that the proposed graph is a validated causal model.

V. LITERATURE BACKGROUND

5.1 Automation bias and monitoring

Automation bias describes the tendency to accept automated recommendations or omit independent checks. Parasuraman and Manzey [1] discuss how automation can change attention and monitoring. In the proposed graph, AI support is linked to verification behavior and independent performance so that the study can examine whether use is accompanied by active checking.

5.2 AI assistance and skill development

AI assistants can take over parts of a task, but they can also function as tutors. Macnamara et al. [2] raise the possibility that repeated delegation may affect the maintenance of expertise. The proposed study therefore distinguishes high assistance from guided assistance that requires users to explain, verify, and complete portions of the work.

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5.3 Retention and retrieval practice

Skill retention depends partly on opportunities to retrieve and apply learned material. The supplied literature identifies practice spacing and retrieval as useful learning strategies [3], while reviews of skill retention indicate that performance may decline when practice is discontinued [4]. These ideas motivate explicit practice and refresher variables.

5.4 Cognitive offloading and feedback

Cognitive offloading refers to using external resources to reduce internal mental demands [5]. Offloading can be beneficial, but repeated substitution for internal processing may reduce opportunities to exercise a target skill. Feedback quality and the user's active engagement are therefore included as separate graph nodes rather than treating all AI use as equivalent.

5.5 Graph theory as an analytical lens

A graph is a pair $G = (V, E)$,where V is a set of vertices and E is a set of edges. In this application, vertices represent measurable constructs and edges represent observed or hypothesized relationships. Weighted edges can encode association magnitude. Degree and strength summarize local connectivity, betweenness centrality identifies vertices that lie on many shortest paths, and density describes the proportion of possible connections that are present. These measures describe network structure; they do not, by themselves, establish causal influence.

VI. PROPOSED GRAPH-THEORETIC MODEL

6.1 Vertex set and edge interpretation

Let $G = (V, E, W)$ be a weighted graph, where V contains the study constructs, E contains links between construct pairs, and W assigns a non-negative weight to each link. The proposed vertex set is:

$$V = \{A, O, P, R, F, V_f, C, X, K, S, H\}$$

Here A denotes AI support intensity; O cognitive offloading; P independent practice; R retrieval practice; F feedback quality; V_f verification behavior; C task complexity; X prior expertise; K cognitive load; S independent skill performance; and H resilience. Additional nodes such as confidence calibration and transfer performance may be included when measured.

An edge (u,v) indicates that two constructs are associated in the study model. For example, (P,S) represents the association between independent practice and independent performance. Edge weights may be estimated from standardized correlations, partial correlations, or another preregistered association measure. The choice must be consistent across the network and reported with uncertainty.

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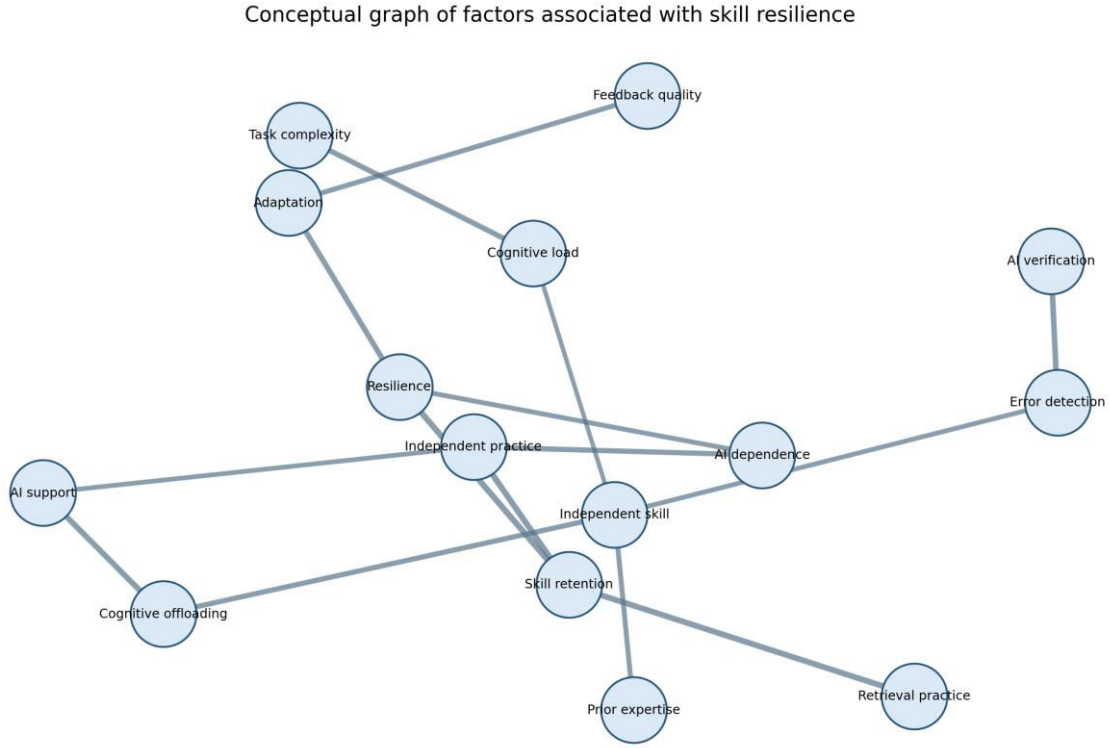


Figure 1. Conceptual weighted network of factors related to human skill resilience. Edge thickness illustrates hypothetical association weights, not empirical estimates.

6.2 Core graph measures

The degree of a vertex is the number of its adjacent vertices. In an unweighted graph, degree centrality is:

$$C_D(v) = \frac{\deg(v)}{|V|-1}$$

For a weighted graph, strength is the sum of incident edge weights:

$$s(v) = \sum_{u:(u,v)\in E} w_{uv}$$

Betweenness centrality measures the fraction of shortest paths between other vertex pairs that pass-through v:

$$C_B(v) = \sum_{s\neq v\neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

Here σ_{st} is the number of shortest paths from s to t and $\sigma_{st}(v)$ is the number of those paths passing through v. For weighted networks, a distance transformation such as $d_{uv} = \frac{1}{w_{uv}}$ may be used, provided all weights are positive and the interpretation is stated.

For a simple undirected graph with n vertices and m edges, density is:

$$D(G) = \frac{2m}{n(n-1)}$$

High centrality identifies structural prominence, not necessarily intervention priority. A highly connected variable may be a useful monitoring target, but intervention claims require experimental or longitudinal evidence.

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6.3 Worked miniature example

Consider a small illustrative network with six vertices P, R, V, S, T, and U. Let P represent practice, R retrieval, V verification, S independent skill, T transfer, and U resilience. Suppose the undirected edges are PR, PV, RV, RS, VS, ST, TU, and SU. This graph contains n=6 vertices and m=8 edges, so its density is 2(8)/(6×5)=0.533. The degrees are deg(P)=2, deg(R)=3, deg(V)=3, deg(S)=4, deg(T)=2, and deg(U)=2. Thus, S has the largest degree in this small example.

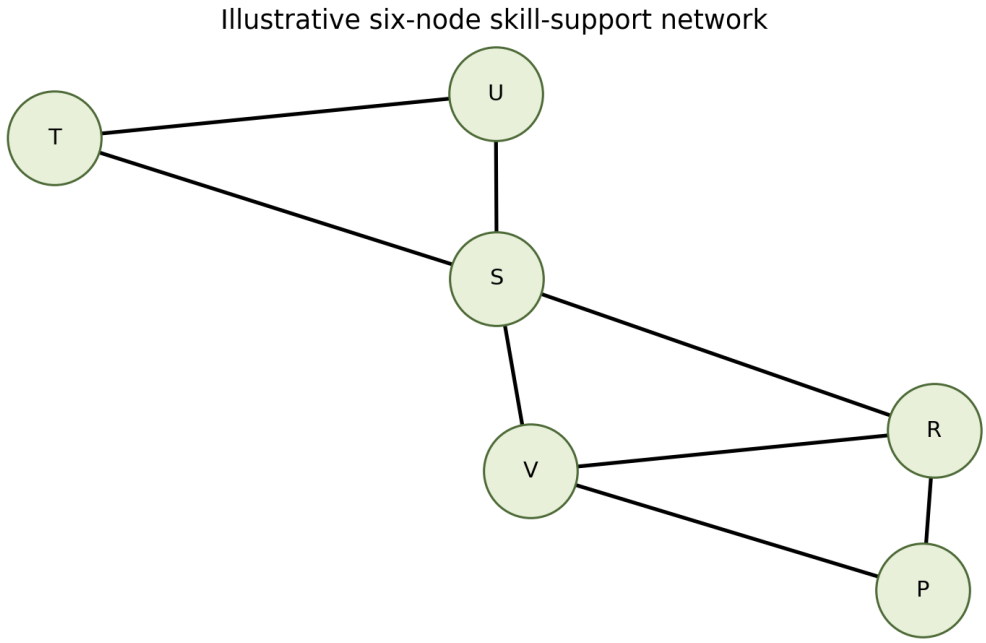


Figure 2. Small illustrative network used to explain degree and density.

The example is deliberately small so that the calculations can be checked manually. It is not participant data and should not be interpreted as a discovered psychological structure. In a real study, vertices would be defined before analysis and edge weights would be estimated from the collected measurements.

VII. RESEARCH METHODOLOGY

7.1 Study design

A longitudinal repeated-measures design is proposed. One primary skill domain should be selected, such as introductory programming, analytical reasoning, or technical diagnosis. Restricting the main study to one domain reduces the risk of combining unlike competencies. Participants complete a baseline unaided assessment, receive training under one of four assistance conditions, and then complete immediate and delayed independent assessments. A refresher session is followed by a final assessment.

7.2 Participants and allocation

The target population may be undergraduate learners or early-career practitioners in the selected domain. A hypothetical planning design uses 120 participants, allocated equally to four conditions (30 per condition). This number is used only to illustrate tables and is not a sample that has been recruited. The final sample size must be justified by an a priori power analysis using the expected time-by-condition effect, attrition, and within-person correlation. Consent, inclusion criteria, exclusion rules, and institutional ethics approval should be documented.

7.3 Assistance conditions

- Independent work: participants complete all learning and assessment tasks without AI.
- High AI assistance: participants may use AI to generate substantial portions of task solutions.

- Guided AI assistance: AI provides hints and explanations, while participants must attempt, verify, and explain their own solutions.
- Guided assistance plus retrieval practice: the guided condition is supplemented by scheduled unaided recall and problem-solving sessions.

The AI system, model version, prompts, settings, access restrictions, and task materials should be recorded. The same assessment rules must apply to all groups.

7.4 Measurement schedule and variables

Time point	Timing	Main measurement
T0	Before training	Unaided baseline score, prior expertise, confidence
T1	Immediately after training	Unaided score; assisted score recorded separately
T2	Two to four weeks later	Delayed unaided retention and transfer score
T3	After refresher practice	Unaided recovery score and confidence calibration

Primary outcome: independent skill score (0–100) under conditions in which AI is unavailable. Secondary outcomes include completion time, error count, error severity, transfer performance, confidence, and assisted performance. AI-use logs may include frequency, duration, proportion of suggestions accepted, and verification behavior. Practice logs should record frequency, spacing, duration, and task variety.

7.5 Operational definitions

Construct	Operational definition
Deterioration	Decrease in unaided score relative to the selected reference assessment.
Retention	Unaided performance preserved at delayed follow-up relative to post-training performance.
Adaptation	Change in performance when task format or context is modified.
Recovery	Improvement in unaided performance between delayed assessment and post-refresher assessment.
Resilience	Capacity to maintain or restore unaided performance when AI availability is reduced.
AI dependence	A preregistered composite of reliance indicators, such as accepted suggestions and low verification frequency.

7.6 Statistical and network analysis

The repeated-measures component can be analyzed with a mixed-effects model. Let Y_it denote the independent score for participant i at time t. A proposed model is:

$$Y_{it} = \beta_0 + \beta_1 Time_t + \beta_2 Condition_i + \beta_3 \Pr actice_{it} + \beta_4 (Time_t \times Condition_i) + u_i + \varepsilon_{it}$$

Here u_i is a participant-specific random intercept and ε_{it} is residual error. Task-level random effects may be added when participants complete multiple tasks. The model should report estimated contrasts, confidence intervals, exact p-values, model diagnostics, and missing-data procedures.

For the graph analysis, each participant or assessment wave may be represented by a network of constructs. Continuous variables should be standardized; edge estimation and any thresholding rule must be preregistered. Bootstrap intervals or stability analysis should be used to assess the robustness of centrality rankings. If the sample is too small for stable

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network estimation, the graph should remain descriptive or be treated as a conceptual model rather than over-interpreted.

7.7 Validity, reliability, and ethics

Use common task instructions, equivalent task difficulty, and blinded scoring where possible. Rubric-based outcomes should be checked for inter-rater reliability. Pilot testing should identify ceiling and floor effects. AI conversations and usage logs should be collected only with informed consent and appropriate privacy safeguards. Hypotheses, primary outcomes, network construction choices, and analysis rules should be preregistered where feasible.

VIII. ILLUSTRATIVE DATA AND ANALYSIS

No real participant observations were provided with the source manuscript. To make the proposed analysis concrete, this section introduces a synthetic example for 120 hypothetical participants (30 per condition). The values are generated for demonstration and must not be represented as measured findings, evidence of effectiveness, or results from an actual experiment.

8.1 Synthetic independent-skill scores

Assessment	Independent work	High AI assistance	Guided AI assistance	Guided + retrieval
T0 Baseline	61	61	61	61
T1 Post-training	72	79	78	78
T2 Delayed	68	62	72	76
T3 Refresher	70	68	77	83

Table 2. Synthetic group means on a 0–100 unaided skill scale. The same illustrative baseline mean is used for all four groups to simplify the demonstration. Standard deviations and inferential statistics are intentionally omitted because no participant-level observations were collected.

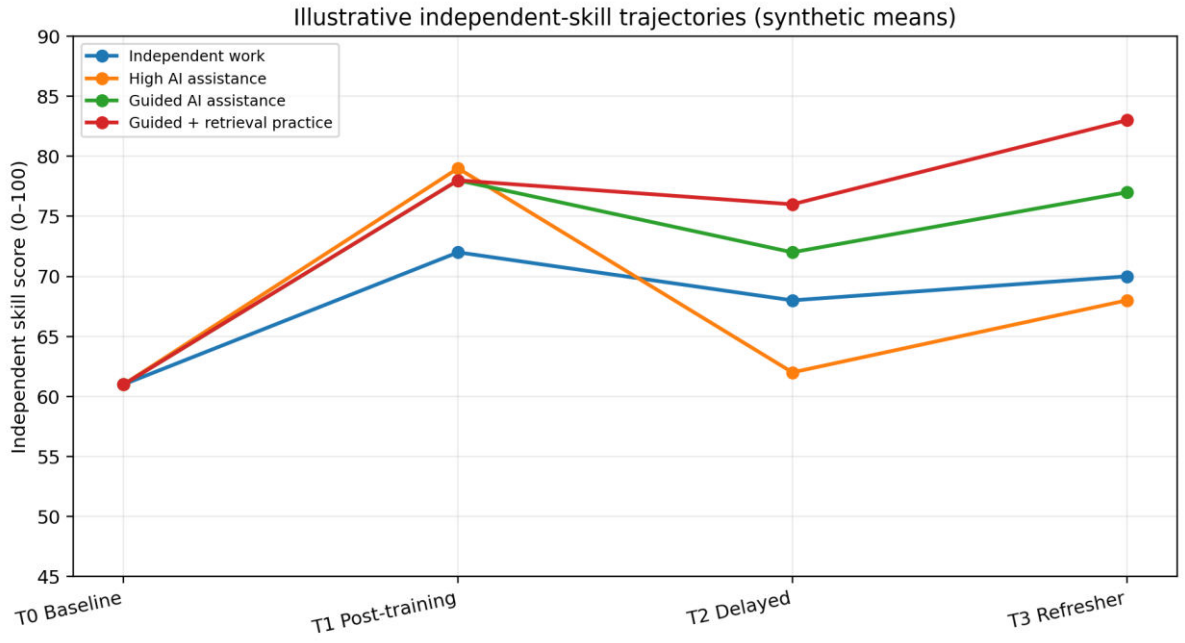


Figure 3. Synthetic trajectories showing how independent performance could be displayed across four assessment occasions.

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8.2 Descriptive change indicators

Condition	T0→T1 change	T1→T2 change	T2→T3 change	Net T0→T3
Independent work	11	-4	2	9
High AI assistance	18	-17	6	7
Guided AI assistance	17	-6	5	16
Guided + retrieval practice	17	-2	7	22

The synthetic trajectories illustrate several patterns that a real study could test: immediate gains may occur in all conditions; delayed unaided scores may differ; and refresher practice may be followed by recovery. In this constructed example, the guided-plus-retrieval condition has the largest net change from baseline. This is a property of the chosen synthetic values and is not evidence that this condition is superior.

8.3 Graph-based interpretation plan

For real observations, the association network could be estimated using standardized relationships among practice, AI dependence, verification, feedback, task complexity, and independent performance. A high strength value for practice would indicate that practice is associated with several other measured constructs or has strong weighted links. A high betweenness value for verification could indicate that it connects AI-use behavior with performance-related variables. Such interpretations should be reported cautiously and checked for stability.

A useful extension is to compare networks across time points or assistance conditions. For example, researchers may examine whether the association between independent practice and independent performance becomes weaker in a high-assistance condition. Formal comparison requires adequate sample size, comparable measurement, and a validated network-comparison procedure.

8.4 What can and cannot be concluded

The synthetic table demonstrates reporting structure only. It cannot support claims about actual deterioration, retention, recovery, statistical significance, effect size, or causal impact. Those conclusions require the planned study to be conducted and the model to be fitted to observed data. The graph figures are conceptual illustrations, not estimated networks.

IX. DISCUSSION

The proposed framework treats human competence as a changing capability that can be strengthened, maintained, or weakened depending on task exposure and learning conditions. Its central safeguard is the separation of AI-assisted output from unaided performance. This distinction prevents an organization from interpreting a high-quality AI-supported result as proof that the user can independently reproduce the task.

The graph model adds a relational perspective. Practice, retrieval, feedback, verification, cognitive offloading, and task complexity may operate together rather than independently. Centrality and density measures provide a compact description of the resulting structure. However, the graph should complement—not replace—longitudinal statistical analysis and experimental design.

In practical settings, AI systems can be configured to preserve meaningful human participation. Examples include asking users to attempt a solution before viewing a suggestion, requiring a short explanation of accepted recommendations, providing feedback rather than complete answers, and scheduling unaided practice. These are design options to be evaluated, not universal prescriptions. Prior work on learning and automation provides reasons to test these safeguards [1], [3], [5].

9.1 Limitations

The framework has several limitations. First, the proposed graph structure is conceptual until edge weights are estimated from data. Second, centrality scores can be unstable in small samples and sensitive to variable selection and edge-estimation methods. Third, findings from one skill domain may not generalize to another. Fourth, participants

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may change their behavior because they know they are being observed. Finally, AI tools evolve quickly, so system version and interaction settings must be documented.

X. CONCLUSION AND FUTURE WORK

This paper presents a graph-theoretic framework for studying human skill dynamics in AI-supported environments. It models AI assistance, cognitive offloading, independent practice, retrieval, feedback, verification, task complexity, expertise, and skill outcomes as connected constructs. Degree, strength, betweenness centrality, and density offer descriptive measures of network structure, while a longitudinal mixed-effects design evaluates changes in independent performance. A synthetic example demonstrates how results may be tabulated without misrepresenting constructed values as empirical evidence.

Future work should collect longitudinal data in a clearly defined task domain, validate the measurement instruments, estimate weighted networks from observed relationships, compare network structure across assistance conditions, and assess whether network indicators improve prediction of delayed independent performance. Researchers may also investigate directed or temporal networks when the data support directional or time-dependent relationships. The framework should be considered a testable proposal until these studies are completed.

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