Cycle-Aware Comparison of Acyclic and Reciprocal Competency Pathways for Construction Human–Robot Collaboration Training

Ebenezer Olukanni, Abiola Akanmu, Ph.D., and Houtan Jebelli, Ph.D.

Abstract— **Preparing construction personnel to work with robots requires not only identifying relevant competencies but also understanding how they relate, including where intermediate competencies or nonsequential relationships may occur. This study compares independently developed theory-driven and expert-derived dependency networks constructed from the same 50 construction human–robot collaboration (HRC) competencies. The networks contained 78 theory-driven relationships generated from systematic instructional logic and 99 expert-derived relationships obtained through a Delphi process. Of 49 direct theory-driven relationships that did not appear as direct expert relationships, 30 (61.2%) were represented through longer same-direction expert pathways. Of 97 theory-reachable competency pairs, 25 retained strict same-direction expert pathways, 48 were mutually reachable, 23 appeared only in reverse, and one was unresolved. The theory network was reducible to 40 relationships without losing reachability, whereas the expert network contained nine reciprocal groups involving 38 of 51 contextualized nodes. These findings show that differences between independently derived competency networks can reflect intermediate competencies, directional differences, or reciprocal structures, providing a more defensible basis for organizing HRC training than treating every dependency as a fixed prerequisite.**

Keywords*— *Human–robot collaboration (HRC), Competency dependency networks, Construction robotics, Cycle-aware pathway analysis

I. Introduction

Construction robots are increasingly being developed for inspection, layout, material transport, fabrication, assembly, and other on-site operations. Despite increasing autonomy, humans remain responsible for supervising robots, interpreting system information, coordinating work, and intervening under uncertain or unsafe conditions [1, 2]. Effective construction human–robot collaboration (HRC) therefore requires preparing personnel to interact with robotic systems safely and effectively.

Previous research has identified construction HRC competencies spanning robot applications, sensors, control, human–robot interfaces, task planning, programming, communication, safety, teamwork, decision-making, spatial awareness, adaptability, and continuous learning [3-6]. Academic and industry experts may also emphasize specific knowledge, skills, and abilities differently [3, 4, 6]. However, these studies establish what personnel need to know and do, not how competencies should be connected for training—whether one provides a foundation for another, an intermediate competency links them, or interdependence precludes a fixed order. Directed prerequisite networks have been used in other educational contexts to represent progression and otherwise hidden curricular structures [7, 8].

This study compares two dependency networks independently developed from the same construction HRC competency set using different evidence sources. The theory-driven network combined semantic similarity, cognitive progression, knowledge–skill–ability relationships, and instructional constraints to systematically represent competency progression, whereas the expert-derived network was independently developed through a Delphi process. Neither is treated as ground truth. Rather, they provide complementary evidence: the theory network offers a systematic candidate structure for training and computational reasoning, while the expert network incorporates practice-informed judgments about construction work, robotics, safety, and workforce preparation.

Comparing them can reveal shared progression, expert-identified intermediate relationships, and differences in directionality. This is important because relying solely on theory may omit relationships identified by experts, while directly translating a highly reciprocal expert network into prerequisites may impose fixed orders where none are supported. For example, one network may directly connect Human–Robot Communication Knowledge to Communication Ability, whereas another may connect Human–Robot Communication Knowledge to Human–Robot Interaction Skill, then to Communication Ability, with a return relationship to Human–Robot Communication Knowledge, forming a reciprocal cycle. Both connect the same competencies, but the first represents a direct, acyclic progression, while the second introduces an intermediate competency and reciprocal development. Thus, networks involving the same competencies may encode different assumptions about progression, intermediate dependencies, directionality, and reciprocity and should not be interpreted as supporting the same fixed prerequisite order. These forms of correspondence must therefore be distinguished before competency networks are used to organize construction HRC training or computational competency-reasoning systems. This study therefore compares the pathway structures of the independently derived theory-driven and expert-derived construction HRC competency networks. Three research questions (RQs) guide the study:

- RQ1: How much competency progression is shared between the theory-driven and expert-derived networks, including progression represented through intermediate pathways?

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- RQ2: How do the theory-driven and expert-derived networks differ in the direction of competency progression?
- RQ3: What training structure is supported by the observed pathway similarities and directional differences?

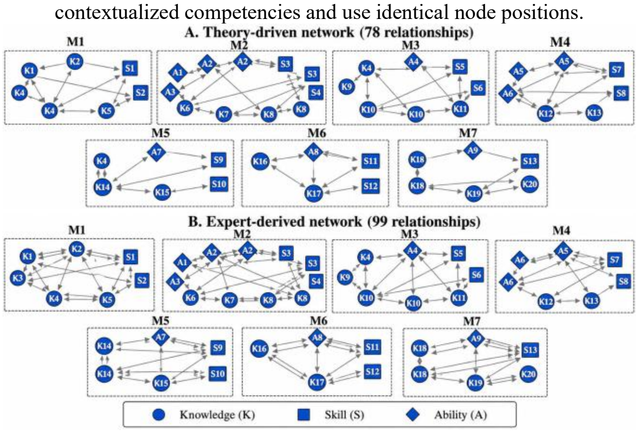
The study contributes a cycle-aware pathway comparison that goes beyond matching individual relationships. It distinguishes broader progression represented at different levels of detail from relationships that differ in direction or occur within reciprocal structures. This distinction can help training designers identify candidate ordered pathways, possible intermediate competencies, and relationships that should not yet be treated as fixed prerequisites.

II. METHODS

A. Network Data and Scope

The study analyzed two directed dependency networks containing 50 unique construction HRC competencies organized into seven instructional modules [9]. The theory-driven network contained 78 directed relationships generated from semantic similarity, cognitive progression, knowledge–skill–ability ordering, and module constraints. The expert-derived network contained 99 directed relationships obtained through a Delphi process. Let the two networks be denoted by $G_T = (V, E_T)$ and $G_E = (V, E_E)$, where V is the common set of module-contextualized competencies, and E_T and E_E are the theory-driven and expert-derived relationship sets, respectively. The edge weights represented different constructs. Theory weights represented semantic similarity, while expert weights represented Delphi consensus. They were therefore retained in their original meanings and not combined or interpreted as equivalent measures of relationship strength. Problem-solving appeared in both Modules 4 and 5. The two occurrences were represented separately as *M4: A4 and M5: A5*, producing 51 module-contextualized nodes representing 50 unique competencies. All relationships analyzed were intra-module. The theory network was a directed acyclic graph, whereas the expert network contained reciprocal relationships and larger directed cycles. Figure 1 shows the two networks using identical competency positions so that differences between panels reflect differences in relationships.

Figure 1. Theory-driven and expert-derived intra-module construction HRC competency networks. Both panels contain the same module-contextualized competencies and use identical node positions.



B. Reachability and Indirect Path Correspondence

To examine pathway correspondence, reachability between two distinct competencies in a directed network G was defined as

$$r_G(u,v) = \begin{cases} 1, & \text{if a directed path exists from } u \text{ to } v, \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

The corresponding set of reachable ordered competency pairs was

$$\mathcal{R}_G = \{(u,v) \in V \times V : u \neq v,\ r_G(u,v) = 1\}. \quad (2)$$

Direct-edge and path-level correspondence between the networks were summarized using Jaccard similarity:

$$J_{\text{edge}} = \frac{|\, E_T \cap E_E \,|}{|\, E_T \cup E_E \,|}, \quad J_{\text{reach}} = \frac{|\, \mathcal{R}_T \cap \mathcal{R}_E \,|}{|\, \mathcal{R}_T \cup \mathcal{R}_E \,|}. \quad (3)$$

Because the networks differed in the number of reachable pairs, directional coverage was also calculated:

$$C_{E|T} = \frac{|\, \mathcal{R}_T \cap \mathcal{R}_E \,|}{|\, \mathcal{R}_T \,|}, C_{T|E} = \frac{|\, \mathcal{R}_T \cap \mathcal{R}_E \,|}{|\, \mathcal{R}_E \,|}. \quad (4)$$

Here, $C_{E/T}$ measures the proportion of theory-reachable pairs also represented in the same direction in the expert network, while $C_{T/E}$ measures the reverse coverage.

Direct relationship disagreement was then examined at the path level. Let the minimum number of expert edges required to reach v from u be $d_E = (u, v)$. A direct theory-driven relationship was classified as having an indirect expert substitution when

$$(u,v) \in E_T/E_E, \quad r_E = (u,v) = 1, \quad d_E = (u,v) \geq 2 \quad (5)$$

The shortest expert path and its intermediate competencies were recorded. This distinguished relationships that were genuinely absent in cases where the expert network represented the same broader progression at a finer level of detail.

C. Cycle-Aware Directional Classification

Path correspondence alone does not establish directional agreement because the expert network contains cycles. Every ordered pair reachable in the theory network was therefore classified according to its complete directional status in the expert network:

$$\Gamma_E(u,v) = \begin{cases} \text{Strict,} & r_E(u,v) = 1 \text{ and } r_E(v,u) = 0, \\ \text{Mutual,} & r_E(u,v) = 1 \text{ and } r_E(v,u) = 1, \\ \text{Reverse-only,} & r_E(u,v) = 0 \text{ and } r_E(v,u) = 1, \\ \text{Unresolved,} & r_F(u,v) = 0 \text{ and } r_F(v,u) = 0. \end{cases} \quad (6)$$

A strict pair retained the theory direction without an expert return path. A mutual pair was reachable in both expert directions. A reverse-only pair was represented only in the direction opposite to that of the theory network. An unresolved pair had no expert path in either direction. Mutual reachability was treated only as a structural property. It does not establish that the competencies should be taught simultaneously or that learning one causes development of the other.

D. Reachability-Preserving Structure and Null-Model Test

Because the theory network was acyclic, transitive reduction was used to remove relationships that did not contribute unique reachability. If $TR(G_T)$ denotes the transitive reduction of the theory network, then

$$\mathcal{R}_{TR(G_T)} = \mathcal{R}_{G_T}. \quad (7)$$

The expert graph required a different procedure because it contained cycles. Strongly connected components were identified using the depth-first-search algorithm developed by Tarjan [10]. A strongly connected component $S \subseteq V$satisfied

$$r_{\mathrm{E}}(u,v) = 1 = r_{\mathrm{E}}(v,u) = 1 \quad \forall u,v \in S, u \neq v. \qquad (8)$$

Each component was then collapsed into a macro-node, producing an acyclic condensation graph. Transitive reduction was applied to the condensation graph to identify a reachability-preserving progression among the structurally reciprocal competency groups. Finally, a 10,000-run module-preserving permutation test evaluated whether observed direct and path correspondence exceeded that expected under the selected null model. Expert competency labels were randomly reassigned within their original modules while the expert topology was preserved. For an observed statistic $\mathrm{M}_{\mathrm{obs}}$, the one-sided empirical probability was calculated as

$$p_{\mathrm{emp}} = \frac{\sum_{b=1}^{B} \mathbf{1}\left(M_b \geq M_{\mathrm{obs}} \right)}{B}, B = 10{,}000 \qquad (9)$$

where M_b is the statistic obtained from permutation *b*. The null model was used to qualify claims of overall network correspondence, not to determine the interpretation of individual relationships.

III. Results and Discussion

A. Path Correspondence Across the Two Networks

The theory and expert networks shared 29 same-direction direct relationships, resulting in J_{edge} of 0.196. The theory network contained 97 reachable ordered competency pairs, whereas the expert network contained 235. Seventy-three ordered pairs were reachable in the same direction in both networks. Thus, $C_{E/T}$ = 75.3%, while $C_{T/E}$ = 31.1%. Reachability similarity was 0.282, compared with the direct-edge similarity of 0.196.

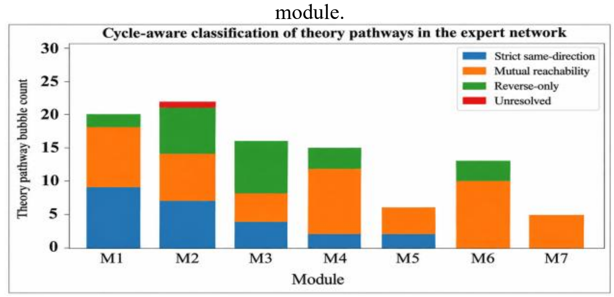
The increase from direct-edge to reachability similarity indicates that some correspondence becomes visible only when complete pathways are considered. However, the asymmetric coverage values also indicate that the expert network exhibits substantially greater reachability than the theory network. This becomes clearer when the 49 theory relationships, absent as direct expert edges, are examined. Thirty of the 49, or 61.2%, were represented through longer same-direction expert pathways. Twenty-one substitutions contained two expert edges, eight contained three, and one contained four. For example, the theory network contained a direct relationship from Safety management to Safety awareness. The expert network represented the progression as ‘Safety management’ to ‘HRC safety and standards’ to ‘Safety awareness’. Similarly, the direct theoretical relationship from Sensors to Spatial awareness was represented through the shortest expert pathway: ‘Sensors’ to ‘Communication modes and technologies’ to Human–robot interface’ to ‘Spatial awareness’. These examples illustrate an important distinction. An immediate relationship that appears in only one network does not necessarily indicate a completely different progression. The independently derived expert structure may retain the same source-to-target progression while introducing intermediate competencies. For HRC training, those intermediate competencies may be consequential. The safety pathway places HRC safety-and-standards knowledge between safety management and safety awareness. The sensing pathway places communication and interface knowledge between sensor knowledge and spatial awareness. The analysis does not establish that these are validated instructional sequences, but it identifies relationships that warrant consideration when organizing training content. RQ1, therefore, shows that a substantially broader pathway correspondence exists even where direct relationship matching suggests disagreement.

B. Directional Agreement, Reciprocity, and Reversal

The 75.3% same-direction coverage reported under RQ1 does not mean that the two networks agreed on a unique direction for 75.3% of theory progression. Of the 97 theory-reachable competency pairs, only 25 (25.8%) retained strict same-direction progression, supporting a candidate ordered progression; 48 (49.5%) were mutually reachable, supporting no unique order; 23 (23.7%) appeared only in the reverse direction, indicating that direction differed across evidence sources; and one (1.0%) was unresolved, requiring additional evidence. The result changes the meaning of the 73 same-direction reachable pairs. Forty-eight also contained a return pathway in the expert network. Consequently, only 25 retained a unique direction.

The directional pattern also varied across modules (Fig. 2). Module 1 contained nine strict, nine mutual, and two reverse-only pairs. Module 2 contained seven strict, seven mutual, seven reverse-only, and the only unresolved pair. Module 3 showed the strongest reversal, with eight reverse-only pairs among 16 theory-reachable pairs. Module 4 contained only two strict pairs but ten mutual pairs. Module 5 contained three strict and three mutual pairs. Module 6 contained no strict pairs, ten mutual pairs, and three reverse-only pairs, while all five Module 7 pairs were mutual.

Figure 2. Cycle-aware directional classification of theory-reachable competency pairs in the expert-derived network by HRC instructional module.



These differences suggest that one sequencing assumption is unlikely to fit the entire HRC competency framework. Foundational robot competencies contained comparatively more uniquely directed pathways, whereas several systems-, safety-, regulatory-, and implementation-related competency groups were embedded in mutually reachable structures. Network analysis cannot establish why a particular reversal or reciprocal relationship occurs. Nor does mutual reachability prove simultaneous learning. It establishes a narrower but important result: the available expert network does not support interpreting those relationships as one unique progression. RQ2, therefore, shows that pathway correspondence and directional correspondence are distinct. The networks can connect the same competencies while organizing their direction differently.

C. Training Structure Supported by the Combined Evidence

The structural analyses further showed that the two networks cannot be reduced or interpreted equivalently. Transitive reduction of the theory network reduced 78 edges to 40 while preserving all 97 reachable competency pairs, indicating that 38 relationships were redundant to its encoded progression. In contrast, the expert network contained nine nontrivial strongly connected components (sizes 7, 5, 5, 4, 4, 4, 4, 3, and 2), involving 38 of 51 contextualized nodes. Collapsing these mutually reachable structures produced an acyclic condensation graph of 22 macro-nodes and 22 macro-relationships, which transitive reduction further reduced to 15. These quantities are not directly comparable: the 40 theory edges connect individual competencies, whereas the 15 expert relationships connect collapsed groups of mutually reachable competencies.

Together, the analyses support five relationship interpretations for construction HRC training: (1) directly aligned pathways, where both networks share the same immediate direction; (2) mediated pathways, where the expert network retains the broader progression through intermediate competencies; (3) strict pathways, where the expert network preserves the theory-implied direction without a return path; (4) mutual pathways, where expert paths occur in both directions and do not support a fixed prerequisite order; and (5) reverse-only or unresolved pathways, where the evidence sources do not support the same progression and additional evidence is needed before imposing a training order. The null-model results also qualify the interpretation of overall agreement. The observed number of shared direct edges was 29, compared with a null mean of 24.59 ($p = 0.131$). The observed number of shared reachable pairs was 73, compared with a null mean of 68.20 ($p = 0.261$). Correspondingly, the observed direct-edge Jaccard similarity of 0.196 and reachability Jaccard similarity of 0.282 did not exceed the selected module-preserving null expectation at conventional significance levels. The study does not claim broad statistical agreement; rather, it identifies how independently derived competency structures relate and why these relationships require different treatment in training design. RQ3 therefore indicates that construction HRC training is better represented by a typed competency structure than a universal prerequisite graph.

IV. Conclusion

Preparing construction personnel to work with robotic systems requires not only identifying relevant competencies but also understanding how they are connected. This study compared two independently developed dependency networks from the same construction HRC competency set. The theory-driven network provided an acyclic representation of competency progression, whereas the expert-derived network contained substantial reciprocal connectivity. Three findings emerged from this study. First, the networks shared broader progression than direct relationship matching suggested, with some theory relationships represented through longer same-direction expert pathways containing intermediate competencies. Second, broader pathway correspondence did not imply directional agreement because many expert pathways were reciprocal or reversed rather than uniquely ordered. Third, the networks supported complementary structures: an acyclic competency progression in the theory network and reciprocal competency groups connected by an acyclic macro-level progression in the expert network. The main contribution is a cycle-aware approach for interpreting multiple evidence sources when organizing construction HRC training. It distinguishes direct alignment, mediated progression, strict direction, mutual reachability, reversal, and unresolved relationships, providing a basis for identifying candidate prerequisites, intermediate competencies, and relationships requiring further validation. The findings remain structural: reachability does not establish causal learning relationships, and the pathways have not been validated against learner, robot-task, or safety performance. The analysis was also limited to intra-module relationships and one expert-derived network. Future work should test whether these pathway types predict competency development and performance during construction HRC.

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