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# Competency Reconstruction and Industry–Education Alignment for Innovation and Entrepreneurship Talent in the Automotive Industry

**Huang Rong[1,a], Liao Shuangshuang[1,b], Mao Shuai[1,c,*]**

*[1]Hubei University of Automotive Technology, Shiyan, China*
*[a]20122004@huat.edu.cn, [b]15272698264@163.com, [c]20120014@huat.edu.cn*
**Corresponding author*

***Abstract:*** *Rapid advances in new-energy vehicles, intelligent connectivity, software-defined vehicles, and data-driven engineering are reshaping competency requirements in the automotive industry. This study uses a sequential mixed-methods design to identify a competency framework and assess perceived industry–education alignment. The qualitative phase draws on 34 semi-structured interviews with 10 enterprise professionals, 10 university faculty members, and 14 students. Interview records were anonymized and condensed during data preparation; semantically similar responses were summarized rather than treated as verbatim transcripts. The qualitative evidence and the actual survey instrument yielded nine competencies organized into three interrelated domains: industry insight, intelligent innovation, and ecosystem collaboration. The quantitative phase analyzed 197 valid questionnaires (72 enterprise professionals, 61 faculty members, and 64 students). Enterprise ratings of competency importance are used as a perceptual proxy for industry demand, whereas faculty and student ratings of current university cultivation are used as a perceptual proxy for educational provision. Welch tests, 95% confidence intervals, Hedges' g, Holm adjustment, importance–performance analysis (IPA), and 3,000 stratified bootstrap replications are employed. All nine perceived demand–provision gaps are statistically significant. The largest gaps concern university–industry collaborative practice (Δ=1.216), data-driven innovation (Δ=1.158), and intelligent tool application (Δ=1.065). These three competencies are also located in the high-importance/low-provision quadrant, with bootstrap priority probabilities of 99.7%, 100.0%, and 96.9%, respectively. Parallel analysis indicates one dominant common factor and the candidate three factors are highly correlated, so the three-domain structure is interpreted as a theoretically and qualitatively grounded content framework rather than three fully distinct latent constructs. The mismatch is structural rather than generalized: provision is relatively stronger in industry cognition but weaker in data-driven, technology-enabled, and authentic collaborative practice.*

***Keywords:*** *New Quality Productive Forces, Automotive Industry, Innovation and Entrepreneurship Talent, Competency Framework, Industry–Education Alignment, Importance–Performance Analysis*

## 1. Introduction

The automotive industry is undergoing a rapid reconfiguration of its technological and organizational foundations. New-energy vehicles, intelligent connectivity, artificial intelligence, industrial software, and data-intensive engineering increasingly shape research and development, manufacturing, supply chains, and mobility services. Recent Chinese studies have examined the implications of new quality productive forces from the perspectives of graduate skill demand, human-capital restructuring, higher-education digitalization, and university–regional coordination [1–2,5–6], while research on vocational education and industry–education integration emphasizes technological innovation, skilled-talent development, and collaborative training mechanisms [3–4,7–8]. International research on Industry 4.0 similarly shows that skill gaps are multi-stakeholder and context dependent and that they cannot be understood adequately through isolated skill lists or a single stakeholder perspective [9]. Automotive-sector studies further indicate that technical and digital competencies increasingly coexist with systems thinking, communication, collaboration, adaptability, and problem-solving requirements [10–11].

Three limitations remain in the relevant literature. First, much of the discussion of new quality productive forces and talent development remains at the macro-policy or institutional level, leaving limited micro-level evidence on how competency requirements are configured within specific industries. Second, studies often examine either employer expectations or educational outcomes, whereas fewer

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studies operationalize demand and educational provision within a common competency framework. Third, identified gaps are frequently reported as rankings or mean differences without testing whether high-priority classifications are stable to sampling variation. Recent reviews therefore call for multi-method and multi-stakeholder approaches to skill-gap measurement [9]. Existing gap studies and IPA-based higher-education research further show that placing industry requirements and education-side performance within a comparable framework can help translate diagnosis into curriculum priorities [12–13].

This study asks three questions: What competency structure characterizes automotive innovation and entrepreneurship talent? Where are the main gaps between perceived industry demand and university educational provision? Which competencies should receive priority in curriculum and industry–education reform? It develops a qualitatively grounded three-domain, nine-competency framework and links it to a quantitative alignment diagnosis.

## 2. Literature Review and Analytical Framework

### *2.1. New Quality Productive Forces and Changing Competency Requirements*

Recent Chinese research identifies several distinct mechanisms through which education may support new quality productive forces. Human-capital restructuring is emphasized as a key higher-education mechanism [2]; digital transformation is associated with the reconfiguration of talent development, data resources, and educational ecosystems [6]; and university–regional coordination and deeper industry–education integration are discussed as routes to improving alignment between educational provision and industrial development [5,8]. Related vocational-education studies reach comparable conclusions from the perspectives of technological innovation, skilled-talent development, and collaborative training [3–4,7]. Recruitment-platform evidence further suggests that positions associated with new quality productive forces place strong emphasis on applied skills and on complementary combinations of knowledge, skills, and broader qualities [1].

The automotive industry offers a particularly relevant setting because digital technologies are tightly coupled with complex physical products and interorganizational production systems. Research in the Thai automotive sector shows that Industry 4.0 changes the knowledge and skill profiles required of industrial engineers, including technological foundations, systems thinking, learning, and communication [10]. Qualitative evidence from the Indian automotive industry similarly indicates that digitalization heightens rather than eliminates the importance of human skills such as problem solving, communication, collaboration, resilience, and rapid decision making [11]. These findings suggest that competency transformation is better understood as a reconfiguration of complementary capabilities than as the simple addition of several digital skills.

### *2.2. Skill Gaps and Industry–Education Alignment*

A skill gap requires an explicit reference point: skills demanded by employers or industries must be distinguished from skills possessed, developed, or perceived on the education side. A recent review of Industry 4.0 skill-gap research emphasizes continuing ambiguity in definitions and measurement and calls for stronger integration of stakeholder perspectives and methods [9]. Empirical work in engineering education has shown that comparing industry expectations with graduate competencies can reveal curriculum priorities, including weaknesses in data use and analytics [12]. IPA-based higher-education research likewise demonstrates how importance and performance information can be translated into strategic improvement priorities [13].

Accordingly, this study uses deliberately bounded constructs. Perceived industry demand is operationalized as enterprise professionals' ratings of the importance of each competency. Perceived educational provision is operationalized as faculty and student ratings of the extent to which universities currently cultivate the same competencies. Their difference is therefore a perceived demand–provision gap, not an objective labor shortage, an objective test of student competence, or a causal effect.

### *2.3. A Three-Domain Competency Framework*

The qualitative evidence and survey content organize nine competencies into three interrelated domains. Industry insight includes awareness of industrial technological change, automotive industry-chain understanding, and policy/regulation/standards awareness. Intelligent innovation includes data-

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driven innovation, intelligent tool application, and cross-boundary integration design. Ecosystem collaboration includes university–industry collaborative practice, interdisciplinary teamwork, and commercialization and entrepreneurship. These domains are treated as substantively meaningful categories for analysis and curriculum design; empirical distinctiveness is assessed rather than assumed.

## 3. Research Design

### *3.1. Sequential Mixed-Methods Design*

The study follows a sequential mixed-methods design. Interviews identify recurring competency requirements and support the framework, while the survey evaluates importance, educational provision, perceived gaps, and improvement priorities.

### *3.2. Interview Participants and Data Preparation*

Thirty-four participants were interviewed: 10 enterprise professionals, 10 university faculty members, and 14 students. Enterprise participants represented vehicle manufacturers, component suppliers, and new-energy-vehicle-related firms and included roles in R&D, human resources, production management, and quality/project management. Interviews addressed perceived competency shortcomings of graduates, digital-tool use, interdisciplinary collaboration, enterprise participation in education, and project-based learning.

During data preparation, the records were anonymized and condensed. Responses expressing highly similar meanings were standardized into concise summaries while preserving their substantive content. The resulting dataset consisted of cleaned and summarized interview records rather than verbatim transcripts. Accordingly, condensed statements are not presented as direct quotations attributable to individual participants. The thematic analysis emphasized transparency and coherence between data preparation, coding, and interpretation [14]. Recurring themes included fragmented industry cognition, lagging knowledge renewal, limited access to first-hand industrial data, weak institutionalization of university–industry cooperation, insufficient teamwork training, limited faculty industrial experience, and uneven use of digital tools.

### *3.3. Competency Indicators and Questionnaire*

The final framework contains three domains and nine indicators. Importance was measured on a five-point Likert scale ranging from 1 (not important at all) to 5 (extremely important). Educational provision used the same nine indicators with a parallel five-point scale assessing the extent of current university cultivation. Using identical competency content for the two evaluations enables item-level alignment while preserving the conceptual distinction between importance and provision.

### *3.4. Sample and Analytical Strategy*

The dataset contains 197 complete responses: 72 enterprise professionals, 61 faculty members, and 64 students. All 18 rating variables are complete and fall within the specified 1–5 range, and no duplicate questionnaire identifiers were detected. Enterprise importance ratings are used as the perceptual proxy for industry demand (n=72); faculty and student provision ratings are pooled as the university-side proxy (n=125), with separate faculty/student analyses used for sensitivity checks.

The analysis proceeds in five steps. First, Cronbach's alpha, KMO, Bartlett's test, parallel analysis, and approximate factor-model diagnostics are used to assess internal consistency and dimensionality without equating reliability with structural validity. Second, one-way ANOVA describes stakeholder differences in importance ratings. Third, Welch independent-samples tests compare enterprise importance with university-side provision, with 95% confidence intervals, Hedges' g, and Holm-adjusted p values. Fourth, data-centered IPA uses the mean of the nine enterprise importance ratings and the mean of the nine university provision ratings as crosshairs. Fifth, 3,000 stratified bootstrap replications resample enterprise and university-side respondents independently and recalculate dynamic crosshairs in each replication to assess the stability of priority classifications. The qualitative themes and their mapping to the competency framework are summarized in Table 1.

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*Table 1: Interview Themes and Their Mapping to the Competency Framework.*

| Interview Theme | Participants Associated with Theme | Competency-Framework Mapping |
|---|---|---|
| Fragmented Industry Cognition and Weak Industry-Chain Framework | 27 | Industry Insight: Industry-Chain / Technological-Change Awareness |
| Knowledge Renewal Lagging Behind Industrial Iteration | 5 | Industry Insight: Technological-Change Awareness |
| Superficial Practice and Narrow Internship Roles | 21 | Ecosystem Collaboration: University–Industry Practice |
| Limited Access to First-Hand Industrial Data | 17 | Intelligent Innovation: Data-Driven Innovation |
| University–Industry Cooperation Dependent on Personal Ties | 20 | Ecosystem Collaboration: University–Industry Practice |
| Misaligned Assessment and Incentive Mechanisms | 26 | Ecosystem Collaboration: Commercialization / Collaborative Practice |
| Insufficient Teamwork Training and Contribution Assessment | 20 | Ecosystem Collaboration: Interdisciplinary Teamwork |
| Limited Industrial Experience Among Faculty | 28 | Cross-Domain Support for Industry Insight and Practice |
| Polarized Digital-Tool Use and Reliance on Self-learning | 20 | Intelligent Pnnovation: Intelligent Tool Application |

Note. Counts represent the number of participants associated with each theme based on the summarized thematic coding records.

## 4. Results

### *4.1. Measurement Diagnostics*

Cronbach's alpha is .914 for the nine importance items and .906 for the nine educational-provision items. Domain-level alphas for importance are .806, .821, and .845, while the corresponding provision alphas are .779, .779, and .822. For the nine importance items, KMO is .932 and Bartlett's test is significant, $\chi^2(36)=954.53$, $p<.001$.

Dimensionality evidence is mixed and is therefore interpreted conservatively. A 1,000-replication parallel analysis suggests one dominant factor. An approximate one-factor ML model yields $\chi^2(27)=61.45$, CFI=.963, RMSEA=.081. A theory- and content-based candidate three-factor model shows good approximate fit, $\chi^2(24)=16.66$, CFI=1.000, RMSEA=.000, but factor correlations are high (.840–.871). The three domains are therefore retained as interrelated substantive domains rather than claimed as fully discriminant latent constructs. The reliability and dimensionality diagnostics are reported in Table 2.

*Table 2: Reliability and Dimensionality Diagnostics.*

| Scale/Test | Items | Cronbach α | Statistic/Information | Factors | Fit Indices |
|---|---|---|---|---|---|
| Overall Importance | 9 | .914 | — | — | — |
| Overall Provision | 9 | .906 | — | — | — |
| Industry Insight (importance) | 3 | .806 | — | — | — |
| Intelligent Innovation (importance) | 3 | .821 | — | — | — |
| Ecosystem Collaboration (importance) | 3 | .845 | — | — | — |
| Industry Insight (provision) | 3 | .779 | — | — | — |
| Intelligent Innovation (provision) | 3 | .779 | — | — | — |
| Ecosystem Collaboration (provision) | 3 | .822 | — | — | — |

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| Scale/Test | Items | Cronbach α | Statistic/Information | Factors | Fit Indices |
|---|---|---|---|---|---|
| KMO | 9 | — | .932 | — | — |
| Bartlett | 9 | — | $\chi^2(36)=954.53$, $p<.001$ | — | — |
| Parallel Analysis | 9 | — | 1,000 permutations | 1 | — |
| One-Factor ML | 9 | — | $\chi^2(27)=61.45$ | — | CFI=.963; RMSEA=.081 |
| Candidate Three-Factor ML | 9 | — | $\chi^2(24)=16.66$ | 3 | CFI=1.000; RMSEA=.000 |

Note. Domain-level reliability is exploratory and follows the theory- and qualitative-based content grouping. Dimensionality diagnostics do not establish three fully discriminant latent constructs.

### *4.2. Stakeholder Perceptions of Importance*

No statistically significant mean differences were detected among enterprise professionals, faculty members, and students for any of the nine importance ratings. F statistics range from .288 to .646, all p values exceed .52, and $\eta^2$ ranges from .0030 to .0066. These nonsignificant findings do not establish equivalence or measurement invariance; the subsequent analysis therefore preserves the role-based distinction between enterprise demand and university-side provision.

### *4.3. Perceived Demand–Provision Gaps*

Enterprise respondents assigned the highest importance to intelligent tool application (M=4.569), data-driven innovation (M=4.542), and university–industry collaborative practice (M=4.472). The corresponding university-side provision means were 3.504, 3.384, and 3.256. By contrast, provision was relatively higher for awareness of industrial technological change (M=3.936), automotive industry-chain understanding (M=3.888), and policy/regulation/standards awareness (M=3.808). This pattern suggested a structural rather than uniform mismatch.

All nine Welch comparisons remained significant after Holm adjustment. The largest gaps were university–industry collaborative practice (Δ=1.216, 95% CI [1.045, 1.387], g=1.997), data-driven innovation (Δ=1.158, 95% CI [0.985, 1.330], g=1.932), and intelligent tool application (Δ=1.065, 95% CI [0.897, 1.234], g=1.786). Commercialization and entrepreneurship also showed a substantial gap (Δ=.932). These differences are interpreted as perceptual demand–provision gaps, not objective competency deficits.

### *4.4. IPA and Robustness*

Using mean crosshairs of 4.352 for demand and 3.570 for provision, IPA placed university–industry collaborative practice, data-driven innovation, and intelligent tool application in the high-demand/low-provision priority quadrant. Across 3,000 stratified bootstrap replications, their priority-classification probabilities were 99.7%, 100.0%, and 96.9%, respectively; the priority pattern was unchanged when faculty and student provision ratings were examined separately. The competency-level demand–provision gap results are reported in Table 3.

*Table 3: Perceived Demand–Provision Gaps, Effect Sizes, and Significance Tests.*

| Competency | Demand M (SD) | Provision M (SD) | Δ | 95% CI | Hedges' g | Holm p |
|---|---|---|---|---|---|---|
| Intelligent Tool Application | 4.569 (0.552) | 3.504 (0.617) | 1.065 | [0.897, 1.234] | 1.786 | <.001 |
| Data-Driven Innovation | 4.542 (0.580) | 3.384 (0.606) | 1.158 | [0.985, 1.330] | 1.932 | <.001 |
| University–Industry Collaborative Practice | 4.472 (0.556) | 3.256 (0.634) | 1.216 | [1.045, 1.387] | 1.997 | <.001 |
| Interdisciplinary Teamwork | 4.403 (0.643) | 3.584 (0.612) | 0.819 | [0.634, 1.003] | 1.309 | <.001 |
| Awareness of Industrial Technological Change | 4.333 (0.605) | 3.936 (0.592) | 0.397 | [0.222, 0.573] | 0.663 | <.001 |
| Cross-Boundary Integration Design | 4.278 (0.587) | 3.464 (0.547) | 0.814 | [0.646, 0.981] | 1.443 | <.001 |

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| Competency | Demand M (SD) | Provision M (SD) | Δ | 95% CI | Hedges' g | Holm p |
|---|---|---|---|---|---|---|
| Commercialization and Entrepreneurship | 4.236 (0.617) | 3.304 (0.710) | 0.932 | [0.742, 1.123] | 1.371 | <.001 |
| Automotive Industry-Chain Understanding | 4.208 (0.604) | 3.888 (0.585) | 0.320 | [0.146, 0.495] | 0.539 | <.001 |
| Policy, Regulation and Standards Awareness | 4.125 (0.649) | 3.808 (0.656) | 0.317 | [0.127, 0.507] | 0.483 | 0.001 |

Note. Enterprise demand n = 72; university-side provision n = 125. Two-sided Welch independent-samples tests were used, with Holm adjustment across nine comparisons. Δ denotes the perceived demand–provision rating gap rather than an objective labor-market shortage.

The IPA distribution of the nine competencies is shown in Figure 1.

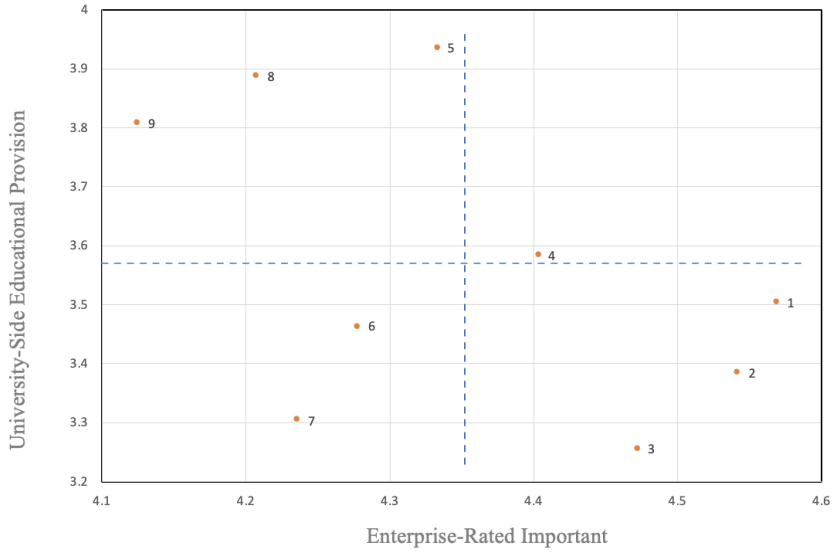



*Figure 1: Competency Demand–Provision IPA.*

Note. 1 = intelligent tool application; 2 = data-driven innovation; 3 = university–industry collaborative practice; 4 = interdisciplinary teamwork; 5 = awareness of industrial technological change; 6 = cross-boundary integration design; 7 = commercialization and entrepreneurship; 8 = automotive industry-chain understanding; 9 = policy, regulation, and standards awareness. Crosshairs represent the mean importance (4.352) and provision (3.570) scores.

## 5. Discussion

### *5.1. From Disciplinary Knowledge to Integrated Competency Portfolios*

The first finding is that automotive innovation talent requirements are not adequately represented by discipline-specific knowledge alone. Interview participants repeatedly referred to industry-chain understanding, knowledge renewal, authentic data, digital tools, and teamwork, while enterprise ratings placed intelligent tool application, data-driven innovation, and university–industry collaborative practice among the most important competencies. This pattern is consistent with automotive Industry 4.0 research showing that technological competencies, systems thinking, learning, and human collaboration increasingly operate as complements [10–11].

The dominant common factor and high inter-domain correlations caution against treating the three domains as independent latent constructs. The nine competencies appear to share an overarching orientation toward interdisciplinary automotive innovation, while the domains remain useful for content organization and curriculum diagnosis.

### *5.2. Structural Mismatch Rather Than Generalized Underprovision*

The most consequential result is the uneven distribution of gaps. University-side provision is relatively stronger for awareness of technological change, industry-chain understanding, and

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policy/standards knowledge, but substantially weaker relative to demand for data-driven innovation, intelligent tool application, and authentic university–industry practice. Universities therefore appear to be responding to industrial change at the level of knowledge and awareness, yet face greater difficulty in converting such knowledge into technology-enabled and practice-based capability.

This interpretation aligns with recent Industry 4.0 skill-gap research, which frames gaps as products of interacting educational, technological, organizational, and stakeholder conditions rather than isolated shortages [9]. It also echoes engineering-education evidence in which data use and analytics emerge as notable gaps between industry expectations and graduate competence [12]. The implication is that adding more content to existing courses is unlikely to be sufficient; the learning environment and task structure must also change.

### *5.3. The Bottleneck is Moving From Knowing to Doing and Collaborating*

The three stable IPA priorities share an action-oriented character. Intelligent tool application requires selecting and using digital tools in engineering tasks. Data-driven innovation requires converting data into analysis, judgment, and design decisions. University–industry collaborative practice requires completing work under authentic organizational processes, standards, deadlines, and resource constraints. These competencies are difficult to develop through lecture-based knowledge transmission alone.

Institutionally, authentic competence development requires sustained project sources, enterprise mentors, access to realistic data, interdisciplinary team organization, and process-based assessment. Chinese studies identify structural misalignment, collaboration barriers, and insufficient integration of innovation resources as persistent constraints on deeper industry–education integration [5,8], while research on digital transformation and vocational-education coordination proposes changes in learning environments and training mechanisms [6–7]. The present micro-level evidence shows how such institutional issues can materialize as a patterned competency-provision mismatch.

## 6. Conclusions and Implications

### *6.1. Main Conclusions*

Drawing on 34 interviews and 197 questionnaires, this study develops a three-domain, nine-competency framework for automotive innovation and entrepreneurship talent and diagnoses perceived alignment between enterprise demand and university educational provision. The dimensionality evidence suggests a strong common orientation across the nine competencies; the three domains are therefore better interpreted as interrelated content categories than as independent latent constructs. The main mismatch is structural rather than generalized: provision is relatively stronger in industry-related cognition but weaker in translating knowledge into data-driven innovation, intelligent tool use, and authentic university–industry collaboration. University–industry collaborative practice, data-driven innovation, and intelligent tool application show the most pronounced perceived gaps and remain stable priorities in the bootstrap IPA.

### *6.2. Implications for Talent Development*

The study contributes by translating the broad discussion of new quality productive forces into an automotive-specific competency framework and by linking competency identification with industry–education alignment using the same nine indicators. Talent development should therefore shift from adding knowledge content to redesigning the mechanisms through which competencies are formed. Universities can organize authentic enterprise projects, embed data-driven innovation in R&D, manufacturing, quality, and supply-chain contexts, teach intelligent tools through engineering problem solving, and use interdisciplinary teams and recurring stakeholder assessment to calibrate curricula. Competencies that persist in the high-demand/low-provision quadrant should receive priority in curriculum time, enterprise mentorship, and practice resources.

### *6.3. Limitations and Future Research*

Several limitations bound the findings. The sample is concentrated mainly in Hubei and surrounding areas and is not probability based, so national generalization should be cautious. Demand and provision are stakeholder perceptions rather than objective labor-market shortages, and the cross-sectional design

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cannot establish causality or temporal change. The discriminant validity of the three content domains also requires further testing with multi-item measures in independent samples, while the qualitative records were condensed after the interviews rather than retained as complete verbatim transcripts. Future research should broaden regional and firm coverage, combine recruitment data, curriculum evidence, student work, and longitudinal designs, and maintain fuller transcription and coding audit trails.

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