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The Mediating Role of Career Knowledge in the Relationships Between IoT Readiness, Career Preparation Behavior, and Career Readiness

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ABSTRACT

This study examines the role of Career Knowledge in linking IoT Readiness and Career Preparation Behavior with Career Readiness among final-year students of the Electrical Engineering Education Program at Universitas Negeri Malang. The study responds to the increasing need for graduates to combine technological competence with adequate career understanding and preparation in facing the demands of Industry 4.0. A quantitative cross-sectional survey design was employed, and the data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4 and 5,000 bootstrap subsamples. The participants consisted of 42 final-year students who had completed or were currently taking IoT-related courses. The results indicate that IoT Readiness significantly predicts Career Knowledge ($\beta = 0.478$, $p = 0.001$), while Career Preparation Behavior also significantly predicts Career Knowledge ($\beta = 0.403$, $p = 0.005$). Career Knowledge, in turn, significantly predicts Career Readiness ($\beta = 0.406$, $p = 0.034$). However, the direct effects of IoT Readiness and Career Preparation Behavior on Career Readiness were not statistically significant. The indirect effect through Career Knowledge was not significant for IoT Readiness at either the 5% or 10% level ($p = 0.103$), whereas the indirect effect for Career Preparation Behavior was not significant at the 5% level and only approached the exploratory 10% level ($p = 0.099$). Therefore, the mediation pattern should be regarded as preliminary evidence requiring confirmation with a larger sample. The model explained 59.7% of the variance in Career Readiness, indicating substantial explanatory power within the studied sample.

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1. INTRODUCTION

The rapid advancement of the Industrial Revolution 4.0 has fundamentally transformed the global industrial landscape, particularly in the electrical engineering sector. The widespread adoption of the Internet of Things (IoT) technology has created new demands for highly skilled graduates who possess not only strong technical competencies but also high levels of career readiness. Career readiness has emerged as a critical factor in bridging the gap between higher education outcomes and the requirements of the modern workforce. In the context of vocational education in Indonesia, especially within Electrical Engineering Education programs, preparing students to face the challenges of the digital era has become an urgent priority.

Despite the growing importance of IoT in industry, many final-year students still face difficulties in translating their technical knowledge into practical career preparedness. Previous studies have highlighted that factors such as technology readiness and proactive career behaviors play significant roles in shaping students' career trajectories. However, the mechanism through which these factors influence career readiness—particularly through the mediating role of career knowledge—remains underexplored, especially in the Indonesian vocational education context.

This study is grounded in Social Cognitive Career Theory (SCCT) and Career Adaptability Theory. It specifically investigates the mediating effect of career knowledge on the relationships between IoT Readiness, Career Preparation Behavior, and Career Readiness among final-year Electrical Engineering Education students at Universitas Negeri Malang. By examining these relationships, the present research seeks to provide both theoretical contributions to the existing literature on career development in the Industry 4.0 era and practical recommendations for curriculum enhancement in vocational higher education institutions.

The remainder of this paper is organized as follows. Section 2 presents the literature review and research hypotheses. Section 3 describes the research methodology. Section 4 reports and discusses the empirical results, including the limitations of the study and directions for future research. Finally, Section 5 concludes the study with theoretical and practical implications.

2. LITERATURE REVIEW AND HYPOTHESES

The present study is grounded in two prominent theoretical frameworks in career development research: Social Cognitive Career Theory (SCCT) proposed by Lent et al. [1] and Career Adaptability Theory developed by Savickas [2]. Social Cognitive Career Theory emphasizes the dynamic interplay among personal, behavioral, and environmental factors in shaping career-related interests, choices, and performance [3], [4]. Within this framework, self-efficacy, outcome expectations, and personal goals play central roles in career development. Career Adaptability Theory, on the other hand, focuses on individuals' capacity to adjust to changing career conditions through four key psychosocial resources: concern, control, curiosity, and confidence (the "4Cs").

In the context of Industry 4.0, IoT Readiness represents a critical environmental and technological factor that influences students' career development [5], [6], [7], [8]. IoT Readiness is defined as the extent to which individuals possess the knowledge, skills, and attitudes necessary to effectively engage with Internet of Things technologies [9], [10], [11]. Students with higher IoT Readiness are expected to demonstrate greater awareness of emerging technological trends, which in turn enhances their understanding of career opportunities in the digital industrial era [12], [13], [14], [15].

Career Preparation Behavior refers to proactive actions undertaken by individuals [16], [17], [18] to explore, plan, and prepare for their future careers, such as participating in internships, attending career workshops, networking with professionals, and acquiring relevant certifications [19], [20], [21], [22]. These behaviors reflect intentional efforts to build career-related resources and are considered important predictors of career success.

Career Knowledge acts as a cognitive mediator in this study. It encompasses students' understanding of career pathways, required competencies, job market demands, and professional development strategies within the electrical engineering and IoT domain [23], [24], [25]. According to SCCT, career knowledge functions as an outcome expectation that bridges the gap between technological readiness and actual career preparation behaviors on one hand, and overall career readiness on the other.

Based on the theoretical foundations and empirical evidence from previous studies, the following hypotheses are proposed:

H1: IoT Readiness has a positive and significant effect on Career Knowledge.

H2: Career Preparation Behavior has a positive and significant effect on Career Knowledge.

H3: Career Knowledge has a positive and significant effect on Career Readiness.

H4: IoT Readiness has a positive and significant effect on Career Readiness.

H5: Career Preparation Behavior has a positive and significant effect on Career Readiness.

H6: Career Knowledge mediates the relationship between IoT Readiness and Career Readiness.

H7: Career Knowledge mediates the relationship between Career Preparation Behavior and Career Readiness.

3. RESEARCH METHOD

3.1. Research Design

This study employed a quantitative approach using a cross-sectional survey design. The Partial Least Squares Structural Equation Modeling (PLS-SEM) technique was chosen because it is suitable for small sample sizes and complex models with both reflective and formative constructs [26], [27], [28]. All analyses were conducted using SmartPLS 4 software with bootstrapping of 5,000 subsamples to ensure robust significance testing.

3.2. Population, Sample, and Data Collection

The population consisted of all final-year students in the Electrical Engineering Education program at Universitas Negeri Malang. Purposive sampling yielded 42 respondents who had completed or were undertaking IoT-related courses and were approaching graduation. A sensitivity power analysis for a regression-equivalent model with two predictors indicated that N = 42 provides approximately 0.80 power at $\alpha = 0.05$ for effects around $f^2 = 0.25$ or larger; consequently, smaller direct and indirect effects may remain underpowered and are interpreted cautiously [29].

Data were collected through an online self-administered questionnaire distributed via Google Forms using a 5-point Likert scale. Prior to the main data collection, the instrument was pre-tested for clarity, validity, and reliability. The questionnaire measured IoT Readiness, Career Preparation Behavior, Career Knowledge, and Career Readiness. To preserve theoretical coverage while limiting model complexity, one representative indicator was retained for each pre-specified dimension. Selection was theory-first: each retained item had to match the conceptual definition of its dimension, while outer loading was used only as a secondary empirical criterion. Thus, all four theoretical dimensions of each construct remained represented, although the reduced number of items is acknowledged as a limitation for measurement breadth and content validity.

Table 1. Selected Indicators Based on Highest Outer Loadings (Parsimonious Selection)

Variable	Dimension	Selected Indicator (Outer Loading)
IoT Readiness (X1)	Sensing	IOT1 (0.868)
	Processing	IOT4 (0.811)
	Integration	IOT8 (0.862)
	Application	IOT10 (0.782)
Career Preparation Behavior (X2)	Exploration	PK1 (0.731)
	Planning	PK4 (0.778)
	Skill Development	PK5 (0.770)
	Industry Orientation	PK8 (0.915)
Career Knowledge (M)	Information	PNK1 (0.852)
	Competency	PNK3 (0.835)
	Trend	PNK5 (0.843)
	Analysis	PNK6 (0.853)
Career Readiness (Y)	Pedagogical	KK2 (0.779)
	Technical	KK4 (0.892)
	Adaptability	KK6 (0.881)
	Self-Efficacy	KK9 (0.866)

3.3. Operational Definitions of Variables

The present study conceptualizes four main variables within the structural model. IoT Readiness (X1) is defined as students' level of knowledge, skills, and attitudes toward Internet of Things technologies. This construct is measured across four key dimensions: Sensing (the ability to understand sensors and transducers), Processing (the ability to process data through programming), Integration (the ability to connect various modules into a unified system), and Application (the ability to implement IoT systems to solve real-world problems).

Career Preparation Behavior (X2) refers to the proactive actions undertaken by students to prepare for their future professional careers. It encompasses four main dimensions: exploration (searching for career

information and opportunities), planning (setting short- and long-term career goals), skill development (participating in training and certification programs beyond the regular curriculum), and industry orientation (understanding professional standards and workplace culture).

Career Knowledge (M), the mediating variable, is conceptualized as students' cognitive understanding of career-related information. It includes knowledge of career opportunities, required industry competencies, current technological trends, and self-assessment of the fit between personal capabilities and professional demands.

Career Readiness (Y) is defined as the overall psychological and practical preparedness of students to enter the professional workforce. This construct covers four dimensions: pedagogical readiness (for those aspiring to become vocational teachers), technical competence, adaptability to diverse work environments, and self-efficacy (confidence in achieving career success).

These operational definitions provide a clear theoretical and empirical foundation for the measurement instruments and the subsequent structural model analysis.

3.4. Data Analysis Procedure

Data analysis followed a two-step PLS-SEM approach: (1) evaluation of the measurement model (reliability, convergent validity, and discriminant validity) and (2) evaluation of the structural model (path coefficients, R^2, f^2, and indirect effects). Given N = 42, the parsimonious specification retained one theoretically representative indicator per dimension after confirming adequate outer loading, rather than selecting indicators solely on statistical performance. Bootstrapping with 5,000 subsamples generated t-statistics and p-values. Model-fit indices were reported descriptively and interpreted cautiously in line with PLS-SEM guidance [28].

The conceptual framework of the study is presented in Figure 1, while the final structural model with path coefficients is shown in Figure 2.

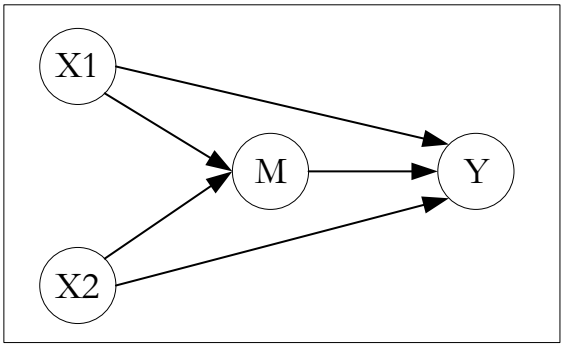


Figure 1. Research Conceptual Model

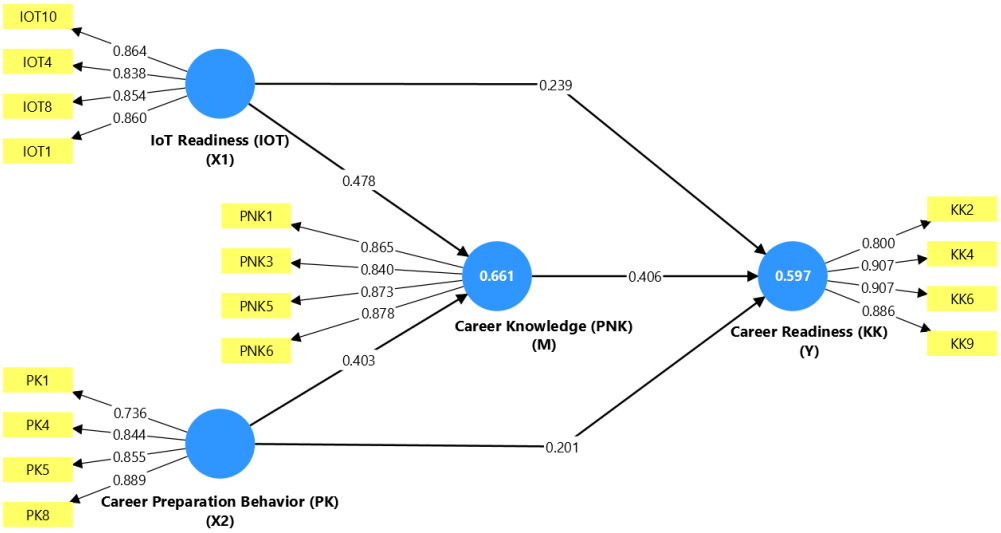


Figure 2. Structural Model Results (PLS-SEM)

4. RESULTS AND DISCUSSION

4.1. Evaluation of the Measurement Model

Before testing the hypotheses, the measurement model was assessed for reliability, convergent validity, and discriminant validity. All constructs satisfied the recommended measurement criteria for PLS-SEM [28]. The results are presented in Table 2.

Table 2. Reliability and Validity of Constructs

Construct	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
Career Readiness (KK)	0.899	0.907	0.930	0.768
IoT Readiness (IOT)	0.877	0.882	0.915	0.730
Career Knowledge (PNK)	0.887	0.893	0.922	0.747
Career Preparation Behavior (PK)	0.851	0.856	0.900	0.694

All Cronbach's Alpha and Composite Reliability values exceeded 0.70, and all AVE values were above 0.50, confirming satisfactory internal consistency and convergent validity.

Discriminant validity was examined using two approaches: the Fornell-Larcker criterion (Table 3) and the Heterotrait-Monotrait (HTMT) ratio (Table 4). Both criteria were met.

Table 3. Discriminant Validity – Fornell-Larcker Criterion (Diagonal values represent √AVE)

Construct	KK	IOT	PNK	PK
Career Readiness (KK)	**0.876**	0.688	0.736	0.668
IoT Readiness (IOT)	0.688	**0.854**	0.760	0.699
Career Knowledge (PNK)	0.736	0.760	**0.864**	0.737
Career Preparation Behavior (PK)	0.668	0.699	0.737	**0.833**

Table 4. Discriminant Validity – HTMT Ratio

Construct	KK	IOT	PNK	PK
Career Readiness (KK)	—	0.765	0.812	0.758
IoT Readiness (IOT)	0.765	—	0.859	0.803
Career Knowledge (PNK)	0.812	0.859	—	0.842
Career Preparation Behavior (PK)	0.758	0.803	0.842	—

All HTMT values were below the conservative threshold of 0.90, indicating adequate discriminant validity.

Collinearity statistics were also checked. The outer model VIF values are shown in Table 5, and the inner model VIF values in Table 6. All VIF values were well below 4.0 (outer model) and 3.0 (inner model), confirming that multicollinearity was not a concern.

Table 5. Collinearity Statistics – Outer Model (VIF)

Indicator	VIF
IOT10	2.234
IOT4	2.181
IOT8	2.332
KK2	2.228
KK4	3.577
KK6	3.962
KK9	3.101
PK1	1.620
PK4	2.388
PK5	2.313
PK8	2.619
PNK1	2.567
PNK3	2.409
PNK5	2.587
PNK6	2.709
IOT1	2.157

Table 6. Collinearity Statistics – Inner Model (VIF)

Path Relationship	VIF
IoT Readiness → Career Readiness (KK)	2.629
IoT Readiness → Career Knowledge (PNK)	1.956
Career Knowledge (PNK) → Career Readiness (KK)	2.946
Career Preparation Behavior (PK) → Career Readiness (KK)	2.435
Career Preparation Behavior (PK) → Career Knowledge (PNK)	1.956

4.2. Evaluation of the Structural Model and Direct Effects

The structural model was evaluated using bootstrapping with 5,000 subsamples. The coefficient of determination (R^2) and effect sizes (f^2) are reported in Table 7. Effect-size interpretation follows the conventional approximate thresholds of 0.02 (small), 0.15 (medium), and 0.35 (large), while values near a boundary are described cautiously [28]. The results of the direct hypothesis testing are presented in Table 8.

Table 7. Coefficient of Determination (R^2) and Effect Sizes (f^2)

Construct	R^2	R^2 Adjusted	f^2 Effect Size on Career Readiness (KK)	f^2 Effect Size on Career Knowledge (PNK)
Career Readiness (KK)	0.597	0.566	—	—
Career Knowledge (PNK)	0.661	0.643	0.139 (small, near medium)	—
IoT Readiness (IOT)	—	—	0.054 (small)	0.344 (medium, near large)
Career Preparation Behavior (PK)	—	—	0.041 (small)	0.245 (medium)

Table 8. Results of Direct Path Hypothesis Testing (H1–H5)

Hypothesis	Path Relationship	β	T-Statistic	p-value	Decision
H1	IoT Readiness → Career Knowledge	0.478	3.362	0.001	Accepted
H2	Career Preparation Behavior → Career Knowledge	0.403	2.821	0.005	Accepted
H3	Career Knowledge → Career Readiness	0.406	2.125	0.034	Accepted
H4	IoT Readiness → Career Readiness	0.239	0.933	0.351	Rejected
H5	Career Preparation Behavior → Career Readiness	0.201	1.437	0.151	Rejected

H1, H2, and H3 were supported, showing that IoT Readiness and Career Preparation Behavior significantly contribute to Career Knowledge, which in turn significantly influences Career Readiness. However, the direct effects of IoT Readiness and Career Preparation Behavior on Career Readiness (H4 and

H5) were not statistically significant. The indirect effects for H6 and H7 did not meet the conventional 5% significance criterion (p = 0.103 and p = 0.099, respectively). Therefore, mediation is not statistically confirmed in this sample; the coefficients should be interpreted as preliminary indications that require verification with a larger sample.

4.3. Mediation Analysis (Indirect Effects)

The indirect effects (H6 and H7) were tested using bootstrapping. The results are presented in Table 9.

Table 9. Results of Indirect Effect Hypothesis Testing (H6–H7)

Hypothesis	Mediation Path	β	T-Statistic	p-value	Decision
H6	IoT Readiness → Career Knowledge → Career Readiness	0.194	1.630	0.103	Rejected*
H7	Career Preparation Behavior → Career Knowledge → Career Readiness	0.164	1.648	0.099	Rejected*

*Note: H6 (p = 0.103) is not significant at either the 5% or exploratory 10% level. H7 (p = 0.099) is not significant at 5% and only narrowly meets an exploratory 10% criterion. Because both mediation hypotheses are rejected under the study's primary 5% significance standard, the indirect coefficients (0.194 and 0.164) are interpreted as preliminary patterns rather than confirmed mediation effects. Replication with a larger sample is required.

4.4. Model Fit

The goodness-of-fit of the structural model was assessed using two primary indices: the Standardized Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI). The results are presented in Table 10.

Table 10. Model Fit Indices

Index	Value	Methodological Guidance	Interpretation
SRMR	0.090	Lower values preferred; no single pass/fail rule [28]	Reported descriptively
NFI	0.666	No universal PLS-SEM cut-off [28]	Reported descriptively

The SRMR value of 0.090 and NFI value of 0.666 are reported as descriptive model-fit information. PLS-SEM guidance cautions against treating fit indices as universal pass/fail criteria, and no generally accepted NFI threshold of 0.60 is assumed here [28]. Accordingly, these values are considered supplementary diagnostics rather than evidence that the model is definitively acceptable or unacceptable.

4.5. Discussion

The findings identify Career Knowledge as an important direct predictor of Career Readiness. IoT Readiness and Career Preparation Behavior both significantly contribute to Career Knowledge, indicating that technical readiness and proactive preparation are associated with a stronger understanding of career pathways, required competencies, and industry expectations.

The non-significant direct paths from IoT Readiness and Career Preparation Behavior to Career Readiness suggest that technical competence and preparation activities do not automatically translate into perceived readiness. However, because the bootstrapped indirect effects were not significant at the primary 5% level, the present data do not statistically confirm full or substantive mediation. The observed indirect coefficients should instead be viewed as a pattern that merits testing with greater statistical power.

The rejection of the direct effects (H4 and H5) suggests a pattern consistent with mediation, although this pattern was not statistically confirmed. Advanced IoT technical skills or intensive career preparation activities alone do not sufficiently generate a sense of career readiness without a deep cognitive understanding of career opportunities, industry competency requirements, and self-professional fit. This finding enriches Social Cognitive Career Theory (SCCT) and Career Adaptability Theory by demonstrating their relevance in the Indonesian vocational education context: technical competencies remain latent until they are effectively translated through structured career knowledge.

The R^2 value of 0.597 for Career Readiness indicates that the model explains 59.7% of its variance in this sample. This explanatory result is meaningful, but it should not be used to override the non-significant indirect-effect tests. The practical role of Career Knowledge is therefore supported primarily by its significant direct association with Career Readiness and by the theoretically coherent pattern of the model.

For the Electrical Engineering Education program at Universitas Negeri Malang, the implications are clear: enhancing IoT laboratory facilities and internship programs is necessary but insufficient. The curriculum must systematically integrate career literacy modules—including industry mapping, competency gap analysis,

and IoT career trend workshops—to transform technical capabilities into integrated, adaptive, and competitive professional readiness.

4.6. Limitations and Future Research

This study has several limitations. First, the relatively small sample size (N = 42) collected from a single institution restricts statistical power and generalizability. Although parsimonious modeling was applied, future research should employ larger samples (N > 200) across multiple universities. Second, the use of self-report questionnaires may introduce common method bias. Third, the cross-sectional design precludes causal inferences.

Future studies are encouraged to adopt longitudinal designs to track changes in IoT Readiness, Career Knowledge, and Career Readiness over time. Comparative research across vocational and non-vocational programs, as well as cross-cultural studies, would enrich the literature. Additionally, incorporating objective measures (e.g., internship performance or actual employment outcomes) alongside perceptual data would strengthen the external validity of the findings.

5. CONCLUSION

This study shows that IoT Readiness and Career Preparation Behavior significantly predict Career Knowledge, and that Career Knowledge significantly predicts Career Readiness among final-year Electrical Engineering Education students. The model explains 59.7% of the variance in Career Readiness. However, the hypothesized indirect effects were not significant at the primary 5% level; therefore, Career Knowledge cannot be claimed as a statistically confirmed mediator in this sample. The observed indirect coefficients should be treated as preliminary evidence that requires replication with a larger and more diverse sample.

These findings reinforce the central thesis that career readiness extends far beyond the mere mastery of practical technical tools. It is fundamentally rooted in the maturity of career information orientation and self-professional awareness. In the context of Industry 4.0, the systematic strengthening of career literacy has become an urgent imperative to transform advanced technical competencies into integrated, adaptive, and competitively superior professional readiness.

The results offer both theoretical contributions to Social Cognitive Career Theory and Career Adaptability Theory and practical implications for curriculum development in vocational higher education institutions, particularly in enhancing the integration of technology readiness with structured career guidance.

AUTHOR CONTRIBUTIONS

Yogi Dwi Mahandi: conceptualization, methodology, data collection, formal analysis, and writing – original draft; **Tuwoso:** supervision, validation, and writing – review & editing; **Hary Suswanto:** methodology, supervision, and writing – review & editing. All authors have read and approved the final version of the manuscript.

DECLARATION OF AI USE

The authors declare that no generative artificial intelligence (AI) or AI-assisted technologies were used in the preparation of this manuscript, including in the conceptualization, data collection, data analysis, interpretation of results, writing, translation, or editing processes. All content of this article is the original work of the authors, who take full responsibility for its accuracy and integrity.

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