Mechanism of Digital Literacy's Impact on College Students' Employability

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ABSTRACT Digital literacy (DL) has become a critical competency for adapting to information-intensive industrial environments; however, the mechanisms through which it enhances employability remain insufficiently understood. This study develops an integrated analytical framework to examine the transmission pathways linking DL to employability (EA) through information extraction (IE) and digital innovation (DI), while considering the moderating role of professional practice assessment (PPA). Based on standardized survey data and structural equation modeling combined with Bootstrap mediation analysis, the results show that DL exerts a significant total effect on EA (0.471), including a direct effect of 0.220 and indirect effects through DI (0.133) and IE (0.118). Furthermore, PPA positively strengthens the transformation of DL into both IE and DI, with moderating coefficients of 0.15 and 0.18, respectively. The findings indicate that digital innovation provides a more stable pathway for capability enhancement, whereas information extraction is more sensitive to practical environments. By interpreting employability development as a multi-stage information acquisition, processing, and transmission process, this study provides a quantitative framework for understanding capability propagation in digital environments and offers empirical support for data-driven talent development strategies.

INDEX TERMS digital literacy, information processing, capability transmission, employability

I. INTRODUCTION

THE convergence of global industrial digitalization and evolving instructional methodologies establishes DL as an essential competency for students transitioning into the technology-driven industry. Examining the relationship between DL and EA bridges higher education practices with labor market requirements. [1-3]. This provides clear value for practice in that it allows institutions to develop effective approaches for developing competency with technology and to increase the extent to which individuals in study show preparation for work [4,5].

While current research has confirmed a positive correlation between DL and EA, the exploration of its internal mechanisms and boundary conditions remains insufficient [6-8]. The main difficulty lies in the fact that, as a multidimensional composite construct, it is unclear through which specific competencies mediated DL influences EA [9]. Most studies focus on direct effects, lacking systematic testing of key transformation mechanisms such as information processing and DI [10]. Furthermore, how the learning and practice context of an individual regulates the above transformation process, as a key boundary condition of the influencing mechanism, has not received sufficient attention and empirical support.

To address these difficulties, existing studies often employ a combination of cross-sectional questionnaire surveys and structural equation modeling to identify path relationships between variables [11,12]. Some studies have further applied the Bootstrap method to test the statistical significance of the mediation effect, improving the credibility of the analysis [13,14]. However, existing methods often separate mediation analysis from moderating analysis, failing to examine the complete chain path of "DL—competency mediation—EA" within an integrated framework, as well as the moderating role of situational factors such as professional practice in the first half of this chain [15,16]. This prevents a complete understanding of the overall mechanism and situational dependence of DL influencing EA.

This study aims to systematically analyze the mediation path and boundary conditions of DL influencing college students' EA within an integrated theoretical framework. By establishing information extraction and DI as parallel mediating variables and setting PPA as a moderating variable, this study constructs a theoretical model that simultaneously covers the chain path of "DL—competency mediation—EA" and the moderating role of situation. This design aims to overcome the limitation of existing studies often separating mediation and moderating analysis, thereby more completely revealing the intrinsic mechanism and situational dependence of DL associated with variations in employability outcomes. By utilizing standardized scale development and structural equation modeling, this study clarifies the specific processes and conditions through which DL transforms into employment competitiveness for professionals.

II. MECHANISM MODEL CONSTRUCTION AND EMPIRICAL SCHEME FOR THE IMPACT OF COLLEGE STUDENTS' DIGITAL LITERACY ON EMPLOYABILITY

A. DECONSTRUCTION OF CORE CONSTRUCT DIMENSIONS AND DERIVATION OF THEORETICAL MODEL

This study focuses on the intrinsic mechanism by which digital literacy (DL) influences college students to EA. It provides a unified definition of core constructs and constructs a testable theoretical model within a consistent symbolic system [17,18]. DL is defined as the comprehensive level of college students' mastery of digital technology tools, digital information resources, and digital application rules in the digital environment, and is considered an exogenous latent variable. In this study, digital application rules refer to the normative understanding and procedural awareness guiding the appropriate use of digital systems, platforms, and tools, rather than the operational execution of information-related tasks. This component represents a foundational cognitive orientation embedded within digital literacy and does not involve the active processes of searching, filtering, or synthesizing work-related information. EA is defined as the comprehensive ability of college students to achieve job competence and sustainable career development in the labor market, and is considered a final endogenous latent variable. IE is defined as the level of an individual's ability to search, filter, and integrate career-related information in the digital environment. Unlike digital application rules within DL, information extraction represents a task-oriented capability that operates at the execution stage of information processing and functions as an outcome of digital literacy rather than as a constitutive component. DI is defined as the ability of an individual to reconstruct problems and generate new solutions based on digital tools. Both are key capability mechanisms in the transformation from DL to EA. PPA is defined as the comprehensive level of frequency and depth of professional-related practical training during university studies. Its core function is to provide application and verification contexts for capabilities, thereby affecting the efficiency of the transformation from DL to intermediate capabilities, and is considered a moderating latent variable.

In terms of capability formation logic, IE and DI are not solely generated linearly by DL, but depend on the degree to which practical contexts activate and strengthen digital capabilities [19,20]. To examine the moderating role of PPA in the competency development stage, an interaction term between DL and strong PPA in professional practice is introduced into the generative model of IE and DI. The structural relationship is expressed as follows:

$$IE = \beta_1 DL + \beta_2 (DL \times PPA) + \epsilon_1 \quad (1)$$

$$DI = \beta_3 DL + \beta_4 (DL \times PPA) + \epsilon_2 \quad (2)$$

In equations (1) and (2), β_1 and β_3 represent the basic effects of DL on IE and DI, β_2 and β_4 represent the moderating effects of PPA on the above transformation process, ϵ_1 and ϵ_2 are the corresponding error terms, and the symbol "$\times$" indicates the interaction between latent variables.

At the capability output level, EA is directly generated from the capability structure formed by IE and DI, while retaining the direct effect of DL on EA. Its unique structural equation is expressed as:

$$EA = \beta_5 DL + \beta_6 IE + \beta_7 DI + \epsilon_3 \quad (3)$$

In equation (3), β_5 represents the direct effect of DL on EA, β_6 and β_7 represent the effects of IE and DI on EA, respectively, and ϵ_3 is the error term in the EA equation.

The model shows the process of development beginning with DL, then showing the change in capacity, and then producing EA. PPA affects only the stage that forms capacity and does not appear in the equation for EA. This approach prevents confusion about the role that different factors play in producing outcomes. The constructs in the structural equation system all provide specific functions that theory establishes, and the use of symbols remains the same across the model. This provides a foundation for measurement that is clear and that allows identification and explanation. The foundation supports the work that follows in developing the measurement model and in conducting the tests that use data.

B. MEASUREMENT TOOL DEVELOPMENT AND DATA ACQUISITION SCHEME

To test the model using data, the study provided measures for the factors of DL, IE, DI, PPA, and EA and developed a survey that could be used to measure these factors. The development of this survey followed from established measures and from theory. The DL measure used scales that follow from the DigComp framework [21]. The measure for individual ability drew on work examining learning using digital means and on work examining behavior relating to developing new approaches [22]. The measures of PPA and EA were developed using theory on learning in particular contexts and using models of ability in work settings [23]. All items in the survey were examined to ensure that language was clear and that the items were appropriate for the context of the study. This process ensured that the measures reflected the theoretical meaning of the factors. Each factor was measured using multiple items to reduce the effect of measurement error on the results that follow from analysis using these measures.

During scale construction, items were systematically screened and revised to reflect distinct functional levels of the latent variables, with DL items capturing general digital norms and rule-based awareness, and IE items capturing concrete information-processing behaviors related to employment contexts. The measure for DL examines how individuals show overall ability with technology and information in contexts that use digital means. The measure for IE examines how individuals show ability to find information, select information, and combine information that relates to work. The measure for DI examines how individuals show ability to examine problems in different forms and develop solutions in contexts that use digital means. The measure for PPA examines the degree that activities relating to work practice appear in the process of study. The measure for EA examines how individuals show overall performance in contexts relating to work. The observed indicators and the variables that the study examines relate in specific forms, and this provides a clear basis for work that follows to establish the values that indicate relationships between factors. Before conducting the survey, the study provided initial testing of the questionnaire. This work examined the internal consistency and structural features of the measures for the latent variables using data from the initial testing [24-26]. The analysis assessed the stable response of the indicators that were used to measure the latent variables DL, IE, DI, PPA, and EA. The analysis that confirmed factors examined the convergent properties of the indicators in relation to the latent variables and the discriminant properties between the different latent variables. Results from these tests indicated that certain items required changes. The study revised these items to develop a final tool for measurement. To further verify discriminant validity among DL, IE, DI, PPA, and EA, the Fornell–Larcker criterion and the heterotrait–monotrait ratio were examined in the confirmatory factor analysis stage. The square roots of the average variance extracted for each construct exceeded the corresponding inter-construct correlations, and all HTMT values remained below the commonly accepted threshold, indicating adequate discriminant validity. Although the structural paths from DL to IE and DI were relatively high, these coefficients reflect theoretically related but empirically distinct constructs rather than measurement overlap. This tool showed satisfactory reliability and satisfactory validity with a structure that was clear. The study collected data from university students and used a standardized form to provide consistent measures across different factors in the study. The sample size followed guidelines relating to the number of factors and parameters that the analysis would estimate in the model using structural relationships, and this approach provided stability for subsequent estimates of relationships and effects between conditions [27,28]. After collecting forms, the data received screening for integrity and consistency, and invalid cases were removed. The remaining data formed the basis for estimating relationships between factors and model parameters. Through the measurement development and data collection that the study used, measurement established connections from factors DL, IE, DI, PPA to EA, and this provided a reliable data foundation for subsequent analysis of structural relationships in the model.

C. DATA ANALYSIS METHODS AND HYPOTHESIS TESTING STRATEGIES

After completing the validation of measurement tools and data quality screening, this study used structural equation modeling (SEM) to comprehensively test the theoretical relationships among DL, IE, DI, PPA, and EA. SEM simultaneously handles the relationship between measurement error and latent variables, making it suitable for complex path analyses involving mediation mechanisms and moderating effects. It can estimate the standardized coefficients of each path and evaluate the overall model fit within a unified framework [29,30]. Model goodness of fit is comprehensively evaluated using multiple fit indices, which are used to systematically test the degree of matching between the theoretical model and the observed data, thereby confirming the rationality of the overall model specification [31,32].

In testing direct and mediation effects, the direct path coefficient of DL to EA, and the indirect path coefficient formed via IE and DI, are estimated based on SEM.The empirical distribution of the indirect effect is estimated using 5000 bias-corrected Bootstrap resamples, from which standard errors and confidence intervals are consistently derived for direct, indirect, and total effects to evaluate the significance of the mediation paths formed by DL→IE→EA and DL→DI→EA. If the confidence interval does not contain zero, the corresponding mediation effect is considered valid, thus verifying the path of DL's influence on EA through the capability transformation mechanism [33]. In the moderating effect test, the interaction effect analysis strategy is used to verify the theoretical hypothesis regarding the impact of PPA on the capability formation stage. By constructing a structural path containing the DL×PPA interaction term, the moderating role of PPA in the transformation process of DL to IE and DI is examined. To enhance the intuitiveness of the moderating effect explanation, simple slope analysis is further combined to characterize the changing trend of the relationship between DL and mediating capability under different practice intensity levels, thereby determining the direction and intensity of the role of situational factors in the capability transformation process [34,35].

After completing the above analysis, the direct, indirect, and moderating effects are integrated and explained to form a complete mechanism by which DL influences EA in college students. The results of structural equation modeling estimation and bootstrap inference are cross-validated to ensure the consistency of the research conclusions in terms of statistical significance and theoretical logic, providing robust methodological support for subsequent results analysis and conclusion derivation.

D. RESEARCH ETHICS STATEMENT

To ensure the compliance of the research process and the protection of participants' rights, this survey strictly adhered to general ethical norms for social science research. The study included university students. These individuals provided informed consent and participated voluntarily. Data that the research collected did not contain information allowing identification of particular individuals. The research processed data to remove features that allow identification and used this for analysis examining overall patterns. Researchers indicated commitment to maintain confidentiality of the data in initial form, and the process of analysis followed principles for ethical research. These procedures ensured the rights and privacy of research participants.

III. RESULTS OF TESTING THE MECHANISM BY WHICH DIGITAL LITERACY AFFECTS EMPLOYABILITY

A. STRUCTURAL EQUATION MODEL VERIFICATION RESULTS

To systematically examine the intrinsic mechanism and regulatory pathway of DL on EA in college students, this study integrates theoretical deduction and questionnaire survey methods to construct and empirically analyze a structural equation model covering DL, IE, DI, PPA and EA. The results of the standardized path coefficient estimation are presented in Table 1.

TABLE 1. Path Coefficients and Significance Test Results of the Structural Equation Model

Path Relationship	Standardized coefficient	Standard error	T value	P value	Significance test
DL → IE	0.42	0.05	8.4	<0.001	Yes
DL → DI	0.38	0.04	9.5	<0.001	Yes
IE → EA	0.28	0.06	4.67	<0.001	Yes
DI→ EA	0.35	0.05	7	<0.001	Yes
DL → EA(Direct)	0.22	0.07	3.14	0.002	Yes
DL × PPA→ IE	0.18	0.05	3.6	<0.001	Yes
DL × PPA → DI	0.15	0.04	3.75	<0.001	Yes

As shown in Table 1, DL exhibits a significant positive association with IE, with a standardized coefficient of 0.42, and the path metric for DL to DI reaches 3.8. These metrics indicate that DL provides significant support for these two capabilities that play a role in the development process. The path metric for IE to EA reaches 2.8, and the path metric for DI to EA reaches 3.5. These results indicate that DI has a higher correlation with EA. The reason for this pattern is that DI more directly reflects the ability to use digital methods to solve problems and create value in a specific context. Analysis shows that DL has an impact of 0.22 on EA. This indicates that the impact of DL is independent of other factors. This study examined the relationship between the actual situation and the process. The results show that the combined impact of PPA and DL on IE and DI is 0.18 and 0.15, respectively. These findings suggest that the actual situation makes the relationship between DL and IE and DI closer. The data indicate that DL affects EA through two different paths. One path works through other factors, while the other path directly affects EA. The analysis reveals that professional practice can have a significant positive impact on the development of specific abilities in individuals.

B. DECOMPOSITION AND COMPARISON OF DIRECT, INDIRECT, AND TOTAL EFFECTS

To systematically analyze the intrinsic effects and boundary conditions of DL on EA in college students, this study integrates structural equation modeling and the Bootstrap mediation test method to construct and empirically test a theoretical model mediated by IE and DI and moderated by professional practice assessment. Finally, the direct, indirect, and total effects of DL on EA are presented through effect decomposition, as shown in Figure 1.

Figure 1 shows that the total effect of DL on EA is 0.471, with a direct effect of 0.220, indicating that DL, in addition to its mediating mechanism, still possesses independent explanatory power. The bias-corrected Bootstrap standard error for the total effect is 0.067, indicating stable estimation across resamples. Among the two mediating paths, the indirect effect of DL on EA through DI is 0.133, slightly higher than the indirect effect through IE (0.118). The two indirect effects are close in magnitude, and the results indicate that both mediating paths are statistically significant within the proposed model. The fact that the effects of both pathways do not include zero supports the significance of the effect in the analysis. The direct effect ranges from 0.085 to 0.355, while the total effect through other factors ranges from 0.142 to 0.367. These ranges confirm that DL affects EA through two independent pathways in the model. The effect of DL on EA is achieved through multiple pathways in the analysis, with the pathway through DI contributing particularly significantly.

C. VISUALIZATION OF THE MODERATING EFFECT OF PROFESSIONAL PRACTICE ASSESSMENT

To examine the mechanism by which digital literacy relates to employability, this study uses analysis combining structural equation modeling and moderating effect analysis. The study examines the effect of professional practice assessment on the process by which digital literacy develops into information retrieval and digital innovation capabilities. This approach reveals how contextual factors affect the path by which these capabilities develop. The specific form of this moderating effect is presented through simple slope analysis, as shown in Figure 2.

Figure 2 shows two upward trend lines illustrating the increasing facilitating effect of Digital Literacy (DL) on the two mediating capabilities as the level of Professional Practice Assessment (PPA) rises. When PPA is low, the predictive coefficients of DL for IE and DI are 0.31 and 0.29, respectively. At a level of PPA that shows moderate values, these measures increase to values of 0.42 and 0.38. When PPA shows high levels, the measures increase further to 0.53 and 0.47. This pattern that increases demonstrates that conditions of PPA that provide substantial features increase the degree to which DL relates to processing of information at significant levels and to use in applications that involve development of different approaches. The increase shows more substantial features in the pathway that relates to IE,

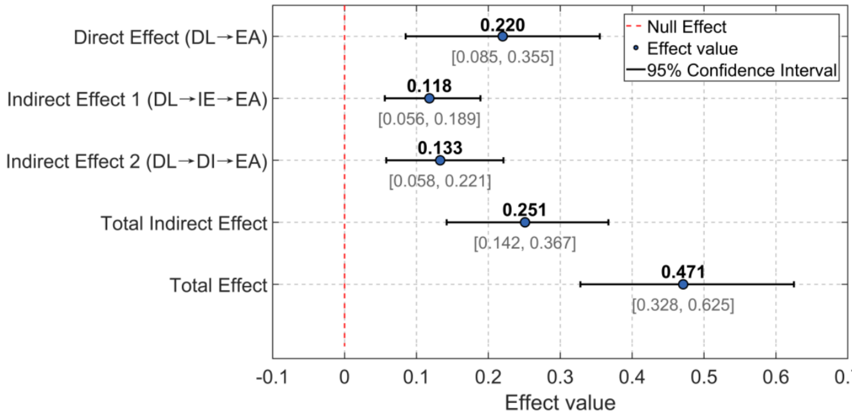

FIGURE 1. Effect Decomposition and Confidence Intervals of the Influence of DL on EA

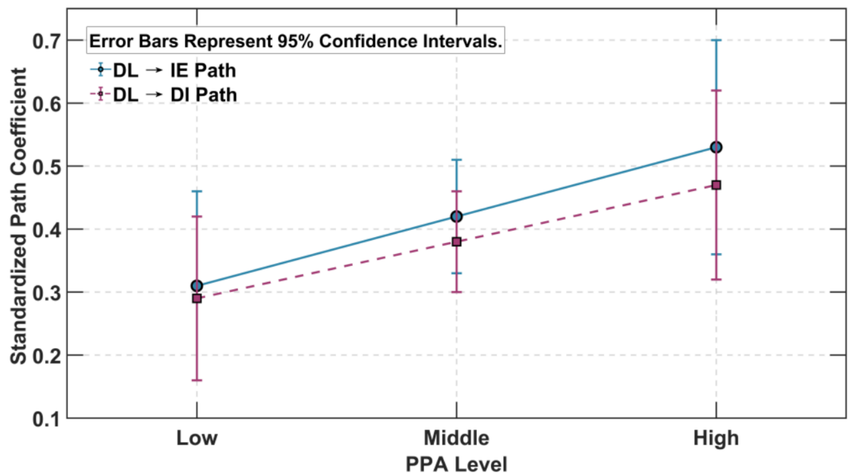

FIGURE 2. Simple Slope Analysis of the Moderating Effect of PPA on the Relationship between DL and Mediating Ability.

and this indicates that this form of use requires opportunities that provide practice to a large degree. These patterns indicate that PPA strengthens the transformation of DL into employment-relevant capabilities.

D. BOOTSTRAP SAMPLING DISTRIBUTION OF KEY MEDIATION PATHS

To further analyze the distribution characteristics of the indirect effects of digital literacy on employability, this study used the Bootstrap repeated sampling method to conduct 5000 samplings on two key mediation paths (DL→IE→EA and DL→DI→EA) to construct the empirical distribution of indirect effects. Figure 3 shows the comparison of the frequency distribution of indirect effects of these two paths.

Figure 3 shows a significant difference in the distribution patterns of the two paths. The peak frequency of the path DL→IE→EA occurs in the range of 0.121 to 0.140, accumulating 1210 occurrences. The peak frequency of the path DL→DI→EA occurs in the range of 0.141 to 0.160, accumulating 1423 occurrences. The former has a relatively broad distribution within the range of 0.101 to 0.160, while the latter shows a higher concentration within the range of 0.141 to 0.200. This distribution characteristic stems from the fact that DI ability has a more direct and stable conversion to DL, thus its effect value clusters in the higher range; IE ability, on the other hand, is more influenced by situational factors, resulting in a relatively dispersed distribution. The results indicate that the path of DL influencing employability through DI ability has a stronger effect intensity and stability, and is a key mechanism for improving college students' EA.

E. A VISUALIZED MODEL INTEGRATING THE INFLUENCE MECHANISMS

To show the main means and conditions relating to DL effects on the ability to find work, this study uses a model examining relationships between factors and includes analysis that measures and assesses the pathways between these factors. The study examines the effects of DL using data that follows two different pathways, one relating to IE and one relating to DI, and the study also examines the effects of PPA in the process that develops ability. The complete integrated model of the above-mentioned relationships is shown in Figure 4.

The mechanism path diagram 4 shows that DL's effect on EA is achieved simultaneously through a direct path and

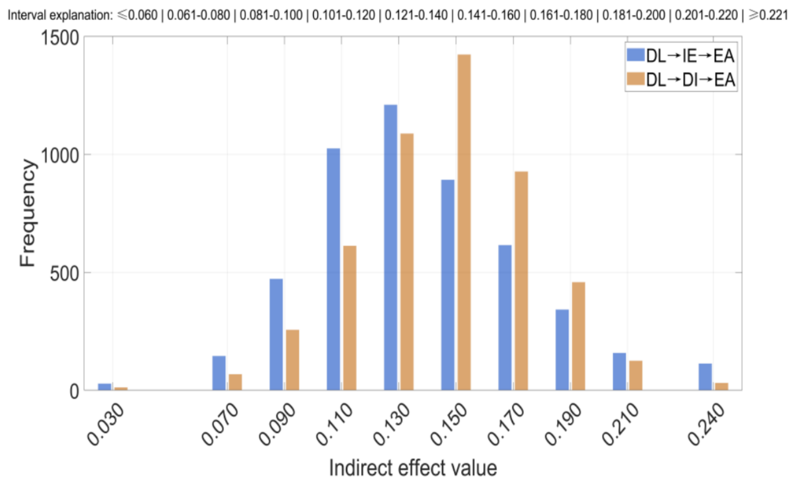

FIGURE 3. Comparison of Frequency Distribution of Indirect Effects in Dual-path Bootstrap

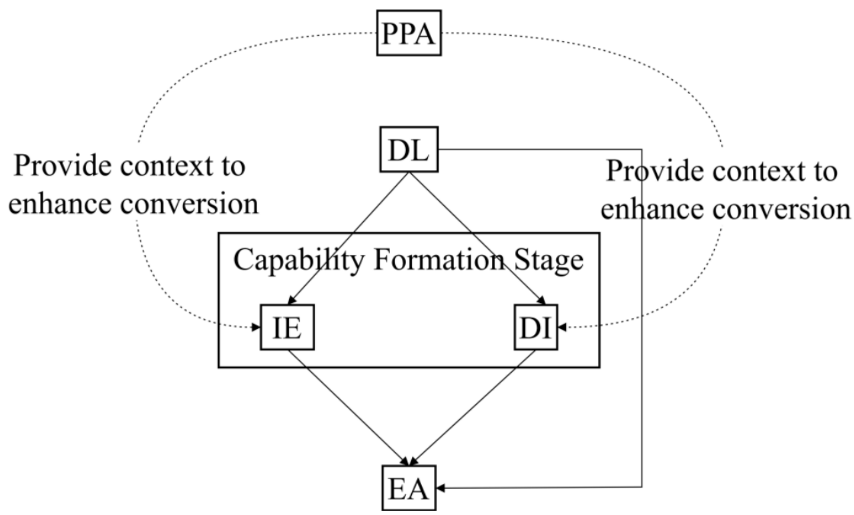

FIGURE 4. Pathway of the Integration Mechanism of DL Influencing Employability

two parallel mediating paths, with both IE and DI serving as parallel and significant mediating mechanisms, reflecting its core role in transforming digital technology into problem-solving capabilities. PPA's moderating effect is limited to the transformation stage of DL into the two mediating capabilities, indicating that practical situations reinforce the application and internalization of digital capabilities by providing authentic tasks and feedback. The model as a whole elucidates the chain-like transmission process of "DL—Capability Transformation—EA" and clarifies the regulatory role of situational factors in the first half of this process, thus presenting the structural pathways and contextual conditions through which DL is statistically associated with EA.

IV. CONCLUSION

This work examines the process relating digital literacy to employability in major college students by presenting a model that integrates digital literacy, ability transformation, and industry-specific employability. The research uses survey data and analysis combining multiple measures to show the process. Digital literacy affects employability using two different abilities. These abilities include information extraction and digital innovation. The work also examines how professional practice context affects these relationships. Findings indicate that digital literacy supports development of the two abilities. The abilities provide an important process linking digital literacy to employability. Digital literacy also shows a separate effect on employability that occurs in a different manner. The study combines analysis of the process that occurs using the abilities and analysis of conditions affecting this process. This approach reveals how digital literacy transforms into employability.

Results from the research provide a basis for emphasizing digital literacy in higher education. The study uses data from a single time point and uses measures that involve self-assessment. These features present certain limitations. Conducting longitudinal research with multi-source data would reveal the evolution of digital literacy over time and demonstrate how these findings adapt to diverse education and industrial training contexts.

AUTHOR CONTRIBUTIONS

Conceptualization – Bin Ge, Xuesong Li and Yaqing Gu; methodology – Bin Ge, Xuesong Li and Yaqing Gu; investigation – Bin Ge, Xuesong Li and Yaqing Gu; writing-original draft preparation – Bin Ge, Xuesong Li and Yaqing Gu. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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