E-ISSN: 2774-5694 P-ISSN: 2776-7388 OPEN ACCESS

International Journal of Management Science and Information Technology
IJMSIT

Volume 6 (2), July-December 2026, 1586-1598
DOI: https://doi.org/10.35870/ijmsit.v6i2.7981

Digital Competence and Learning Agility as Predictors of Self-Perceived Employability among Fresh Graduates

Tanesa Putri Arvira [1*], Rohimat Nurhasan [2], Riyad Sabilul Muminin [3]
[1*,2] Management Study Program, Faculty of Economics, Universitas Garut, Garut Regency, West Java Province, Indonesia
[3] Digital Business Study Program, Faculty of Economics, Universitas Garut, Garut Regency, West Java Province, Indonesia

Email: tanesaputriarvira@gmail.com [1*], rohimat.nurhasan@uniga.ac.id [2], riyadhsyabil@uniga.ac.id [3]

Article history:
Received July 13, 2026
Revised July 31, 2026
Accepted August 4, 2026

Abstract

Fresh graduates enter a labour market shaped by intensifying competition and rapid digitalization. This environment requires both digital competence and the capacity to learn adaptively, as these individual resources may influence how graduates evaluate their ability to obtain and sustain employment. This study examined whether Digital Competence and Learning Agility predict Self-Perceived Employability among 2024–2025 graduates of Universitas Garut. A quantitative cross-sectional survey was conducted using self-report questionnaires completed by 150 respondents selected through accidental sampling. The data were analysed with partial least squares structural equation modelling in SmartPLS 3. Hypotheses were assessed through 5,000 bootstrap subsamples, a two-tailed test, and a 5% significance level. Digital Competence positively predicted Self-Perceived Employability ($\beta = 0.529$, $t = 10.545$, $p < 0.001$), as did Learning Agility ($\beta = 0.573$, $t = 13.086$, $p < 0.001$). Together, the two predictors explained 64.7% of the variance in Self-Perceived Employability ($R^2 = 0.647$), indicating moderate explanatory power. The study contributes by combining the DigComp 2.2 conception of Digital Competence with Learning Agility in a single predictive model of graduate employability perceptions. Practically, the findings support integrated university initiatives that strengthen digital capability and adaptive learning during the transition from higher education to employment.

Keywords:
Digital Competence; Learning Agility; Self-Perceived Employability; Fresh Graduates; PLS-SEM.

1. INTRODUCTION

Digital transformation is reshaping occupations, recruitment practices, and the capabilities expected of workers. Artificial intelligence, automation, information systems, and digital platforms now influence not only organizational processes but also the requirements for entering and remaining in employment. (World Economic Forum, 2025) projects that structural labour-market transformation through 2030 will affect approximately 22% of current jobs, generating about 170 million new roles while displacing about 92 million. These shifts increase the value of technological literacy, resilience, flexibility, agility, and continuous learning.

The changing employment landscape creates particular challenges for university graduates moving from education into work. (Badan Pusat Statistik, 2026) reported that Indonesia's open unemployment rate in November 2025 was 4.74%, which was 0.11 percentage points lower than in August 2025. Although the decline was favourable, the figure confirms that labour absorption remains an ongoing national issue. This context is especially relevant to graduates of Universitas Garut because the institution is located in West Java, a province with its own labour-market constraints and opportunity structures.

Aggregate employment indicators describe whether people are working, unemployed, or outside the labour force, but they do not capture how individuals assess their own employment capacity and prospects. A job seeker may believe that they possess strong capabilities despite not yet having obtained work, while an employed person may remain uncertain about retaining the current position or securing another one. Self-Perceived Employability addresses this subjective dimension by referring to an individual's assessment of the capacity and opportunity to obtain and maintain employment that is compatible with their attributes and qualifications (Noviati et al., 2024).

Recent evidence indicates that employability beliefs vary with individual characteristics and resources. (Bennett et al., 2022) identified differences in business students' employability beliefs across gender and year of study, including judgments about programme relevance, work readiness, and the transferability of learning to employment. (Shomotova et al., 2024) found that leadership potential was positively associated with undergraduate students' Self-Perceived Employability. Although these studies focused on active students and examined predictors other than those used here, they support the view that employability perceptions are shaped by personal resources rather than by employment status alone.

A similar diversity of transition experiences is evident among Universitas Garut graduates. A synthesis of institutional tracer-study records and alumni recapitulations for 2024–2025 indicates that some graduates had entered employment, whereas others were seeking work, continuing their education, operating businesses, or undertaking other activities. Differences in job-search duration and in the alignment between educational background and employment show that graduates do not follow a uniform transition pathway. These records provide an objective account of post-graduation activity, while Self-Perceived Employability captures how graduates evaluate their own capacity and labour-market prospects (Universitas Garut, 2025).

Graduation also does not produce a uniform change in employability perceptions. (Grosemans et al., 2023) reported that perceived employability increased on average after graduation, yet individual trajectories differed substantially. Some graduates improved, whereas those who began with relatively low perceived employability often remained at a low level. This variation highlights the need to identify personal resources associated with how fresh graduates evaluate their employment prospects.

Digital Competence is one such resource in a technology-intensive labour market. DigComp 2.2 defines digital competence as an integrated set of knowledge, skills, and attitudes that enables people to engage with digital technologies confidently, critically, safely, and responsibly (Vuorikari et al., 2022). For fresh graduates, this competence is relevant to locating and assessing vacancies, communicating professionally, preparing digital application materials and portfolios, participating in online recruitment, and using technology in the workplace.

Prior research has linked digital capabilities to several employability-related outcomes. (Kee et al., 2023) associated components of digital skill acquisition with perceived employability among young people. (Potgieter et al., 2023) related readiness for the digital world of work to university students' employability competency, while (Adegbite, 2024) identified digital literacy as a mechanism connecting work-integrated learning with graduate employability. (Wut et al., 2025) further showed that perceived artificial intelligence literacy was related to students' internal and external employability. These studies establish the relevance of digital capability, but they operationalized it as digital skills, digital work readiness, digital literacy, or AI literacy rather than through the five competence areas of DigComp 2.2.

Learning Agility constitutes a second resource that may be particularly important for new graduates. It refers to the willingness and ability to learn from experience and to apply that learning when confronting unfamiliar or changing circumstances (Wardhani et al., 2022). Fresh graduates generally have limited professional experience and must quickly adjust to new technologies, organizational expectations, work routines, and interpersonal demands. The ability to extract lessons from experience and transfer them to new situations may therefore strengthen their assessment of employment capability.

Empirical studies connect Learning Agility with a range of career-related outcomes. (Azhar et al., 2024). linked it to work readiness among final-year accounting students. (Park et al., 2022) examined its association with career resilience and marketability, and (Gerçek & Özveren, 2025) related it to creativity and proactive career behaviour. These outcomes are conceptually relevant to career transitions, yet they are not equivalent to Self-Perceived Employability. (Noviati et al., 2024) treated Self-Perceived Employability as an outcome, but their predictors were online social support, social media user type, and career adaptability.

The research gap is therefore conceptual, empirical, and contextual. Conceptually, limited work has integrated competence for functioning in digital environments with the capacity to learn and adapt. Empirically, studies of digital capability and Learning Agility have employed different constructs, outcomes, and respondent groups, making their joint contribution to Self-Perceived Employability unclear. Contextually, evidence remains limited for fresh graduates from regional Indonesian universities, whose access to labour-market information, professional networks, career services, and employment opportunities may differ from those of students or graduates in major metropolitan settings.

This study addresses these limitations by integrating Digital Competence based on DigComp 2.2 and Learning Agility within a single predictive model of Self-Perceived Employability among fresh graduates of Universitas Garut. The model treats digital capability and adaptive learning as distinct but complementary individual resources. Accordingly, the study examines whether each construct positively predicts graduates' assessments of their capacity and opportunity to obtain employment.

1.1. The Relationship between Digital Competence and Self-Perceived Employability

Digital Competence concerns the critical, safe, responsible, and purposeful use of digital technology. DigComp 2.2 organizes this capability into five areas: Information and Data Literacy, Communication and Collaboration, Digital Content Creation, Safety, and Problem Solving (Vuorikari et al., 2022). Together, these areas extend beyond basic technical operation and include judgment, communication, responsible conduct, and the ability to address technology-related needs.

These capabilities are directly relevant to the contemporary job-search process. Fresh graduates must identify credible vacancy information, communicate with employers, prepare digital curricula vitae and portfolios, manage a professional online identity, and participate in virtual selection procedures. Competence in these activities can provide a stronger basis for assessing readiness for recruitment and digitally mediated work.

Evidence from related research supports this expectation. Digital skill acquisition has been linked to perceived employability among young people (Kee et al., 2023), while readiness for the digital world of work has been associated with employability competency among university students (Potgieter et al., 2023). (Wut et al., 2025) reported a relationship between perceived AI literacy and internal and external employability. (Suarta et al., 2024) also emphasized digital skills in meeting accounting-work requirements, and (Duggal et al., 2024) connected digitally transformed working conditions with perceived employability.

The present study extends this evidence by using the full five-area DigComp 2.2 framework and by focusing specifically on Self-Perceived Employability among fresh graduates of Universitas Garut. Digital Competence is expected to strengthen graduates' evaluations of their ability to navigate recruitment, present their capabilities, and respond to technology-based job requirements. The first hypothesis is therefore stated as follows:

H1: Digital Competence positively predicts Self-Perceived Employability among fresh graduates of Universitas Garut.

1.2. The Relationship between Learning Agility and Self-Perceived Employability

Learning Agility is the willingness and ability to learn from experience and to transfer that learning to new or changing situations. The construct comprises People Agility, Results Agility, Mental Agility, and Change Agility (Wardhani et al., 2022) These dimensions describe learning through interaction, producing results under unfamiliar conditions, examining problems from different perspectives, and remaining open to experimentation and change. (Milani et al., 2024) similarly positioned Learning Agility as an individual difference related to acquiring new skills, adapting, and remaining receptive to change at work.

The construct is relevant to fresh graduates because early career entry involves extensive novelty. Graduates must adjust to professional communication, unfamiliar tasks, organizational rules, new technologies, and performance expectations that differ from academic routines. The capacity to seek feedback, reflect on experience, revise ineffective strategies, and apply lessons in new settings can strengthen their confidence in handling these demands.

Previous studies have connected Learning Agility with outcomes that support career entry and development. (Azhar et al., 2024) found a relationship with work readiness among graduating accounting students. (Park et al., 2022) associated Learning Agility with career resilience and marketability, while (Gerçek & Özveren, 2025) linked it to proactive career behaviour. Although these studies did not directly examine Self-Perceived Employability, they indicate that adaptive learning is relevant to how individuals prepare for and navigate career transitions.

Fresh graduates who can convert experience into effective action are likely to judge themselves as more capable of responding to changing job requirements and pursuing employment opportunities. On this basis, the second hypothesis is formulated as follows:

H2: Learning Agility positively predicts Self-Perceived Employability among fresh graduates of Universitas Garut.

2. RESEARCH METHOD

2.1. Research Design

The study employed an explanatory quantitative survey with a cross-sectional design. Data were collected during a single observation period to examine the predictive relationships of Digital Competence and Learning Agility with Self-Perceived Employability. A quantitative approach was appropriate because the constructs were measured through a structured instrument and the proposed relationships were assessed using numerical data.

Digital Competence and Learning Agility were specified as exogenous constructs, whereas Self-Perceived Employability was modelled as the endogenous construct. The relationships were estimated using partial least squares structural equation modelling (PLS-SEM) in SmartPLS 3. This approach enabled simultaneous evaluation of the measurement and structural models, including construct validity and reliability, path coefficients, explained variance, effect sizes, and predictive relevance (Hair et al., 2022)

The design also allowed the numerical magnitudes of the two path coefficients and their effect sizes to be compared. Such comparisons were used only to identify which predictor produced the larger estimate in the fitted model; they were not treated as statistical evidence that one coefficient was significantly larger than the other. Because the study relied on cross-sectional self-report data, accidental sampling, and respondents from one institution, the results are interpreted as predictive associations or statistical effects within the estimated model. The design does not establish temporal precedence and therefore cannot provide strong causal evidence.

2.2. Participants and Data Collection

The study population comprised 1,650 diploma and undergraduate graduates of Universitas Garut from the 2024 and 2025 graduation cohorts. This total included 1,307 graduates from 2024 and 343 from 2025. Eligibility was determined by graduation year rather than by employment status at the time of the survey because the study focused on the early transition from higher education to work.

An operational sample estimate was calculated using the Slovin formula based on the stated population size and a 10% error tolerance (Sugiyono, 2023):

$$n = \frac{N}{1 + N(e)^2}$$

where n denotes the estimated sample size, N denotes the population size, and e denotes the error tolerance. Using a population of 1,650 graduates and an error tolerance of 10%, the calculation was as follows:

$$n = \frac{1.650}{1 + 1.650(0.10)^2}$$

$$n = \frac{1,650}{17.5} = 94.29$$

The resulting estimate was 94.29 respondents. This calculation served as an operational target for data collection and was not presented as evidence of probability-based representativeness because the actual sampling procedure was non-probabilistic.

Data collection yielded 150 complete and eligible responses, all of which were retained for analysis. This final sample exceeded the operational estimate. Respondents were recruited through non-probability accidental sampling on the basis of accessibility, willingness to participate, and conformity with the inclusion criteria (Sugiyono, 2023). Eligible participants were diploma or undergraduate graduates of Universitas Garut from 2024 or 2025 who completed every section of the questionnaire.

The questionnaire was administered online and used a five-point Likert response format: 1 = Strongly Disagree, 2 = Disagree, 3 = Somewhat Disagree, 4 = Agree, and 5 = Strongly Agree. The measures were self-reported because participants evaluated their own Digital Competence, Learning Agility, and Self-Perceived Employability. Empirical validity and reliability were subsequently assessed through the PLS-SEM measurement model.

2.3. Measurement Instrument

A structured questionnaire was developed to measure Digital Competence, Learning Agility, and Self-Perceived Employability. The conceptual frameworks determined the dimensions used for each construct, whereas the statement items were written by the researchers from the operational definitions, dimensions, and indicators. Consequently, the number of items reported here refers to the instrument developed for fresh graduates of Universitas Garut and not to a direct reproduction of every item in the cited sources.

Digital Competence was operationalized using the five areas of DigComp 2.2: Information and Data Literacy, Communication and Collaboration, Digital Content Creation, Safety, and Problem Solving (Vuorikari et al., 2022). Twenty statements were developed to reflect the use of digital technology in academic activities, job searching, recruitment preparation, and early-career contexts.

Learning Agility was represented by People Agility, Results Agility, Mental Agility, and Change Agility (Wardhani et al., 2022). The study adopted the four-dimensional conceptual structure rather than directly reproducing the complete adapted scale. Sixteen statements were therefore developed for the characteristics and experiences of fresh graduates.

Self-Perceived Employability was operationalized through the Personal Attribute and Job dimensions used in the framework reported by (Noviati et al., 2024). The cited measure was not reproduced item for item; instead, its conceptual definitions, dimensions, and indicators informed the development of 12 statements concerning respondents' personal capacity and their perceived opportunity to obtain work compatible with their qualifications.

All three variables were specified as first-order reflective constructs. The dimensions served as conceptual domains for item development, while measurement-model evaluation and structural testing were conducted at the overall construct level.

Each statement used the five-point response scale described above. Empirical assessment included outer loadings, Cronbach's alpha, rho_A, composite reliability, average variance extracted (AVE), and the heterotrait-monotrait ratio (HTMT).

Table 1. Operationalization of the Research Constructs

Construct	Dimensions	Number of Items	Conceptual Basis
Digital Competence	Information and Data Literacy; Communication and Collaboration; Digital Content Creation; Safety; Problem Solving	20 items (DC1–DC20)	(Vuorikari et al., 2022)
Learning Agility	People Agility; Results Agility; Mental Agility; Change Agility	16 items (LA1–LA16)	(Wardhani et al., 2022)
Self-Perceived Employability	Personal Attribute; Job	12 items (SPE1–SPE12)	(Noviati et al., 2024)

Source: Authors, 2026

2.4. Data Analysis

The survey data were analysed using PLS-SEM in SmartPLS 3. The technique was selected to evaluate the measurement properties of the three constructs and estimate the structural relationships linking Digital Competence and Learning Agility to Self-Perceived Employability (Hair et al., 2022). The analysis proceeded in two stages: assessment of the reflective measurement model followed by evaluation of the structural model. Convergent validity was examined through outer loadings and AVE. Outer loadings above 0.70 and AVE values above 0.50 were treated as acceptable.

Internal consistency was assessed using Cronbach's alpha, rho_A, and composite reliability, with values above 0.70 indicating adequate reliability. Discriminant validity was evaluated using HTMT, applying a threshold below 0.90. After the measurement model met the stated criteria, the structural model was examined for predictor collinearity, path coefficients, explained variance, effect size, and predictive relevance. Inner VIF values were used to identify collinearity among the exogenous constructs.

The coefficient of determination (R^2) represented the proportion of variation in Self-Perceived Employability explained by the two predictors. Effect size (f^2) values of 0.02, 0.15, and 0.35 were interpreted as small, medium, and large, respectively. Stone-Geisser's Q^2 was obtained through blindfolding, with values above zero indicating predictive relevance. Hypotheses were evaluated through bootstrapping with 5,000 subsamples. A two-tailed test at the 5% level was applied; a structural path was considered statistically significant when the t-statistic exceeded 1.96 and the p-value was below 0.05. The sign of the estimated path coefficient indicated the direction of the relationship.

3. RESULTS AND DISCUSSION

3.1. Results

3.1.1. Respondent Characteristics

The final sample comprised 150 graduates from the 2024 and 2025 cohorts. Women accounted for 77 respondents (51.33%) and men for 73 (48.67%), yielding a nearly balanced gender distribution. By graduation year, 77 participants (51.33%) graduated in 2025 and 73 (48.67%) in 2024.

Most respondents were 23-24 years old (83 participants; 55.33%). A further 43 respondents (28.67%) were aged 21-22, 18 (12.00%) were aged 25-26, and 6 (4.00%) were 27 or older. The age distribution is consistent with a sample largely situated in the initial transition from higher education to employment.

Half of the sample came from the Faculty of Economics (76 respondents; 50.67%). The remaining participants represented the Faculty of Agriculture (25; 16.67%), the Faculty of Islamic Education and Teacher Training (19; 12.67%), the Faculty of Communication and Information (18; 12.00%), and other faculties (12; 8.00%).

The largest study-program groups were the bachelor's programmes in Management (34 respondents; 22.67%) and Accounting (29; 19.33%). Communication Studies contributed 18 respondents (12.00%), Agrotechnology 15 (10.00%), and Islamic Education 12 (8.00%). Other programmes collectively accounted for 42 respondents (28.00%).

At the time of data collection, 99 respondents (66.00%) were employed, 36 (24.00%) were seeking work, and 15 (10.00%) were continuing their education. The sample therefore included graduates with varied academic backgrounds and transition statuses, although graduates from the Faculty of Economics and those already employed were more strongly represented.

3.1.2. Descriptive Analysis of the Research Variables

Descriptive analysis summarized respondents' assessments of Digital Competence, Learning Agility, and Self-Perceived Employability. For each dimension, item scores were summed and divided by the number of statements in that dimension, producing an average total score per item.

With 150 respondents and a five-point Likert scale, the theoretical minimum score was 150 and the maximum was 750. The category interval was calculated as follows:

$$\text{Interval width} = \frac{\text{Maximum score} - \text{Minimum score}}{\text{Number of categories}}$$

$$\text{Interval width} = \frac{750 - 150}{5} = 120$$

The resulting intervals were used to classify the descriptive scores as presented Table 2.

Table 2. Respondent Score Categories

No.	Score Interval	Assessment Category
1	150-270	Very Low
2	271-390	Low
3	391-510	Moderately High
4	511-630	High
5	631-750	Very High

Source: Authors' calculations based on survey data, 2026

Using these intervals, Digital Competence scored 458, Learning Agility scored 452, and Self-Perceived Employability scored 466; all three were classified as moderately high. These statistics describe respondents' perceptions of each construct and are not used to infer structural relationships.

Table 3. Descriptive Results

Construct	Dimension	Score	Category
Digital Competence (X1)	Information and Data Literacy	459	Moderately High
	Communication and Collaboration	457	Moderately High
	Digital Content Creation	459	Moderately High
	Safety	457	Moderately High
	Problem Solving	458	Moderately High
Average Digital Competence		458	Moderately High
Learning Agility (X2)	People Agility	450	Moderately High
	Results Agility	452	Moderately High
	Mental Agility	451	Moderately High
	Change Agility	454	Moderately High
Average Learning Agility		452	Moderately High
Self-Perceived Employability (Y)	Personal Attribute	467	Moderately High
	Job	465	Moderately High
Average Self-Perceived Employability		466	Moderately High

Source: Authors' calculations based on survey data, 2026

Digital Competence had an average score of 458. Information and Data Literacy and Digital Content Creation were the highest-scoring dimensions, each at 459. The result suggests that respondents perceived themselves as reasonably capable of locating, evaluating, and organizing digital information and of producing digital content for academic, job-search, and early-career purposes. Problem Solving scored 458. Communication and Collaboration and Safety were slightly lower, both at 457. The pattern indicates comparatively greater scope for strengthening professional digital communication, coordination through online platforms, responsible technology use, protection of personal data, and recognition of digital risks.

Learning Agility averaged 452. Change Agility produced the highest dimension score (454), indicating a moderately strong willingness to adjust learning approaches and behaviour when facing unfamiliar circumstances. Results Agility scored 452 and Mental Agility 451, while People Agility was the lowest dimension at 450. Learning through interaction, responding constructively to feedback, understanding alternative perspectives, and adapting within social relationships therefore represent areas that may require greater development. These capabilities are particularly relevant because early-career learning occurs through supervisors, colleagues, mentors, and collaborative work as well as through individual experience.

Self-Perceived Employability recorded the highest construct average, at 466. Personal Attribute scored 467, suggesting that respondents held moderately favourable views of the personal qualities, abilities, and resources they could bring to the labour market. The Job dimension scored 465 and was slightly lower than Personal Attribute. Respondents therefore appeared somewhat less confident about the fit between their qualifications and available employment opportunities. This aspect concerns understanding labour-market requirements, matching personal competence to vacancy criteria, and identifying work that corresponds to an educational background.

Overall, the three constructs were classified as moderately high. Digital Competence was strongest in information management and content creation, Learning Agility in responding to change, and Self-Perceived Employability in personal attributes. These results provide a descriptive profile only and do not establish association or influence among the variables.

3.1.3. Measurement Model Evaluation

The reflective measurement model was evaluated to determine whether the indicators represented Digital Competence, Learning Agility, and Self-Perceived Employability with adequate reliability and validity. The assessment covered indicator reliability through outer loadings, internal consistency through Cronbach's alpha, rho_A, and composite reliability, convergent validity through AVE, and discriminant validity through HTMT. The stated decision rules were outer loadings above 0.70, Cronbach's alpha, rho_A, and composite reliability above 0.70, AVE above 0.50, and HTMT values below 0.90 (Hair et al., 2022).

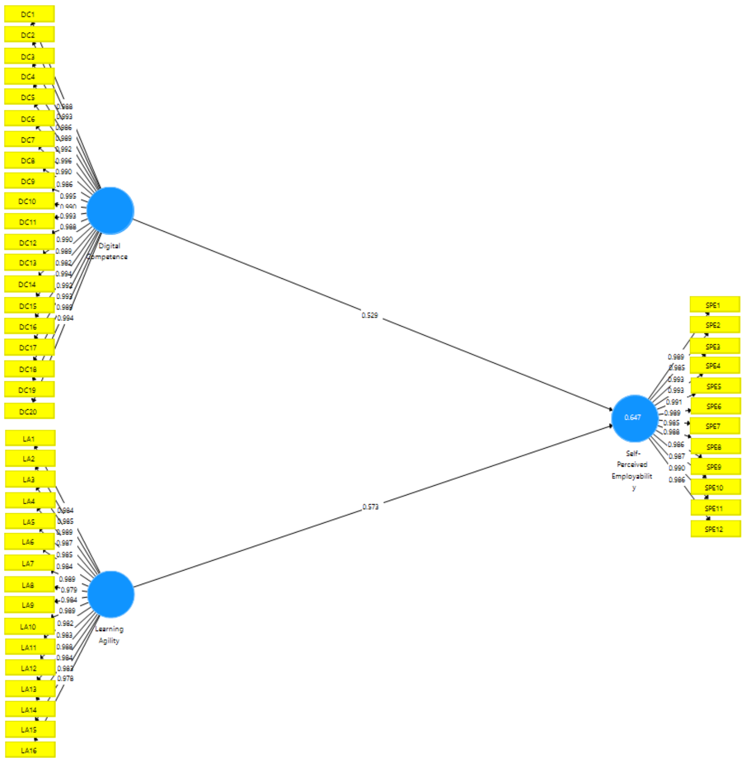

Figure 1. Outer Loading Model (Source: SmartPLS output, 2026)

As shown in Figure 1, every indicator loaded above 0.70 on its intended construct. Outer loadings ranged from 0.982 to 0.996 for Digital Competence, from 0.978 to 0.989 for Learning Agility, and from 0.985 to 0.993 for Self-Perceived Employability. No indicator fell below the acceptance threshold. All indicators were therefore retained, and the results supported indicator reliability for each construct.

The loading results were considered together with AVE for convergent validity and with Cronbach's alpha, rho_A, and composite reliability for internal consistency.

3.1.3.1. Indicator Reliability, Construct Reliability, and Convergent Validity

Indicator reliability was assessed through outer loadings, construct reliability through Cronbach's alpha, rho_A, and composite reliability, and convergent validity through AVE. The respective acceptance criteria were values above 0.70 for the loading and reliability coefficients and above 0.50 for AVE (Hair et al., 2022).

Table 4. Construct Reliability and Convergent Validity

Construct	Number of Items	Outer Loading Range	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Digital Competence	20	0.982-0.996	0.999	0.999	0.999	0.981
Learning Agility	16	0.978-0.989	0.998	0.998	0.998	0.969
Self-Perceived Employability	12	0.985-0.993	0.998	0.998	0.998	0.977

Source: Authors' calculations based on SmartPLS output, 2026

Table 4 confirms that all outer loadings exceeded 0.70: 0.982-0.996 for Digital Competence, 0.978-0.989 for Learning Agility, and 0.985-0.993 for Self-Perceived Employability. The indicators therefore satisfied the stated indicator-reliability criterion. Digital Competence produced values of 0.999 for Cronbach's alpha, rho_A, and composite reliability. The corresponding coefficients for Learning Agility and Self-Perceived Employability were 0.998. Each construct consequently met the internal-consistency threshold.

AVE was 0.981 for Digital Competence, 0.969 for Learning Agility, and 0.977 for Self-Perceived Employability. Because all values exceeded 0.50, the constructs met the convergent-validity criterion. The reliability coefficients were extremely close to 1.00. Although this indicates exceptionally high internal consistency, it may also signal semantic similarity or redundancy among items within the same construct and should be considered when refining the instrument in future research.

3.1.3.2. Discriminant Validity

Discriminant validity was examined to determine whether each construct was empirically distinct from the others. HTMT values below 0.90 were treated as evidence that discriminant validity had been established.

Table 5. Heterotrait-Monotrait Ratio (HTMT)

	Digital Competence	Learning Agility	Self-Perceived Employability
Digital Competence			
Learning Agility	0.064		
Self-Perceived Employability	0.566	0.608	

Source: Authors' calculations based on SmartPLS output, 2026

The HTMT value was 0.064 between Digital Competence and Learning Agility, 0.566 between Digital Competence and Self-Perceived Employability, and 0.608 between Learning Agility and Self-Perceived Employability. Each value was below 0.90. The three constructs were therefore sufficiently distinct at the empirical level and satisfied the stated discriminant-validity criterion.

Taken together, the indicator reliability, internal consistency, convergent validity, and discriminant validity results supported the adequacy of the measurement model. Structural-model evaluation was therefore undertaken.

3.1.4. Structural Model Evaluation

After the measurement model met the stated criteria, the structural model was assessed to determine how Digital Competence and Learning Agility explained Self-Perceived Employability. The evaluation included inner VIF, R^2 and adjusted R^2, f^2, and Q^2.

3.1.4.1. Collinearity Assessment

Inner VIF values were examined to ensure that excessive collinearity between Digital Competence and Learning Agility did not distort the path estimates. Values below 5.00 were considered acceptable (Hair et al., 2022).

Table 6. Inner VIF Values

	Digital Competence	Learning Agility	Self-Perceived Employability
Digital Competence			1.004
Learning Agility			1.004
Self-Perceived Employability			

Source: Authors' calculations based on SmartPLS output, 2026

Digital Competence and Learning Agility each produced an inner VIF of 1.004 for Self-Perceived Employability. These values were well below 5.00, indicating that predictor collinearity did not present a material problem and that the path estimates could be interpreted.

3.1.4.2. Coefficient of Determination

The coefficient of determination indicates the proportion of variation in the endogenous construct explained by the predictors included in the structural model.

Table 7. Coefficient of Determination

Endogenous Construct	R^2	Adjusted R^2
Self-Perceived Employability	0.647	0.642

Source: Authors' calculations based on SmartPLS output, 2026

Self-Perceived Employability had an R^2 of 0.647. Digital Competence and Learning Agility therefore explained 64.7% of its observed variance, while 35.3% remained outside the model. The adjusted R^2 was 0.642, indicating that the two predictors explained 64.2% of the variance after adjustment for model complexity. Under the interpretive criteria adopted in the study, the explanatory power was moderate (Hair et al., 2022).

3.1.4.3. Effect Size

The f^2 statistic represents the change in R^2 associated with removing an exogenous construct from the model. Values of 0.02, 0.15, and 0.35 were interpreted as small, medium, and large effects, respectively (Hair et al., 2022).

Table 8. Effect Sizes (f^2)

	Digital Competence	Learning Agility	Self-Perceived Employability	Category
Digital Competence			0.790	Large
Learning Agility			0.928	Large

Source: Authors' calculations based on SmartPLS output, 2026

Digital Competence had an f^2 of 0.790 and Learning Agility an f^2 of 0.928. Both exceeded 0.35 and were classified as large effects on Self-Perceived Employability.

Learning Agility produced the larger numerical effect size. Its removal would therefore generate a greater reduction in R^2 than the removal of Digital Competence. This comparison concerns magnitude only; f^2 does not test whether the difference between the two structural effects is statistically significant.

3.1.4.4. Predictive Relevance

Stone-Geisser's Q^2 was obtained through blindfolding. A value above zero was treated as evidence of predictive relevance, while values of 0.02, 0.15, and 0.35 represented small, medium, and large relevance under the criteria adopted in the study (Hair et al., 2022).

Table 9. Predictive Relevance (Q^2)

	SSO	SSE	Q^2 (=1-SSE/SSO)
Digital Competence	3000.000	3000.000	
Learning Agility	2400.000	2400.000	
Self-Perceived Employability	1800.000	676.916	0.624

Source: Authors' calculations based on SmartPLS output, 2026

Self-Perceived Employability produced a Q^2 of 0.624, which was above zero and exceeded the 0.35 benchmark. The model therefore demonstrated high predictive relevance for the endogenous construct under the blindfolding assessment. This Q^2 value reflects the model's predictive relevance for omitted data points in the blindfolding procedure. It should not be interpreted as direct evidence of out-of-sample predictive performance, which would require a procedure such as PLSpredict. Overall, the structural assessment identified no material collinearity, moderate explanatory power, large effect sizes for both predictors, and high predictive relevance under blindfolding.

3.1.5. Hypothesis Testing

Direct effects were tested with 5,000 bootstrap subsamples using a two-tailed test at the 5% level. A hypothesis was supported when the estimated path had the predicted direction, the t-statistic exceeded 1.96, and the p-value was below 0.05.

Table 10. Path Coefficients

Structural Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	t-statistic (|O/STDEV|)	p-value	Decision
Digital Competence -> Self-Perceived Employability	0.529	0.528	0.050	10.545	<0.001	H1 supported
Learning Agility -> Self-Perceived Employability	0.573	0.575	0.044	13.086	<0.001	H2 supported

Source: Authors' calculations based on SmartPLS output, 2026

Digital Competence positively predicted Self-Perceived Employability ($\beta = 0.529$, $t = 10.545$, $p < 0.001$). The coefficient had the hypothesized positive direction and met the statistical significance criteria; H1 was therefore supported. Learning Agility also positively predicted Self-Perceived Employability ($\beta = 0.573$, $t = 13.086$, $p < 0.001$). The direction and significance criteria were satisfied, supporting H2.

The Learning Agility coefficient (0.573) was numerically larger than the Digital Competence coefficient (0.529), and its f^2 was also higher (0.928 versus 0.790). These estimates suggest a relatively stronger structural contribution in the fitted model, but the difference cannot be declared statistically significant because no formal comparison between the two path coefficients was conducted.

3.2. Discussion

3.2.1. Digital Competence and Self-Perceived Employability

The findings support a positive relationship between Digital Competence and Self-Perceived Employability. Graduates who reported stronger digital capability also tended to evaluate their employment capacity and prospects more favourably. Digital competence therefore functions not merely as a technical skill set but as an individual resource relevant to judgments about employability. The relationship can be understood through the role of technology across the school-to-work transition. Information and Data Literacy enables graduates to locate vacancies, assess source credibility, interpret competence requirements, and compare opportunities. These activities reduce information uncertainty and provide a more informed basis for judging person-job fit.

The result aligns with a broader body of evidence connecting digital capability with employability-related outcomes. (Kee et al., 2023) linked digital skill acquisition with perceived employability among young people. (Potgieter et al., 2023) associated digital work readiness with employability competency, while (Wut et al., 2025) found that perceived AI literacy was related to both internal and external employability. (Suarta et al., 2024) highlighted the importance of digital skills for accounting work, and (Duggal et al., 2024) connected digitally transformed working conditions with perceived employability. The present study extends this pattern by operationalizing Digital Competence through all five DigComp 2.2 areas and testing it among fresh graduates.

The descriptive profile adds practical nuance. Communication and Collaboration and Safety scored slightly below the other digital dimensions. Graduates may therefore be more confident in finding information and creating content than in managing professional online interaction, collaborative platforms, privacy, and digital risk. Digital preparation for employment should consequently include social, ethical, and security-related capability rather than focusing only on functional technology use. Institutional tracer records further show that Universitas Garut graduates follow diverse post-graduation pathways (Universitas Garut, 2025). These records are not direct evidence of the tested relationship, but they illustrate why graduates need digital resources to identify, evaluate, and pursue opportunities under varying transition conditions.

3.2.2. Learning Agility and Self-Perceived Employability

Learning Agility was also positively related to Self-Perceived Employability. Graduates who were more willing and able to learn from experience reported more favourable assessments of their capacity to deal with employment demands. The finding positions adaptive learning as an important resource during a period characterized by limited work experience and considerable novelty. The mechanism lies in the transfer of learning across situations. Recruitment processes, job tasks, workplace technologies, organizational rules, and professional relationships may all be unfamiliar to new graduates. Learning Agility enables individuals to reflect on feedback, identify ineffective responses, revise their approach, and apply lessons when circumstances change.

Each dimension contributes to this adaptive process. People Agility supports learning through interaction and openness to alternative perspectives. Results Agility concerns the ability to perform under unfamiliar or demanding conditions. Mental Agility allows problems to be reconsidered from different angles, while Change Agility supports experimentation and constructive engagement with change. Together, these capabilities can strengthen graduates' confidence that they can respond to uncertainty in both job search and early employment. Related studies provide support through adjacent career outcomes. (Azhar et al., 2024) associated Learning

Agility with work readiness, (Park et al., 2022) with career resilience and marketability, and (Gerçek & Özveren, 2025) with proactive career behaviour.

(Milani et al., 2024) likewise described Learning Agility as a capacity for acquiring new skills and adjusting to workplace change. The current findings extend this evidence to graduates' subjective assessment of employability. The descriptive results indicate that Change Agility was relatively strongest, whereas People Agility received the lowest score. Graduates may therefore be open to change while still needing greater capability to learn through feedback, interpersonal differences, mentoring, and collaboration. This distinction matters because workplace adaptation is inherently social and depends on the effective use of other people as learning resources.

Learning Agility displayed a numerically larger path coefficient and effect size than Digital Competence. Within the specified model, adaptive learning was therefore more strongly associated with Self-Perceived Employability. This finding should not be interpreted as proof of statistical dominance because the difference between coefficients was not directly tested. The result is also consistent with the dynamic nature of post-graduation transitions. (Grosemans et al., 2023) showed that changes in perceived employability differ across graduates and that individuals who begin with low perceptions may remain disadvantaged. Adaptive learning may help explain why graduates respond differently to comparable transition demands.

Taken together, Digital Competence and Learning Agility offer complementary explanations. Digital Competence equips graduates to function within technology-mediated recruitment and work, whereas Learning Agility supports the acquisition and transfer of new learning when requirements change. Their integration provides a broader account of Self-Perceived Employability than either resource alone.

3.2.3. Theoretical Implications

The principal theoretical contribution is the integration of DigComp 2.2-based Digital Competence and Learning Agility within one predictive model of Self-Perceived Employability. Previous research has typically treated digital skills, digital work readiness, AI literacy, employability competency, work readiness, career resilience, marketability, or proactive career behaviour as separate constructs and outcomes. Recent Self-Perceived Employability research has examined differences in employability beliefs, the contribution of personal resources, and changes following graduation (Bennett et al., 2022; Grosemans et al., 2023; Shomotova et al., 2024). This study extends that literature by testing digital and adaptive-learning resources simultaneously among graduates of a regional university.

The results show that both resources are associated with employability perceptions. Digital Competence represents the ability to access information, communicate professionally, present capability, protect digital assets, and solve technology-related problems. Learning Agility represents the capacity to draw lessons from experience, receive feedback, think flexibly, and adjust to change. Self-Perceived Employability is therefore associated not only with what graduates can do in digital environments but also with how effectively they can continue learning when those environments and their requirements evolve. The combination of the two constructs links preparedness for digitalization with preparedness for change.

Learning Agility generated larger numerical estimates than Digital Competence, suggesting a relatively stronger structural relationship in this sample. This comparison remains descriptive because the study did not test the statistical significance of the difference between coefficients. The theoretical claims are limited to predictive association and statistical effects within a cross-sectional model. Temporal ordering and strong causal inference cannot be established from the design.

3.2.4. Practical Implications

The findings provide a basis for Universitas Garut to integrate Digital Competence and Learning Agility into student development and graduate career services. The proposed directions are derived from both the descriptive profile and the structural relationships observed in the model. Digital development should give particular attention to Communication and Collaboration and to Safety, the two relatively lower-scoring dimensions. Relevant activities include professional communication through digital media, collaborative work using online platforms, the development of digital profiles and portfolios, and instruction on privacy, data protection, online etiquette, and responsible technology use.

Learning Agility initiatives should prioritize People Agility. Cross-programme projects, mentoring by alumni and practitioners, team simulations, case-based learning, and structured feedback can strengthen the ability to learn from others, process differing viewpoints, and adapt within changing social environments. The comparatively lower Job dimension of Self-Perceived Employability also points to the value of stronger career-centre services. Competence mapping, curriculum vitae development, interview simulations, current labour-market information, and systematic matching between graduate qualifications and vacancy requirements may help graduates evaluate opportunities more accurately.

Because Learning Agility produced the larger numerical coefficient and effect size, adaptive learning deserves substantial attention in graduate-development programmes. It should nevertheless be developed alongside Digital Competence because both constructs made positive and statistically significant contributions to Self-Perceived Employability. These recommendations do not constitute evidence that the proposed programmes will cause an improvement in employability perceptions. Their effectiveness should be assessed through dedicated programme evaluation or subsequent intervention research.

4. CONCLUSION

This study examined Digital Competence and Learning Agility as predictors of Self-Perceived Employability among 2024–2025 graduates of Universitas Garut using a cross-sectional quantitative survey and PLS-SEM. Digital Competence positively and significantly predicted Self-Perceived Employability. Graduates who reported stronger capacity to manage digital information, communicate and collaborate through technology, create content, maintain digital safety, and solve technology-related problems also reported more favourable employability perceptions.

Learning Agility likewise produced a positive and significant relationship. The ability to learn from experience, respond to feedback, adjust to change, and transfer learning to unfamiliar situations was associated with higher Self-Perceived Employability. Learning Agility yielded a path coefficient of 0.573 and an f^2 of 0.928, compared with 0.529 and 0.790 for Digital Competence. These values indicate a larger numerical contribution for Learning Agility, although the difference was not formally tested and cannot be treated as statistically significant.

Together, the two constructs explained 64.7% of the variance in Self-Perceived Employability, leaving 35.3% unexplained by the model. The findings support an integrated view in which digital capability and adaptive learning jointly contribute to how graduates evaluate their employment capacity and prospects. The results should be interpreted as predictive associations rather than strong causal effects. Cross-sectional self-report data, accidental sampling, and the use of one institution limit temporal inference and generalizability.

Future research should employ longitudinal designs, probability-based sampling where feasible, multiple institutions, and additional data sources. Potential extensions include work experience, career adaptability, social support, professional networks, career-service quality, and local labour-market conditions.

ACKNOWLEDGEMENTS

The authors thank Universitas Garut for providing the facilities, institutional data, and access required for this study. Appreciation is also extended to those who contributed technical and informational support and to all respondents who completed the questionnaire. Their participation made the data collection and completion of the research possible.

REFERENCES

Adegbite, W. M. (2024). Unpacking mediation and moderating effect of digital literacy and life-career knowledge in the relationship between work-integrated learning and graduate employability. Social Sciences & Humanities Open, 10, 101161. https://doi.org/10.1016/j.ssaho.2024.101161

Azhar, Z., Jalaludin, D., Ghani, E. K., Ramayah, T., & Nelson, S. P. (2024). Learning agility quotient and work readiness of graduating accounting students: Embracing the dynamics of IR4.0. Accounting Education, 33(4), 450-472. https://doi.org/10.1080/09639284.2023.2211567

Bennett, D., Ananthram, S., Lindsay, S., Benati, K., & Jevons, C. (2022). Employability beliefs of business students by gender and year of study: Implications for higher education. The International Journal of Management Education, 20(2), 100654. https://doi.org/10.1016/j.ijme.2022.100654

Duggal, H. K., Khatri, P., Thomas, A., & Pironti, M. (2024). Changing learning paradigms: An interplay of digital Taylorism and technostress on perceived employability. Journal of Management History, 30(2), 166-194. https://doi.org/10.1108/JMH-12-2022-0089

Grosemans, I., De Cuyper, N., Forrier, A., & Vansteenkiste, S. (2023). Graduation is not the end, it is just the beginning: Change in perceived employability in the transition associated with graduation. Journal of Vocational Behavior, 145, 103915. https://doi.org/10.1016/j.jvb.2023.103915

Hair, J. F., Jr., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). SAGE Publications.

Kee, D. M. H., Anwar, A., Gwee, S. L., & Ijaz, M. F. (2023). Impact of acquisition of digital skills on perceived employability of youth: Mediating role of course quality. Information, 14(1), 42. https://doi.org/10.3390/info14010042

Milani, R., Sommovigo, V., Ghirotto, L., & Setti, I. (2024). Individual differences in learning agility at work: A mixed methods study to develop and validate a new scale. Human Resource Development Quarterly, 35(4). https://doi.org/10.1002/hrdq.21528

Noviati, N. P., Nu'man, T. M., Iqbal, M. M., & Akmala, L. A. (2024). Self-perceived employability in the digital era: Analysis of online social support, social media user type, and career adaptability. Psikologika: Jurnal Pemikiran dan Penelitian Psikologi, 29(2), 307-326. https://doi.org/10.20885/psikologika.vol29.iss2.art8

Park, Y., Lim, D. H., & Lee, J. Y. (2022). Internal marketability, external marketability, and career resilience: The mediating role of learning agility. Sustainability, 14(24), 16447. https://doi.org/10.3390/su142416447

Potgieter, I. L., Coetzee, M., & Ferreira, N. (2023). University students' digital world of work readiness in relation to their employability competency. Journal of Learning Development in Higher Education, 27.

Shomotova, A., Karabchuk, T., & Ibrahim, A. (2024). Leadership potential and self-perceived employability of undergraduate students in the United Arab Emirates. International Journal of Educational Research Open, 7, 100335. https://doi.org/10.1016/j.ijedro.2024.100335

Badan Pusat Statistik [Statistics Indonesia]. (2026, February 5). November 2025: Tingkat Pengangguran Terbuka (TPT) sebesar 4,74 persen dan rata-rata upah buruh sebesar 3,33 juta rupiah [Press release]. https://www.bps.go.id/id/pressrelease/2026/02/05/2547/november-2025--tingkat-pengangguran-terbuka--tpt--sebesar-4-74-persen-dan-rata-rata-upah-buruh-sebesar-3-33-juta-rupiah-.html

Suarta, M., Suwintana, K., Sudiadnyani, G. A. O., & Sintadevi, N. P. R. (2024). Employability and digital technology: What skills employers want from accounting workers? Accounting Education, 33(3), 274-295. https://doi.org/10.1080/09639284.2023.2196665

Sugiyono. (2023). Metode penelitian kuantitatif, kualitatif, dan R&D (2nd ed.). Alfabeta.

Universitas Garut. (2025). Data tracer study dan rekap alumni Universitas Garut tahun 2024–2025 [Unpublished institutional data].

Vuorikari, R., Kluzer, S., & Punie, Y. (2022). DigComp 2.2: The digital competence framework for citizens: With new examples of knowledge, skills and attitudes. Publications Office of the European Union. https://doi.org/10.2760/115376

Wardhani, N. S., Sulastiana, M., & Ashriyana, R. (2022). Adaptasi alat ukur learning agility pada karyawan untuk meningkatkan organizational agility: Versi bahasa Indonesia [Adaptation of employee learning agility scale for organizational agility: Indonesian version]. Psikologika: Jurnal Pemikiran dan Penelitian Psikologi, 27(2), 243-264. https://doi.org/10.20885/psikologika.vol27.iss2.art4

World Economic Forum. (2025). Future of jobs report 2025. World Economic Forum.

Wut, T. M., Chan, E. A., Wong, H. S., & Chan, J. K. Y. (2025). Perceived artificial intelligence literacy and employability of university students. Education + Training, 67(2), 258-274. https://doi.org/10.1108/ET-06-2024-0272