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# From Digital Competence to Self-Reported Academic Performance: The Mediating Role of Learning Agility in Higher Education Students

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## ABSTRACT

**Purpose** – This study examines the associations of digital competence with self-reported academic performance and learning agility, as well as the association between learning agility and self-reported academic performance. It also tests whether learning agility statistically mediates the relationship between digital competence and self-reported academic performance among undergraduate students in digitally intensive higher education environments.
**Design/methodology/approach** – This study used an explanatory cross-sectional survey with 587 undergraduate respondents and partial least squares structural equation modelling (PLS-SEM). The analysis distinguished direct, indirect, and total associations, evaluated the reflective measurement model, and included a power-based sample-adequacy check and a post hoc full-collinearity assessment for potential common-method bias.
**Finding/Results** – Digital competence was positively associated with self-reported academic performance ($\beta = .460$, $p < .001$) and learning agility ($\beta = .602$, $p < .001$), while learning agility was positively associated with self-reported academic performance ($\beta = .323$, $p < .001$). The indirect association through learning agility was significant ($\beta = .195$, $p < .001$), consistent with complementary partial mediation. The model explained 36.2% of the variance in learning agility and 49.5% of the variance in self-reported academic performance.
**Originality/Value** – This study offers a process-oriented, but non-causal, interpretation of the relationship between digital competence and students' perceived academic effectiveness by identifying learning agility as a plausible adaptive correlate. The findings should be interpreted conditionally on the study's cross-sectional, self-report design and on the aggregate specification of digital competence.

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## 1. Introduction

Digitalisation has become a structural feature of higher education (Spante et al., 2018; Sánchez-Caballé et al., 2020). Students now learn in environments characterised by digital learning platforms, online information sources, internet-based communication, and assignments that increasingly depend on the management of digital information. In this context, digital competence has become an important capability for effective academic participation (Martzoukou et al., 2020; Tzafilkou et al., 2022). Nevertheless, previous reviews show that research on digital competence in higher education remains diverse in terms of definitions, dimensions, and measurement approaches (López-Núñez et al., 2024; Zhao et al., 2021; Mejías-Acosta et al., 2024). Digital competence should therefore not be treated as a single attribute, but rather as a context-dependent capability whose meaning depends on how it is operationalised (Barboutidis & Stiakakis, 2023).

In the present study, digital competence is defined more specifically in relation to academic contexts. Rather than positioning it as a construct that covers the full range of digital citizenship, digital ethics, or digital safety, this study focuses on students' ability to use digital technologies for academic purposes, particularly to access, use, create, communicate, manage, and evaluate digital information (Fan & Wang, 2022; Wang et al., 2021). This framing is consistent with the indicators used in the study, namely fundamental digital knowledge and skills, access to digital information, use of digital information, creation of digital information and media, digital communication, management of digital information, and evaluation of digital information. In digitally intensive higher education environments, these activities form a central part of students' learning processes.

Although the importance of digital competence is widely acknowledged, the literature remains stronger in documenting its relevance than in explaining the processes through which it is associated with student outcomes (Javier-Aliaga et al., 2024). Several studies report positive relationships between digital competence and student learning or academic performance (Chaw & Tang, 2024; Mehrvarz et al., 2021; Cabero-Almenara et al., 2023; Engel et al., 2023; Widowati et al., 2023). However, the mechanism underlying this relationship remains insufficiently clear (Galindo-Domínguez & Bezanilla, 2021). This limitation matters because academic success in digitally intensive higher education settings is likely to depend not only on students' perceived competence, but also on how they adapt that competence to changing academic demands, new information, and dynamic ways of learning.

This study examines learning agility as one plausible adaptive correlate linking digital competence and self-reported academic performance. Learning agility is understood here as students' adaptive learning orientation towards acquiring, retaining, exploring, and applying new knowledge. This definition is aligned with the five indicators used in the study and with prior higher-education research that operationalises learning agility as an orientation toward new learning experiences, retention of new information, optimism about learning, exploration, and application (Kim et al., 2018). The construct is not treated as equivalent to academic self-efficacy or self-regulated learning: self-efficacy refers primarily to beliefs about capability for particular tasks, whereas self-regulated learning encompasses a broader cycle of goal setting, monitoring, strategy use, and regulation (Panadero, 2017; Javier-Aliaga et al., 2024). Nevertheless, conceptual overlap remains possible, so learning agility is interpreted cautiously as an adaptive learning orientation rather than as a fully distinct causal mechanism.

This study also builds on Mehrvarz et al. (2021), who reported that digital informal learning statistically mediated the relationship between digital competence and academic performance.

Their work shifted attention from a direct-only model towards an indirect-association model rooted in digital informal learning behaviour (He & Zhu, 2017). The present study examines whether learning agility, conceptualised as a broader adaptive learning orientation, is also associated with the digital competence–academic performance relationship. Because the data are cross-sectional, this mediation is interpreted as a statistical decomposition of associations rather than evidence of temporal or causal transmission (Edisherashvili et al. 2022).

From a theoretical perspective, the proposed pattern can be interpreted through human capital theory and a capability-based view. Human capital theory suggests that competence is a productive resource associated with individuals' capacity to perform effectively (Sweetland, 1996). The capability-based view further emphasises the value of mobilising competence under changing conditions (Teece, 2007). In higher education, digital competence may therefore be interpreted as an enabling academic capability, while learning agility represents an adaptive orientation that may co-occur with the effective use of that capability. These perspectives provide an interpretive framework for the observed associations; they do not, in a cross-sectional design, establish the temporal ordering among the constructs.

This study is guided by two research questions. First, how is digital competence associated with learning agility and self-reported academic performance among undergraduate students? Second, is the indirect association between digital competence and self-reported academic performance through learning agility statistically significant? These questions are relevant to digitally mediated higher education, while the scope of inference remains limited to relationships observed in the participating sample.

## 2. Literature Review & Hypothesis Development

### 2.1 Digital competence and self-reported academic performance

In this study, digital competence refers to students' ability to use digital technologies effectively for academic purposes, particularly to access, use, create, communicate, manage, and evaluate digital information. In higher education, this form of digital competence is relevant because most academic activities now rely on students' ability to work with digital information, resources, and media. Students who are more digitally competent should therefore be better prepared to deal with technology-mediated academic tasks.

The expected positive association can be interpreted through human capital theory. This theory treats competence as a productive resource linked to individuals' capacity to perform effectively (Sweetland, 1996). In academic contexts, students who are better able to search for, assess, use, and manage digital information may also report greater effectiveness in understanding course materials, completing assignments, and using learning resources. This interpretation is consistent with empirical evidence reporting positive relationships between digital competence and student learning or academic performance (Chaw & Tang, 2024; Mehrvarz et al., 2021).

Accordingly, the first hypothesis is formulated as follows: H1. Digital competence is positively associated with self-reported academic performance.

### 2.2 Digital competence and learning agility

In this study, learning agility is understood as students' adaptive learning orientation towards acquiring, retaining, exploring, and applying new knowledge. Students with this orientation tend to be more open to new learning experiences, more confident that they can learn new information, more willing to explore new knowledge, and more active in seeking ways to use what they have learned. Learning agility therefore reflects students' readiness to respond positively to changing learning demands.

The expected association between digital competence and learning agility can be interpreted through the capability-based view. This perspective suggests that competence is especially valuable when individuals can use it under changing conditions (Teece, 2007). In higher education, students who perceive themselves as more digitally competent may encounter fewer barriers when engaging with new tools, platforms, or information, and may also report greater openness and confidence in learning. Kim et al. (2018) similarly reported a positive relationship between perceived digital competence and learning agility among students.

Accordingly, the second hypothesis is formulated as follows: H2. Digital competence is positively associated with learning agility.

**2.3 Learning agility and self-reported academic performance**

In this study, academic performance is conceptualised as self-reported academic performance, namely students' perceptions of the adequacy of their academic skills, their competence in completing coursework, their efficiency in performing coursework, and their academic achievement relative to expectations. The focus is therefore not on objective indicators such as grade point average, but on students' perceptions of their academic effectiveness.

The expected association between learning agility and self-reported academic performance can be interpreted in relation to the self-regulated learning literature. Successful learning involves monitoring, adjusting, and directing learning processes in response to task demands (Panadero, 2017). Although learning agility is not identical to self-regulated learning, both emphasise adaptive responses to changing demands. Students who are more open to new learning experiences, more optimistic about learning new information, and more active in applying new knowledge may therefore also perceive themselves as more effective in coursework. Meta-analytic evidence further indicates that adaptive self-regulatory processes are positively associated with academic performance (Theobald, 2021).

Accordingly, the third hypothesis is formulated as follows: H3. Learning agility is positively associated with self-reported academic performance.

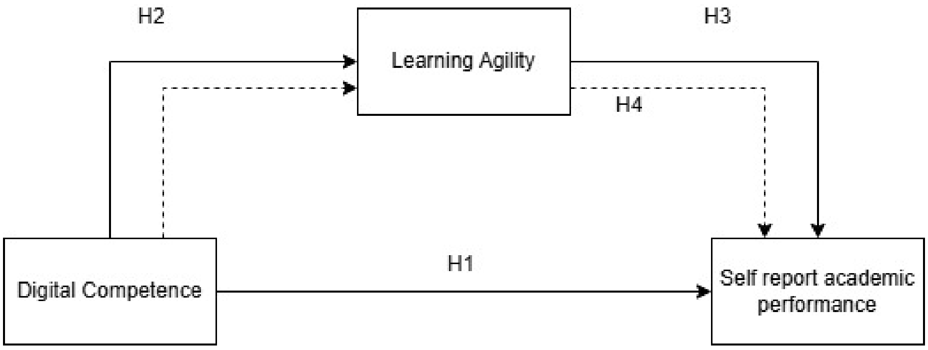
**2.4 The mediating role of learning agility**

If digital competence is associated with students' ability to interact effectively with digital information and technology-mediated tasks, part of its relationship with self-reported academic performance may be shared with learning agility. Students who report stronger digital competence may also report greater openness to new knowledge, more active exploration, and stronger application of what they learn. In a cross-sectional mediation model, this logic is tested as an indirect statistical association rather than as proof that digital competence temporally precedes learning agility (Lee & Song, 2022).

This interpretation is consistent with the capability-based view, which emphasises the use of competence under changing conditions (Teece, 2007). In the present statistical model, digital competence is treated as an enabling capability and learning agility as a potential adaptive correlate. Previous studies have also identified intermediate learning processes in relationships between digital competence and educational outcomes (Mehrvarz et al., 2021; Heidari et al., 2021). The present study tests whether learning agility provides an additional indirect association, while avoiding causal claims that cannot be supported by simultaneous self-report measurement.

Accordingly, the fourth hypothesis is formulated as follows: H4. The relationship between digital competence and self-reported academic performance is statistically mediated by learning agility.

**Figure 1.** Research model




## 3. Methodology

### 3.1 Research design

This study employed an explanatory cross-sectional survey design. The design was used to estimate associations among latent constructs and to test a statistical indirect effect involving learning agility. Because all focal variables were measured at the same point in time, the design does not establish temporal precedence or causal ordering among digital competence, learning agility, and self-reported academic performance.

### 3.2 Context and participants

The analytic sample comprised 587 active undergraduate respondents enrolled in Indonesian higher education. Recruitment used non-probability sampling. The retained study information does not provide an institution-level sampling frame, the number and type of participating universities, the number of invitations distributed, or a response/completion rate. Accordingly, the sample is treated as the participating respondent group rather than as a nationally representative sample of Indonesian undergraduates.

Eligibility required respondents to be active undergraduate students enrolled in higher education in Indonesia, regardless of prior formal digital-literacy education. A power-based sample-adequacy check was conducted for the most complex endogenous equation, which contains two predictors. Using $\alpha$ = .05, statistical power = .80, and a conservative small expected effect size of $f^2$ = .02, the minimum required sample is approximately 485 observations; the observed sample of 587 exceeds this benchmark (Faul et al., 2009). This supports sample-size adequacy for detecting small associations, but it does not resolve limitations associated with non-probability recruitment, uneven subgroup sizes, or unmeasured institutional and socioeconomic heterogeneity.

### 3.3 Measures

Digital competence was adopted from Suwanroj et al. (2019). The original instrument was developed and confirmed as a second-order construct comprising seven first-order competency domains and 24 observed variables. In the original validation, component-level construct reliability ranged from .75 to .95 and average variance extracted ranged from .51 to .86. This provenance is important because the seven domains were designed to be substantively distinguishable components contributing to an overarching digital competence construct rather than interchangeable indicators of a single narrow trait.

In the present dataset, the 24 digital-competence indicators are mapped to the seven original domains as follows: FD1–FD4 = Fundamental of digital; AD1–AD3 = Accessing digital information; UD1–UD3 = Using digital information; CD1–CD3 = Creating digital information and media; COM1–COM4 = Communicating digital information; MD1–MD3 = Managing digital information; and ED1–ED4 = Evaluating digital information. The domain-to-indicator mapping is also reported in Table 1 so that the measurement specification can be evaluated against the original scale structure.

For the structural model reported here, the 24 indicators were retained in the aggregate reflective specification used in the original analysis. This should be treated as a study-specific operationalisation of overall perceived digital competence, not as evidence that the seven domains are psychometrically interchangeable. A reflective–reflective higher-order model would more closely mirror Suwanroj et al. (2019), but a re-estimated higher-order model and a structural path-stability comparison are not available from the retained analysis output. Consequently, the reported structural associations are conditional on the aggregate specification and no robustness claim is made across alternative digital-competence specifications.

Learning agility was measured using the five student-level items reported by Kim et al. (2018): LA1, "New experiences are learning opportunities for me"; LA2, "I easily retain new information"; LA3, "I'm optimistic that I can learn new information"; LA4, "I enjoy researching new information"; and LA5, "I look for ways to use new information." These items operationalise a relatively narrow adaptive orientation toward novelty, retention, learning optimism, exploration, and application. The construct overlaps conceptually with academic self-efficacy, curiosity, learning orientation, and self-regulated learning, but it is not treated as equivalent to those constructs. In particular, academic self-efficacy focuses on perceived capability for academic tasks, whereas self-regulated learning encompasses broader goal-setting, monitoring, strategy, and regulatory processes (Panadero, 2017; Javier-Aliaga et al., 2024).

The learning-agility items were adopted rather than newly developed for this study. Separate evidence of a formal cross-cultural adaptation protocol, expert-panel review, pilot testing, or convergent/discriminant comparison with academic self-efficacy or self-regulated learning is not available in the retained study documentation. The present manuscript therefore does not claim a new validation of learning agility for Indonesian undergraduates; it interprets the construct cautiously and reports the item-level sensitivity evidence available from the fitted measurement model.

Self-reported academic performance was measured with four reflective indicators adapted from the prior literature and reflects students' perceptions of their academic skills, competence in completing coursework, efficiency in performing coursework, and performance relative to expectations (Mehrvarz et al., 2021). All focal items were measured on a seven-point Likert scale, with higher scores indicating higher levels of the corresponding self-reported construct.

**Table 1.** Operationalization variable

| Construct | Definition | Indicator | Scale |
|---|---|---|---|
| Digital competence | Students' perceived capability to use digital technologies and information for academic and learning | FD1–FD4: Fundamental of digital; AD1–AD3: Accessing digital information; UD1–UD3: Using digital information; CD1–CD3: Creating | Likert 1–7 |

| | | | |
|---|---|---|---|
| | purposes, operationalised across seven competency domains (Suwanroj et al., 2019). | digital information and media; COM1–COM4: Communicating digital information; MD1–MD3: Managing digital information; ED1–ED4: Evaluating digital information. | |
| Learning agility | A student-level adaptive learning orientation toward engaging with, retaining, exploring, and applying new information (Kim et al., 2018; DeRue et al., 2012). | LA1: New experiences are learning opportunities for me; LA2: I easily retain new information; LA3: I'm optimistic that I can learn new information; LA4: I enjoy researching new information; LA5: I look for ways to use new information. | Likert 1–7 |
| Self-reported academic performance | Students' perceived competence and effectiveness in performing academic tasks and meeting expected academic outcomes (Mehrvarz et al., 2021). | AP1–AP4: perceived academic skills, coursework competence, task efficiency, and performance relative to expectations. | Likert 1–7 |

**3.4 Data analysis**

The data were analysed using SmartPLS 4. PLS-SEM was used as a variance-based approach for estimating the measurement model, structural associations, and the statistical indirect effect. The measurement model was assessed using outer loadings, Cronbach's alpha, rho_A, composite reliability, average variance extracted (AVE), HTMT, and the Fornell–Larcker criterion. The structural model was evaluated using original-sample path coefficients (β), bootstrap-based t statistics and 95% confidence intervals, coefficients of determination ($R^2$), effect sizes ($f^2$), and inner VIF values. SRMR is reported only as a descriptive approximate-fit index and is not treated as evidence of causal or predictive validity. $Q^2$ and PLSpredict outputs are not available in the retained analysis output; accordingly, the manuscript makes no claim of out-of-sample predictive validity. The exact bootstrap resample count and detailed preprocessing log are likewise not preserved in the retained output and should be documented prospectively in replication studies.

Because digital competence, learning agility, and self-reported academic performance were assessed in the same questionnaire at one time point, common-method variance is a relevant concern. As a post hoc diagnostic, full-collinearity VIFs were calculated from the construct correlation matrix following the logic proposed by Kock (2015). Values below 3.3 were treated as indicating no severe common-method collinearity signal; however, this diagnostic cannot eliminate common-method bias or substitute for temporal separation, multiple data sources, or objective academic outcomes.

## 4. Results and Discussion

### 4.1 Respondent Profile

Tables 2 and 3 describe the composition of the 587 respondents. These distributions are reported to bound the interpretation of the structural results rather than to infer population-level demographic trends.

**Table 2.** Respondent's demography based on Age and gender

| Age\Gender | Male | Female | Total |
|---|---|---|---|
| 17-20 | 87 | 177 | **264** |
| 21-24 | 134 | 187 | **321** |
| 25-28 | 0 | 1 | **1** |
| Upper 29 | 1 | 0 | **1** |
| **Total** | **222** | **365** | **587** |

The sample included 365 female respondents (62.2%) and 222 male respondents (37.8%). The age distribution was concentrated between 17 and 24 years. The imbalance is not itself a validity problem, but it means that the estimated associations may partly reflect the composition of the participating sample. No gender-based substantive comparison is reported because measurement invariance and multigroup analysis were not performed.

**Table 3.** Respondent's demography based on field of study

| Fields of study | Total |
|---|---|
| Agricultural and Environmental Sciences | **11** |
| Business, Management, and Economics | **275** |
| Education | **77** |
| Health and Medical Sciences | **38** |
| Interdisciplinary and Other Fields | **14** |
| Natural Sciences and Engineering | **53** |
| Social Sciences and Humanities | **106** |
| Art and design | **13** |
| **Total** | **587** |

Field-of-study representation was also uneven. Business, Management, and Economics accounted for 275 respondents (46.8%), while several fields contained very small groups, including Agricultural and Environmental Sciences (n = 11), Art and Design (n = 13), and Interdisciplinary and Other Fields (n = 14). These cell sizes are insufficient for a stable all-field multigroup comparison. The structural estimates are therefore unadjusted for field, institution type, year of study, prior digital-literacy training, socioeconomic status, device access, and internet quality. The findings should not be generalised to all Indonesian higher education students without replication using a more explicitly stratified sampling design and measurement-invariance testing.

**4.2 Measurement model**

The measurement model was evaluated at both the indicator and construct levels. Outer loadings ranged from 0.586 to 0.843, and all indicators were significant in the bootstrap output ($p < .001$). Most indicators approached or exceeded the conventional .70 benchmark, although UD2 (0.586), COM3 (0.617), COM4 (0.635), COM2 (0.649), and LA1 (0.602) were lower. These items were retained because they represent substantively distinct content within the adopted measures and because construct-level reliability and convergent validity remained acceptable. For digital competence, however, retention within the aggregate model should not be read as evidence that all 24 indicators are interchangeable across the seven original domains.

A loading-based sensitivity calculation was conducted for LA1 because it had the lowest loading in the learning-agility block. Using the fitted loadings, retaining all five items yields composite reliability = .835 and AVE = .505. Excluding LA1 without re-estimating the model would raise the loading-based AVE to approximately .540 but slightly reduce composite reliability to approximately .824. Both values remain acceptable, and LA1 was retained because it is the item that most directly captures viewing new experiences as learning opportunities. This calculation is a measurement sensitivity check only; it is not a re-estimated structural model and therefore does not establish path robustness to item deletion.

At the aggregate construct level, Table 4 shows satisfactory internal consistency reliability and convergent validity: Cronbach's alpha ranged from 0.758 to 0.962, rho_A from 0.783 to 0.965, composite reliability from 0.835 to 0.965, and AVE from 0.505 to 0.657. These statistics support the three aggregate constructs used in the fitted model. They do not provide first-order reliability or discriminant-validity evidence for the seven digital-competence domains because those domains were not estimated as separate constructs in the reported model.

**Table 4.** Construct reliability and convergent validity

| Construct | Cronbach's alpha | rho_A | Composite reliability | AVE |
|---|---|---|---|---|
| Academic performance | 0.826 | 0.832 | 0.884 | 0.657 |
| Digital competence | 0.962 | 0.965 | 0.965 | 0.538 |
| Learning agility | 0.758 | 0.783 | 0.835 | 0.505 |

As shown in Table 5, HTMT values ranged from 0.679 to 0.726, indicating adequate separation among the three aggregate constructs. Table 6 similarly shows that the square roots of AVE on the diagonal (0.811 for self-reported academic performance, 0.734 for digital competence, and 0.710 for learning agility) exceeded the corresponding inter-construct correlations. These results support discriminant validity among the aggregate constructs but do not eliminate conceptual overlap between learning agility and unmeasured neighbouring constructs such as academic self-efficacy or self-regulated learning.

The construct-level full-collinearity VIF values were 1.982 for self-reported academic performance, 1.989 for digital competence, and 1.775 for learning agility. All were below the conservative 3.3 threshold proposed by Kock (2015), which indicates that severe common-method collinearity is not evident in this diagnostic. Nevertheless, because all focal variables were self-reported by the same respondents at the same time, common response tendencies and self-perception inflation cannot be ruled out.

**Table 5.** Discriminant validity (HTMT)

| Construct pair | HTMT |
|---|---|
| Digital competence ↔ Academic performance | 0.726 |
| Learning agility ↔ Academic performance | 0.720 |
| Learning agility ↔ Digital competence | 0.679 |

**Table 6.** Fornell-Larcker criterion

| Construct | Academic performance | Digital competence | Learning agility |
|---|---|---|---|
| Academic performance | 0.811 | | |
| Digital competence | 0.655 | 0.734 | |
| Learning agility | 0.600 | 0.602 | 0.710 |

**4.3 Structural model**

Table 7 separates the variance-explained statistics from the direct structural paths and reports original-sample coefficients rather than sample means. Digital competence explained 36.2% of the variance in learning agility ($R^2 = 0.362$), while digital competence and learning agility jointly explained 49.5% of the variance in self-reported academic performance ($R^2 = 0.495$). The $f^2$ values were 0.568 for the digital competence–learning agility path, 0.268 for the digital competence–self-reported academic performance path, and 0.132 for the learning agility–self-reported academic performance path. Inner VIF values ranged from 1.000 to 1.568. The SRMR value of 0.067 is reported descriptively; it is not interpreted as proof of model fit or predictive validity.

**Table 7.** PLS results for variances and relationships among variables

| Outcome / path | β (O) | STDEV | $R^2$ | $f^2$ | VIF | t | p |
|---|---|---|---|---|---|---|---|
| Self-reported academic performance | | | .495 | | | | |
| Learning agility | | | .362 | | | | |
| Digital competence → Self-reported academic performance | .460 | .045 | | .268 | 1.568 | 10.233 | < .001 |
| Digital competence → Learning agility | .602 | .037 | | .568 | 1.000 | 16.326 | < .001 |
| Learning agility → Self-reported academic performance | .323 | .045 | | .132 | 1.568 | 7.148 | < .001 |

**Figure 2.** PLS-SEM model output

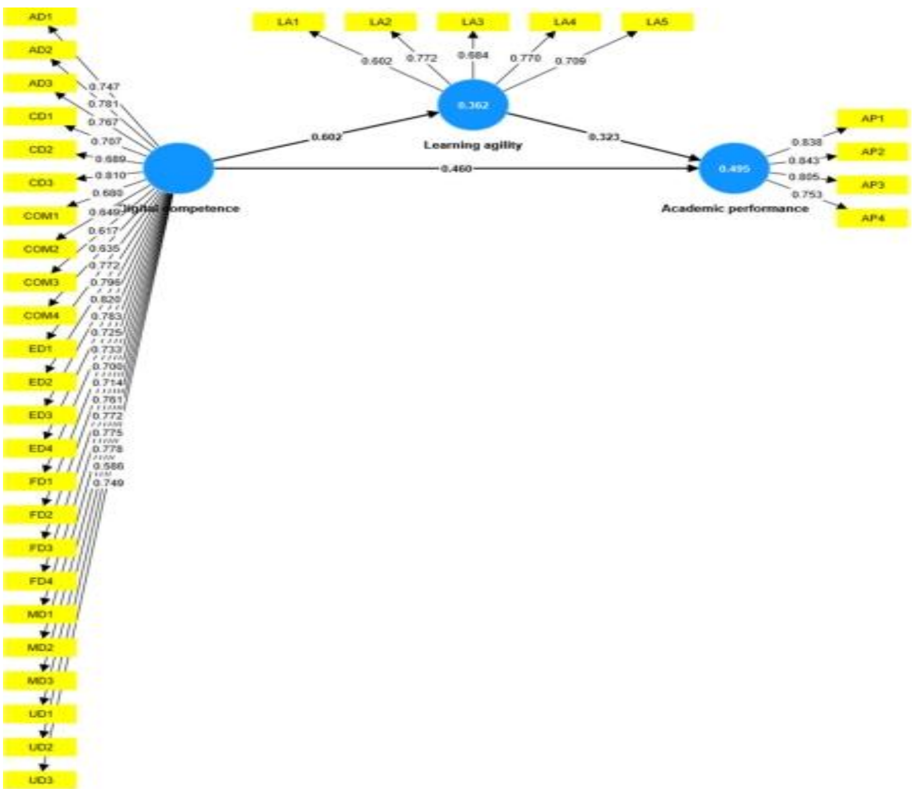


Figure 2 presents the estimated PLS-SEM model, including indicator loadings, standardized path coefficients, and $R^2$ values for the endogenous constructs. The figure summarises positive cross-sectional associations among digital competence, learning agility, and self-reported academic performance and shows the variance explained in the two endogenous constructs.

**4.4 Mediation analysis**

Table 8 presents the path coefficients and hypothesis testing results. All three direct associations were positive and statistically significant. Digital competence was positively associated with self-reported academic performance (β = .460, t = 10.233, p < .001, 95% CI [.369, .545]), supporting H1, and with learning agility (β = .602, t = 16.326, p < .001, 95% CI [.519, .665]), supporting H2. Learning agility was positively associated with self-reported academic performance (β = .323, t = 7.148, p < .001, 95% CI [.232, .412]), supporting H3. The indirect association between digital competence and self-reported academic performance through learning agility was also significant (β = .195, t = 6.800, p < .001, 95% CI [.139, .252]). Because the direct and indirect associations were both significant and had the same sign, the pattern is classified as complementary partial mediation, supporting H4. The total association was β = .655 (t = 20.475, p < .001, 95% CI [.586, .711]). The ratio .195/.655 = 29.7% is reported only as a descriptive proportion of the statistical total association and must not be interpreted as the proportion of a causal effect transmitted through learning agility.

**Table 8.** Summary of hypothesis testing results

| Hypothesis | Path | β | t | p | 95% CI | Decision |
|---|---|---|---|---|---|---|
| H1 | Digital competence → Self-reported academic performance | .460 | 10.233 | < .001 | [.369, .545] | Supported |
| H2 | Digital competence → Learning agility | .602 | 16.326 | < .001 | [.519, .665] | Supported |
| H3 | Learning agility → Self-reported academic performance | .323 | 7.148 | < .001 | [.232, .412] | Supported |
| H4 | Digital competence → Learning agility → Self-reported academic performance | .195 | 6.800 | < .001 | [.139, .252] | Supported (partial) |

**Discussion**

The main contribution of this study is to show that the association between digital competence and self-reported academic performance is statistically consistent with an additional indirect association through learning agility. The analysis does not establish a causal pathway, because all constructs were measured simultaneously. Relative to Mehrvarz et al. (2021), who identified digital informal learning as an intermediate process, the present results suggest that an adaptive learning orientation may represent another correlate within the broader relationship between digital competence and students' perceived academic effectiveness.

Digital competence was positively associated with self-reported academic performance and learning agility, while learning agility was positively associated with self-reported academic performance. The significant direct and indirect coefficients form a complementary partial mediation pattern in the statistical sense. These results support interpreting digital competence as an academically relevant perceived capability that covaries with both students' adaptive learning orientation and their perceived effectiveness in coursework.

The positive association between digital competence and self-reported academic performance is consistent with the view that digital competence represents a form of academically relevant human capital. Students who report greater ability to access, evaluate, manage, and use digital information also tend to report greater effectiveness in academic tasks. This pattern is consistent with human capital theory (Sweetland, 1996) and with prior empirical evidence linking digital competence to student outcomes (Chaw & Tang, 2024; Mehrvarz et al., 2021). Because the outcome is self-reported, the finding should be understood as an association between perceived digital capability and perceived academic effectiveness rather than as evidence that digital competence raises objective achievement.

The strongest structural association was between digital competence and learning agility. This result is consistent with the proposition that students who perceive fewer barriers in using digital tools and information may also report greater openness, optimism, exploration, and application of new knowledge. At the same time, the learning-agility measure contains elements that conceptually neighbour academic self-efficacy, curiosity, and self-regulated learning. Because these neighbouring constructs were not included in the model, the present study cannot demonstrate incremental validity beyond them. Learning agility is therefore interpreted as a plausible adaptive orientation rather than a uniquely established mechanism.

The positive association between learning agility and self-reported academic performance is consistent with the broader idea that students' perceived academic effectiveness is related not only to what they know, but also to how they approach novelty and changing learning demands. This interpretation converges with the self-regulated learning literature, which emphasises monitoring and adjustment in academic learning (Panadero, 2017), while preserving the distinction between the broader self-regulation construct and the narrower five-item learning-agility measure used here.

The mediation results provide a more differentiated statistical account of the three constructs. The direct association between digital competence and self-reported academic performance remained significant while the positive indirect association through learning agility was also significant; therefore, the pattern is complementary partial mediation. This classification indicates that the data are consistent with simultaneous direct and indirect associations. It does not demonstrate that digital competence temporally produces learning agility or that learning agility carries a fixed share of a causal effect.

A capability-based perspective provides one interpretive lens for this pattern. Digital competence can be viewed as an enabling perceived capability, while learning agility reflects an adaptive orientation that may accompany more effective engagement with changing academic demands (Teece, 2007). The theory helps organise the observed relationships, but the cross-sectional design does not adjudicate among alternative temporal sequences. Reverse or reciprocal relationships remain plausible: students who perceive themselves as academically successful may develop greater confidence in their digital competence, and students with pre-existing learning agility may be more motivated to develop digital skills.

These findings complement Mehrvarz et al. (2021) by showing that a significant indirect association can also be observed when learning agility is used as the mediator. This does not imply that learning agility replaces digital informal learning or other established learning-process variables. Rather, the relationship between digital competence and academic outcomes may be statistically represented through several partially overlapping learning-related constructs, a possibility that should be compared directly in future multi-mediator or longitudinal models.

The digital-competence measurement specification is another important boundary on interpretation. The adopted Suwanroj et al. (2019) instrument was originally validated as a second-order structure with seven first-order domains, whereas the fitted model used an aggregate reflective representation. The aggregate reliability and validity statistics are acceptable, but they may mask uneven competence profiles across accessing, using, creating, communicating, managing, evaluating, and fundamental digital skills. The present analysis therefore cannot identify which digital domain is most strongly associated with learning agility or perceived academic performance, and it does not establish that the structural paths would be identical under a higher-order specification.

The substantive questions are relevant to digitally intensive higher education, but the empirical generalisation must remain bounded. The sample was non-probability based, nearly half of respondents were from Business, Management, and Economics, and institution-level sampling information was not available for analysis. Accordingly, the coefficients should be treated as evidence from the participating undergraduate sample rather than as national estimates for Indonesian higher education. Replication across institution types, regions, disciplines, and student backgrounds is needed before making broader claims.

The results also require caution because all focal variables were self-reported in the same questionnaire. The full-collinearity VIF diagnostic did not indicate severe common-method collinearity, but this does not eliminate common-method variance, generalized self-confidence, social-desirability tendencies, or positive self-perception as alternative explanations for part of the observed relationships. Future work should combine objective GPA or course grades with temporal separation and repeated measurement.

**5. Conclusion and Suggestion**

The findings indicate a complementary partial mediation pattern in the statistical relationship among digital competence, learning agility, and self-reported academic performance. Digital competence was positively associated with self-reported academic performance both directly and indirectly through learning agility. Because the study is cross-sectional and all focal measures are self-reported, these coefficients should not be interpreted as evidence that digital competence causally produces learning agility or academic performance.

The study contributes by placing learning agility alongside other learning-related constructs that may help describe the association between digital competence and student outcomes. The result complements prior evidence on digital informal learning while also highlighting the need to compare learning agility directly with academic self-efficacy, self-regulated learning, and related adaptive constructs before claiming unique explanatory value.

Several limitations materially bound the conclusions. Digital competence was estimated in an aggregate reflective form even though the adopted source instrument was originally multidimensional and second-order. Learning agility had the lowest reliability and convergent-validity statistics in the model and was not validated against neighbouring constructs. The non-probability sample was heterogeneous and uneven across gender and fields of study, while institution-level sampling information and theoretically relevant controls were unavailable. All focal variables were self-reported at one time point, so common-method inflation and reverse ordering remain plausible. Finally, $Q^2$ and PLSpredict were not available,

and the exact bootstrap and preprocessing settings were not preserved in the retained output; therefore, no out-of-sample predictive claim is made.
Within these boundaries, the findings suggest a practical emphasis on combining digital-skill development with learning environments that encourage students to engage with unfamiliar information, explore alternatives, and apply new knowledge. Such interventions should be evaluated with objective academic outcomes and longitudinal designs before being interpreted as performance-enhancing mechanisms.

**6. Limitations and Future Research**

Future research should directly address the measurement, sampling, and design limitations identified in this study. First, the seven digital-competence domains should be estimated as first-order constructs within a theoretically appropriate higher-order model, with domain-level reliability, convergent validity, discriminant validity, collinearity/weights where relevant, and a robustness comparison of the structural paths across alternative specifications. Second, learning agility should be validated in student populations through expert content review, pilot testing, and discriminant or incremental-validity comparisons with academic self-efficacy, curiosity, learning orientation, and self-regulated learning. Third, sampling should be explicitly stratified by institution type, region, field, and year of study; subgroup comparisons should be preceded by measurement-invariance testing and should include theoretically relevant controls such as prior achievement, socioeconomic background, digital-literacy training, device access, and internet quality. Fourth, future studies should combine self-report data with objective GPA or course grades, temporal separation, and longitudinal or experimental designs. Finally, future PLS-SEM studies should retain complete preprocessing and bootstrapping settings and report $Q^2$ and PLSpredict when predictive claims are made.

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**Declaration of AI and AI-assisted technologies in the writing process**

During the preparation of this work, the authors used ChatGPT, developed by OpenAI, to assist with language refinement, grammatical correction, and improvement of the clarity and structure of the manuscript. After using this tool, the authors carefully reviewed, verified, and edited the content as needed and take full responsibility for the accuracy, originality, and content of the publication.

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