

Decomposing Ecosystem Effects On Digital Entrepreneurial Intention Among International Students In Busan: A Pls-Sem Study

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Abstract—Digital entrepreneurship offers international students a route to convert cross-border knowledge, platform access, and local resources into new venture opportunities. However, aggregate evidence can overstate ecosystem effects when student populations differ sharply by academic discipline. This study examines regulatory accessibility, digital ecosystem resources, cross-cultural adaptability, and digital entrepreneurial intention among 120 international students in Busan, South Korea. A mixed-measurement partial least squares structural equation model specified regulatory accessibility and ecosystem resources as formative composites and cultural adaptability and entrepreneurial intention as reflective constructs. The pooled model showed a strong association between ecosystem resources and entrepreneurial intention, whereas regulatory accessibility and cultural adaptability were not significant. Predictive assessment yielded positive Q^2_{predict} values for all intention indicators. However, a control-adjusted robustness model reduced the ecosystem coefficient to 0.081 ($p = 0.392$); academic discipline became the dominant correlate, with Engineering/IT positive and Humanities/Arts negative relative to Business/Logistics. The findings reveal an aggregation-driven composition effect: apparent ecosystem influence largely reflects disciplinary clustering rather than a general within-student mechanism. The study offers a cautionary perspective on measurement and modeling in digital entrepreneurial ecosystem research and recommends discipline-sensitive entrepreneurship programming, transparent data provenance, and longitudinal designs before drawing policy conclusions.

Keywords— *Academic discipline; Digital entrepreneurship; Entrepreneurial ecosystem; International students; PLS-SEM*

I. INTRODUCTION

Digital technologies have altered where entrepreneurial opportunities arise, how ventures are assembled, and who can participate in cross-border markets. Digital artifacts, platforms, payment systems, and social networks reduce some entry barriers while simultaneously creating new dependencies on platform governance, data visibility, logistics, and institutional legitimacy (Nambisan, 2017; Nambisan et al., 2019; von Briel et al., 2018). These shifts are particularly consequential for international students. They combine temporary mobility, bicultural market knowledge, multilingual networks, and access to host-country supply systems. However, they also operate under visa, employment, and business-registration constraints that were generally designed for conventional place-bound work.

Busan provides a salient setting for examining this tension. The city's Study Busan 30K strategy seeks to attract 30,000 international students by 2028 and increase transitions from study status to employment or job-seeking status (Busan Metropolitan City, 2026). Its foreign-student ordinance authorizes education, counseling, and support for employment and startups, creating an explicit municipal mandate for entrepreneurial integration (Busan Metropolitan City, 2025). At the national level, however, D-2 students must obtain permission for part-time employment and are generally limited to specified forms of student work (Study in Korea, 2026). The resulting institutional configuration is both enabling and constraining.

Entrepreneurial ecosystem research argues that entrepreneurship is embedded in interdependent institutional, cultural, social, and material conditions (Spigel, 2017; Stam & van de Ven, 2021; Wurth et al., 2022). Digital ecosystem research adds platforms, digital infrastructure, and distributed collective intelligence to this configuration (Elia et al., 2020; Sussan & Acs, 2017; Zahra et al., 2023). Nevertheless, two empirical problems remain. First, ecosystem constructs are often modeled reflectively, even though access to finance, platforms, logistics, mentorship, and policy support are non-interchangeable components that form an ecosystem rather than manifestations of it. Second, pooled student samples may generate large structural paths because academic disciplines differ in exposure to technology, commercialization routines, and venture-oriented curricula. Such compositional heterogeneity can create an aggregate association that is weak or absent within disciplines.

This study addresses these issues using a mixed-measurement PLS-SEM model and a control-adjusted robustness analysis. It asks: (1) How are regulatory accessibility, digital ecosystem resources, and cross-cultural adaptability associated with digital entrepreneurial intention? (2) Does the pooled ecosystem association persist after accounting for academic discipline, visa status, and Korean-language proficiency? The contribution is threefold. Theoretically, the study distinguishes formed ecosystem conditions from reflective psychological constructs. Methodologically, it demonstrates why strong pooled PLS paths require heterogeneity checks before being translated into policy. In practice, it identifies academic discipline as a central segmentation variable for international student entrepreneurship programs in Busan.

Digital Entrepreneurship and Ecosystem Resources

Digital entrepreneurship refers to entrepreneurial processes and outcomes that are enabled, shaped, or constituted by digital technologies (Nambisan, 2017). Digital technologies can compress coordination time, expand market reach, recombine resources, and shift agency from established organizations toward distributed actors (von Briel et al., 2018). Reviews of the field emphasize that digital venturing is inherently contextual: platform rules, technological affordances, user communities, and complementary institutions influence which opportunities are discoverable and executable (Zaheer et al., 2019; Zahra et al., 2023).

An entrepreneurial ecosystem is not a single support service. It is a configuration of interdependent conditions, actors, and resources that enable or constrain productive entrepreneurship (Acs et al., 2017; Stam, 2015; Stam & van de Ven, 2021). In a digital setting, platform access, digital payment infrastructure, market information, mentorship, logistics, and university or municipal support jointly form the resource environment available to prospective entrepreneurs (Elia et al., 2020; Sussan & Acs, 2017). Because these facets need not move together and omitting one changes the domain of the construct, the present study treats digital ecosystem resources as a formative composite. Greater resource availability should increase perceived feasibility and lower the coordination costs of venture initiation. Recent student-focused studies similarly report positive associations between environmental or ecosystem support and digital entrepreneurial intention (Narmaditya et al., 2024).

H1. Digital ecosystem resources are positively associated with digital entrepreneurial intention.

Regulatory Accessibility

Institutional conditions determine which entrepreneurial actions are legitimate, administratively feasible, and financially viable. Entrepreneurial ecosystem scholarship consistently identifies formal institutions and policy implementation as framework conditions rather than peripheral background variables (Audretsch & Belitski, 2017; Stam & van de Ven, 2021). For international students, regulatory accessibility encompasses the practical clarity and usability of visa, work-permit, registration, taxation, and business support arrangements. These facets form a composite because a favorable score on one dimension cannot conceptually substitute for the absence of another. Korean evidence also indicates that perceived access to startup immigration support and individual capability are relevant to international students' entrepreneurial intentions (Kim et al., 2025).

H2. Regulatory accessibility is positively associated with digital entrepreneurial intention.

Cross-Cultural Adaptability

International students must interpret host-country institutions while simultaneously understanding consumer expectations, payment habits, and social networks in their home markets. Cross-cultural adaptability can therefore support opportunity recognition, supplier communication, trust formation, and the transfer of market knowledge across borders. Unlike ecosystem conditions, adaptability is modeled reflectively because its indicators are treated as manifestations of an underlying capability. Research on international student entrepreneurship increasingly positions cross-cultural competence as a mechanism that connects psychological resources to entrepreneurial intention and behavior (Zhong et al., 2025).

H3. Cross-cultural adaptability is positively associated with digital entrepreneurial intention.

Academic Discipline as a Source of Compositional Heterogeneity

Academic disciplines structure exposure to technical tools, business models, project-based commercialization, professional identities, and peer networks. Engineering and information technology students may encounter digital product development and scalable problem-solving routines; business and logistics students may receive more direct venture and market training; humanities and arts students may possess valuable cultural and creative capabilities but encounter fewer formal pathways to commercialization. Consequently, discipline can influence both perceived ecosystem resources and entrepreneurial intention. If discipline is omitted, a pooled structural path may combine within-discipline association with between-discipline mean differences. The study, therefore, first estimates the hypothesized PLS-SEM model and then incorporates discipline, visa status, and language proficiency into a robustness model.

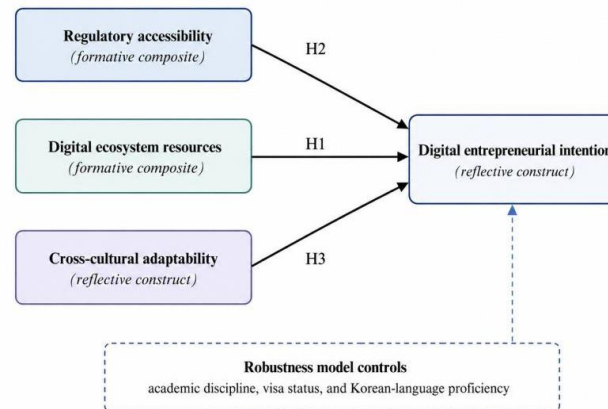


Figure 1. Conceptual Model

II. METHOD

Research Design and Analytical Sample

The study uses a cross-sectional quantitative design and analyzes data from 120 international students across 24 variables: respondent identifier, academic discipline, visa status, Korean-language proficiency, and 20 measurement indicators. No missing values were present.

The sample comprises 55 Engineering/IT records (45.8%), 43 Business/Logistics records (35.8%), and 22 Humanities/Arts records (18.3%). Most records are D-2 visa holders ($n = 113$, 94.2%), with seven D-10 records. Korean-language proficiency is concentrated in TOPIK levels 3–4 ($n = 61$, 50.8%) and 1–2 ($n = 51$, 42.5%); eight records report TOPIK 5–6. The small D-10 and TOPIK 5–6 cells require conservative interpretation of control coefficients.

TABLE I. SAMPLE PROFILE (N = 120)

Characteristic	Category	n	%
Academic discipline	Engineering / IT	55	45.8
	Business / Logistics	43	35.8
	Humanities / Arts	22	18.3
Visa status	D-2	113	94.2

Characteristic	Category	n	%
	D-10	7	5.8
Korean proficiency	TOPIK 1-2	51	42.5
	TOPIK 3-4	61	50.8
	TOPIK 5-6	8	6.7

Construct Specification

Four five-indicator blocks were analyzed. Regulatory accessibility (REG1-REG5) and digital ecosystem resources (ECO1-ECO5) were specified formatively (Mode B). Their indicators represent potentially non-interchangeable conditions that jointly define each composite. Cross-cultural adaptability (CUL1-CUL5) and digital entrepreneurial intention (INT1-INT5) were specified reflectively (Mode A). The dataset retains item codes rather than verbatim questionnaire wording. Observed response ranges were 1-3 for REG, 1-4 for ECO, 1-5 for CUL, and 1-4 for INT.

TABLE II. MEASUREMENT AND STRUCTURAL SPECIFICATION

Construct	Indicators	Specification	Rationale
Regulatory accessibility	REG1-REG5	Formative (Mode B)	Institutional and administrative conditions jointly form accessibility.
Digital ecosystem resources	ECO1-ECO5	Formative (Mode B)	Resource facets jointly form the usable digital entrepreneurship ecosystem.
Cross-cultural adaptability	CUL1-CUL5	Reflective (Mode A)	Indicators manifest an underlying adaptive capability.
Digital entrepreneurial intention	INT1-INT5	Reflective (Mode A)	Indicators manifest an underlying intention to engage in digital entrepreneurship.

PLS-SEM Procedure

A variance-based PLS path model was estimated using a reproducible Python implementation of the iterative path-weighting algorithm. PLS-SEM was selected because the model combines formative composites and reflective constructs and because the research objective is explanatory-predictive rather than exact covariance reproduction (Hair et al., 2019, 2021). Manifest variables were standardized before estimation. The inner model regressed digital entrepreneurial intention on regulatory accessibility, digital ecosystem resources, and cross-cultural adaptability.

Measurement assessment followed the construct type. Formative blocks were evaluated using indicator collinearity, outer-weight magnitude and significance, and outer loadings as supplementary information. Reflective blocks were evaluated using indicator loadings, Cronbach's alpha, composite reliability (ρ_C), average variance extracted (AVE), and heterotrait-monotrait ratio (HTMT) (Henseler et al., 2015). Structural assessment included inner VIF, standardized path coefficients, nonparametric bootstrap confidence intervals, R^2 , adjusted R^2 , and f^2 . The bootstrap used 1,000 resamples. Predictive assessment used repeated 10-fold cross-validation and compared PLS prediction errors with a linear-model benchmark following the predictive orientation recommended by Shmueli et al. (2019).

The inverse-square-root logic of Kock and Hadaya (2018) indicates that $N = 120$ is adequately powered for paths of approximately 0.23 or larger at conventional significance and power levels. However, it is not designed to detect small effects reliably. Consequently, nonsignificant small coefficients are interpreted as inconclusive or negligible in this dataset rather than as proof of no population relationship.

Robustness Model

To test whether the pooled structural relation reflected sample composition, a post-estimation robustness model regressed the PLS intention score on the three PLS predictor scores plus standardized indicator variables for academic discipline, visa status, and language proficiency. Business/Logistics, D-10, and TOPIK 1-2 served as reference categories. Confidence intervals were obtained from 10,000 bootstrap resamples of the row-level score dataset. This second-stage model is reported as a robustness analysis, not as a replacement for the PLS measurement model.

III. RESULTS AND DISCUSSION

Descriptive Patterns

Construct-level raw means were 2.020 for REG, 2.948 for ECO, 2.663 for CUL, and 3.255 for INT. The most pronounced descriptive differences occurred by academic discipline. On standardized PLS scores, Engineering/IT records were above the sample mean for ecosystem resources (0.706) and intention (0.836). In contrast, Humanities/Arts records were markedly below the mean for ecosystem resources (-1.904) and intention (-1.784). Business/Logistics records were near the sample mean. These parallel between-discipline shifts foreshadow the composition effect examined below.

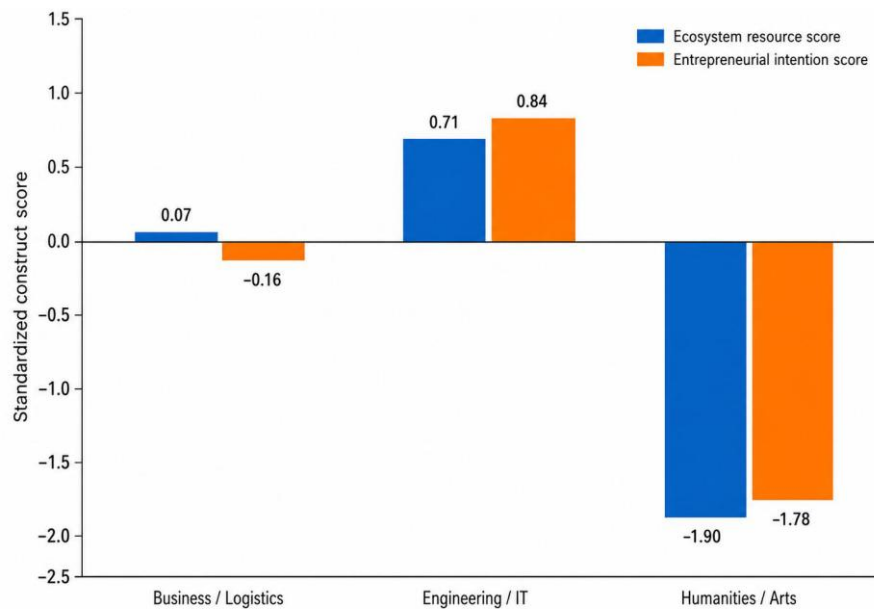


Figure 2. Ecosystem Resources and Entrepreneurial Intention by Academic Discipline

Measurement Model

Formative indicator collinearity was acceptable. REG VIF values ranged from 1.046 to 1.164, while ECO VIF values ranged from 2.282 to 3.008. All five ECO outer weights were positive and statistically significant, supporting their contribution to the ecosystem composite. REG outer weights were mixed and nonsignificant, and supplementary loadings were also heterogeneous. The REG composite was retained for theoretical completeness, but its empirical meaning and structural effect should be interpreted cautiously until the original item wording and direction are verified.

The reflective constructs met conventional reliability and convergent validity criteria. CUL loadings ranged from 0.968 to 0.985, Cronbach's alpha was 0.988, ρC was 0.990, and AVE was 0.952. The very high reliability suggests possible item redundancy and should motivate scale shortening or wording diversification in future data collection. INT loadings ranged from 0.804 to 0.847, with an alpha of 0.884, ρC of 0.915, and AVE of 0.684. HTMT between CUL and INT was 0.085, indicating a clear empirical distinction between the two reflective constructs.

TABLE III. MEASUREMENT-MODEL ASSESSMENT

Construct	Type	VIF range	Weight range	Indicator result	α	ρC	AVE
REG	Formative	1.046–1.164	–0.467–0.476	None significant	–	–	–
ECO	Formative	2.282–3.008	0.161–0.282	All significant	–	–	–
CUL	Reflective	–	–	Loadings 0.968–0.985	0.988	0.990	0.952
INT	Reflective	–	–	Loadings 0.804–0.847	0.884	0.915	0.684

Note. HTMT(CUL, INT) = 0.085. Formative weights were assessed with 1,000 bootstrap resamples.

Pooled Structural Model

The pooled PLS-SEM model explained 80.3% of the variance in digital entrepreneurial intention ($R^2 = 0.803$; adjusted $R^2 = 0.798$; bootstrap 95% CI [0.743, 0.870]). Structural collinearity was negligible, with inner VIF values ranging from 1.021 to 1.045. Digital ecosystem resources exhibited a large positive path to intention ($\beta = 0.896$, $p < 0.001$, 95% CI [0.845, 0.941]), supporting H1 in the pooled model. Regulatory accessibility was essentially zero ($\beta = -0.003$, $p = 0.961$), and cross-cultural adaptability was also nonsignificant ($\beta = -0.008$, $p = 0.845$); H2 and H3 were not supported. The ecosystem effect size was extremely large ($f^2 = 3.917$), while the other effects were negligible.

TABLE IV. POOLED PLS-SEM STRUCTURAL RESULTS

Hyp.	Path	β	SE	t	p	95% CI	f^2	Decision
H2	REG $\rightarrow$ INT	–0.003	0.053	–0.049	0.961	[–0.086, 0.114]	0.000	Not supported
H1	ECO $\rightarrow$ INT	0.896	0.024	36.724	< .001	[0.845, 0.941]	3.917	Supported
H3	CUL $\rightarrow$ INT	–0.008	0.039	–0.196	0.845	[–0.081, 0.072]	0.000	Not supported

Note. R^2 (INT) = 0.803; adjusted $R^2 = 0.798$; 1,000 bootstrap resamples.

Predictive Assessment

All five intention indicators produced positive Q^2 predict values, ranging from 0.456 to 0.617. PLS root-mean-square error was lower than the linear-model benchmark for every indicator, and PLS mean absolute error was lower for four of five indicators. These results indicate strong pooled out-of-sample predictive performance. However, prediction alone does not identify the source of the predictive signal; the control analysis shows that discipline composition accounts for much of it.

TABLE V. OUT-OF-SAMPLE PREDICTIVE ASSESSMENT

Indicator	RMSE PLS	RMSE LM	MAE PLS	MAE LM	Q^2 predict
INT1	0.483	0.536	0.433	0.472	0.483
INT2	0.470	0.493	0.418	0.420	0.554
INT3	0.528	0.573	0.464	0.489	0.456
INT4	0.461	0.486	0.419	0.418	0.527
INT5	0.426	0.465	0.365	0.383	0.617

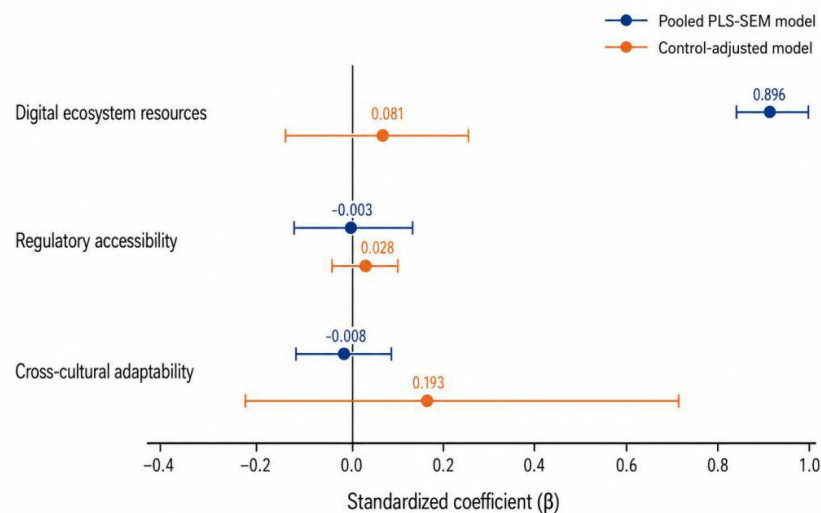
Note. Repeated 10-fold cross-validation. Positive Q^2 predict indicates improvement over the naïve mean benchmark.

Control-Adjusted Robustness Model

The pooled ecosystem path did not survive adjustment for observed composition. After adding discipline, visa, and language controls, the ecosystem coefficient fell from 0.896 to 0.081 ($p = 0.392$; 95% CI [–0.107, 0.266]). REG and CUL remained nonsignificant. In contrast, Engineering/IT was strongly positive relative to Business/Logistics ($\beta = 0.466$, $p < 0.001$), while

Humanities/ Arts was strongly negative ($\beta = -0.545$, $p < 0.001$). D-2 status showed a small positive coefficient ($\beta = 0.053$, $p = 0.037$), but the estimate is fragile because the D-10 reference group includes only seven records. Language-proficiency indicators were nonsignificant. The adjusted model explained 92.1% of the variance in intention scores (bootstrap 95% CI [0.899, 0.946]).

Within-discipline sensitivity estimates reinforce this result. The ECO-INT coefficient was 0.352 in Business/Logistics, -0.019 in Engineering/IT, and -0.412 in Humanities/Arts; the latter estimates are imprecise because of modest group sizes. The pattern is inconsistent with a uniform ecosystem effect and indicates that the large pooled path is primarily an aggregation-driven association produced by between-discipline mean differences.



Note. The control-adjusted model includes academic discipline, visa status, and Korean-language proficiency controls.

Figure 3. Pooled and Control-Adjusted Structural Coefficients
TABLE VI. CONTROL-ADJUSTED ROBUSTNESS RESULTS

Predictor	β	Bootstrap SE	p	95% CI
Regulatory accessibility	0.028	0.027	0.294	[-0.025, 0.080]
Digital ecosystem resources	0.081	0.095	0.392	[-0.107, 0.266]
Cross-cultural adaptability	0.193	0.250	0.442	[-0.300, 0.702]
Engineering / IT	0.466	0.046	< .001	[0.379, 0.557]
Humanities / Arts	-0.545	0.089	< .001	[-0.725, -0.372]
D-2 visa	0.053	0.025	0.037	[0.002, 0.103]
TOPIK 3-4	-0.143	0.210	0.497	[-0.579, 0.264]
TOPIK 5-6	-0.220	0.211	0.298	[-0.645, 0.201]

Note. Reference categories: Business/Logistics, D-10, and TOPIK 1-2. $R^2 = 0.921$; 10,000 bootstrap resamples of the post-estimation score model.

Theoretical Interpretation

The pooled model initially appears to deliver a straightforward ecosystem result: access to digital entrepreneurial resources is closely associated with intention, while regulation and cultural adaptability contribute little. This pattern is consistent with digital entrepreneurship theory, which emphasizes the enabling role of platforms, complementary infrastructure, and distributed access to resources (Elia et al., 2020; Nambisan, 2017; Zahra et al., 2023). The formative specification also performs well empirically: all ecosystem indicators make significant contributions without problematic collinearity.

The robustness model changes the substantive interpretation. Once an academic discipline is represented, the ecosystem path becomes small and statistically uncertain. The strong pooled association, therefore, does not reflect a stable individual-level mechanism across the sample. Instead, Engineering/IT records combine high ecosystem scores with high intention, while Humanities/Arts records combine low ecosystem scores with low intention. The model captures these between-group differences and attributes them to the ecosystem composite when discipline is omitted. This result is an aggregation-driven composition effect, closely related to the family of ecological and Simpson-type biases.

This result advances entrepreneurial ecosystem research in two ways. First, it reinforces calls to specify mechanisms rather than treat ecosystems as undifferentiated contextual causes (Wurth et al., 2022). Ecosystem resources may matter through discipline-specific channels—technical prototyping, market experimentation, creative commercialization, or logistics capability—rather than through a common main effect. Second, it shows that predictive strength and high R^2 do not by themselves establish a generalizable structural explanation. PLS-SEM's predictive orientation is valuable, but the predictive signal can originate from sample composition. Heterogeneity analysis is therefore not optional when groups differ in education, nationality, industry, or platform architecture.

Regulatory Accessibility and Cultural Adaptability

The negligible REG path should not be interpreted as evidence that regulation is irrelevant. The regulatory composite's nonsignificant and directionally mixed weights indicate that the measurement block requires substantive verification. If some items represent barriers and others represent support, unrecorded reverse coding could suppress both weights and structural relations. Moreover, a tightly clustered observed range of 1–3 limits variance. Before theory is evaluated, the authors must verify the item wording, the scale direction, and whether regulatory facets should be modeled as barriers, enablers, or separate composites.

CUL demonstrates excellent convergence but extremely high internal consistency. Reliability near 0.99 commonly signals semantic redundancy rather than superior measurement. Its nonsignificant structural effect may mean that cultural adaptability is a background capability that affects behavior through opportunity recognition, self-efficacy, or network activation rather than directly through intention. A revised model could test mediated paths and use a shorter, more differentiated scale. Longitudinal evidence would be especially useful because adaptability may influence the conversion of intention into action over time rather than at the time of intention.

Policy and Managerial Implications

For Busan, the results argue against a uniform entrepreneurship-support package for all international students. Engineering/IT students appear ready for venture-building pathways that connect prototypes, artificial intelligence, software, digital manufacturing, and export-market validation. Business/Logistics students may benefit from platform analytics, cross-border fulfillment, pricing, and compliance modules. Humanities/Arts students should not be interpreted as lacking entrepreneurial potential; their low measured intention may reflect weaker access to commercialization scripts and ecosystem visibility. Programs for this group should translate cultural content, design, language, media, and K-beauty-related creative assets into platform business models, intellectual-property strategies, and portfolio-based micro-venture experiments.

Municipal and university support should therefore be segmented, staged, and evaluated. A shared foundation can cover Korean business law, visa compliance, taxation, digital payments, and consumer protection. Discipline-specific studios can then address technical commercialization, creative-industry monetization, or cross-border market operations. The city's statutory authority to support international students' employment and startups provides an institutional basis for such programming (Busan Metropolitan City, 2025). Nevertheless, any student entrepreneurship pathway must be coordinated with national immigration authorities, as ordinary D-2 work permits do not automatically authorize independent business activity (Study in Korea, 2026).

For K-beauty firms and platform intermediaries, international students can serve as cultural and market-boundary spanners. However, engagement should occur through legally compliant internships, consulting arrangements, university projects, or approved startup pathways. Firms should not treat informal student commerce as a substitute for formal export compliance. Instead, they can partner with universities to run supervised market-testing labs using anonymized customer insight, localized content, and traceable logistics.

Methodological Implications

Three methodological practices emerge from the analysis. First, researchers should specify ecosystems as composites when their indicators are constitutive and non-interchangeable. Treating them reflectively can inflate reliability and obscure the theoretical domain. Second, pooled structural paths should be accompanied by controls, multigroup analyses, finite-mixture procedures, or tests of observable heterogeneity. Third, predictive assessment should be interpreted jointly with an explanation. A model can predict well because it captures group membership, even when its focal theoretical path is not robust within groups.

IV. CONCLUSIONS

This study used mixed-measurement PLS-SEM to examine digital entrepreneurial intention in a dataset of 120 international students from Busan. The pooled model suggested that digital ecosystem resources were overwhelmingly associated with intention and produced strong out-of-sample predictions. Regulatory accessibility and cross-cultural adaptability were nonsignificant. A control-adjusted analysis, however, showed that the ecosystem coefficient largely disappeared once academic discipline was included. Engineering/IT and Humanities/Arts membership accounted for the dominant differences relative to Business/Logistics.

The principal conclusion is therefore not that ecosystems do not matter, but that their apparent effect cannot be separated from disciplinary composition in the current data. Ecosystem interventions are likely to operate through differentiated educational and professional pathways. Future research should collect a larger probability-based or well-documented purposive sample, retain verbatim item metadata, verify scale direction, obtain ethics approval, and follow students longitudinally from intention to venture action. Cross-national and platform-specific comparisons—such as K-beauty social commerce across East Asian and Southeast Asian student networks—would provide a valuable next step once industry and nationality variables are measured directly.

Limitations

The study has six principal limitations. The cross-sectional design precludes causal inference. The analytical sample is modest and uneven across disciplines. The dataset provides item codes but not verbatim wording or scale provenance, limiting construct-content verification. Nationality, university, venture experience, platform usage, and K-beauty involvement are not included in the dataset. Finally, the control-adjusted model uses estimated construct scores, and subgroup estimates are imprecise, especially for Humanities/Arts, D-10, and TOPIK 5–6 records.

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