

## Research Article

# Technology-Supported Student-Centered Science Learning and Digital Competence Development in Upper Secondary Classrooms

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Digital competence is increasingly recognized as a core outcome of science education, yet evidence remains limited. This study examined whether technology-supported science instruction was associated with stronger multidimensional digital competence than conventional instruction and explored how seven competence dimensions were structurally related. A quasi-experimental pretest-posttest non-equivalent control group design was conducted with 180 Grade 11 students from four intact classes in two public schools. Over eight weeks, the experimental group engaged in inquiry- and project-based digital science learning, whereas the comparison group received instruction. Digital competence was assessed using a 28-item questionnaire and seven performance-based tasks. The experimental group showed larger gains across all dimensions, with significant baseline-adjusted differences across all outcomes (all  $p < 0.001$ ) and moderate-to-large effects (partial  $\eta^2 = 0.26-0.29$ ). More importantly, the pattern suggests that technology-supported student-centered science learning is associated not only with stronger technical performance but also with an integrated competence profile spanning information handling, data interpretation, communication, collaboration, problem-solving, creativity, and operational fluency. The structural findings further suggest that information literacy and digital communication may function as foundational competencies supporting analytical, collaborative, technical, and creative performance, with the strongest pathway from Digital Communication Skills to Collaborative Technology Use ( $\beta = 0.58$ ). These findings imply that digital competence in science is best fostered when digital tools are embedded in inquiry, communication, collaboration, and production tasks rather than taught as isolated technical skills. Because the study involved only four intact classes, the findings should be interpreted as comparative and exploratory rather than definitive causal evidence.

**KEYWORDS** digital competence • digital inclusion • inquiry-based learning • student-centered learning • performance-based assessment • technology-enhanced learning • quality education

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## 1. INTRODUCTION

The rapid digitalization of education has fundamentally reshaped how science is taught and learned in secondary classrooms. In contemporary science education, students are increasingly expected to search for scientific information online, evaluate the credibility of digital sources, analyze datasets using digital tools, collaborate through shared platforms, and communicate evidence-based explanations in multimodal formats. Although these expectations are highly relevant, international evidence indicates that students' digital development does not automatically result from access to technology alone. The ICILS 2023 International Report shows that computer and information literacy remains uneven across education systems, while Eurydice's recent policy analysis demonstrates that the integration of digital competence into curricula, teacher preparedness, and assessment structures varies considerably across countries [1], [2]. Taken together, these findings suggest that digital competence is shaped less by the mere availability of technology than by the extent to which digital learning is intentionally designed, scaffolded, and assessed in classrooms. This issue is particularly salient in upper secondary science, where students are expected to engage in increasingly complex, inquiry-oriented, and discipline-specific uses of digital tools.

Current scholarship increasingly conceptualizes digital competence as a multidimensional construct rather than a narrow set of technical or operational skills. In DigComp 2.2, digital competence is defined as an integrated combination of information and data literacy, communication and collaboration, digital content creation, safety, and problem solving [3]. This broader conceptualization is especially relevant to science education because scientific learning involves more than operating devices or software; it requires students to locate and evaluate trustworthy evidence, interpret data representations, communicate findings, create digital products, and make reasoned decisions based on data. Subject-specific scholarship further reinforces this perspective. The DiKoLAN framework argues that science-related digital competence encompasses both general digital practices and competencies that are particularly salient in science, such as documentation, data handling, simulation, and presentation [4]. Thus, digital literacy in the context of scientific practice is not fully captured by generic models and should instead be understood in relation to disciplinary activities such as data collection, analysis, interpretation, and scientific communication [5]-[9].

This multidimensional perspective has important pedagogical implications. Student-centered learning is particularly relevant because it positions students as active investigators, collaborators, interpreters, and producers of knowledge. A recent systematic review of literature reviews found that educational technologies support student-centered learning most effectively when

they foster cognitive engagement, metacognitive regulation, participation, and knowledge construction rather than the passive delivery of content [10]. In science education, this is especially significant because student-centered environments often rely on inquiry, problem-solving, collaborative reasoning, and artifact creation, all of which closely align with the development of digital competence. Supporting this view, Ješková et al. [11] found that active STEM learning can strengthen inquiry-related skills when students engage in authentic investigative tasks. Likewise, Chen and Chen [12] showed in their systematic review that technology-enhanced collaborative inquiry in K-12 classrooms supports inquiry processes, student engagement, and scientific skills when digital tools are meaningfully aligned with inquiry activities. Bilici and Yilmaz [13] further demonstrated that collaborative digital storytelling in biology education can improve not only academic achievement but also critical thinking, co-regulation, and narrative skills. Collectively, these studies suggest that student-centered, technology-supported science instruction provides a productive environment for the development of broad digital competence.

However, the empirical literature remains fragmented in several important respects. First, many studies still examine digital competence through isolated indicators, such as information search, communication, or technical skill, rather than treating it as an interconnected structure. This is problematic because authentic science learning rarely draws on only one digital capability at a time. Students often need to search for and evaluate information, transform data into evidence, discuss interpretations with peers, and present findings through digital products within the same learning sequence [14]-[17]. Research on the structure of digital literacy suggests that digital competence is better understood as multidimensional and internally related than as a single undifferentiated ability. For example, Reichert et al. [18] found evidence for both a general digital literacy dimension and more specific dimensions tied to authentic software use, indicating that competence may be structurally integrated rather than simply additive. This perspective is particularly relevant to science education, where multiple digital practices are simultaneously mobilized during inquiry- and project-based learning.

A second limitation concerns assessment. Much of the literature still relies heavily on self-report measures, even though perceived competence may differ substantially from demonstrated performance. Porat et al. [19] showed that students' perceived digital literacy can exceed their actual performance on digital tasks, highlighting the risks of relying solely on self-assessment. More recent work by González-Mujico [20] similarly argues for assessment approaches that move beyond self-perception by incorporating rubric-based and performance-oriented evaluation. This concern is

reinforced by Pedaste et al. [21], who developed a multidimensional digital competence test and demonstrated the value of validated instruments capable of capturing multiple latent dimensions of competence. In the same vein, Mattar et al. [22] found that DigComp-based assessment tools remain dominated by questionnaire formats and that validation procedures are uneven across instruments. These findings suggest that stronger research designs should combine questionnaire-based indicators with performance-based tasks to provide a more credible account of students' digital competence.

A third gap concerns context and conceptual modeling. Although recent scholarship has expanded understanding of digital competence, relatively few studies have examined how multiple dimensions of digital competence develop together within classroom-based, student-centered science learning in upper secondary education. This matters because science learning is not simply a generic digital activity; it is a disciplinary practice shaped by evidence evaluation, data interpretation, collaborative inquiry, and representational work. Recent subject-specific research, therefore, suggests that digital competence should be examined in relation to the epistemic and procedural demands of science itself [4], [5], [23]–[25]. Moreover, even when multiple dimensions are measured, relatively few studies investigate how these dimensions relate to one another within an integrated empirical model. This issue is important because some dimensions may function as enabling capabilities for others. For example, information literacy may support digital data analysis, while collaborative use of technology and digital communication may facilitate creativity in digital projects and problem-solving with digital tools.

Against this background, the present study examines digital competence as a multidimensional outcome of student-centered, technology-supported science learning in upper secondary classrooms. Rather than treating digital competence as a single, generic ability, the study focuses on seven dimensions particularly relevant to digitally mediated science learning: information literacy, digital data analysis, collaborative technology use, digital communication skills, problem-solving with digital tools, creativity in digital projects, and technical digital proficiency. The study contributes to the literature in three ways. First, it situates digital competence within a science-learning context in which multiple digital practices are simultaneously mobilized. Second, it combines questionnaire-based indicators with performance-based tasks to move beyond self-report and provide a more credible picture of students' demonstrated competence. Third, it examines the structural relations among the seven competence dimensions, thereby addressing not only whether student-centered digital instruction is associated with stronger competence development, but also how these dimensions may be interconnected. Accordingly, this study asks: (1) How does

student-centered, technology-supported instruction influence the development of students' multidimensional digital competence in upper secondary science education? and (2) What structural relationships exist among the seven dimensions of students' digital competence in this instructional context?

## 2. LITERATURE REVIEW

### 2.1. Digital Competence as Context-situated Construct

Digital competence cannot be adequately understood as mere technical ability to operate devices or software. Contemporary frameworks increasingly conceptualize it as a multidimensional construct that integrates the cognitive, technical, communicative, and problem-oriented capacities required for meaningful participation in digitally mediated environments. In the DigComp 2.2 framework, for example, digital competence comprises information and data literacy, communication and collaboration, digital content creation, safety, and problem solving. This broader conceptualization is particularly important in educational contexts because students are expected not only to access digital tools but also to evaluate information critically, communicate appropriately, collaborate productively, and create knowledge-rich digital outputs [3].

In science education, however, a generic account of digital competence remains insufficient. Science learning requires students to work with disciplinary evidence, interpret data representations, reason from sources, and communicate evidence-based claims. Subject-specific scholarship, therefore, argues that digital competence should be contextualized within the epistemic demands of the discipline. The DiKoLAN framework is especially relevant in this regard because it distinguishes science-specific digital competency areas from more general digital abilities and demonstrates that digital participation in science is both disciplinary and operational. In upper secondary science classrooms, students are often required to search for and evaluate digital scientific information, analyze experimental data, collaborate in shared digital spaces, communicate explanations in multimodal formats, and produce technology-supported artifacts. Accordingly, the present study conceptualizes digital competence as a science-relevant system of interrelated dimensions rather than as a collection of isolated digital subskills [3], [4].

This multidimensional framing is also methodologically important. Recent assessment research shows that digital competence cannot be fully captured through highly general or purely self-perceived indicators. Pedaste et al. [21], for example, developed a school-based digital competence test that identified distinguishable dimensions while also providing evidence of broader higher-order structures, suggesting that digital competence is both multidimensional and internally

organized. This finding supports the argument that competence dimensions should be modeled as related domains rather than interpreted as independent attributes. On this basis, the present study operationalizes digital competence through seven dimensions closely aligned with the demands of digitally supported science learning: information literacy, digital data analysis, collaborative technology use, digital communication skills, problem-solving with digital tools, creativity in digital projects, and technical digital proficiency.

## 2.2. Student-Centered Digital Science Learning as the Developmental Context of Competence

The theoretical rationale for linking these seven dimensions is grounded in student-centered learning, particularly inquiry-based and project-based science instruction. Student-centered pedagogy positions learners as active constructors of knowledge rather than passive recipients of information. In science classrooms, this means that students are expected to investigate questions, collect and interpret evidence, discuss competing explanations, and communicate conclusions through meaningful tasks. Educational technology reinforces this pedagogical orientation when it is embedded in activities that support inquiry, collaboration, feedback, and production rather than simple content delivery [8], [26]–[29]. A recent systematic review of literature reviews by Shehata et al. [10] found that educational technologies most effectively facilitate student-centered learning by supporting cognitive and metacognitive processes, followed by motivational and affective dimensions. This suggests that technology is most educationally powerful when it is aligned with active knowledge construction.

This argument is particularly compelling in science education. Active learning, as represented in inquiry-based science education, has been shown to improve inquiry skills among upper secondary students when consistently implemented across STEM disciplines and supported by digital technologies and formative scaffolding [11], [30]–[32]. Likewise, Chen and Chen [12], in their systematic review of technology-enhanced collaborative inquiry in K–12 classrooms, reported positive effects on content knowledge, inquiry processes, and scientific skills such as argumentation. These findings are directly relevant to the present study, which does not assume that digital competence develops independently of pedagogy. Rather, it assumes that inquiry, collaboration, explanation, and digital production constitute the activity structures through which the seven competence dimensions are developed and interconnected.

Student-centered digital science learning is also consistent with socio-constructivist theory, which holds that knowledge is co-constructed through dialogue, interaction, and shared problem solving. In technology-supported inquiry settings, students typically work with

shared digital documents, simulations, communication platforms, and multimedia tools to coordinate ideas and produce joint outputs. Such environments do not merely enhance engagement; they create conditions under which communication, collaboration, and creative digital production become mutually reinforcing. Reviews of technology-supported collaborative creativity likewise show that digital collaborative practices are typically grounded in student-directed or social-constructivist pedagogies and that dialogue, joint ideation, and negotiated production are central to creative outcomes. This literature provides an important foundation for the present model, particularly for the pathways linking communication, collaboration, and creativity.

## 2.3. Why Digital Competence Should Be Assessed Beyond Self-Report

A further reason for adopting a stronger conceptual model concerns the current state of digital competence measurement. Many studies still rely primarily on self-report scales, although such instruments are useful mainly for capturing confidence, perception, or self-evaluated familiarity. González-Mujico [20] argues that advancing the field requires moving beyond self-assessment and supplementing perceived competence with external evaluations of actual performance. In that study, rubric-based frameworks were developed specifically to compare self-reported competence with competence evidenced in oral, written, and instructional practice. This critique is directly relevant here because a multidimensional theoretical model is more convincing when paired with multidimensional evidence rather than a single perceptual measure.

Pedaste et al. [21] make a similar point from a school-based measurement perspective. Their work demonstrates that comprehensive digital competence assessment requires instruments capable of differentiating among multiple dimensions while also capturing broader higher-order structures. Taken together, these studies suggest that digital competence development should be examined through both perceived and demonstrated performance, particularly when the goal is to understand how competence dimensions relate to one another in authentic learning environments. For this reason, the conceptual model adopted in the present study is not only pedagogically grounded but also methodologically aligned with an assessment logic that combines self-report and performance-based evidence.

Although prior research has established associations between digital competence and academic outcomes, most studies have employed cross-sectional or correlational designs, thereby limiting causal inference. Moreover, empirical models rarely examine multiple dimensions of digital competence simultaneously as predictors of science achievement. This gap underscores the need for quasi-experimental research to test structured pathways linking foundational digital skills,

collaborative practices, and higher-order problem-solving competencies to academic performance outcomes.

The reviewed literature, therefore, points to a clear methodological strategy: digital competence should be conceptualized as a multidimensional construct, assessed using multiple sources of evidence, and analyzed in relation to the pedagogical environments in

which it develops. The present study is designed to address these three requirements simultaneously.

To provide a consolidated overview of the most relevant contributions in the fields of digital competence and student-centered digital science learning, selected studies are reviewed in this section in Table 1.

**Table 1.** Key studies informing the conceptual framework, measurement strategy, and intervention rationale

Authors	Focus	Method	Main Findings	Relevance to This Study
Vuorikari et al. (2023) [3]	DigComp 2.2 digital competence framework	Framework/report	Defines digital competence as a multidimensional construct encompassing information literacy, communication, content creation, safety, and problem-solving.	Provides the overarching conceptual basis for multidimensional digital competence.
Mattar et al. (2022) [22]	DigComp-based digital competence assessment tools	Literature review	Shows that many available instruments rely heavily on questionnaires and vary in their validation procedures.	Supports the need for stronger and more transparent assessment design.
Pedaste et al. (2023) [21]	School-based digital competence test	Instrument development and validation	Demonstrates that distinguishable competence dimensions can also form broader higher-order structures.	Supports multidimensional operationalization and structured measurement.
Shehata et al. (2024) [10]	Educational technologies and student-centered learning	Systematic review of literature reviews	Finds that educational technologies support student-centered learning most effectively when they foster cognitive and metacognitive engagement.	Supports the pedagogical rationale for student-centered digital learning.
Ješková et al. (2022) [11]	Active STEM learning and inquiry skills	Quasi-experimental study	Reports significant improvement in inquiry skills when inquiry-based STEM learning is implemented consistently and supported appropriately.	Supports inquiry-based science learning as a developmental context.
Chen & Chen (2024) [12]	Technology-enhanced collaborative inquiry in K-12	Systematic review	Finds positive effects on content knowledge, inquiry processes, and scientific skills when digital tools are aligned with inquiry stages.	Supports the integration of digital tools with collaborative inquiry activity structures.
Bilici & Yilmaz (2024)[13]	Collaborative digital storytelling in biology education	Quasi-experimental study	Shows positive effects on academic achievement and skill development, including co-regulation and narrative performance.	Supports the relevance of collaborative digital production and communication.
González-Mujico (2024) [20]	Digital competence beyond self-assessment	Framework development and validation	Shows that rubric-based external assessment can complement self-report and reveal gaps between perceived and demonstrated competence.	Supports combining questionnaire and performance-based evidence in the present study.

#### 2.4. Conceptual Framework & Hypothesis Development

The proposed framework integrates constructivist, cognitivist, and socio-constructivist perspectives to explain how digital competence develops in student-centered science learning. From a constructivist perspective, learners actively construct knowledge through engagement with evidence, tasks, and tools rather than passively receiving information [33]–[35]. From a cognitivist perspective, competence development depends on how learners organize, interpret, and transform information into meaningful mental representations that support reasoning and problem solving [36]. From a socio-constructivist perspective, learning is mediated through dialogue, shared activity, and participation in socially organized practices, making communication and collaboration central rather than

peripheral to competence development [37]. Recent work in STEM education supports integrating these traditions when analyzing digitally mediated, inquiry-based learning environments, particularly those that emphasize active learning, scientific inquiry, and collaborative knowledge construction [10], [11], [38], [39].

In addition, subject-specific research on digital competence in science suggests that digitally competent participation in science learning involves interrelated activities such as collecting and interpreting data, generating conclusions, and sharing findings, rather than isolated technical acts [4], [5]. Accordingly, the present framework assumes that digital competence develops through linked pathways in which foundational informational and communicative capabilities support more complex analytical, collaborative, technical, and

creative performances. This assumption is also consistent with the intervention sequence in the present study, which begins with information literacy and data work, then emphasizes communication, collaboration, and problem solving, and culminates in digital project production.

#### 2.4.1. From information literacy to data analysis and communication

Information literacy is positioned as a foundational competence because meaningful participation in science learning depends on students' ability to locate, evaluate, organize, and synthesize credible information. In digitally mediated science tasks, data are not interpreted in isolation; rather, students must first determine whether sources, datasets, and representations are trustworthy, relevant, and conceptually appropriate. Recent science-specific work supports this view by showing that digital literacy in scientific practice includes data collection, interpretation, conclusion generation, and dissemination, all of which presuppose the meaningful selection and use of information [5]. Likewise, research on science literacy instruction has shown that when students are explicitly taught to find, evaluate, comprehend, discuss, and cite scientific evidence, their science literacy and communication capabilities improve in more integrated ways [40], [41]. Accordingly, students with stronger information literacy should be better able to select appropriate evidence, understand digital representations, and use information productively in digital data analysis. Thus, information literacy is theorized as an antecedent of digital data analysis.

*H1: Information literacy (IL) has a positive effect on digital data analysis (DDA).*

Information literacy is also expected to contribute directly to digital communication skills. In science learning, communication is not merely expressive; it is evidence-based and requires the ability to justify claims, distinguish reliable from unreliable information, and synthesize information into coherent explanations. Research on scientific communication instruction has shown that explicit support for information retrieval, scientific reading and writing, data representation, and knowledge presentation strengthens students' scientific literacy and communication outcomes [41]–[43]. Similarly, studies in biology and science literacy instruction indicate that students' engagement with scientific literature and evidence supports the development of communication-related competencies, especially when learners are asked to discuss, explain, and present evidence to others [40], [44], [45]. In school science, communication-focused pedagogies such as socio-scientific issues approaches also improve students' ability to understand others' ideas, articulate positions, and engage in reasoned exchange [46]–[49]. Therefore,

students with stronger information literacy should be better positioned to justify, explain, and communicate ideas in digital discussions, shared documents, and presentations.

*H7: Information literacy (IL) has a positive effect on digital communication skills (DCS).*

#### 2.4.2. From digital data analysis to problem solving with digital tools

Digital data analysis is expected to support problem-solving with digital tools, as science-related problem-solving often depends on students' ability to interpret representations, identify patterns, evaluate evidence, and use digital outputs to guide decisions. In digitally supported science learning, students do not merely process data; they use data to frame questions, test interpretations, and select appropriate procedures for addressing task demands. From this perspective, data analysis functions not only as an analytical competence but also as a basis for digitally mediated problem solving. Students who are more capable of analyzing digital data should therefore be better able to use digital tools to investigate problems, adapt strategies, and generate evidence-based solutions.

*H2: Digital data analysis (DDA) has a positive effect on problem solving with digital tools (PSDT).*

#### 2.4.3. From digital communication to collaborative technology use

Digital communication skills are expected to support collaborative technology use because collaboration in digital environments depends fundamentally on the quality of interaction among group members. Students working on shared science tasks must articulate claims, exchange feedback, negotiate interpretations, coordinate roles, and maintain coherence across platforms and artifacts. Research on collaborative online learning shows that successful digital collaboration requires high-quality cognitive, metacognitive, and relational interaction, including active participation and task-related communication [50]–[53]. In K–12 science contexts, technology-enhanced collaborative inquiry likewise depends on tools and activity structures that sustain students' engagement in inquiry stages such as discussion, argumentation, and the co-construction of explanations [12]. Related science classroom research further suggests that communication-rich pedagogies improve students' ability to understand others' perspectives and engage in shared reasoning, thereby strengthening the interactional basis for collaboration [46]. Hence, in the present model, digital communication is not treated as a parallel skill but as a functional enabler of productive collaborative technology use.

*H3: Digital communication skills (DCS) have a positive effect on collaborative technology use (CTU).*

#### 2.4.4. From problem solving to technical proficiency

At first glance, technical digital proficiency may seem to precede problem-solving. In this study, however, it is conceptualized not as mere exposure to digital devices, but as operational fluency developed through repeated, goal-directed use of digital tools in authentic learning tasks. This perspective is consistent with digital competence frameworks that define problem-solving as identifying digital needs, selecting appropriate tools, using technologies creatively, and resolving technical difficulties, suggesting that technical operation and problem-solving are closely intertwined rather than separate domains [58], [59]. When students solve science-related problems using simulations, virtual laboratories, and other digital tools, they must navigate interfaces, manipulate features, interpret feedback, and troubleshoot obstacles under real constraints. These activities resemble the interactive digital environments described by the OECD, in which students use computational tools to explore systems and iteratively construct solutions [60]. Research further indicates that performance in digital environments is partly tool-dependent, such that repeated engagement can strengthen familiarity, confidence, and procedural flexibility [18]. In STEM settings, simulation-based and technology-supported problem solving has also been shown to enhance problem-solving capacity and broader digital development [54], [61], [62]. Therefore, the present study proposes that problem-solving with digital tools positively predicts technical digital proficiency, treating this direction as exploratory rather than definitive [63].

*H4: Problem-solving with digital tools (PSDT) has a positive effect on technical digital proficiency (TDP)*

#### 2.4.5. From technical proficiency and collaboration to digital creativity

Creativity in digital projects is treated as a higher-order outcome because it requires students not only to express ideas, but also to integrate conceptual understanding, tool use, multimodal design, and, often, collaboration. Technical digital proficiency is expected to support creativity because students cannot fully exploit digital affordances for innovative production if they lack fluency in operating platforms, configuring functions, or resolving routine technical barriers. Research on technology-enhanced creativity shows that digital tools can support idea development, product creation, process scaffolding, and creative evaluation when used in pedagogically meaningful ways [8], [64]–[66]. Systematic review evidence likewise indicates that emerging technologies can promote student creativity, especially in interactive learning environments, although these effects depend

strongly on implementation quality [67]. More specifically, research in digital fabrication spaces shows that open-ended prototyping can simultaneously strengthen students' perceived technical skills and creativity, suggesting that technical fluency can free cognitive resources for experimentation, adaptation, and originality [68]. Therefore, students with stronger technical proficiency should be better able to transform scientific ideas into coherent, innovative digital products.

*H5: Technical digital proficiency (TDP) has a positive effect on creativity in digital projects (CDP).*

Collaborative use of technology is also expected to enhance creativity in digital projects. In student-centered science environments, creative digital production is rarely an entirely individual act; rather, it often emerges through shared planning, feedback exchange, revision, and the integration of multiple perspectives and representations. A scoping review of digital technology and social creativity in science education found that technology can function as a medium for collaborative and creative thinking and can help organize collective creativity processes in science learning [69], [70]. In addition, Bilici and Yilmaz [13] showed that collaborative digital storytelling in biology education improved not only academic achievement, but also co-regulation and narrative performance, indicating that collaborative digital production may support broader creative development. Therefore, collaborative technology use is theorized as a second positive predictor of creativity in digital projects.

*H6: Collaborative technology use (CTU) has a positive effect on creativity in digital projects (CDP)*

## 2.5. Synthesis of the Proposed Model

The proposed framework conceptualizes digital competence development in upper secondary science learning as a structured progression from foundational information work to analytical reasoning, from evidence-based communication to collaborative participation, and from applied problem solving to technically and creatively productive performance. Rather than treating these dimensions as isolated skills, the model presents them as interconnected constructs that develop through meaningful engagement in student-centered, technology-supported science learning environments. At the same time, the framework does not assume a rigid or universal developmental sequence. Instead, it proposes a theoretically grounded set of directional relationships that can be explored and empirically tested in science education contexts.

Figure 1 shows the hypothesized relationships among the seven digital competence constructs. The model suggests that information literacy and digital communication serve as important upstream resources

for more advanced forms of data analysis, collaboration, problem-solving, technical performance, and digital creativity. In this sense, students' ability to locate, evaluate, and communicate information is positioned as a foundation for more complex scientific and digital practices. The framework, therefore, reflects a developmental logic in which foundational informational and communicative capacities support increasingly sophisticated analytical, collaborative, technical, and creative forms of participation in science learning.

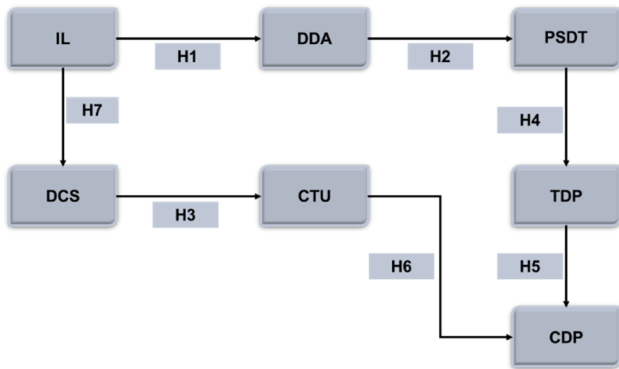


Figure 1. Conceptual Framework of Study

### 3. MATERIALS AND METHODS

#### 3.1. Study Design

This study employed a quasi-experimental pretest-posttest nonequivalent control group design to examine whether student-centered, technology-supported science instruction was associated with stronger development of multidimensional digital competence than conventional instruction. Because the participating schools maintained intact classroom groupings, random assignment at the

individual level was not feasible. Consistent with reporting guidance for nonrandomized intervention studies, the study design, comparison condition, participant flow, intervention delivery, and analytic strategy are reported transparently to support interpretability and replication [71]. Given the use of intact classes, the intervention effects are interpreted as comparative, class-based estimates rather than definitive individual-level causal effects. Two Grade 11 natural science classes were assigned to the experimental condition (n = 85), and two comparable classes were assigned to the comparison condition (n = 95), yielding a total sample of 180 students. The study was conducted in two public upper secondary schools with sufficient infrastructure to support technology-enhanced science learning.

#### 3.2. Participants, Sampling and Eligibility Criteria

Schools were selected through purposive sampling based on three criteria: (1) the availability of upper secondary natural science programs, (2) access to basic digital learning infrastructure, including computer laboratories or internet-enabled devices, and (3) administrative and teacher willingness to participate in the intervention. Students were eligible if they were enrolled in Grade 11 natural science classes, attended the course regularly during the intervention period, and provided informed consent to participate. Students were excluded from the final analytic sample if they had prolonged absences during the intervention, did not provide the required consent, or failed to complete both the pretest and posttest assessments. These criteria were intended to ensure consistent exposure to the instructional condition and to support interpretable assessment of change over time.

Table 2. Baseline demographic and digital access characteristics of the study participants (N = 180)

Demographic variable	Category	Experimental (n = 85)	Comparison (n = 95)	Total	Percentage
Gender	Male	43	47	90	50.00%
	Female	42	48	90	50.00%
Age (years)	16	27	29	56	31.10%
	17	29	31	60	33.30%
	18	29	35	64	35.60%
Class section	A	27	31	58	32.20%
	B	29	33	62	34.40%
	C	29	31	60	33.30%
Prior digital experience	Low	15	17	32	17.80%
	Medium	45	49	94	52.20%
	High	25	29	54	30.00%
Access to digital devices	Personal computer/laptop	55	59	114	63.30%
	Tablet/smartphone only	30	36	66	36.70%
Frequency of digital tool use	Rarely (<1/week)	11	13	24	13.30%
	Sometimes (1-3/week)	45	49	94	52.20%

Demographic variable	Category	Experimental (n = 85)	Comparison (n = 95)	Total	Percentage
Device ownership	Often (4-7/week)	29	33	62	34.40%
	Own device	51	55	106	58.90%
	Share device	34	40	74	41.10%
Extracurricular technology use	Yes	41	45	86	47.80%
	No	44	50	94	52.20%

### 3.3. Intervention and Comparison Conditions

The experimental condition consisted of an eight-week student-centered digital science intervention grounded in inquiry-based and project-based learning. The intervention comprised 24 sessions, each lasting 45 minutes, delivered over three sessions per week. Both the experimental and comparison groups covered the same natural science content and were allocated equivalent curricular time; the principal difference lay in the instructional organization and the extent to which digital tools were integrated into inquiry, collaboration, communication, and project work. Student-centered, technology-enhanced pedagogies are theoretically well aligned with competence development because they require learners to search, interpret, discuss, create, and solve problems in authentic task settings [10], [11].

The intervention followed a coherent progression of competence demands. Weeks 1-2 emphasized information literacy through guided searches of scientific sources and digital note-making. Weeks 3-4 focused on digital data analysis using spreadsheets, graphing tools, and data generated through virtual laboratory activities. Weeks 5-6 emphasized digital communication, collaborative technology use, and problem-solving through group investigations, multimedia explanations, and simulation-based tasks. Weeks 7-8 culminated in digital project work requiring creativity and technical proficiency in the production of science-related digital artifacts. The comparison group followed the same curriculum through more conventional teacher-led instruction, including lectures, textbook exercises, individual assignments, and only limited use of digital tools.

The instructional content covered core upper secondary natural science topics, including ecosystems and environmental sustainability, motion, force, and

energy, chemical reactions and acids and bases, and scientific data interpretation and experimentation. These topics were selected to preserve curricular equivalence while allowing meaningful integration of digital tools into inquiry-oriented science tasks.

### 3.4. Teacher Preparation and Implementation Fidelity

Regular upper secondary natural science teachers delivered the intervention. Before implementation, teachers assigned to the experimental condition participated in a two-day workshop focused on student-centered pedagogy, inquiry-based learning, project facilitation, formative feedback, and technology integration in science instruction. Teachers in the comparison group continued their usual instructional practice and did not receive intervention-specific training. Because implementation quality is a known determinant of intervention outcomes, fidelity was monitored explicitly rather than assumed [72]-[74]. Accordingly, any observed differences in outcomes should be interpreted as reflecting the combined influence of student-centered digital instruction and structured teacher preparation, rather than pedagogy alone.

Implementation fidelity was assessed using a 12-item classroom observation checklist aligned with the core components of the intervention, including active learning, collaborative interaction, digital tool integration, learner autonomy, and formative feedback. Two trained observers conducted three unannounced observations in each experimental class, yielding six total observations, each lasting approximately 30 minutes. Fidelity adherence was calculated as the percentage of observed intervention indicators relative to the total number of checklist indicators. Interobserver agreement was estimated using Cohen's kappa, which is appropriate for agreement on observed categorical indicators.

**Table 3.** Observation-based implementation indicators for the intervention and comparison classrooms

Parameter	Experimental group	Comparison group
Number of classes observed	2	2
Total observation sessions	6	6
Observation duration per session	30 minutes	30 minutes
Total observation time	180 minutes	180 minutes
Mean fidelity adherence (%)	91.2	5.2
SD	4.6	2.1
Minimum adherence (%)	84.5	2.3
Maximum adherence (%)	96.8	8.4

Parameter	Experimental group	Comparison group
Inter-observer agreement (Cohen's $\kappa$ )	0.89	0.91
Fidelity interpretation	High implementation fidelity	No intervention exposure

### 3.5. Measures

#### 3.5.1. Conceptualization of Digital Competence

Digital competence was operationalized as a seven-dimensional construct comprising information literacy (IL), digital data analysis (DDA), collaborative technology use (CTU), digital communication skills (DCS), problem solving with digital tools (PSDT), creativity in digital projects (CDP), and technical digital proficiency (TDP). This multidimensional operationalization was informed by the broader logic of DigComp 2.2, which conceptualizes digital competence as extending beyond technical operation to include information processing, communication, creation, and problem solving, as well as by DiKoLAN, which emphasizes that digitally mediated competence in science-related contexts is domain-sensitive rather than fully generic [3], [4].

#### 3.5.2. Questionnaire Instrument

The questionnaire was designed to capture students' self-reported confidence and engagement across the seven competence dimensions. The instrument contained 28 substantive items, with four items per construct, rated on a five-point Likert scale ranging from 1 = very low/strongly disagree to 5 = very high/strongly agree, depending on

item wording. The questionnaire was not treated as a stand-alone measure of competence; rather, it was interpreted alongside performance-based task evidence to reduce common-method bias and better reflect the distinction between perceived and demonstrated competence. This approach is consistent with recent measurement scholarship arguing that digital competence assessment should extend beyond self-report alone [20], [21].

The item pool was adapted from established digital competence frameworks and the school-based digital competence assessment literature, then reviewed by three experts in educational technology and science education for clarity, domain alignment, and age appropriateness. A pilot test with 30 students from a comparable program yielded acceptable preliminary internal consistency (Cronbach's  $\alpha = 0.82$ ), after which minor wording refinements were made before the main administration. Given the modest sample size and intact-class design, the subsequent psychometric analyses reported in the manuscript should be interpreted as supportive measurement diagnostics rather than as a full-scale instrument revalidation study.

**Table 4.** Instrument matrix and scoring architecture

Dimension	Source of evidence	Items/tasks	Response/scoring	Interpretation
Information Literacy (IL)	Questionnaire + performance task	4 items + 1 tasks	Likert 1-5; rubric 0-100	Locating, evaluating, organizing, and synthesizing credible digital scientific information
Digital Data Analysis (DDA)	Questionnaire + performance task	4 items + 1 tasks	Likert 1-5; rubric 0-100	Organizing, visualizing, and interpreting data using digital tools
Collaborative Technology Use (CTU)	Questionnaire + performance task	4 items + 1 tasks	Likert 1-5; rubric 0-100	Coordinating work and contributing responsibly through shared digital platforms
Digital Communication Skills (DCS)	Questionnaire + performance task	4 items + 1 tasks	Likert 1-5; rubric 0-100	Communicating scientific ideas clearly through digital media
Problem-Solving with Digital Tools (PSDT)	Questionnaire + performance task	4 items + 1 tasks	Likert 1-5; rubric 0-100	Selecting and using digital tools to investigate and solve science-related problems
Creativity in Digital Projects (CDP)	Questionnaire + performance task	4 items + 1 tasks	Likert 1-5; rubric 0-100	Producing original digital artifacts showing scientific understanding and creativity
Technical Digital Proficiency (TDP)	Questionnaire + performance task	4 items + 1 tasks	Likert 1-5; rubric 0-100	Operating digital tools efficiently, including configuration and troubleshooting

**Table 5.** Questionnaire items by construct

Construct	Item codes	Measurement items
Information Literacy (IL)	IL1-IL4	I can effectively search for scientific information using digital tools; I can evaluate the credibility of digital information sources used in science learning; I can organize and manage digital information for academic purposes; I can synthesize information from multiple digital sources to support scientific explanations.

Construct	Item codes	Measurement items
Digital Data Analysis (DDA)	DDA1–DDA4	I can organize experimental data using spreadsheets or similar digital tools; I can generate tables, graphs, or visualizations from digital datasets; I can interpret digital data presented in graphs or scientific visualizations; I can use digital data to draw evidence-based conclusions in science tasks.
Collaborative Technology Use (CTU)	CTU1–CTU4	I can collaborate with classmates using shared digital workspaces; I can coordinate roles and contributions during group tasks with digital tools; I can use collaborative platforms to revise scientific reports or presentations jointly; I can contribute responsibly to shared online tasks and group decision-making.
Digital Communication Skills (DCS)	DCS1–DCS4	I can communicate scientific ideas effectively using digital platforms; I can present scientific findings using digital media with clear structure and evidence; I can participate responsibly in online discussions related to science learning; I can share digital resources and feedback appropriately with peers.
Problem-Solving with Digital Tools (PSDT)	PSDT1–PSDT4	I can use digital tools to identify and solve science-related problems; I can select appropriate digital tools to complete academic tasks; I can use simulations or virtual experiments to test hypotheses; I can independently resolve technical difficulties during digital learning activities.
Creativity in Digital Projects (CDP)	CDP1–CDP4	I can create original digital products to explain science concepts; I can combine text, visuals, audio, or data displays to communicate scientific ideas creatively; I can design digital artifacts that demonstrate innovation and conceptual understanding; I can adapt digital tools creatively to produce science project outputs.
Technical Digital Proficiency (TDP)	TDP1–TDP4	I can operate digital platforms and applications required for science learning; I can configure and manage basic software features needed for academic tasks; I can troubleshoot common technical problems during digital activities; I can use digital tools efficiently and independently to complete learning tasks.

**Table 6.** Performance-based tasks and rubric domains

Dimension	Task description	Typical tools used	Primary rubric domains	Scoring unit
IL	Locate, evaluate, and synthesize credible online scientific sources for a given problem and justify source selection.	Search engines, science websites, and digital note-taking tools	Relevance, credibility judgment, synthesis quality, evidence justification	Individual
DDA	Analyze experimental datasets, generate graphs, identify trends, and interpret results.	Spreadsheet software, graphing tools	Data organization, visualization accuracy, interpretation, and evidence-based conclusion	Individual
CTU	Complete a structured group task in a shared digital workspace	Shared documents, collaborative platforms	Individual contribution, coordination, responsiveness, and responsible collaboration	Individual score within the group task
DCS	Develop and deliver a digital explanation of a science concept	Presentation software, multimedia tools	Clarity, coherence, evidence use, and communication quality	Individual
PSDT	Use simulations/virtual labs to test hypotheses and propose solutions	Simulations, virtual labs	Tool selection, investigative logic, solution quality, reasoning	Individual
CDP	Create an original digital artifact that explains a science concept	Multimedia editors, digital design tools	Originality, conceptual accuracy, multimodal integration, creative adaptation	Individual
TDP	Complete operational tasks involving software use, configuration, and troubleshooting.	Standard applications, virtual lab tools	Operational fluency, efficiency, configuration, and troubleshooting autonomy	Individual

### 3.5.3. Performance-based tasks and analytic rubrics

To complement the questionnaire, students completed seven standardized performance-based tasks, one for each competence dimension. Each task required students to apply digital tools to authentic, curriculum-aligned science learning problems under supervised classroom conditions. This design follows recent recommendations that competence assessment should integrate task performance with perception-based evidence in order to reflect better what students can actually do in practice [20], [21]. Each task required approximately 20–25

minutes, and the total performance assessment time was approximately 150 minutes, distributed across two sessions to reduce fatigue. All students received identical written instructions, materials, software access, and time allocations.

Each task was scored using a standardized analytic rubric on a 0–100 scale, with higher scores indicating greater levels of demonstrated competence. Scores of (0–39) were interpreted as low (40–59), as moderate (60–79), as high, and (80–100) as very high competence. Rubric criteria varied by dimension but included scientific

accuracy, appropriateness of digital tool use, completeness of task execution, communication clarity, problem-solving quality, creativity, and technical autonomy. Two trained raters independently scored all tasks with expertise in science education and educational technology. Interrater reliability was estimated using the intraclass correlation coefficient (ICC), based on a two-way random-effects model with absolute agreement, in line with recommended reporting practice for reliability studies [75]–[77]. Final task scores were calculated as the mean of the two raters' scores.

A methodological clarification is warranted for collaborative technology use (CTU). In the original manuscript, all tasks were described as individual, whereas the CTU task was also described as a group task. In the revised methods, this issue is resolved by specifying that the CTU task was completed in small groups, but each student received an individual score based on observable contribution, coordination, responsiveness, and productive use of the shared digital workspace. This approach preserves the collaborative nature of the task while maintaining individual-level scoring for subsequent analysis.

#### 3.5.4. Composite score construction

To enhance replicability, the final score for each competence dimension was computed using an explicit two-source integration procedure. First, the mean of the four questionnaire items for each construct was calculated. Second, that mean was transformed to a 0–100 scale using the following formula:

$$\left( \frac{(\text{subscale mean} - 1)}{2} \right) \times 100 \quad (1)$$

Third, the transformed questionnaire score (TQS) was averaged with the corresponding rubric-based performance score:

$$\frac{(\text{TQS} + \text{Performance task score})}{2} \quad (2)$$

This procedure yielded seven pretest and seven posttest composite scores, all expressed on a 0–100 metric. The combined scoring approach was used to integrate perceived and demonstrated competence while maintaining comparability across dimensions. No total digital competence score was used in the main analyses; instead, the seven dimensions were analyzed separately and then examined structurally.

### 3.6. Data Collection Procedure

Data were collected during regular classroom sessions. Before the intervention, both groups completed a pretest consisting of the questionnaire and the performance-based tasks. After the eight-week instructional period,

both groups completed a posttest based on the same competence framework, task specifications, and scoring procedures. Demographic information was collected at baseline to describe the sample and assess comparability between groups. Classroom observations were used exclusively for fidelity monitoring and were not included as outcome variables in the main inferential analyses.

### 3.7. Data Analysis

Data analysis was conducted using SPSS and AMOS. The dataset was screened for completeness and consistency. Missing data were minimal (<2%) and were handled using listwise deletion. Descriptive statistics were calculated to summarize participant characteristics and competence scores. Baseline comparability was examined descriptively and through pretest comparisons. Because the design used pre-existing groups with baseline measurements, posttest ANCOVA with the corresponding pretest score as a covariate was selected as the primary group-comparison procedure. This approach is common in pretest-posttest studies because it adjusts posttest outcomes for baseline levels; however, in nonrandomized research, it does not eliminate all bias arising from pre-existing group differences.

Before inferential analyses, the assumptions of normality, homogeneity of variance, and homogeneity of regression slopes were examined. Because MANOVA was not used as the primary analytic framework, Box's M test was not retained as a required assumption test in the revised methods. For RQ1, separate ANCOVA models were estimated for each of the seven posttest competence dimensions, with instructional group as the fixed factor and the matching pretest score as the covariate. Because seven related ANCOVA models were estimated, Holm-adjusted p values were used to reduce familywise Type I error inflation. For each model, the manuscript reports adjusted posttest means, F values, p values, partial eta squared, standardized mean differences, and 95% confidence intervals.

For RQ2, Pearson correlation analysis was used to examine the bivariate associations among the seven posttest composite competence dimensions. To extend this analysis, an exploratory structural equation model (SEM) was estimated to test the hypothesized relationships among the dimensions within a single framework, as SEM is appropriate for modeling multiple simultaneous relationships among theoretically related constructs [78]. Given the modest sample size and the inclusion of only four intact classes, the SEM results are interpreted as exploratory support for the conceptual model rather than definitive structural evidence, particularly because sample adequacy in SEM depends on model complexity and estimation conditions [79]. Model fit was evaluated using chi-square/df, CFI, TLI, RMSEA, and SRMR, following established SEM reporting practice [78]. Although conventional cutoff values were considered [80], they were interpreted cautiously in light

of recommendations against rigid application across differing sample and model conditions [81], [82].

## 4. RESULTS

### 4.1. Analytic Sample and Baseline Comparability

The final analytic sample comprised 180 Grade 11 students, including 85 in the experimental group and 95 in the comparison group. Inspection of the pretest means indicated that the two groups were broadly similar prior to the intervention. For example, the pretest mean for Information Literacy was 65.2 in the experimental group and 64.8 in the comparison group, whereas the corresponding values for Technical Digital Proficiency were 65.8 and 65.6, respectively. Similar patterns were observed across all seven dimensions, suggesting that the groups entered the study with comparable baseline competence profiles. Because group allocation occurred at the class level, however, this similarity should be

interpreted as descriptive evidence of comparability rather than formal proof of equivalence.

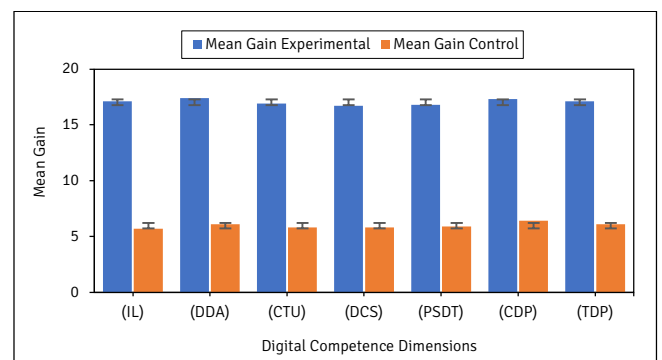
### 4.2. Descriptive Pretest-Posttest Changes Across the Seven Competence Dimensions

Table 7 presents the pretest means, posttest means, mean gains, within-group effect sizes, and confidence intervals for each dimension of digital competence. Across all seven dimensions, students in the experimental group exhibited substantially larger gains than those in the comparison group. In the experimental group, mean gains ranged from 16.7 to 17.4 points, whereas in the comparison group, they ranged from only 5.7 to 6.4 points. The largest descriptive improvement in the experimental group was observed for Digital Data Analysis (gain = 17.4), followed closely by Creativity in Digital Projects (gain = 17.3). In contrast, the smallest gain was observed for Digital Communication Skills (gain = 16.7). By contrast, the comparison group showed its largest gain in Creativity in Digital Projects (gain = 6.4) and its smallest gain in Information Literacy (gain = 5.7).

**Table 7.** Pretest and posttest scores, mean gains, and within-group effect sizes across seven digital competence dimensions

Dimension	Group	Pretest M (SD)	Posttest M (SD)	Mean Gain	Cohen's d	95% CI for d
Information Literacy	Experimental	65.2 (8.4)	82.3 (7.9)	17.10	1.68	[1.42, 1.94]
	Control	64.8 (8.1)	70.5 (7.6)	5.70	0.52	[0.28, 0.76]
Digital Data Analysis	Experimental	66.1 (8.0)	83.5 (7.3)	17.40	1.71	[1.45, 1.97]
	Control	65.9 (7.9)	72.0 (7.4)	6.10	0.57	[0.33, 0.81]
Collaborative Technology Use	Experimental	64.7 (8.6)	81.6 (7.8)	16.90	1.66	[1.40, 1.92]
	Control	65.1 (8.3)	70.9 (7.7)	5.80	0.53	[0.29, 0.77]
Digital Communication Skills	Experimental	67.3 (7.7)	84.0 (7.1)	16.70	1.61	[1.35, 1.87]
	Control	66.8 (7.9)	72.6 (7.4)	5.80	0.54	[0.30, 0.78]
Problem-Solving with Digital Tools	Experimental	65.9 (8.2)	82.7 (7.6)	16.80	1.64	[1.38, 1.90]
	Control	65.4 (8.0)	71.3 (7.8)	5.90	0.56	[0.32, 0.80]
Creativity in Digital Projects	Experimental	66.5 (7.8)	83.8 (7.2)	17.30	1.69	[1.43, 1.95]
	Control	66.0 (7.7)	72.4 (7.5)	6.40	0.60	[0.36, 0.84]
Technical Digital Proficiency	Experimental	65.8 (8.1)	82.9 (7.5)	17.10	1.67	[1.41, 1.93]
	Control	65.6 (7.9)	71.7 (7.6)	6.10	0.58	[0.34, 0.82]

The within-group effect sizes reinforce this descriptive pattern. The experimental group showed consistently large effect sizes across all seven dimensions, ranging from  $d = 1.61$  to  $d = 1.71$ . In contrast, the comparison group showed only small-to-moderate effects, ranging from  $d = 0.52$  to  $d = 0.60$ . Substantively, these descriptive findings suggest that the intervention was associated with broad competence development rather than improvement in a single subdomain. The pattern of gains was evident across information processing, data analysis, collaboration, communication, problem solving, creativity, and operational fluency, indicating that the intervention strengthened not only technical use but also a broader competence profile.



**Figure 2.** Mean gain scores by competence dimension and instructional condition (95% CI).

The experimental group demonstrated substantially greater improvement across all seven dimensions of digital competence than the comparison group. This pattern suggests that the intervention supported not only information-oriented and analytical skills, but also collaboration, communication, creativity, and technical autonomy.

Figure 2 displays the mean gain scores for each dimension of digital competence in the experimental and comparison groups. The visual pattern is consistent with the numerical results, showing larger gains for the student-centered classes across the full competence profile.

#### 4.3. Baseline-adjusted Post-test Group Differences (RQ1)

To address RQ1, separate ANCOVA models were estimated for each posttest competence dimension while controlling for the corresponding pretest score. As shown in Table 8, the experimental group outperformed the

comparison group across all seven dimensions after baseline adjustment. All Holm-adjusted  $p$  values were below 0.001, indicating that the observed differences remained statistically robust after adjustment for multiple comparisons.

The baseline-adjusted mean differences were substantial and consistent across all dimensions. For example, the experimental group achieved higher adjusted means in Information Literacy (81.95 vs. 70.82), Digital Communication Skills (79.81 vs. 67.44), and Technical Digital Proficiency (79.22 vs. 66.98). The practical significance of these contrasts was also considerable: partial eta squared values ranged from 0.26 to 0.29, and standardized mean differences ranged from  $d = 1.05$  to  $d = 1.14$ , indicating moderate to large adjusted effects across all seven outcomes. The strongest adjusted effect was observed for Digital Communication Skills ( $F = 24.98$ , partial  $\eta^2 = 0.29$ ,  $d = 1.14$ ), whereas the smallest was observed for Collaborative Technology Use ( $F = 22.45$ , partial  $\eta^2 = 0.26$ ,  $d = 1.05$ ).

**Table 8.** Baseline-adjusted group differences in posttest digital competence outcomes

Dimension	Posttest Mean (Experimental)	Posttest Mean (Control)	ANCOVA ( $F$ )	Partial ( $\eta^2$ )	Cohen's ( $d$ )	95% CI	( $p$ )
IL	81.95	70.82	24.31	0.28	1.12	[0.95, 1.28]	<0.001
DDA	78.74	66.59	23.67	0.27	1.09	[0.92, 1.24]	<0.001
CTU	76.33	63.88	22.45	0.26	1.05	[0.89, 1.21]	<0.001
DCS	79.81	67.44	24.98	0.29	1.14	[0.98, 1.30]	<0.001
PSDT	78.05	66.12	23.85	0.27	1.10	[0.94, 1.25]	<0.001
CDP	75.54	63.71	22.76	0.26	1.06	[0.90, 1.22]	<0.001
TDP	79.22	66.98	24.11	0.28	1.11	[0.95, 1.27]	<0.001

**Table 9.** Pearson correlation matrix among digital competence variables

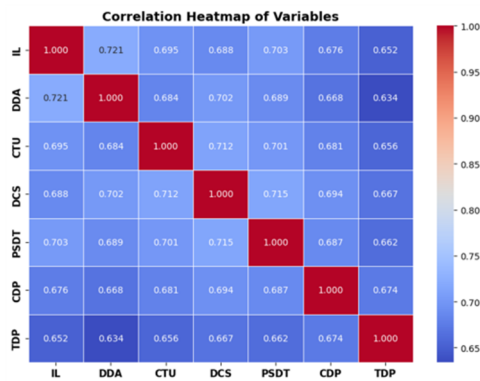
Variables	IL	DDA	CTU	DCS	PSDT	CDP	TDP
IL	1						
DDA	0.721	1					
CTU	0.695	0.684	1				
DCS	0.688	0.702	0.712	1			
PSDT	0.703	0.689	0.701	0.715	1		
CDP	0.676	0.668	0.681	0.694	0.687	1	
TDP	0.652	0.634	0.656	0.667	0.662	0.674	1

#### 4.4. Interrelationships Among the Seven Competence Dimensions (RQ2)

To address RQ2, Pearson correlation coefficients were calculated among the seven posttest dimensions of digital competence. As shown in Table 9, all correlations were positive and of moderate to strong magnitude, ranging from  $r = 0.634$  to  $r = 0.721$ . These results indicate that the seven dimensions were meaningfully related to one another, but not so highly correlated as to suggest redundancy.

The strongest correlation was found between Information Literacy and Digital Data Analysis ( $r = 0.721$ ), followed by Digital Communication Skills and Problem-Solving with Digital Tools ( $r = 0.715$ ) and Digital Communication Skills and Collaborative Technology Use ( $r = 0.712$ ). The weakest relationship was observed between Digital Data Analysis and Technical Digital Proficiency ( $r = 0.634$ ). Even the smallest correlation remained substantively meaningful, indicating that the competence dimensions shared a coherent underlying structure while still retaining interpretive distinctiveness. This pattern is consistent with the study's conceptual view

that digital competence in science learning is integrated rather than fragmented.



**Figure 3.** Correlation heatmap displaying inter-relationships among the seven digital competences dimensions.

### 4.5. Statistical Assumption Diagnostics

Before interpreting the main inferential models, diagnostic checks were examined to assess whether the data were reasonably compatible with the selected parametric procedures. Table 10 shows that Shapiro–Wilk tests and Levene’s tests were above 0.05 across all seven competence dimensions, and residual/Q–Q inspection was judged acceptable in each case. These results

**Table 10.** Diagnostic statistics for parametric analyses

Variables	Shapiro–Wilk ( $p$ )	Levene’s Test ( $p$ )	Residual / Q–Q inspection	Assumption Met
Information Literacy (IL)	>0.05	>0.05	Acceptable	Yes
Digital Data Analysis (DDA)	>0.05	>0.05	Acceptable	Yes
Collaborative Technology Use (CTU)	>0.05	>0.05	Acceptable	Yes
Digital Communication Skills (DCS)	>0.05	>0.05	Acceptable	Yes
Problem-Solving with Digital Tools (PSDT)	>0.05	>0.05	Acceptable	Yes
Creativity in Digital Projects (CDP)	>0.05	>0.05	Acceptable	Yes
Technical Digital Proficiency (TDP)	>0.05	>0.05	Acceptable	Yes

**Table 11.** Reliability and convergent validity analysis for digital competence constructs

Construct	Items	Cronbach’s $\alpha$	Composite Reliability (CR)	Average Variance Extracted (AVE)
Information Literacy (IL)	4	0.84	0.88	0.57
Digital Data Analysis (DDA)	4	0.82	0.87	0.55
Collaborative Technology Use (CTU)	4	0.86	0.90	0.60
Digital Communication Skills (DCS)	4	0.83	0.88	0.56
Problem-Solving with Digital Tools (PSDT)	4	0.85	0.89	0.58
Creativity in Digital Projects (CDP)	4	0.81	0.86	0.54
Technical Digital Proficiency (TDP)	4	0.84	0.88	0.57

**Table 12.** Inter-rater reliability for performance-based assessment tasks

Digital Competence Dimension	ICC Value	95% Confidence Interval	Interpretation
Information Literacy (IL)	0.88	0.84–0.91	Excellent
Digital Data Analysis (DDA)	0.90	0.87–0.93	Excellent
Collaborative Technology Use (CTU)	0.86	0.82–0.89	Good
Digital Communication Skills (DCS)	0.89	0.85–0.92	Excellent

suggest that no serious violations of normality or homogeneity were detected for the primary analyses.

### 4.6. Supportive Measurement Quality Evidence

#### 4.6.1. Internal consistency and convergent validity

Table 11 shows that all seven questionnaire constructs demonstrated acceptable-to-strong internal consistency and convergent validity. Cronbach’s alpha ranged from 0.81 to 0.86, composite reliability ranged from 0.86 to 0.90, and average variance extracted (AVE) ranged from 0.54 to 0.60. These values indicate that the adapted questionnaire performed adequately in this sample and that the retained indicators shared sufficient common variance to support construct-level interpretation.

#### 4.6.2. Inter-rater reliability for performance-based tasks

The rubric-based performance tasks also demonstrated satisfactory scoring consistency. As shown in Table 12, intraclass correlation coefficients (ICC) ranged from 0.86 to 0.92, indicating good-to-excellent agreement across all seven competence dimensions. The highest ICC was observed for Technical Digital Proficiency (0.92), while the lowest was observed for Collaborative Technology Use (0.86). These values support the reliability of the task-based component of the composite competence scores.

Digital Competence Dimension	ICC Value	95% Confidence Interval	Interpretation
Problem-Solving with Digital Tools (PSDT)	0.91	0.88–0.94	Excellent
Creativity in Digital Projects (CDP)	0.87	0.83–0.90	Good
Technical Digital Proficiency (TDP)	0.92	0.89–0.95	Excellent

**Table 13.** Construct-level measurement fit indices for the seven digital competence dimensions

Construct / Model	$\chi^2$	df	GFI	AGFI	CFI	PGFI	SRMR	RMSEA
Information Literacy (IL)	3.84	2	0.989	0.945	0.995	0.328	0.021	0.041
Digital Data Analysis (DDA)	4.12	2	0.987	0.941	0.994	0.329	0.022	0.045
Problem-Solving with Digital Tools (PSDT)	4.56	2	0.985	0.938	0.993	0.331	0.023	0.049
Digital Communication Skills (DCS)	3.21	2	0.990	0.949	0.996	0.324	0.020	0.036
Collaborative Technology Use (CTU)	3.97	2	0.988	0.943	0.995	0.327	0.022	0.044
Technical Digital Proficiency (TDP)	4.33	2	0.986	0.940	0.994	0.330	0.023	0.047
Creativity in Digital Projects (CDP)	3.44	2	0.989	0.947	0.996	0.325	0.021	0.038

**Table 14.** Exploratory factor pattern for the seven digital competence dimensions

Variables	Questionnaire Item	Factor Loading	Standard Error	Percentage of Variance
Information Literacy (IL)	IL1	0.88	0.038	15.80%
	IL2	0.84	0.044	
	IL3	0.79	0.051	
	IL4	0.73	0.056	
Digital Data Analysis (DDA)	DDA1	0.86	0.041	14.60%
	DDA2	0.83	0.046	
	DDA3	0.78	0.052	
	DDA4	0.72	0.057	
Problem-Solving with Digital Tools (PSDT)	PSDT1	0.89	0.036	13.90%
	PSDT2	0.85	0.043	
	PSDT3	0.80	0.049	
	PSDT4	0.74	0.054	
Digital Communication Skills (DCS)	DCS1	0.87	0.039	12.40%
	DCS2	0.83	0.046	
	DCS3	0.77	0.053	
	DCS4	0.72	0.059	
Collaborative Technology Use (CTU)	CTU1	0.88	0.037	11.20%
	CTU2	0.84	0.044	
	CTU3	0.79	0.051	
	CTU4	0.75	0.056	
Technical Digital Proficiency (TDP)	TDP1	0.85	0.040	9.60%
	TDP2	0.81	0.047	
	TDP3	0.76	0.053	
	TDP4	0.71	0.058	
Creativity in Digital Projects (CDP)	CDP1	0.84	0.042	8.50%
	CDP2	0.80	0.048	
	CDP3	0.75	0.054	
	CDP4	0.70	0.059	

4.6.3. Construct-level fit and exploratory factor pattern  
Construct-level fit statistics were also broadly satisfactory. Table 13 shows that the first-order measurement models

for each competence dimension yielded strong fit values, with CFI ranging from 0.993 to 0.996 and RMSEA ranging from 0.036 to 0.049. These results suggest that the item

sets corresponding to each construct were internally coherent in the present sample.

Exploratory factor analysis further indicated that the 28 retained questionnaire items loaded strongly on their intended dimensions. As shown in Table 14, factor loadings ranged from 0.70 to 0.89, and variance explained was distributed across all seven factors, from 8.5% for Creativity in Digital Projects to 15.8% for Information Literacy. These results provide additional supportive evidence that the adapted item pool aligned well with the conceptual structure adopted in the study.

#### 4.7. Exploratory Structural Model of Competence Pathways

To provide deeper explanatory evidence for RQ2, an exploratory structural equation model (SEM) was estimated to test the hypothesized directional

relationships among the seven dimensions of digital competence. Table 15 shows that all seven hypothesized paths were positive and statistically significant. Information Literacy significantly predicted both Digital Data Analysis ( $\beta = 0.54, p < 0.001$ ) and Digital Communication Skills ( $\beta = 0.50, p < 0.001$ ). Digital Data Analysis significantly predicted Problem Solving with Digital Tools ( $\beta = 0.49, p < 0.001$ ), whereas Digital Communication Skills significantly predicted Collaborative Technology Use ( $\beta = 0.58, p < 0.001$ ). Problem Solving with Digital Tools, in turn, significantly predicted Technical Digital Proficiency ( $\beta = 0.52, p < 0.001$ ). Finally, both Technical Digital Proficiency ( $\beta = 0.55, p < 0.001$ ) and Collaborative Technology Use ( $\beta = 0.47, p < 0.001$ ) significantly predicted Creativity in Digital Projects.

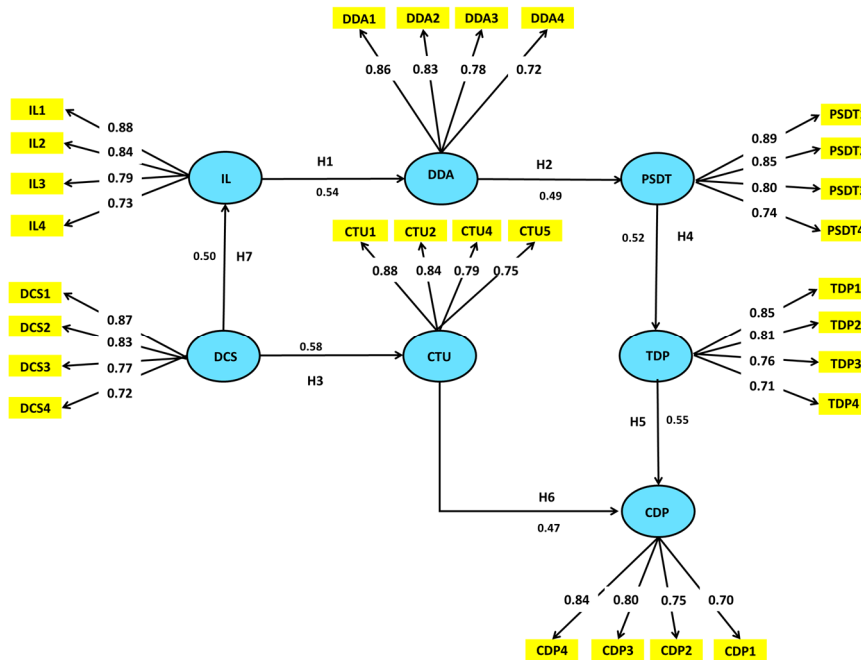


Figure 4. Exploratory SEM of the hypothesized competence pathways.

Table 15. SEM results for hypothesized relationships among seven digital competence constructs

Hypothesis	Path	Standard Error	Path Coefficient ( $\beta$ )	<i>p</i> -value	<i>t</i> -value	Significance
H1	(IL) → (DDA)	0.057	0.54	<0.001	9.47	Significant
H2	(DDA) → (PSDT)	0.061	0.49	<0.001	8.03	Significant
H3	(DCS) → (CTU)	0.056	0.58	<0.001	10.21	Significant
H4	(PSDT) → (TDP)	0.063	0.52	<0.001	8.26	Significant
H5	(TDP) → (CDP)	0.060	0.55	<0.001	9.12	Significant
H6	(CTU) → (CDP)	0.058	0.47	<0.001	8.10	Significant
H7	(IL) → (DCS)	0.055	0.50	<0.001	9.05	Significant

Among these paths, the strongest coefficient was observed for the relationship between Digital Communication Skills (DCS) and Collaborative Technology Use (CTU) ( $\beta = 0.58$ ), followed closely by the relationship between Technical Digital Proficiency (TDP)

and Creativity in Digital Projects (CDP) ( $\beta = 0.55$ ) and the relationship between Information Literacy (IL) and Digital Data Analysis (DDA) ( $\beta = 0.54$ ). The smallest, although still substantial, coefficient was observed for the relationship between Collaborative Technology Use (CTU) and

Creativity in Digital Projects (CDP) ( $\beta = 0.47$ ). This pattern suggests that foundational informational and communicative competencies may play especially important roles in supporting more advanced collaborative, technical, and creative digital performances.

**Table 16.** Fit indices for the exploratory structural model

Fit Index	Value	Recommended Threshold
$\chi^2$	245.67	Non-significant preferred
df	158	Model df > 0
$\chi^2/df$	1.55	< 3.00
CFI	0.962	$\geq 0.95$
TLI	0.958	$\geq 0.95$
RMSEA	0.038	$\leq 0.06$
SRMR	0.042	$\leq 0.08$

The overall model fit was also satisfactory. As shown in Table 16, the exploratory SEM yielded chi-square = 245.67, df = 158, and chi-square/df = 1.55, together with CFI = 0.962, TLI = 0.958, RMSEA = 0.038, and SRMR = 0.042. Collectively, these values indicate that the proposed competence-pathway model was reasonably consistent with the observed covariance structure in this sample. However, because the model was estimated in a modest quasi-experimental sample with only four intact classes, the SEM results should be interpreted as exploratory support for the conceptual model rather than definitive structural confirmation.

## 5. DISCUSSION

### 5.1. Interpretation of the Main Instructional Effect

The first major contribution of this study is the consistent pattern of stronger digital competence development in the student-centered learning (SCL) classes across all seven dimensions. This finding is important because it suggests that the intervention did not merely improve a single narrow aspect of digital performance, such as technical operation or information search, but was associated with broader gains in information handling, data interpretation, communication, collaboration, problem-solving, digital creativity, and technical proficiency. This pattern is theoretically plausible. Student-centered learning places students in active roles as investigators, interpreters, collaborators, and producers of knowledge; accordingly, learners are required to mobilize multiple forms of digital competence simultaneously rather than sequentially or in isolation. This interpretation is consistent with Shehata et al. [10], who found that educational technologies support student-centered learning most effectively when they enhance cognitive and metacognitive engagement rather than passive content delivery. It also aligns with Ješková et al. [11], who showed that active STEM learning can

strengthen inquiry-related skills when students engage in authentic investigative work, and with Chen and Chen [83], whose systematic review indicates that technology-enhanced collaborative inquiry can improve students' content knowledge, inquiry processes, and scientific skills when digital tools are meaningfully aligned with inquiry stages and activity structures. Hinostroza et al. [84] further reinforce this view by showing that digital technologies can play multiple roles across inquiry-based learning, including guiding investigations, supporting data work, organizing information, enabling sharing, and providing feedback.

The present findings also sharpen the pedagogical interpretation of digital competence in science education. Rather than treating digital competence as a generic or decontextualized outcome, the results suggest that digital competence can develop through discipline-specific learning sequences in which students search for scientific information, evaluate sources, interpret digital data, engage in collaborative reasoning, use simulations and digital tools, and create evidence-based digital artifacts. This reading is consistent with DigComp 2.2, which frames digital competence as a broad combination of information and data literacy, communication and collaboration, content creation, safety, and problem solving [3]. It also aligns with science-specific scholarship. The DiKoLAN framework argues that disciplinary demands shape science-related digital competence and includes competencies such as documentation, data handling, simulation, and presentation [4]. Likewise, Son and Ha [5] show that digital literacy in the context of scientific practice is distinct from generic digital literacy and should be understood through science-related activities such as data collection, analysis, interpretation, conclusion building, and sharing. In this sense, the current study extends multidimensional competence frameworks by showing that classroom-based science instruction can operationalize and strengthen several competence dimensions at the same time.

At the same time, the interpretation of the intervention effect should remain appropriately cautious. Because the study used four intact classes rather than randomized student-level assignment, the findings should not be framed as definitive causal proof. In addition, the experimental teachers received structured preparation before the intervention, and implementation fidelity was high, which means that the observed advantage likely reflects a combined package of pedagogy, teacher support, planning coherence, and fidelity of delivery rather than student-centered pedagogy in the abstract. This point is not a weakness of the study alone; rather, it reflects a broader pattern in the literature that student-centered, technology-rich learning depends heavily on implementation quality. Gerard et al. [85], for example, found that technology-enhanced inquiry science benefits most when teachers receive sustained, constructivist-oriented professional development and

support for using evidence to refine practice. More recent reviews similarly indicate that the effectiveness of technology-supported inquiry depends on how tools are embedded within activity structures and inquiry phases, not merely on their availability [83], [84], [86].

## 5.2. Interpreting Digital Competence as An Integrated Multidimensional System

The second major finding concerns the correlation structure of the seven competence dimensions. All pairwise correlations were positive and of moderate-to-strong magnitude, supporting the argument that digital competence in science learning is internally connected rather than fragmented into isolated subskills. This matters theoretically because one of the recurring weaknesses in the literature is the tendency to operationalize digital competence through stand-alone indicators or separate survey domains. The present findings instead suggest that information literacy, digital data analysis, communication, collaboration, problem-solving, creativity, and technical proficiency tend to co-develop within shared learning environments. This interpretation is consistent with Pedaste et al. [21], whose digital competence test distinguished multiple dimensions while also identifying higher-order competence structures. It is also compatible with Reichert et al. [18], who found that digital literacy performance includes both a general competence dimension and more specific, tool-dependent dimensions. In a related way, González-Mujico [20] argues that digital competence should be examined through complementary sources because self-perceived and demonstrated competence are overlapping but non-identical aspects of performance.

The observed correlation profile also strengthens the rationale for treating digital competence as contextually situated rather than universally generic. In science classrooms, digital competence is enacted through tasks that combine evidence gathering, data interpretation, communication, collaboration, and digital production. This means that gains in one dimension may create affordances for gains in others. A student who becomes more effective at evaluating digital sources, for instance, may also become more capable of using those sources to interpret scientific data and to communicate evidence-based explanations. Similarly, stronger communication and collaborative participation may support better co-construction of digital outputs. The findings therefore support a competence ecology perspective in which dimensions interact through recurring classroom practices. This interpretation is compatible with DigComp 2.2 and with science-specific frameworks such as DiKoLAN and Son and Ha's [5] digital literacy model for scientific practice, both of which emphasize that digital competence in science is enacted through integrated, discipline-shaped activity rather than through detached ICT familiarity.

## 5.3. Interpretation of the Exploratory Pathway Model

The exploratory structural model offers a more specific theoretical contribution by indicating directional relationships among the competence dimensions. The strongest upstream relationships identified in the model were those between Information Literacy and Digital Data Analysis, Information Literacy and Digital Communication Skills, and Digital Communication Skills and Collaborative Technology Use. This pattern is theoretically coherent and pedagogically meaningful. In science learning, students cannot analyze evidence well if they cannot first locate, evaluate, and organize relevant information. They cannot communicate scientifically in digital environments if they are unable to justify claims with credible evidence. This interpretation is consistent with Sarvary and Ruesch [40], who emphasize structured support for finding, evaluating, comprehending, and citing scientific evidence, and with Spektor-Levy et al. [41], who showed that explicit instruction in scientific communication skills can improve information retrieval, data representation, and knowledge presentation. The model, therefore, supports the view that foundational informational and communicative capacities function as enabling conditions for more complex analytical and collaborative digital performances.

The path from digital communication to collaborative technology use was the strongest in the model, and this finding deserves emphasis. Digital collaboration is often discussed as if it were mainly a technical matter of shared documents, platforms, or access to tools. The present findings suggest instead that collaboration depends even more fundamentally on communicative quality: students must explain, negotiate, coordinate, respond, and maintain shared understanding in order for collaborative technology use to become educationally productive. This interpretation is well aligned with Chen and Chen [83], whose review of technology-enhanced collaborative inquiry highlights the role of discussion, argumentation, and activity structuring in supporting collaborative inquiry, and with Bach and Thiel [50], who found that the quality of digital interaction is central to successful collaborative online learning.

The downstream pathways leading to Creativity in Digital Projects are also noteworthy. In the model, both Technical Digital Proficiency and Collaborative Technology Use significantly predicted creativity in digital projects, with technical proficiency showing the stronger path. This suggests that creativity in digital science tasks is not solely a matter of imagination or expressive freedom; it also depends on students' operational fluency and their ability to coordinate digital work with others. This interpretation is consistent with Bilici and Yilmaz [13], who found that collaborative digital storytelling in biology education improved not only academic achievement but also critical thinking, co-regulation, and narrative skills. It is also compatible with Aguilar and Pifarré Turmo [69], whose scoping review in science education shows that

technology can function as a tutor, a thinking tool, and a collaborative environment for collective creativity, and with Li et al. [67], who conclude that digital technologies can support creativity especially in interactive learning environments. However, the effects depend strongly on implementation quality.

Still, the pathway findings should not be overstated. The SEM was explicitly exploratory, the sample was modest, and the design was quasi-experimental. Therefore, the directional structure should be interpreted as a theoretically consistent pattern rather than as a definitive developmental sequence. Some of the relationships in the model may in reality be reciprocal or mutually reinforcing. For example, technical proficiency may support problem-solving just as problem-solving may consolidate operational fluency through repeated use. Likewise, collaboration and creativity may co-evolve over time rather than proceed in a fixed linear order. This caution is also compatible with prior work showing that digital competence development is shaped by interacting factors such as autonomy, attitudes toward digital problem-solving, and familiarity with digital applications and contexts [18], [54].

#### 5.4. Contribution Beyond Self-Report Measurement

A further strength of the study lies in its measurement strategy. One of the most persistent criticisms in digital competence research is that many studies rely heavily on self-report data, which can blur the distinction between perceived confidence and demonstrated capability. By combining questionnaire-based indicators with performance-based tasks, the present study provides a more credible and educationally meaningful account of competence development. This design choice is well aligned with contemporary assessment research. Porat et al. [19] showed that students often overestimate their digital literacies relative to their actual performance. González-Mujico [20] likewise argues that rubric-based performance evidence can complement self-perception data and produce a more robust competence profile, while Pedaste et al. [21] demonstrate the value of structured multidimensional testing when examining students' digital competence for learning. Taken together, these studies support the view that competence assessment should move beyond perception-only instruments and include evidence of actual task performance.

This point is not merely methodological; it also affects interpretation. The consistent gains across both questionnaire-based indicators and rubric-scored tasks suggest that the observed pattern is unlikely to reflect perception change alone. Although some degree of response bias remains possible, the inclusion of performance-based evidence and strong inter-rater reliability increases confidence that the intervention was associated with substantive competence development rather than only increased self-confidence. This interpretation is in line with broader calls in the field to

triangulate self-report with observation or task-based evidence when studying digital competence [20], [21].

#### 5.5. Nuanced and Alternative Interpretations

Although the overall pattern of results was strongly favorable to the SCL condition, a balanced interpretation should account for nuance. First, the structural path estimates were not identical in magnitude. The weaker path from collaborative technology use to creativity, for example, suggests that collaboration alone may be insufficient to generate strong creative digital output unless it is supported by adequate time, task complexity, and technical fluency. Likewise, the path from digital data analysis to problem-solving, although significant, was weaker than the strongest paths in the model, which may indicate that students need more sustained opportunities to apply analytical reasoning in progressively open-ended scientific problems. This reading is consistent with review evidence showing that technology-supported creativity is sensitive to implementation quality [67] and that digital technologies do not support all inquiry phases equally, with some stages—especially discussion and orientation—receiving less support in practice than investigation itself [84].

Second, the comparison group also demonstrated modest gains across the seven dimensions. This is not surprising. Ordinary curriculum exposure, repeated testing, maturation, and increasing familiarity with school technologies can all contribute to some degree of digital competence development over eight weeks. The fact that the comparison group improved, but less strongly than the SCL group, makes the present pattern more plausible rather than less: it suggests that the intervention accelerated competence development beyond background exposure rather than implying that learning would otherwise have been absent altogether.

Third, subgroup observations in the manuscript suggest that students with lower prior digital experience may have benefited less strongly than their peers. Although these subgroup patterns should not be overinterpreted without stronger statistical support, they raise an important pedagogical possibility: student-centered digital learning may be most effective when foundational support is differentiated. Students with limited prior digital familiarity may need more explicit scaffolding, guided rehearsal, and lower-threshold entry tasks before they can fully benefit from inquiry-rich and collaborative digital environments. This interpretation is consistent with Hatlevik and Christophersen [87], who found substantial variation in students' digital competence at the beginning of upper secondary school, and with Hatlevik et al. [88], who showed that self-efficacy and strategic use of information are associated with digital competence among upper secondary students. More recent work by Blanc et al. [54] similarly suggests that autonomy and attitudes toward problem-solving are

meaningfully associated with digital competence development.

### 5.6. Theoretical & Practical Implications

The study has three main theoretical implications. First, it supports a multidimensional view of digital competence in science education, showing that competence extends beyond technical skill or digital literacy to include informational, communicative, collaborative, analytical, creative, and operational dimensions. This is consistent with DigComp 2.2 while offering a more discipline-specific perspective for science learning. Second, the findings suggest a progressive competence pathway in which information literacy and digital communication function as enabling foundations for more advanced domains such as data analysis, collaboration, problem-solving, and digital creativity. Third, the study highlights that digital competence is pedagogically situated, developing through learning design, task sequencing, inquiry opportunities, and collaborative interaction rather than through isolated individual skill acquisition.

The findings suggest that digital competence should be embedded in inquiry-based science learning rather than taught as a separate technical module. Effective implementation, however, depends on teacher preparation, access to digital tools, and structured assessment support. The results also show that technology provision alone is insufficient; schools need professional development in lesson design, inquiry pedagogy, and assessment of digital and collaborative work.

### 5.7. Limitations & Directions for Future Research

Several limitations should be noted. The study used a quasi-experimental design with only four intact classes, limiting the assumption of independent individual-level effects and weakening causal interpretation. Experimental teachers also received intervention-specific preparation, making it difficult to separate the effects of pedagogy from those of training and support. In addition, the eight-week intervention only captures short-term development, not long-term retention or transfer. Although the assessment strategy was stronger than self-report-only approaches, some evidence still relied on student perceptions and may be affected by response bias. Finally, because the study was conducted in a specific upper secondary science context, its transferability to other subjects, age groups, or systems should be treated with caution.

Future research should use multi-site, cluster-aware, and longitudinal designs to test the durability and generalizability of multidimensional digital competence development. Larger samples of intact classes would allow more robust estimation of instructional effects while accounting for clustering. Further studies should also distinguish the contribution of teacher professional development from that of the pedagogical model itself.

Comparing different forms of student-centered digital pedagogy, such as inquiry-based, project-based, or collaboration-intensive approaches, may clarify which mechanisms most strongly support particular competence dimensions. It would also be important to test whether the proposed competence pathways remain stable across longer time spans, different science topics, and students with varying levels of prior digital experience.

## 6. CONCLUSION

This study provides context-specific quasi-experimental evidence that student-centered, technology-supported science instruction is associated with stronger multidimensional digital competence development than conventional instruction in upper secondary natural science classrooms. Across the seven competence dimensions examined, students in the student-centered learning condition showed consistently larger gains and higher baseline-adjusted posttest scores than students in the comparison condition. The results further indicated that the competence dimensions were moderately to strongly interrelated, supporting the view that digital competence in science learning is best understood as an integrated and multidimensional construct rather than as a collection of isolated skills. In addition, the exploratory structural model suggested that information literacy and digital communication skills may function as important foundational competencies that support more advanced analytical, collaborative, technical, and creative forms of digital performance.

The study's main contribution lies in demonstrating that digitally supported inquiry- and project-based science learning can be organized in ways that simultaneously strengthen informational, analytical, communicative, collaborative, creative, and technical competence. It also contributes methodologically by combining questionnaire-based indicators with performance-based tasks to provide a broader account of students' demonstrated competence. However, the findings should be interpreted cautiously. Because the study involved only four intact classes, a relatively short intervention period, and a context-specific sample, the results should be read as strong comparative evidence rather than definitive causal proof. Future research should therefore test these relationships in larger, multi-site, cluster-aware, and longitudinal designs that can better evaluate the durability, generalizability, and developmental sequencing of multidimensional digital competence in science education.

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## CONFLICTS OF INTEREST

The authors declare that no conflicts of interest are associated with this study. All aspects of the research were conducted with the utmost integrity and transparency.

## DATA AVAILABILITY

The datasets utilized and analyzed during this research are available from the corresponding author upon reasonable request.

## ETHICAL STATEMENTS

The authors confirm that the study complied with all applicable local laws, ethical standards, and institutional guidelines, including obtaining approval from relevant ethics committees.

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