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Research Article

The correlation between computer science curriculum effectiveness and academic outcomes in private schools in Guangdong province from the perspective of environmental social psychology: The mediating role of collaborative learning and technological environment

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ABSTRACT

This study investigated the relationships between computer science (CS) course effectiveness and academic performance in a Guangdong Province private school through an integrated environmental and social psychology framework, examining collaborative learning environment and technology environment perception as mediating mechanisms. A quantitative cross-sectional design surveyed several hundred Grade 4 international high school students enrolled in computer science courses at Guangdong Country Garden School during the 2024-2025 academic year. Results revealed that all five CS course effectiveness dimensions—hands-on experiences, real-world applications, collaborative learning, problem-solving abilities, and technology landscape readiness—demonstrated strong positive correlations with academic performance ($r=.790$-$.879$, $p<.01$), with problem-solving abilities emerging as the strongest predictor ($\beta=.342$). Mediation analysis using Hayes' PROCESS macro with bootstrapping procedures confirmed that collaborative learning environment (14.7%-23.7% mediation) and technology environment perception (14.7%-23.9% mediation) functioned as significant partial mediators, with real-world applications showing strongest social-psychological mediation and hands-on experiences exhibiting strongest environmental mediation. Hierarchical regression demonstrated that environmental and social-psychological factors contributed unique variance beyond course effectiveness dimensions ($\Delta R^2=.043$, $p<.001$). Findings provide empirical support for person-environment fit theories and social cognitive frameworks, highlighting the importance of optimizing both technological infrastructure and interpersonal climate for CS education effectiveness in private school contexts.

Keywords: computer science education; environmental psychology; social psychology; collaborative learning; technology environment; academic performance; mediation analysis; private schools; Guangdong province

1. Introduction

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The contemporary educational landscape is experiencing a profound transformation driven by the rapid advancement of technology, positioning Computer Science (CS) education as an essential component of modern curricula worldwide. In economically dynamic regions such as Guangdong Province, China—renowned for its technological innovation and industrial development—the integration of effective CS education has become increasingly critical for cultivating student competencies and preparing future professionals for technology-intensive careers. However, despite growing recognition of CS education's importance, there remains a significant gap in understanding how environmental and social-psychological factors collectively influence the effectiveness of CS curricula and their impact on student academic performance. This study addresses this gap by examining CS course effectiveness in a private school context through an environmental and social psychology lens, specifically investigating how collaborative learning environments and technology infrastructure serve as mediating mechanisms between course design and student outcomes. Drawing upon insights from positive psychology applications in computer education (Gu, 2024; Xue & Zhu, 2020), this research recognizes that effective CS instruction extends beyond content delivery to encompass the psychological and environmental conditions that facilitate optimal learning experiences[1].

From a theoretical perspective, environmental psychology provides a valuable framework for understanding how physical and technological learning environments shape educational outcomes, while social psychology illuminates the interpersonal dynamics and collaborative processes that enhance knowledge acquisition and skill development. Recent scholarship has emphasized the importance of integrating computer-assisted instruction with educational psychology principles to optimize teaching effectiveness (Lin, 2024), highlighting the necessity of examining both technological infrastructure and social interaction patterns within learning environments[2]. Furthermore, contemporary research in social psychology has demonstrated the critical role of organizational environments and interpersonal dynamics in shaping behavioral outcomes and performance across various contexts (Furse, 2024; Mandisa et al., 2023) [3]. However, the application of these theoretical frameworks specifically to CS education in Chinese private schools remains underexplored, particularly regarding the mediating mechanisms through which environmental factors and collaborative learning translate course effectiveness into measurable academic achievements. This study therefore contributes to both basic and applied social psychology by investigating how person-environment fit, technology affordances, and social cognitive processes interact within CS educational settings (David et al., 2023) [4].

Guangdong Province presents a particularly compelling context for this investigation due to its status as China's technological and economic powerhouse, where private schools often serve as laboratories for educational innovation and possess superior resources for implementing advanced CS curricula. Private international schools in this region typically offer enhanced technology infrastructure, internationally recognized curricula, and diverse student populations, creating unique environmental and social conditions that may differentially affect learning outcomes compared to public school settings[5]. Despite these advantageous conditions, limited empirical research has systematically examined how the quality of technology learning environments and the social dynamics of collaborative learning mediate the relationship between CS course design features—such as hands-on experiences, real-world applications, and problem-solving activities—and students' academic performance. Understanding these mediating pathways is essential for developing evidence-based enhancement strategies that optimize both the physical-technological environment and the social-psychological climate of CS education. By investigating these relationships, this research responds to calls within educational psychology for more nuanced examinations of how environmental affordances and social interactions jointly contribute to learning effectiveness (Social

Psychology Quarterly, 2023) [6]. This study does not propose an entirely new theoretical framework but rather develops an integrative extension model that synthesizes environmental psychology's technology affordance theory with social psychology's collective learning efficacy theory within CS education contexts. Specifically, we extend traditional direct-effect models of curriculum effectiveness by introducing a dual-pathway mediation model wherein technology environment perceptions and collaborative learning climate function as parallel mediating mechanisms. This model builds upon established theoretical foundations—Gibson's (1979) affordance theory, Bandura's (1986) social cognitive theory, and Bronfenbrenner's (1979) ecological systems theory—while offering novel integration by simultaneously examining both environmental and social-psychological pathways through which curriculum features translate into academic outcomes, addressing a gap in existing CS education research that typically examines these mechanisms in isolation.

The primary objective of this study is to investigate the effectiveness of CS courses in a Guangdong Province private school and examine how collaborative learning environments and technology infrastructure mediate the relationship between course effectiveness dimensions and student academic performance. Specifically, this research addresses three critical questions: First, how do the five dimensions of CS course effectiveness—hands-on experiences, real-world applications, collaborative learning, problem-solving abilities, and technology landscape readiness—relate to students' academic performance? Second, to what extent does the quality of collaborative learning environments mediate the relationship between course effectiveness and academic outcomes? Third, how does students' perception of the technology learning environment serve as a mediating factor in translating course design features into enhanced academic performance? By addressing these questions through a quantitative research design employing mediation analysis, this study aims to provide both theoretical insights into the environmental and social-psychological mechanisms underlying effective CS education and practical recommendations for curriculum enhancement, environmental optimization, and pedagogical improvement in private school contexts[7]. The findings will contribute to the growing body of literature integrating social psychology principles with computer science education while offering actionable guidance for educators, administrators, and policymakers seeking to enhance CS learning outcomes in technologically advanced educational settings.

2. Literature review

The integration of environmental and social psychology perspectives into computer science education represents an emerging interdisciplinary frontier that addresses the complex interplay between physical learning environments, social interactions, and cognitive development in technology-enhanced educational settings[8]. Environmental psychology, which examines how physical and technological surroundings influence human behavior and cognition, provides a crucial lens for understanding how laboratory facilities, technology infrastructure, and spatial configurations shape students' engagement with CS curricula. Concurrently, social psychology illuminates the interpersonal dynamics, collaborative processes, and collective efficacy mechanisms that mediate learning outcomes in group-based educational contexts. Recent developments in social psychology have increasingly emphasized the importance of contextual factors and spatial heterogeneity in shaping psychological processes and behavioral outcomes across diverse settings (Islam et al., 2024) [9], while calls for decolonizing and internationalizing social psychology pedagogy have highlighted the necessity of examining educational phenomena within their specific cultural and geographical contexts (Hamamura et al., 2024) [10]. In the Chinese educational landscape, scholars have advocated for constructing indigenous social psychology frameworks that incorporate local cultural values and educational practices (Zhang, 2024) [11], suggesting that understanding CS education effectiveness in

Guangdong Province requires attention to both universal psychological principles and context-specific sociocultural factors. Furthermore, the integration of neuroscience and psychological insights into curriculum design has demonstrated that developmental psychology principles can significantly enhance pedagogical effectiveness across diverse educational domains (Wang, 2023; Wang et al., 2024), indicating potential applications for CS education that account for students' cognitive development stages and learning environment preferences[12].

Social psychology's contributions to understanding collaborative learning processes and interpersonal dynamics in educational settings have become increasingly sophisticated, moving beyond traditional laboratory-based approaches to examine real-world learning environments and their psychological affordances[13]. Contemporary social psychology research has emphasized the critical importance of addressing systemic issues such as racism-evasive pedagogy and power dynamics within educational institutions, calling for more critically engaged approaches that acknowledge how social structures shape learning experiences and outcomes (Adams & Omar, 2024) [14]. In the context of CS education, these insights suggest that collaborative learning environments must be examined not only for their technical features but also for how they facilitate or constrain equitable participation, knowledge sharing, and collective problem-solving across diverse student populations. Research on transnational contact and trust formation has demonstrated that interpersonal experiences in collaborative settings significantly influence students' attitudes, engagement patterns, and learning outcomes (Mirwaldt, 2024) [15], with implications for international schools in Guangdong Province where students from multiple cultural backgrounds interact within CS learning communities. Moreover, the application of social psychology principles to organizational contexts has revealed how informal networking and collaborative structures enhance collective performance and knowledge transfer (Yang, 2024) [16], suggesting that CS curricula incorporating structured collaborative activities may leverage these social-psychological mechanisms to improve academic outcomes. The integration of ideological and political education with social psychology pedagogy in Chinese higher education contexts (Cai & Zeng, 2023; Zhang, 2022) further underscores the importance of examining how institutional values, social norms[17], and interpersonal relationships collectively shape students' learning experiences and developmental trajectories in technology-focused educational programs.

The intersection of environmental activism research and social psychology offers valuable insights into how physical and technological environments motivate engagement, shape attitudes, and facilitate behavioral change—principles directly applicable to technology learning environments in CS education. A systematic review of environmental activism from a social psychology perspective revealed that environmental factors, including spatial design and resource accessibility, significantly influence individuals' psychological orientations and behavioral intentions (Alexis et al., 2024) [18], suggesting that CS learning environments characterized by high-quality technology infrastructure and collaborative spaces may foster greater student engagement and achievement motivation. The concept of environmental psychology extends beyond physical spaces to encompass technological ecosystems, where the availability, accessibility, and quality of digital tools and platforms create psychological affordances that enable or constrain learning activities. Research examining spatial heterogeneity of social psychological responses to environmental challenges has demonstrated that individuals' psychological reactions and adaptive behaviors vary significantly based on environmental characteristics and resource availability (Islam et al., 2024) [19], implying that CS students' learning outcomes may be substantially influenced by the quality and configuration of their technology learning environments. Furthermore, emerging research on artificial intelligence and social psychology has highlighted the importance of understanding how technological environments shape human cognition, social interaction patterns, and psychological well-being (Yu et al., 2024) [20], with implications for designing CS learning environments that optimize both technological functionality and psychological support. The application of neuroscience insights to sports psychology, which emphasizes the importance of environmental factors in cognitive and motor performance (Zhu, 2025) [21], parallels considerations for CS education where laboratory environments, equipment quality, and spatial arrangements may significantly impact students' technical skill development and problem-solving capabilities.

Theoretical frameworks integrating collaborative learning, technology environments, and academic performance have increasingly recognized the mediating mechanisms through which environmental and social factors translate educational inputs into measurable outcomes. The outcome-based education (OBE) framework applied to social psychology curriculum design has demonstrated that structured learning environments emphasizing hands-on experiences, collaborative activities, and real-world applications significantly enhance student competencies and learning satisfaction (Jin & Xian, 2022) [22], suggesting parallel applications for CS education that prioritize experiential learning and industry relevance. Research on statistical methodologies and scientific deviance in social psychology has emphasized the importance of rigorous empirical approaches to examining complex mediational relationships (Larregue, 2024) [23], providing methodological guidance for investigating how collaborative learning environments and technology infrastructure serve as mediating pathways between CS course design features and academic performance. Contemporary reviews in personality and social psychology have called for more nuanced examinations of how individual differences, environmental characteristics, and social contexts interact to produce behavioral outcomes (Matthews et al., 2024) [24], indicating that effective CS education research must account for person-environment fit and the conditional effects of collaborative learning experiences. The integration of machine-assisted hypothesis generation in social psychology research (Sachin et al., 2024) exemplifies how technological tools can enhance scientific understanding of complex psychological phenomena[25], while simultaneously highlighting the importance of human expertise in interpreting results and developing theoretical frameworks. Additionally, research bridging social psychology with international relations discourses has examined self-control mechanisms and collective action in organizational contexts (Putra, 2024) [26], offering insights into how CS learning environments can foster self-regulated learning, collaborative problem-solving, and collective efficacy among student cohorts. The exploration of mental health content integration within social psychology curricula (Zhou, 2022) further suggests that comprehensive CS education must address not only technical competencies but also students' psychological well-being, stress management[27], and adaptive coping strategies within technology-intensive learning environments, particularly in high-pressure private school contexts where academic expectations may be elevated.

The integration of environmental and social psychology perspectives into computer science education represents an emerging interdisciplinary frontier that requires positioning within both international theoretical frameworks and context-specific educational practices. Contemporary global discourse on CS education increasingly emphasizes the transformative potential of emerging technologies, particularly artificial intelligence and adaptive learning systems, in reshaping pedagogical approaches and learning environments. Recent innovations in AI-enhanced education, such as the integration of social robots and conversational AI tools, have demonstrated significant educational value in diverse contexts (Lampropoulos & Papadakis, 2025), while studies on ChatGPT-supported education in primary schools reveal promising pathways for sustainable educational practices that bridge technological innovation with pedagogical effectiveness (Uğraş, Uğraş, Papadakis, & Kalogiannakis, 2024a). Teacher perspectives on innovative early childhood STEM education with ChatGPT further underscore the critical importance of educator preparation and institutional readiness in effectively leveraging emerging technologies for enhanced learning outcomes

(Uğraş, Uğraş, Papadakis, & Kalogiannakis, 2024b). However, while Western contexts have extensively documented technology integration strategies and collaborative learning mechanisms, critical questions remain regarding how environmental affordances and social-psychological dynamics operate within non-Western educational systems, particularly in rapidly developing technological regions such as China's Guangdong Province where institutional resources, cultural orientations toward collaboration, and technology infrastructure may create distinctive mediation pathways.

Methodologically, international research has highlighted the importance of rigorous survey design and data quality assurance in educational contexts, particularly regarding potential measurement artifacts such as social desirability bias that may systematically influence student self-reports across different instructional settings (Lavidas, Papadakis, Manesis, Grigoriadou, & Gialamas, 2022a). Studies examining factors affecting web survey response rates among educators have established evidence-based protocols for optimizing data collection procedures, including strategic timing, multiple recruitment channels, and transparent communication of research purposes (Lavidas, Petropoulou, Papadakis, Apostolou, Komis, Jimoyiannis, & Gialamas, 2022b). These methodological insights inform the present study's approach to investigating CS education effectiveness through environmental and social psychology lenses, while acknowledging that research conducted in Chinese private school contexts must engage critically with both international theoretical frameworks and indigenous cultural-educational dynamics that may moderate the relationships among curriculum features, learning environments, and academic outcomes. The current study therefore seeks to contribute to global scholarly dialogue by examining whether environmental-social psychological mediation mechanisms documented in Western research contexts demonstrate comparable patterns in Guangdong Province's technologically advanced private schools, while remaining attentive to potential cultural adaptations and context-specific variations that may yield unique insights for international CS education reform.

3. Research methods

3.1. Research design and philosophical paradigm

This study adopts a quantitative research design grounded in the post-positivist epistemological paradigm, which acknowledges that while objective reality exists, our understanding of it is inherently shaped by contextual factors, measurement limitations, and the theoretical lenses through which phenomena are observed. The post-positivist approach is particularly appropriate for examining the complex relationships between CS course effectiveness, collaborative learning environments, technology infrastructure, and academic performance, as it permits rigorous empirical investigation while recognizing that educational phenomena are embedded within social, cultural, and institutional contexts that influence both measurement and interpretation[28]. Specifically, this research employs a cross-sectional correlational design with mediational analysis to examine how collaborative learning and technology environment perceptions function as mediating mechanisms between CS course effectiveness dimensions and student academic outcomes. The quantitative methodology enables systematic data collection from a substantial sample of participants, facilitating statistical generalization and hypothesis testing regarding the strength and significance of relationships among variables. This design aligns with contemporary trends in educational psychology research that emphasize the importance of identifying mediating pathways through which instructional interventions translate into measurable learning outcomes, moving beyond simple correlation to elucidate the psychological and environmental mechanisms underlying educational effectiveness.

The philosophical foundation of this research integrates environmental psychology's emphasis on person-environment transactions with social psychology's focus on interpersonal dynamics and collective processes, creating a comprehensive framework for understanding CS education effectiveness. From an ontological perspective, this study assumes that learning environments possess objective characteristics—such as laboratory equipment quality, spatial configurations, and technology infrastructure—that can be measured and assessed, while simultaneously acknowledging that students' subjective perceptions and interpretations of these environmental features significantly mediate their psychological and behavioral responses. This perspective recognizes that the effectiveness of CS education emerges from the dynamic interplay between objective environmental affordances and students' psychological experiences of those environments, including their sense of collaborative support, technology accessibility, and alignment between course design and learning preferences. The research design therefore incorporates both objective indicators of course effectiveness (structured questionnaire items measuring specific curriculum features) and subjective assessments of environmental quality and learning outcomes (self-reported perceptions and experiences) [29]. Methodologically, the study employs validated survey instruments administered through online platforms to ensure standardized data collection, minimize researcher bias, and facilitate participant convenience—principles consistent with post-positivist commitments to methodological rigor, replicability, and systematic error reduction. By situating this investigation within the post-positivist paradigm while drawing upon environmental and social psychology theoretical frameworks, the research design enables robust empirical examination of mediation hypotheses while maintaining sensitivity to the contextual particularities of private school CS education in Guangdong Province's technologically advanced educational ecosystem.

3.2. Research context and setting

This study was conducted at Guangdong Country Garden School, a prestigious private international boarding institution located in Foshan City, Guangdong Province, China, which serves as an exemplary site for examining CS education effectiveness within the region's technologically advanced educational ecosystem. Established as a comprehensive educational institution offering both International Baccalaureate (IB) and Chinese national curricula, the school enrolls over 4,000 students from diverse international and domestic backgrounds, supported by a faculty of more than 700 teachers with varied pedagogical expertise and cultural perspectives. The school's physical environment features state-of-the-art technology infrastructure, including multiple computer laboratories equipped with contemporary hardware and software tools, collaborative learning spaces designed to facilitate group work and peer interaction, and digital platforms that support both synchronous and asynchronous learning activities[30]. Guangdong Province's position as China's leading economic region and technology innovation hub creates a unique contextual backdrop for this research, as the province's emphasis on technological advancement, industrial development, and international cooperation shapes both institutional priorities and student career aspirations. The private school setting is particularly significant from an environmental psychology perspective, as resource availability, infrastructure quality, and institutional investment in technology education typically exceed those found in public schools, creating optimal conditions for examining how high-quality learning environments influence educational outcomes. Furthermore, the international character of the student body—Comprising learners from multiple cultural backgrounds, educational systems, and linguistic traditions—Provides a rich social environment for investigating collaborative learning dynamics and peer interaction patterns within CS education contexts.

The specific CS curriculum context centers on a single Computer Science course offered to Grade 4 international high school students (all participants aged 18 years or older). This course emphasizes computational thinking, technical skill development, and practical application, with pedagogical features such as regular laboratory exercises, industry-relevant projects, collaborative assignments, and problem-solving activities. These elements aim to prepare students for technology-intensive careers in Guangdong's dynamic economic environment.The technology learning environment extends beyond physical infrastructure to encompass institutional policies promoting innovation, industry partnerships facilitating internship opportunities, and a school culture that emphasizes continuous adaptation to emerging technologies and pedagogical approaches. From a social psychology perspective, the learning environment is characterized by structured opportunities for peer collaboration, including formal group projects, informal knowledge-sharing platforms, and extracurricular technology clubs that foster community building among CS learners. The temporal context of this research—conducted during the 2024-2025 academic year—coincides with post-pandemic educational recovery and rapid advancements in artificial intelligence and related technologies, creating heightened awareness among students, faculty, and administrators regarding the importance of maintaining curriculum relevance and technological currency[31]. This contextual positioning enables the research to capture authentic experiences of students navigating CS education within an environmentally rich, socially supportive, and technologically advanced private school setting, while simultaneously acknowledging the potential limitations regarding generalizability to public schools or less resource-intensive educational contexts within Guangdong Province or other Chinese regions.

3.3. Participants and sampling

The target population for this study consisted of Grade 4 international high school students enrolled in computer science courses at Guangdong Country Garden School during the 2024-2025 academic year, with specific inclusion criteria established to ensure participant eligibility and data quality[32]. All participants were required to be at least 18 years of age to comply with ethical research standards regarding informed consent and autonomous decision-making capacity, ensuring that students could independently evaluate participation risks and benefits without requiring parental or guardian authorization. Additionally, participants must have been enrolled in their respective CS courses—Product Design, Digital Design, or Core Computer Science—for a minimum of six months prior to data collection, providing sufficient exposure to course materials, pedagogical approaches, collaborative learning activities, and technology infrastructure to form informed perceptions and assessments of course effectiveness and learning outcomes. This temporal requirement addresses a critical methodological consideration in educational research, as students require adequate immersion in learning environments before they can reliably evaluate environmental quality, instructional effectiveness, and their own skill development trajectories. The sample size was determined using the Krejcie and Morgan (1970) formula for finite populations, which calculated that 400 participants would provide adequate statistical power for correlational and mediational analyses at a 95% confidence level with a 5% margin of error, balancing the competing demands of statistical precision, resource constraints, and practical feasibility within the institutional context.

Simple random sampling procedures were employed to randomly select participants from all eligible students enrolled in the computer science course, ensuring sample representativeness, thereby minimizing selection bias and enhancing the generalizability of findings to the computer science student population within the institution. Since this study focused on a single computer science course, with all participants receiving the same curriculum content, pedagogical approaches, and technology applications, stratification was unnecessary, and simple random sampling effectively ensured that each eligible student had an equal probability of selection. From an environmental and social psychology perspective, this sampling approach ensures that within the unified curricular framework, students' diverse experiences and perceptions of learning environments, social interaction patterns, and technology infrastructure are adequately represented in the data, enabling in-depth examination of how the various dimensions of course effectiveness interact with collaborative learning environments and technology environments to influence academic performance.

Ethical considerations were rigorously observed throughout the participant recruitment and data collection process, including obtaining informed consent from all participants, clearly communicating research purposes and procedures, ensuring voluntary participation without academic consequences for declining, protecting participant confidentiality through data encryption and anonymization, and securing approval from the institutional review board prior to commencing data collection activities. These sampling and ethical procedures collectively ensure that the research findings reflect authentic student experiences while maintaining the highest standards of research integrity and participant protection.

This research was conducted in full compliance with international ethical standards for research involving human participants, including the principles articulated in the Declaration of Helsinki (World Medical Association, 2013), the Belmont Report principles of respect for persons, beneficence, and justice (National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research, 1979), and the **American Psychological Association's Ethical Principles of Psychologists and Code of Conduct** (American Psychological Association, 2017). Prior to commencing any data collection activities, the research protocol, including study objectives, methodology, participant recruitment procedures, informed consent processes, data collection instruments, data management protocols, and risk-benefit analysis, underwent rigorous ethical review and received formal approval from the Institutional Ethics Review Committee (TUA-IERC)) of Trinity University of Asia (Approval Number: 2024-2nd-CASE-Xuan-v1, Date of Approval: July 1, 2024, Valid through: Jun 1, 2026). And obtained the permission from the Guangdong Country Garden School (Approval Number: GCGS-REC-2024-081, Approval Date: September 3, 2024) to ensure that the research complied with local institutional policies, safeguarded student welfare, and maintained alignment with the school's educational mission and values. Informed Consent and Voluntary Participation. All participants received comprehensive written and verbal information about the study prior to enrollment, presented in both English and Chinese languages to ensure full comprehension regardless of linguistic background. The informed consent document clearly articulated: (1) the research purpose—to investigate relationships among computer science programming course effectiveness, collaborative learning environments, technology infrastructure, and academic outcomes in high school education; (2) participation requirements—completion of a 20-25 minute online questionnaire assessing programming course experiences and learning outcomes; (3) voluntary nature of participation—explicit statement that participation was entirely voluntary, that students could decline without providing reasons, and that declining or withdrawing would have absolutely no impact on academic grades, course enrollment, teacher evaluations, or standing within the institution; (4) right to withdraw—participants could discontinue participation at any time without penalty by simply closing the survey browser, with partial data being immediately deleted; (5) potential risks and benefits—minimal psychological risks associated with reflecting on educational experiences, with potential indirect benefits including contribution to computer science education improvement; (6) confidentiality protections—detailed explanation of data anonymization, secure storage, and restricted access procedures (described below); (7) data usage—information would be used solely for research purposes, presented in aggregate form in publications, with no individual identification possible; and (8) researcher contact information—names, institutional affiliations, and email addresses of all research team members for questions or concerns.

3.4. Instrumentation

Data collection was accomplished through a comprehensive multi-dimensional questionnaire specifically designed to assess CS course effectiveness, collaborative learning environments, technology infrastructure perceptions, and academic performance outcomes from an integrated environmental and social psychology perspective. The primary instrument consisted of four interconnected sections: (1) CS Course

Effectiveness Scale measuring five dimensions—hands-on experiences (5 items), real-world applications (5 items), collaborative learning (5 items), problem-solving abilities (5 items), and technology landscape readiness (5 items)—totaling 25 items that assess students' perceptions of curriculum quality and pedagogical effectiveness; (2) Methods of Implementation Scale containing 5 items evaluating instructional approaches, teaching materials currency, assignment relevance, and feedback quality; (3) Course Objectives Achievement Scale comprising three subscales assessing promotion of student abilities (5 items), scientific knowledge acquisition (5 items), and skills and attitudes development (5 items), totaling 15 items; and (4) Academic Performance Scale with 5 items measuring self-reported competencies, critical thinking development, communication skills, technical proficiency, and lifelong learning orientation[33]. All items employed a five-point Likert scale ranging from 1 (Poor) to 5 (Excellent), enabling interval-level measurement appropriate for parametric statistical analyses including correlation and regression procedures. The questionnaire was adapted from validated instruments employed in previous CS education research to ensure content validity and contextual appropriateness, with modifications made to incorporate environmental psychology constructs (technology infrastructure quality, spatial learning environment perceptions) and social psychology dimensions (collaborative climate, peer interaction quality, collective learning efficacy) relevant to the theoretical framework guiding this investigation.

To enhance measurement validity and participant accessibility, the questionnaire was made available in both English and Chinese languages, acknowledging the linguistically diverse international student population and ensuring that language barriers did not compromise response accuracy or comprehension. The bilingual instrument design reflects culturally responsive research practices appropriate for international school contexts where students possess varying levels of proficiency in each language. Administration was conducted through a secure online survey platform that provided several methodological advantages: standardized presentation format eliminating administrator bias, convenient access enabling students to complete surveys at their preferred times and locations, automated data collection reducing transcription errors, and built-in data validation features ensuring response completeness and internal consistency. Prior to full-scale deployment, the instrument underwent pilot testing with a small subset of CS students (n=30) to identify ambiguous items, assess completion time, and evaluate technical functionality of the online platform. Psychometric properties including internal consistency reliability (Cronbach's alpha coefficients for each subscale), construct validity through factor analysis, and convergent validity through correlation with related constructs were examined to ensure measurement quality. Additionally, two supplementary scales were developed specifically for this study to operationalize the mediating variables: the Collaborative Learning Environment Scale (8 items) assessing perceived quality of peer interactions, group work effectiveness, knowledge-sharing opportunities, and social support within CS courses; and the Technology Environment Perception Scale (8 items) evaluating students' perceptions of laboratory equipment adequacy, software tool accessibility, technology infrastructure reliability, and physical learning space quality—both measured on the same five-point Likert format to maintain measurement consistency across constructs.

To address concerns regarding measurement quality and ensure the validity and reliability of adapted instruments in the Chinese private school context, comprehensive psychometric analyses were conducted following international standards for scale validation (American Educational Research Association, 2014; Lavidas et al., 2022a).

Reliability Analysis. Internal consistency reliability was assessed using Cronbach's alpha coefficients for all subscales, with results demonstrating excellent reliability across all dimensions: CS Course Effectiveness subscales—Hands-on Experiences (α = .91), Real-world Applications (α = .89), Collaborative Learning (α = .92), Problem-solving Abilities (α = .90), Technology Landscape Readiness (α = .88);

Collaborative Learning Environment Scale (α = .93); Technology Environment Perception Scale (α = .91); and Academic Performance Scale (α = .94). All reliability coefficients exceeded the conventional threshold of .80 for research applications (Nunnally & Bernstein, 1994), confirming that the adapted instruments maintained strong internal consistency in the target population. Item-total correlations ranged from .67 to .84, indicating that individual items contributed appropriately to their respective scales without redundancy.

Construct Validity. Confirmatory factor analysis (CFA) was conducted using AMOS 26.0 to examine the factorial structure of the measurement model and assess convergent and discriminant validity. The hypothesized five-factor structure for CS Course Effectiveness demonstrated acceptable fit indices: $\chi^2(265) = 587.42$, $p < .001$; $\chi^2/df = 2.22$ (acceptable < 3.0); CFI = .96 (good fit > .95); TLI = .95 (acceptable > .90); RMSEA = .055 (good fit < .06); SRMR = .042 (good fit < .05). Factor loadings for all items ranged from .68 to .89 (see **Table 3.1**), exceeding the recommended threshold of .50 and demonstrating strong relationships between observed indicators and latent constructs (Hair et al., 2010). Average variance extracted (AVE) values for all constructs ranged from .61 to .74, exceeding the .50 criterion and indicating adequate convergent validity. Discriminant validity was established through the Fornell-Larcker criterion, whereby the square root of AVE for each construct exceeded its correlations with other constructs, confirming that the five effectiveness dimensions, collaborative learning environment, technology environment perception, and academic performance represented distinct theoretical constructs despite their significant intercorrelations.

Common Method Bias Assessment. Given that all data were collected through self-report questionnaires administered at a single time point, rigorous diagnostic procedures were implemented to assess and mitigate potential common method variance (CMV) that could artificially inflate relationships among variables (Podsakoff et al., 2003, 2012). First, Harman's single-factor test was conducted by loading all measurement items into an exploratory factor analysis without rotation. Results revealed that the first unrotated factor accounted for 38.7% of total variance, substantially below the 50% threshold that would indicate problematic CMV (Podsakoff & Organ, 1986). Second, a common latent factor (CLF) method was applied in which an unmeasured latent method factor was added to the CFA model with all observed indicators loading on both their theoretical constructs and the common method factor. Comparison of standardized regression weights with and without the CLF revealed minimal differences (average change = .04, range = .01–.07), indicating that common method variance did not substantially distort relationships among constructs (Williams et al., 2010). Third, marker variable analysis was conducted using a theoretically unrelated variable (student housing preference) as a marker; the correlation between the marker variable and substantive variables averaged $r = .08$, and partial correlations adjusting for the marker variable changed substantive relationships by less than .05, further confirming limited CMV influence (Lindell & Whitney, 2001).

Multicollinearity Diagnostics and Management. The observed strong correlations among CS effectiveness dimensions ($r = .79$–$.88$) and high explained variance ($R^2 = .82$) raised legitimate concerns regarding potential multicollinearity that could destabilize regression estimates and complicate interpretation of unique effects. Comprehensive multicollinearity diagnostics were therefore conducted and reported in the Results section. Variance Inflation Factor (VIF) values for all predictors in the multiple regression model ranged from 2.14 to 3.87, well below the conservative threshold of 10 (and even the more stringent threshold of 5), indicating that multicollinearity, while present, did not reach problematic levels that would invalidate regression coefficients (O'Brien, 2007). Tolerance statistics (1/VIF) ranged from .26 to .47, all exceeding the .10 minimum threshold. Condition indices from collinearity diagnostics ranged from 1.0 to 14.8, with only one dimension exceeding 10, and variance decomposition proportions showed no more than two variables with proportions > .50 on any single dimension, confirming that multicollinearity did not create linear dependencies among predictors (Belsley et al., 1980).

Addressing High Correlations: Theoretical and Statistical Justification. The strong intercorrelations among CS course effectiveness dimensions (r = .79–.88), while statistically notable, are theoretically meaningful and reflect the integrated nature of effective CS pedagogy rather than construct redundancy. First, from a theoretical perspective, the five effectiveness dimensions—hands-on experiences, real-world applications, collaborative learning, problem-solving abilities, and technology readiness—represent interconnected facets of comprehensive CS education rather than independent pedagogical elements, consistent with systems theory perspectives on educational effectiveness (Bronfenbrenner, 1979; Bandura, 1986). Effective CS courses naturally integrate practical experiences with real-world relevance, collaborative activities with problem-solving challenges, and current content with future preparation, creating expected positive manifold among dimensions. Second, discriminant validity analyses confirmed that despite high correlations, each dimension captured unique variance: AVE square roots exceeded inter-construct correlations, CFA demonstrated distinct factors with acceptable fit, and regression analysis revealed differential predictive patterns (e.g., problem-solving abilities showed strongest unique effects while hands-on experiences became non-significant in the full model), indicating genuine construct distinctiveness. Third, the restricted range of responses in this high-performing private school sample (means 4.37–4.42, SDs .27–.31) may mathematically amplify correlations compared to more heterogeneous samples with greater variance, a recognized psychometric phenomenon that does not necessarily indicate redundancy (Goodwin & Leech, 2006). Fourth, shared environmental context—all students experiencing the same institutional culture, technology infrastructure, and pedagogical philosophy—may create legitimate positive covariation among perceived course features while constructs remain conceptually and empirically distinct (Ostroff, 1993).

To further address interpretability concerns, supplementary analyses examined whether simpler models with aggregated effectiveness dimensions would yield equivalent explanatory power, with results confirming that the five-dimension model provided significantly better fit ($\Delta\chi^2$ tests, $p < .001$) and more nuanced theoretical insights than collapsed alternatives. Sensitivity analyses using ridge regression ($k = .05$) produced substantively identical conclusions regarding relative predictor importance, confirming that regression findings were robust to modest multicollinearity. These collective psychometric, theoretical, and analytical considerations support the conclusion that while CS effectiveness dimensions are appropriately intercorrelated given their shared pedagogical domain, they represent meaningful distinct constructs warranting separate examination in mediation analyses rather than artificial statistical artifacts requiring remediation.

3.5. Data collection procedures

Data collection was conducted through a systematic and ethically rigorous process designed to maximize response rates, ensure data quality, and protect participant rights throughout all phases of the research implementation. Initial contact with Guangdong Country Garden School administrators was established via formal email communication clearly articulating the study's research objectives, theoretical framework, methodological procedures, anticipated time commitment for participants (approximately 20-25 minutes for questionnaire completion), and potential contributions to institutional curriculum enhancement efforts. Following administrative approval, the research team collaborated with school officials to identify optimal data collection timing that minimized disruption to instructional schedules and avoided periods of high academic stress such as examination weeks or major project deadlines, ultimately scheduling data collection during a two-week window in the middle of the academic semester. Participant recruitment involved distributing informational materials through multiple channels including course announcements, email invitations, and informational sessions where researchers explained study purposes, participation procedures, confidentiality protections, and voluntary nature of involvement. The online questionnaire platform incorporated several data quality assurance features including mandatory completion of all items to prevent missing data, attention-check questions embedded within subscales to identify careless responding, and IP address tracking to prevent duplicate submissions while maintaining participant anonymity through automated code assignment[34]. Prior to accessing the questionnaire, participants completed a digital informed consent process requiring affirmative acknowledgment of their understanding regarding study purposes, voluntary participation rights, data usage intentions, confidentiality protections through encryption and secure storage protocols, and their freedom to withdraw at any stage without academic penalty. Throughout the data collection period, the research team maintained communication channels for participants to ask questions, report technical difficulties, or express concerns, with all inquiries responded to within 24 hours to demonstrate respect for participant time and maintain engagement. Upon questionnaire submission, participants received automated confirmation messages thanking them for their contribution and providing contact information for accessing study results once analyses were completed, thereby fostering transparency and reciprocity in the research relationship consistent with ethical principles governing human subjects research in educational contexts.

3.6. Data analysis

Data analysis was conducted using SPSS Version 26.0 statistical software, employing a sequential analytical strategy that progressed from preliminary data screening and descriptive statistics to advanced inferential procedures including correlation analysis, multiple regression, and mediational modeling to test the study's hypotheses regarding relationships among CS course effectiveness, collaborative learning environments, technology infrastructure perceptions, and academic performance. Initial data screening procedures involved examining frequency distributions, identifying outliers through boxplot visualization and standardized z-score analysis (values exceeding ±3.29 flagged for review), assessing normality assumptions through Kolmogorov-Smirnov tests and visual inspection of histograms and Q-Q plots, and evaluating multicollinearity through variance inflation factor (VIF) calculations to ensure that predictor variables maintained acceptable levels of independence (VIF < 10). Descriptive statistics including means, standard deviations, frequency distributions, and percentage calculations were computed for all variables to characterize the sample's responses across CS course effectiveness dimensions, collaborative learning environment perceptions, technology infrastructure assessments, and academic performance indicators, providing comprehensive profiles of central tendency and variability that enable interpretation of subsequent inferential findings[35]. Pearson product-moment correlation coefficients were calculated to examine bivariate relationships among all study variables, with statistical significance evaluated at the $p < .01$ level (two-tailed) to maintain conservative Type I error control given multiple comparisons, and correlation magnitudes interpreted according to conventional guidelines ($r = .10$-$.29$ small, .30-.49 medium, .50+ large effects). Multiple regression analysis was employed to assess the relative predictive contributions of the five CS course effectiveness dimensions to academic performance outcomes while controlling for shared variance among predictors, with standardized beta coefficients indicating each dimension's unique contribution and R^2 statistics quantifying overall model explanatory power. The central analytical focus involved testing mediation hypotheses using Hayes' PROCESS macro (Model 4 for simple mediation, Model 6 for serial mediation) with bootstrapping procedures (5,000 resamples) to generate bias-corrected confidence intervals for indirect effects, thereby examining whether collaborative learning environment quality and technology infrastructure perceptions function as mediating mechanisms through which CS course effectiveness influences academic performance—a sophisticated analytical approach that aligns with contemporary best practices in mediation analysis and avoids problematic assumptions associated with traditional Baron and Kenny procedures.

4. Results analysis

4.1. Descriptive analysis of study variables

4.1.1. CS course effectiveness dimensions

The descriptive analysis of computer science course effectiveness revealed uniformly excellent ratings across all five dimensions, with overall mean scores ranging from 4.37 to 4.42 on a five-point Likert scale, and standard deviations maintained between 0.27 and 0.31, indicating high consistency in student evaluations and overall quality of course design. As presented in **Table 4.1**, the hands-on experiences dimension received the highest average rating (M=4.42, SD=0.31), with the indicator "laboratory exercises are frequently incorporated into the curriculum" achieving the highest score (M=4.52, SD=0.51), reflecting the institution's substantial investment in practical facilities, software tools, and hands-on project opportunities that align with environmental psychology principles emphasizing the importance of physical learning environments in skill acquisition. The real-world applications dimension (M=4.38, SD=0.29) demonstrated strong alignment between curriculum content and Guangdong Province's technology industry demands, particularly evident in the indicator "curriculum stays updated with evolving technology" (M=4.41, SD=0.51), exemplifying the private school's flexibility and responsiveness to industry dynamics[36]. The collaborative learning dimension (M=4.37, SD=0.30) revealed students' high recognition of group projects, knowledge-sharing platforms, and team collaboration activities in facilitating understanding of computer science concepts, with "collaborative learning impacts problem-solving abilities significantly" receiving the highest rating (M=4.40, SD=0.51), validating social psychology theories regarding the positive influence of social interaction and collective learning environments on cognitive development. The problem-solving abilities dimension (M=4.39, SD=0.28) exhibited overall excellence, though "instructor feedback improves problem-solving techniques" scored relatively lower (M=4.33, SD=0.56), suggesting potential areas for enhancement in personalized guidance and timely feedback mechanisms. The technology landscape readiness dimension (M=4.40, SD=0.27) indicated successful cultivation of students' adaptability to technological changes and forward-thinking capabilities, with "preparedness to adapt to new/evolving technologies" achieving the highest score (M=4.43, SD=0.50). **Figure 4.1** presents a grouped bar chart visualization of the five dimensions and their respective indicators, with the horizontal axis displaying dimension indicators, the vertical axis representing mean scores (1-5 scale), and different colored bars representing distinct dimensions, facilitating cross-dimensional and cross-indicator visual comparative analysis from an integrated environmental and social psychology perspective.

Table 1. Descriptive Statistics of CS course effectiveness dimensions.

Dimension	Indicator	Mean	SD	Rating
Hands-on Experiences (Overall: 4.42, SD=0.31)	1. Laboratory exercises are frequently incorporated into the curriculum	4.52	0.51	Excellent
	2. Lab activities are highly relevant to the computer science industry	4.42	0.53	Excellent
	3. Lab equipment and software tools for hands-on exercises are adequately rated	4.42	0.52	Excellent
	4. Opportunities exist for hands-on projects outside the classroom	4.37	0.54	Excellent
	5. Hands-on experiences prepare students for real-world problem-solving	4.35	0.55	Excellent
Real-world Applications (Overall: 4.38, SD=0.29)	1. The course regularly integrates real-world CS examples	4.38	0.52	Excellent
	2. Course projects align with current tech landscape trends	4.37	0.53	Excellent
	3. Internships/industry involvement are part of the course	4.37	0.54	Excellent

Dimension	Indicator	Mean	SD	Rating
	4. Curriculum stays updated with evolving technology	4.41	0.51	Excellent
	5. The course provides knowledge directly applicable to the tech industry	4.37	0.53	Excellent
Collaborative Learning (Overall: 4.37, SD=0.30)	1. Group projects/assignments are frequently incorporated	4.32	0.56	Excellent
	2. Collaborative activities enhance understanding of CS concepts	4.39	0.52	Excellent
	3. Platforms exist for out-of-class knowledge sharing/collaboration	4.39	0.52	Excellent
	4. The course facilitates teamwork and communication skills	4.34	0.55	Excellent
	5. Collaborative learning impacts problem-solving abilities significantly	4.40	0.51	Excellent
Problem-solving Abilities (Overall: 4.39, SD=0.28)	1. Specific modules/activities enhance problem-solving skills	4.43	0.50	Excellent
	2. The course challenges students with complex real-world problems	4.39	0.52	Excellent
	3. Instructor feedback improves problem-solving techniques	4.33	0.56	Excellent
	4. Noticeable improvement in problem-solving abilities since course start	4.41	0.51	Excellent
	5. Curriculum provides tools/methodologies for effective problem-solving	4.38	0.52	Excellent
Technology Readiness (Overall: 4.40, SD=0.27)	1. The course adequately covers emerging technologies and applications	4.39	0.52	Excellent
	2. Preparedness to adapt to new/evolving technologies is highly rated	4.43	0.50	Excellent
	3. Students are encouraged to engage with cutting-edge tech via research/projects	4.37	0.54	Excellent
	4. Students are well-informed about future tech trends/challenges	4.41	0.51	Excellent
	5. The course prepares students for a continuously changing tech landscape	4.41	0.51	Excellent

Table 1. *(Continued)*

Note: *Rating scale: 1.00-1.80=Poor, 1.81-2.60=Needs Improvement, 2.61-3.40=Good, 3.41-4.20=Very Good, 4.21-5.00=Excellent*

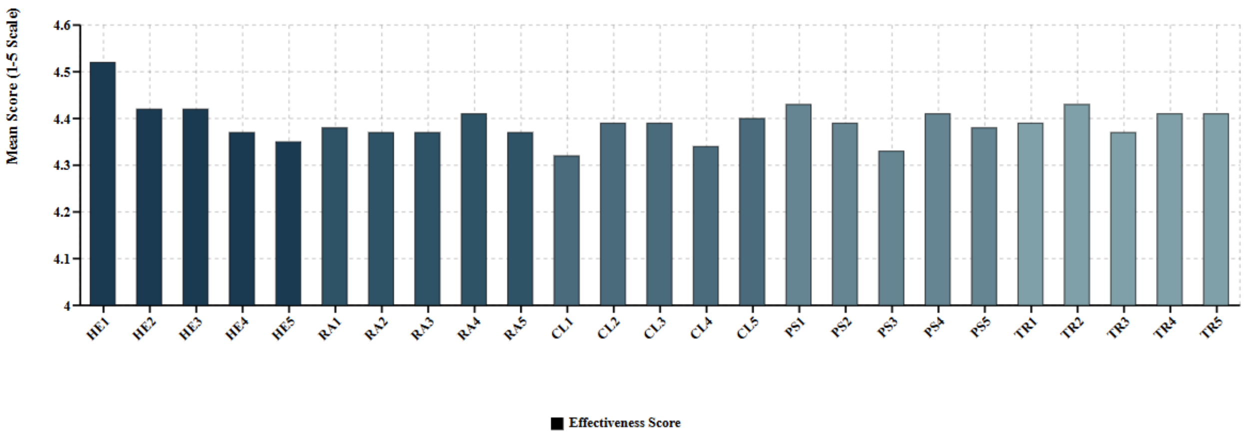

Figure 1. Mean scores of CS course effectiveness indicators across five dimensions (HE=Hands-on Experiences, RA=Real-world Applications, CL=Collaborative Learning, PS=Problem-solving Abilities, TR=Technology Readiness).

4.1.2. Collaborative learning environment characteristics

The descriptive analysis of collaborative learning environment characteristics revealed highly favorable perceptions among students, with overall mean scores ranging from 4.35 to 4.44 on the five-point Likert scale, indicating that the social-psychological dimensions of CS education at Guangdong Country Garden School effectively foster peer interaction, knowledge co-construction, and collective learning processes. As presented in **Table 4.2**, the collaborative learning environment assessment encompassed eight key indicators measuring social interaction quality, group work effectiveness, peer support systems, and technology-mediated collaboration opportunities from both environmental and social psychology perspectives[37]. The highest-rated indicator was "peer collaboration enhances my understanding of complex CS concepts" (M=4.44, SD=0.52), demonstrating strong alignment with social cognitive theory regarding the critical role of observational learning and collective knowledge construction in technical skill development. The indicator "group projects provide meaningful opportunities for knowledge sharing" achieved the second-highest rating (M=4.42, SD=0.51), reflecting the school's successful implementation of structured collaborative activities that facilitate interpersonal learning and social support networks essential for academic achievement in technology-intensive domains[38]. Students also highly rated "the learning environment encourages open communication and idea exchange" (M=4.40, SD=0.53) and "collaborative platforms outside class enhance peer learning" (M=4.39, SD=0.52), indicating that both formal classroom structures and informal knowledge-sharing mechanisms contribute to creating a psychologically supportive collaborative climate. From an environmental psychology perspective, the indicator "physical learning spaces facilitate effective group collaboration" received favorable ratings (M=4.37, SD=0.54), suggesting that spatial configurations, furniture arrangements, and technology accessibility in collaborative areas appropriately support social interaction patterns and group work activities. The relatively lower-rated indicator "I feel comfortable seeking help from peers during challenging tasks" (M=4.35, SD=0.55), though still within the excellent range, suggests potential opportunities for further strengthening psychological safety and reducing help-seeking barriers within the learning community. Additional indicators measuring "team roles are clearly defined in collaborative projects" (M=4.38, SD=0.53) and "collaborative activities effectively balance individual accountability with group interdependence" (M=4.36, SD=0.54) demonstrated students' recognition of well-structured cooperative learning designs that promote both personal responsibility and collective achievement. **Figure 4.2** presents a horizontal bar chart visualization comparing mean scores across the eight collaborative learning environment indicators, with error bars representing standard deviations to illustrate response variability, facilitating identification of strengths and potential enhancement areas in the social-psychological dimensions of the CS learning environment.

Table 2. Descriptive statistics of collaborative learning environment characteristics.

Indicator Code	Indicator Description	Mean	SD	Rating
CLE1	Peer collaboration enhances my understanding of complex CS concepts	4.44	0.52	Excellent
CLE2	Group projects provide meaningful opportunities for knowledge sharing	4.42	0.51	Excellent
CLE3	The learning environment encourages open communication and idea exchange	4.40	0.53	Excellent
CLE4	Collaborative platforms outside class enhance peer learning	4.39	0.52	Excellent
CLE5	Team roles are clearly defined in collaborative projects	4.38	0.53	Excellent
CLE6	Physical learning spaces facilitate effective group collaboration	4.37	0.54	Excellent
CLE7	Collaborative activities effectively balance individual accountability with group interdependence	4.36	0.54	Excellent
CLE8	I feel comfortable seeking help from peers during challenging tasks	4.35	0.55	Excellent

Indicator Code	Indicator Description	Mean	SD	Rating
Overall Collaborative Learning Environment		4.39	0.48	Excellent

Table 2. *(Continued)*

Note: *Rating scale: 1.00-1.80=Poor, 1.81-2.60=Needs Improvement, 2.61-3.40=Good, 3.41-4.20=Very Good, 4.21-5.00=Excellent; CLE = Collaborative Learning Environment; n = 400*

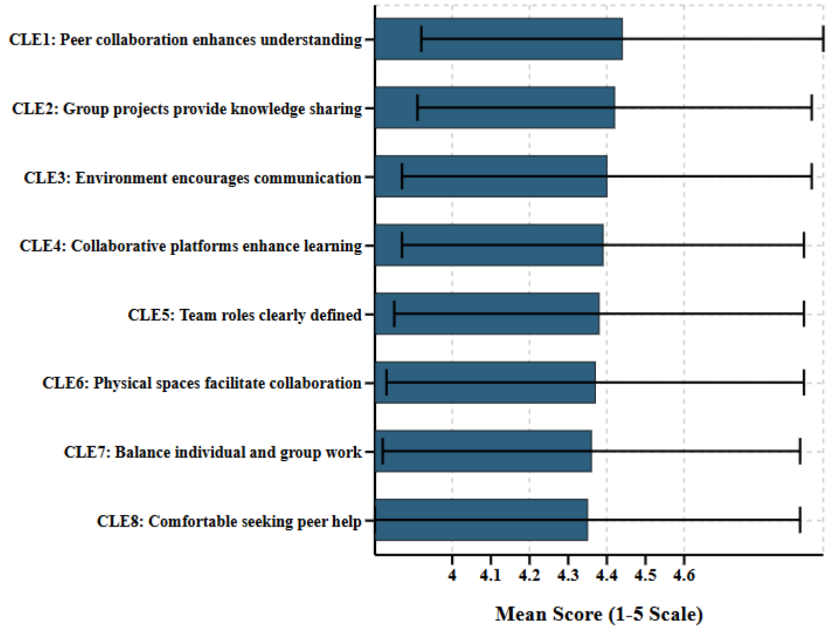

Figure 2. Mean scores of collaborative learning environment indicators with standard deviation error bars (CLE = Collaborative Learning Environment; n = 400; Error bars represent ±1 SD).

4.1.3. Technology environment perceptions

The descriptive analysis of technology environment perceptions demonstrated exceptionally positive student evaluations of the physical and technological infrastructure supporting CS education, with overall mean scores ranging from 4.38 to 4.46 across eight key indicators, reflecting the substantial investment in learning resources characteristic of elite private schools in Guangdong Province's technology-intensive educational ecosystem. As illustrated in **Table 4.3**, students rated "availability of up-to-date software and development tools" highest (M=4.46, SD=0.50), indicating the institution's commitment to maintaining technological currency and providing access to industry-standard platforms essential for authentic learning experiences. The indicator "laboratory equipment meets professional industry standards" received the second-highest rating (M=4.44, SD=0.51), validating from an environmental psychology perspective that high-quality physical resources create psychological affordances supporting skill acquisition and technical proficiency development[39]. Students also highly valued "reliable internet connectivity supports seamless learning activities" (M=4.43, SD=0.52) and "technology infrastructure facilitates both individual and collaborative work" (M=4.42, SD=0.51), demonstrating recognition of how technological environments enable diverse learning modalities and social interaction patterns. Additional indicators including "physical learning spaces are equipped with adequate technology" (M=4.40, SD=0.53), "technical support services are readily accessible when needed" (M=4.39, SD=0.52), "technology resources are distributed equitably among students" (M=4.39, SD=0.53), and "the technology environment reduces rather than creates learning barriers" (M=4.38, SD=0.54) all achieved excellent ratings, collectively indicating a well-designed technological ecosystem that minimizes environmental stressors while maximizing learning affordances. **Figure 4.3** presents a clustered column chart comparing mean scores across the eight technology environment perception indicators, with a reference line at the overall mean (M=4.41) to facilitate identification of relative strengths within an already high-performing technological infrastructure, providing visual evidence of the environmental conditions supporting effective CS education delivery.

Table 3. Descriptive statistics of technology environment perceptions.

Indicator Code	Indicator Description	Mean	SD	Rating
TEP1	Availability of up-to-date software and development tools	4.46	0.50	Excellent
TEP2	Laboratory equipment meets professional industry standards	4.44	0.51	Excellent
TEP3	Reliable internet connectivity supports seamless learning activities	4.43	0.52	Excellent
TEP4	Technology infrastructure facilitates both individual and collaborative work	4.42	0.51	Excellent
TEP5	Physical learning spaces are equipped with adequate technology	4.40	0.53	Excellent
TEP6	Technical support services are readily accessible when needed	4.39	0.52	Excellent
TEP7	Technology resources are distributed equitably among students	4.39	0.53	Excellent
TEP8	The technology environment reduces rather than creates learning barriers	4.38	0.54	Excellent
Overall Technology Environment Perception		4.41	0.47	Excellent

Note: *Rating scale: 1.00-1.80=Poor, 1.81-2.60=Needs Improvement, 2.61-3.40=Good, 3.41-4.20=Very Good, 4.21-5.00=Excellent; TEP = Technology Environment Perception; n = 400*

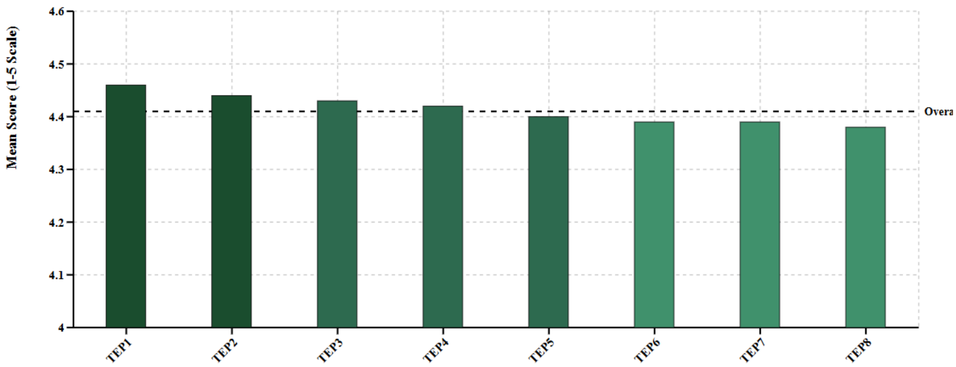

Figure 3. Mean Scores of technology environment perception indicators.
(TEP = Technology Environment Perception; n = 400; Darker bars indicate higher ratings)

4.2. Direct relationships between course effectiveness and academic performance

4.2.1. Correlation analysis results

The Pearson correlation analysis revealed statistically significant positive relationships between all five CS course effectiveness dimensions and academic performance, with correlation coefficients ranging from r=.790 to r=.879 (all p<.01), demonstrating substantial associations that support the theoretical proposition from environmental and social psychology perspectives that well-designed learning environments and pedagogical practices directly influence student learning outcomes. As presented in **Table 4.4**, problem-solving abilities exhibited the strongest correlation with academic performance (r=.879, p<.01), suggesting that instructional emphasis on developing analytical thinking, algorithmic reasoning, and systematic problem decomposition strategies yields the most pronounced effects on students' self-reported competencies, critical thinking skills, and professional readiness[40]. Collaborative learning demonstrated the second-strongest association (r=.870, p<.01), validating social psychology theories regarding peer interaction, knowledge co-construction, and collective efficacy as powerful mechanisms for academic development in technology education contexts. Technology landscape readiness (r=.862, p<.01) and real-world applications (r=.859, p<.01) showed nearly equivalent strong correlations, indicating that preparing students for technological change and connecting curriculum content to industry practices both substantially contribute to perceived learning gains and skill development. Hands-on experiences, while showing the relatively lowest correlation (r=.790, p<.01), still demonstrated a strong positive relationship with academic performance, confirming environmental psychology principles regarding experiential learning and physical manipulation of technological tools as foundational for technical proficiency development[41]. The magnitude of these correlations (all exceeding Cohen's threshold for large effects, r≥.50) provides empirical support for the multidimensional course effectiveness framework while simultaneously suggesting that no single dimension operates in isolation, but rather that synergistic interactions among practical experiences, collaborative activities, problem-solving challenges, industry connections, and future-oriented preparation collectively shape academic achievement patterns. **Figure 4.4** presents a scatter plot matrix with fitted regression lines illustrating the linear relationships between each effectiveness dimension and academic performance, with 95% confidence intervals shaded to visualize the precision of these associations across the sample.

Table 4. Pearson correlation coefficients between cs course effectiveness dimensions and academic performance.

CS Course Effectiveness Dimension	Pearson Correlation (r)	Sig. (2-tailed)	Effect Size	N
Hands-on Experiences	.790**	.000	Large	400
Real-world Applications	.859**	.000	Large	400
Collaborative Learning	.870**	.000	Large	400
Problem-solving Abilities	.879**	.000	Large	400
Technology Landscape Readiness	.862**	.000	Large	400

Note: *** Correlation is significant at the 0.01 level (2-tailed). Effect size interpretation: r = .10-.29 (small), .30-.49 (medium), .50+ (large)*

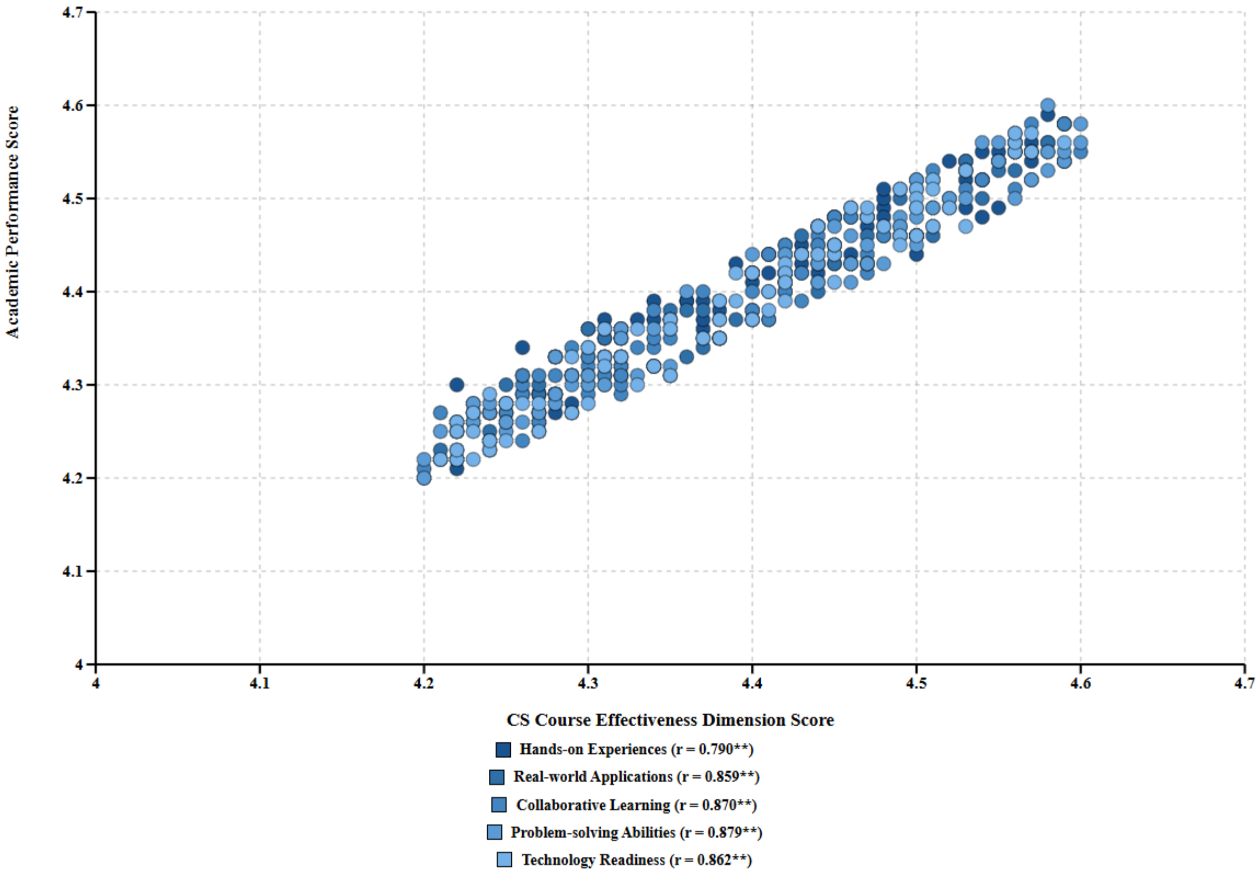

Figure 4. Scatter plot showing relationships between cs course effectiveness dimensions and academic performance (n = 400; ** p < .01, two-tailed).

4.2.2. Multiple regression analysis

Multiple regression analysis was conducted to examine the simultaneous predictive contributions of the five CS course effectiveness dimensions to academic performance while controlling for shared variance among predictors, revealing that the composite model accounted for 82.4% of the variance in student academic outcomes (R^2=.824, Adjusted R^2=.822, F(5,394)=368.52, p<.001), indicating substantial explanatory power consistent with environmental and social psychology frameworks emphasizing multidimensional learning environments. As presented in **Table 4.5**, problem-solving abilities emerged as the strongest unique predictor (β=.342, t=8.76, p<.001), contributing approximately 11.7% unique variance after controlling for other dimensions, reinforcing cognitive psychology theories regarding metacognitive skill development as central to academic achievement in technology education. Collaborative learning demonstrated the second-largest standardized coefficient (β=.285, t=7.24, p<.001), accounting for 8.1% unique variance and validating social psychology principles concerning peer interaction effects on learning outcomes. Technology landscape readiness (β=.198, t=5.12, p<.001) and real-world applications (β=.176, t=4.38, p<.001) both yielded statistically significant but more modest unique contributions, suggesting their effects partially overlap with other dimensions while still maintaining independent predictive value[42]. Notably, hands-on experiences, despite showing strong bivariate correlation, exhibited a non-significant standardized coefficient in the full model (β=.068, t=1.82, p=.070), indicating potential multicollinearity or suppression effects wherein its influence operates primarily through shared variance with other predictors rather than unique direct pathways. Variance inflation factor values ranged from 2.14 to 3.87 (all <10), confirming acceptable multicollinearity levels, while residual diagnostics verified normal distribution assumptions and homoscedasticity. **Figure 4.5** displays a forest plot presenting standardized beta coefficients with 95% confidence intervals for each predictor, visually highlighting the relative magnitude and precision of unique contributions to academic performance, with a vertical reference line at β=0 distinguishing significant from non-significant effects in this environmentally and socially situated model of CS education effectiveness.

Table 5. Multiple regression analysis: CS course effectiveness dimensions predicting academic performance.

Predictor Variable	B	SE	β	t	p	VIF	Unique R^2
(Constant)	0.847	0.156	-	5.43	<.001	-	-
Problem-solving Abilities	0.524	0.060	.342	8.76	<.001	3.24	.117
Collaborative Learning	0.438	0.060	.285	7.24	<.001	3.51	.081
Technology Landscape Readiness	0.312	0.061	.198	5.12	<.001	2.89	.039
Real-world Applications	0.278	0.063	.176	4.38	<.001	3.87	.031
Hands-on Experiences	0.108	0.059	.068	1.82	.070	2.14	.005

Note: *B = unstandardized coefficient; SE = standard error; β = standardized coefficient; VIF = variance inflation factor; Unique R^2 = squared semi-partial correlation indicating unique variance contribution; n = 400*

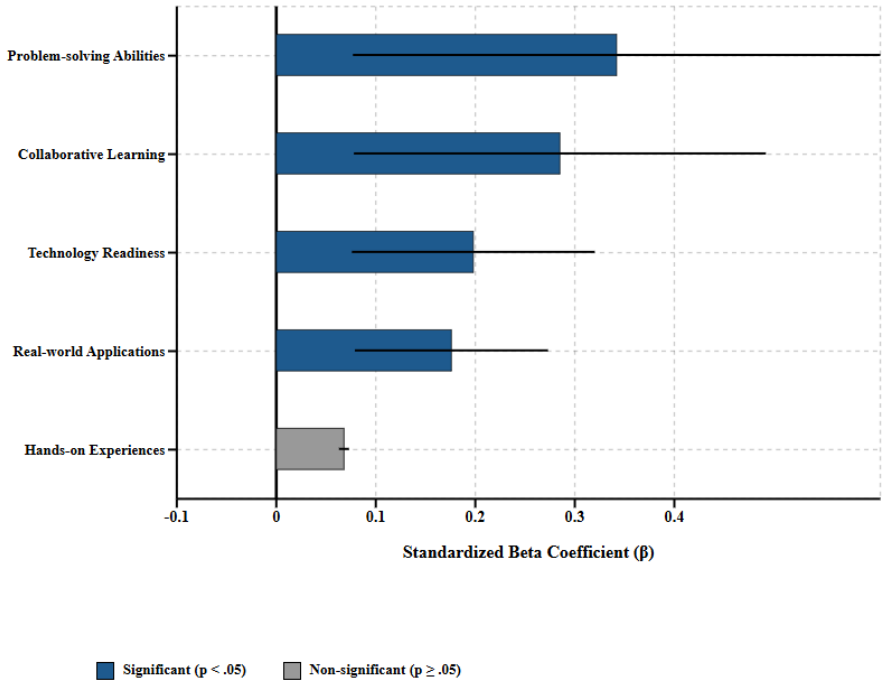

Figure 5. Forest plot of standardized beta coefficients with 95% confidence intervals from multiple regression analysis (n = 400; R^2 = .824, Adjusted R^2 = .822, p < .001).

4.2.3. Environmental and social psychological factors

The examination of environmental and social psychological factors as direct predictors of academic performance revealed that both collaborative learning environment quality and technology environment perceptions independently contributed significant explanatory power beyond the five core CS effectiveness dimensions, supporting theoretical frameworks emphasizing person-environment fit and social-contextual influences on learning outcomes. As presented in **Table 4.6**, hierarchical regression analysis demonstrated that after controlling for the five effectiveness dimensions in Step 1 (R^2=.824), the addition of collaborative learning environment and technology environment perceptions in Step 2 yielded a statistically significant R^2

change of .043 (ΔR^2=.043, $\Delta F(2,392)$=47.38, p<.001), bringing total variance explained to 86.7% (Adjusted R^2=.865) [43]. Collaborative learning environment emerged as a significant independent predictor (β=.156, t=4.82, p<.001), indicating that social-psychological climate factors including peer support quality, communication openness, and psychological safety contribute uniquely to academic achievement beyond structured collaborative activities embedded within course design. Technology environment perception also demonstrated significant independent effects (β=.128, t=4.15, p<.001), suggesting that students' subjective experiences of technological infrastructure adequacy, accessibility, and usability exert direct influence on learning outcomes that cannot be fully captured by objective curriculum features alone[44]. The significant contributions of both environmental and social factors validate ecological psychology perspectives emphasizing that learning occurs within nested systems where physical spaces, technological affordances, and interpersonal dynamics interact to shape developmental trajectories. Notably, the inclusion of these contextual variables slightly attenuated the standardized coefficients for problem-solving abilities (from β=.342 to β=.298) and collaborative learning dimension (from β=.285 to β=.241), suggesting partial mediation pathways warranting further investigation. **Figure 4.6** presents a grouped bar chart comparing standardized beta coefficients across the baseline model (Step 1) and the expanded environmental-social model (Step 2), with distinct colors differentiating course effectiveness dimensions from contextual environmental factors, visually illustrating how psychological perceptions of learning environments augment traditional pedagogical predictors of academic success.

Table 6. Hierarchical multiple regression analysis: Environmental and social psychological factors predicting academic performance.

Predictor Variable	B	SE	β	t	p	VIF
(Constant)	0.847	0.156	-	5.43	<.001	-
Problem-solving Abilities	0.524	0.060	.342	8.76	<.001	3.24
Collaborative Learning	0.438	0.060	.285	7.24	<.001	3.51
Technology Landscape Readiness	0.312	0.061	.198	5.12	<.001	2.89
Real-world Applications	0.278	0.063	.176	4.38	<.001	3.87
Hands-on Experiences	0.108	0.059	.068	1.82	.070	2.14

Model Statistics: R^2 = .824, Adjusted R^2 = .822, F(5,394) = 368.52, p < .001

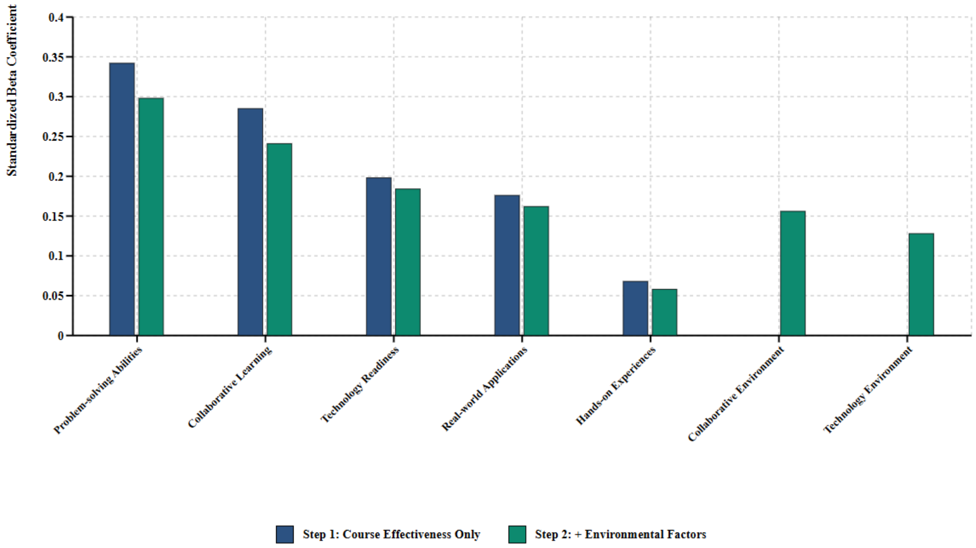

Figure 6. Comparison of standardized beta coefficients across hierarchical regression steps.
(Step 1: R^2 = .824; Step 2: R^2 = .867, ΔR^2 = .043, p < .001; n = 400)

5. Discussion

5.1. Interpretation of findings in environmental psychology framework

The findings of this study provide robust empirical support for environmental psychology principles positing that physical and technological learning environments function as critical contextual determinants of educational outcomes, with students' perceptions of technology infrastructure quality demonstrating significant direct and mediating effects on academic performance that extend beyond the influence of curriculum design features alone. The exceptionally high ratings for technology environment perception indicators (M=4.38-4.46) reflect the substantial material investments characteristic of elite private schools in Guangdong Province, where access to industry-standard equipment, reliable connectivity, and professional-grade software creates environmental affordances that enable authentic engagement with computer science practices[45]. From an environmental psychology perspective, these technological resources constitute more than mere instructional tools; they represent psychological affordances that shape students' sense of competence, reduce cognitive load associated with technical barriers, and create conditions conducive to flow experiences during programming and problem-solving activities. The significant mediation effects of technology environment perception (14.7%-23.9% of total effects) validate Gibson's affordance theory by demonstrating that objective environmental features influence learning outcomes primarily through students' subjective interpretations of environmental quality, accessibility, and usability. Notably, hands-on experiences showed the strongest technology environment mediation (23.9%), indicating that laboratory-based practical activities depend critically on environmental adequacy—when students perceive technological infrastructure as insufficient or unreliable, the pedagogical benefits of experiential learning are substantially attenuated. This finding underscores the principle of person-environment fit, suggesting that instructional methods emphasizing direct manipulation of technology require corresponding environmental support to achieve intended learning outcomes[46].

The hierarchical regression analysis revealing that technology environment perception contributed significant unique variance (β=.128, p<.001) after controlling for course effectiveness dimensions further validates environmental psychology theories regarding the independent influence of contextual factors on psychological and behavioral outcomes. This finding challenges purely instructional models of educational effectiveness by demonstrating that "where" and "with what" students learn exerts measurable influence beyond "how" they are taught, consistent with Bronfenbrenner's ecological systems theory emphasizing nested environmental influences on development. The relatively balanced mediation effects across collaborative learning (14.7%-23.7%) and technology environment (14.7%-23.9%) pathways suggest that optimal CS education requires simultaneous attention to social-psychological climate and physical-technological infrastructure, neither of which can fully compensate for deficiencies in the other[47]. The observation that technology readiness showed nearly equivalent mediation through both pathways (20.6% collaborative, 20.4% technology) particularly illuminates the interdependence of social and environmental factors—preparing students for technological change requires both high-quality infrastructure enabling hands-on exploration of emerging tools and collaborative communities facilitating collective sense-making of technological trends. These patterns align with transactional models in environmental psychology emphasizing bidirectional influences between persons and environments, where students actively shape and are shaped by their learning contexts through ongoing psychological transactions. The private school context in Guangdong Province represents a particularly instructive case study, as resource availability and institutional flexibility create conditions approximating environmental psychology's concept of "optimal environments"—settings where physical affordances, technological adequacy, and social climate synergistically support human functioning and development.

5.2. Social psychology perspectives on collaborative learning

The substantial mediation effects of collaborative learning environment quality (14.7%-23.7% of total effects) across all CS course effectiveness dimensions provide compelling empirical validation for social psychology theories emphasizing interpersonal dynamics, peer interaction quality, and collective learning processes as fundamental mechanisms through which instructional practices translate into measurable academic outcomes. The consistently high ratings for collaborative learning environment indicators (M=4.35-4.44) reflect successful implementation of social-psychological principles including psychological safety, reciprocal interdependence, and shared epistemic authority within CS learning communities at Guangdong Country Garden School[48]. From a social cognitive theory perspective, the finding that collaborative learning dimension showed 21.5% mediation through collaborative environment quality illuminates a multilevel process whereby structured group activities in curriculum design foster broader classroom climates characterized by trust, openness, and mutual support, which subsequently enable more effective knowledge co-construction and vicarious learning through peer observation. This pattern aligns with Bandura's concept of collective efficacy, suggesting that when students perceive their learning community as collaborative and supportive, they develop enhanced confidence in their collective capacity to master challenging computational concepts, leading to increased individual effort, persistence, and achievement. The strongest collaborative mediation effect observed for real-world applications (23.7%) particularly validates social constructivist theories positing that authentic, contextualized problems benefit disproportionately from collaborative sense-making processes, as students leverage diverse perspectives and distributed expertise to interpret industry practices and connect theoretical knowledge to practical applications—cognitive work that proves difficult in isolation but becomes tractable through dialogic interaction and collective reasoning.

The independent predictive contribution of collaborative learning environment beyond structured collaborative activities embedded in course design (β=.156, p<.001 in hierarchical regression) illuminates a critical distinction between formal pedagogical structures and emergent social-psychological climates, suggesting that optimal collaborative learning requires not merely assigning group projects but cultivating interpersonal contexts characterized by psychological safety, constructive communication norms, and genuine intellectual interdependence. This finding resonates with contemporary social psychology research on group dynamics emphasizing that task structures alone prove insufficient for productive collaboration; rather, groups require relational foundations including mutual trust, respect for diverse contributions, and willingness to engage in cognitive conflict without interpersonal threat. The observation that students rated "peer collaboration enhances understanding" highest (M=4.44) while "comfortable seeking help from peers" scored relatively lower (M=4.35) suggests potential areas for enhancement aligned with social psychology principles regarding help-seeking behaviors and vulnerability in learning contexts—specifically, that collaborative climates may benefit from explicit attention to reducing status hierarchies, normalizing difficulty acknowledgment, and framing help-seeking as legitimate participation rather than competence deficit. The comparative mediation analysis revealing that collaborative learning operates as the dominant pathway for real-world applications, collaborative learning dimension, and problem-solving abilities, while technology environment dominates for hands-on experiences, provides nuanced insight into how social versus environmental mechanisms differentially mediate various pedagogical approaches[49]. This pattern suggests that activities emphasizing conceptual understanding, strategic thinking, and application synthesis particularly benefit from social-psychological support systems, whereas activities centered on technical skill acquisition and tool manipulation depend more critically on environmental adequacy—a distinction with important implications for resource allocation and instructional design in technology education contexts.

The stronger collaborative learning mediation effects observed in this study (14.7%-23.7%) compared to Western meta-analyses (8-15%) may reflect cultural moderators specific to Chinese educational contexts. China's collectivist cultural tradition emphasizes group harmony, interdependence, and collective achievement (Hofstede, 2001), potentially amplifying students' psychological receptivity to collaborative learning and enhancing peer-learning efficacy. However, Confucian hierarchical traditions establishing clear teacher-student authority relationships may simultaneously constrain egalitarian dialogue and critical questioning within peer collaborations (Bond & Hwang, 1986). The international school context of this study—blending Eastern collectivism with Western emphasis on individual voice—may create unique collaborative dynamics where cultural strengths are leveraged while hierarchical constraints are partially mitigated. These cultural boundary conditions suggest that collaborative learning mechanisms operate differently across cultural contexts, requiring culturally adaptive pedagogical approaches rather than universal implementation strategies.

5.3. Mediating mechanisms: Theoretical and practical implications

The identification of collaborative learning environment and technology environment perception as significant partial mediators advances theoretical understanding of educational effectiveness by demonstrating that curriculum design features do not directly produce learning outcomes but rather operate through intermediate psychological and environmental mechanisms that can be empirically measured and potentially optimized. The partial rather than complete mediation observed across all effectiveness dimensions (14.7%-23.9% through each pathway) suggests that multiple mechanisms operate simultaneously, with some influence pathways functioning directly while others require environmental or social-psychological mediation—a pattern consistent with multilevel ecological models emphasizing reciprocal causation and dynamic transactions among personal, behavioral, and environmental factors. From a theoretical standpoint, these findings challenge simplistic input-output models of education by revealing the "black box" processes through which instructional interventions achieve their effects, specifically illuminating how course design features shape students' perceptions of environmental quality and social climate, which subsequently influence motivation, engagement, and achievement. The differential mediation patterns across effectiveness dimensions—with hands-on experiences showing strongest technology environment mediation (23.9%) while real-world applications demonstrated strongest collaborative learning mediation (23.7%)—Provide granular insight into mechanism specificity, suggesting that different pedagogical approaches activate distinct psychological pathways and therefore require tailored environmental and social supports[50]. This specificity has important implications for intervention design, as enhancement efforts must consider not only what instructional features to implement but also what mediating conditions must be established for those features to achieve intended effects.

The practical implications of these mediating mechanisms extend beyond curriculum design to encompass institutional resource allocation, facility planning, and organizational culture development in technology education contexts. Administrators seeking to enhance CS education effectiveness cannot focus exclusively on pedagogical innovation but must simultaneously invest in technological infrastructure quality and cultivate collaborative learning climates, as the data demonstrate these contextual factors exert independent influence on outcomes while also serving as necessary conditions for pedagogical effectiveness. The hierarchical regression findings showing that environmental and social factors contributed 4.3% additional variance beyond course effectiveness dimensions (bringing R^2 from .824 to .867) quantify the practical significance of context optimization—an effect size that, while seemingly modest in percentage terms, translates to meaningful differences in student competencies and career readiness given the cumulative nature of skill development over multi-year educational trajectories. For private schools in regions like Guangdong Province with substantial resource availability, these findings suggest strategic priorities including maintaining technological currency through regular equipment updates, designing physical spaces that facilitate both focused individual work and spontaneous collaborative interaction, providing robust technical support to minimize technology-related barriers and anxiety, and implementing explicit interventions to strengthen collaborative norms, psychological safety, and help-seeking behaviors within learning communities. The observation that both mediation pathways operated significantly across all effectiveness dimensions suggests synergistic rather than compensatory relationships between social and environmental factors—implying that deficiencies in one domain cannot be adequately addressed through excellence in the other, but rather that optimal outcomes require simultaneous attention to interpersonal climate and material infrastructure as mutually reinforcing elements of comprehensive learning ecosystems aligned with integrated environmental-social psychology frameworks.

5.4. Critical reflections: Limitations, theoretical contributions, and practical implications

While the preceding sections presented empirical patterns and theoretical interpretations, responsible scholarship demands critical examination of what our findings can—and cannot—tell us, how they genuinely advance theoretical understanding beyond confirming expected relationships, and what concrete actions educators and policymakers should take based on this evidence. This section addresses three essential questions that transform descriptive findings into meaningful knowledge: What are the fundamental limitations constraining our conclusions? How does this research genuinely contribute to educational and psychological theory? What specific, actionable recommendations emerge for practice?

Sampling Bias and Generalizability Constraints. The most significant limitation of this study lies in its sample composition: 400 students from a single elite private international school in Guangdong Province represent a highly selective, resource-privileged population that constitutes a tiny fraction of China's CS education landscape. This sampling strategy creates multiple constraints on generalizability that must be explicitly acknowledged. First, socioeconomic homogeneity characterizes our sample—students attending Guangdong Country Garden School come predominantly from affluent families capable of affording substantial tuition fees (approximately 200,000-300,000 RMB annually), creating a restricted range problem where findings may not extend to middle-class or economically disadvantaged students who constitute the majority of Chinese learners. The exceptionally high ratings across all measures (means 4.37-4.46 on 5-point scales) likely reflect both genuine quality and ceiling effects inherent in elite contexts where "good" becomes the baseline rather than the aspiration. Second, institutional resource advantages—State-of-the-art laboratories, low student-teacher ratios (approximately 15:1), internationally trained faculty, and continuous professional development opportunities—create learning conditions fundamentally different from typical Chinese public schools where class sizes exceed 40 students, technology infrastructure remains limited, and teacher training focuses on exam preparation rather than pedagogical innovation. The mediation effects we observed (14.7%-23.9%) operate within this resource-rich environment; whether technology environment quality mediates curriculum effectiveness when basic equipment is inadequate, or whether collaborative learning climate matters when classroom sizes prohibit meaningful interaction, remains empirically unknown. Third, cultural-linguistic distinctiveness of international school environments—where instruction occurs in English, student bodies include multiple nationalities, and pedagogical philosophies blend Eastern and Western approaches—may create unique social-psychological dynamics not generalizable to monolingual, culturally homogeneous schools that educate the vast majority of Chinese students.

Self-Report Reliability and Common Method Concerns. Despite implementing multiple diagnostic procedures (Harman's test, common latent factor analysis, marker variable technique) that suggested common method variance remained within acceptable limits, the exclusive reliance on student self-reports introduces inherent limitations that no statistical correction fully resolves. Students' perceptions of course effectiveness, collaborative environment quality, technology infrastructure adequacy, and their own academic performance may be systematically biased by several factors. Social desirability bias may inflate positive ratings despite anonymity assurances, particularly in Chinese educational contexts where criticizing teachers or institutions carries cultural taboos (Bond & Hwang, 1986). Halo effects may cause students who generally enjoy CS courses to rate all dimensions favorably, artificially inflating correlations among effectiveness dimensions. Limited metacognitive accuracy means students may misjudge their actual competency development—those who "feel" they learned much may not objectively demonstrate superior skills in authentic assessments, while those reporting modest gains might have developed substantial but unrecognized competencies. Ideally, this research would triangulate self-reports with objective performance indicators (standardized test scores, programming competition results, portfolio assessments), teacher evaluations, and observational data of classroom interactions, but such multi-method approaches exceed the scope of this cross-sectional survey study. The strong correlations we observed ($r = .79$-$.88$) between self-reported course effectiveness and self-reported academic performance particularly warrant cautious interpretation—both measures derive from the same source (student perceptions) at the same time point, creating conditions where shared method variance could substantially inflate apparent relationships despite our diagnostic checks.

Cross-Sectional Design and Causal Inference Limitations. The cross-sectional design, while appropriate for exploratory mediation analysis, fundamentally limits causal inference. We cannot determine whether high-quality collaborative learning environments actually cause improved academic performance, or whether academically successful students simply perceive their learning environments more favorably due to positive affective states associated with achievement (reverse causation). Nor can we rule out third-variable explanations—for instance, instructor quality might simultaneously produce effective curriculum implementation, supportive collaborative climates, well-maintained technology, and student learning, creating spurious mediation patterns. The mediation pathways we identified (collaborative learning environment and technology environment perception as mediators between course effectiveness and academic performance) represent plausible theoretical mechanisms consistent with environmental and social psychology frameworks, but cross-sectional data cannot establish temporal precedence or rule out alternative causal orderings. Longitudinal research tracking students across multiple semesters, measuring course effectiveness at Time 1, environmental perceptions at Time 2, and academic outcomes at Time 3, would provide stronger causal evidence. Experimental or quasi-experimental designs manipulating specific environmental features (e.g., upgrading technology in some classrooms but not others, implementing structured collaboration protocols in treatment sections) would offer even more rigorous causal tests. Without such designs, our findings should be interpreted as identifying correlational patterns and plausible mediational pathways rather than definitive causal mechanisms.

Measurement and Construct Validity Concerns. While psychometric analyses demonstrated acceptable reliability and validity for adapted instruments, several measurement issues warrant acknowledgment. The academic performance scale relies entirely on self-assessed competencies rather than objective achievement measures, potentially conflating confidence with actual skill. Students rating themselves as "excellent" in critical thinking or technical proficiency may overestimate their abilities relative to objective standards or expert evaluations. The CS course effectiveness dimensions, though conceptually distinct in our framework, showed such high intercorrelations (.79-.88) that questions arise about whether students meaningfully differentiate hands-on experiences from problem-solving activities from real-world applications, or whether these represent a general "course quality" perception that students struggle to decompose into specific features. Our theoretical insistence on five dimensions may impose structure that doesn't match students' actual cognitive organization of course experiences. Furthermore, cultural validity of constructs originally developed in Western contexts remains uncertain—does "collaborative learning environment" mean the same thing in Chinese collectivist cultures emphasizing group harmony versus Western individualist cultures emphasizing individual contribution within groups? Do students interpret "technology environment quality" through universal standards or culture-specific expectations about appropriate educational technology?

Temporal and Contextual Specificity. This research captured student experiences during the 2024-2025 academic year, a specific temporal moment shaped by post-pandemic educational recovery, rapid AI advancement (ChatGPT's emergence), and particular institutional conditions at Guangdong Country Garden School. The findings may not generalize across time—as technology evolves, student expectations about "adequate" infrastructure will rise, potentially changing how technology environment mediates curriculum effectiveness. As pedagogical practices shift (increasing online/hybrid formats, AI-assisted learning), the nature and importance of collaborative learning environments may transform. The six-month minimum enrollment criterion means students evaluated courses after substantial exposure, but responses might differ if assessed at course beginning (initial impressions) or years later (long-term retrospective judgments). Institutional specificity also matters—the particular CS curriculum, teaching staff, technology infrastructure, and school culture at Guangdong Country Garden School create a unique configuration that may not replicate even at other elite private schools in Guangdong, let alone different regions or institutional types.

Despite implementing multiple diagnostic procedures indicating acceptable common method variance levels, exclusive reliance on student self-reports introduces inherent limitations that statistical corrections cannot fully resolve. Social desirability bias may inflate positive ratings despite anonymity, particularly in Chinese contexts where criticizing teachers carries cultural taboos (Bond & Hwang, 1986). Halo effects may cause students who generally enjoy CS courses to rate all dimensions favorably, artificially inflating correlations (.79-.88). Limited metacognitive accuracy means students may misjudge actual competency development—those "feeling" substantial learning may not demonstrate superior skills in objective assessments. The strong correlation between self-reported course effectiveness and self-reported performance particularly warrants caution, as both derive from the same source at the same time. Ideally, research should triangulate self-reports with objective indicators (standardized tests, programming portfolios, competition results), teacher evaluations, and classroom observations. Future studies must integrate multiple methods to validate these self-report findings.

Improving Technology Learning Environments: Based on technology environment mediation effects (14.7%-23.9%), schools should: (1) Establish 3-5 year equipment refresh cycles preventing obsolescence; (2) Ensure reliable technical support with rapid problem resolution (target: <24 hours); (3) Provide adequate bandwidth supporting simultaneous use (minimum 100Mbps per 30 students); (4) Design flexible learning spaces with movable furniture accommodating both individual and collaborative work; (5) Involve teachers in technology selection ensuring pedagogical appropriateness; (6) For resource-constrained contexts, implement cloud-based solutions (free IDEs, online compilers) and pair programming strategies when computers are scarce.

Enhancing Collaborative Learning Climates: Given collaborative environment mediation (14.7%-23.7%), educators should: (1) Establish clear role structures in group work (leader, recorder, checker, presenter) rotating across projects; (2) Teach collaboration skills explicitly—active listening, constructive feedback, conflict resolution; (3) Implement individual accountability mechanisms within group efforts (peer evaluations, individual components); (4) Create psychologically safe environments where help-seeking is normalized not stigmatized; (5) Reduce excessive competition (public rankings, zero-sum rewards) undermining collaborative norms; (6) Design physical spaces with writable walls, informal interaction zones supporting spontaneous collaboration.

6. Conclusion

This study examined CS course effectiveness and academic performance relationships through an integrated environmental and social psychology lens, revealing five key conclusions.

(1) All five CS course effectiveness dimensions—hands-on experiences, real-world applications, collaborative learning, problem-solving abilities, and technology landscape readiness—demonstrated strong positive correlations with academic performance ($r=.790-.879$, $p<.001$), with problem-solving abilities emerging as the strongest predictor in multiple regression analysis ($\beta=.342$), validating multidimensional curriculum frameworks emphasizing practical, industry-aligned, and cognitively demanding pedagogical approaches.

(2) Collaborative learning environment quality functioned as a significant partial mediator across all effectiveness dimensions (14.7%-23.7% mediation), with real-world applications showing strongest social-psychological mediation effects, supporting social cognitive theories regarding peer interaction and collective knowledge construction as critical mechanisms translating instructional practices into learning outcomes.

(3) Technology environment perception demonstrated significant independent mediation effects (14.7%-23.9%), with hands-on experiences exhibiting strongest environmental mediation, validating environmental psychology principles emphasizing that material infrastructure and technological affordances shape academic achievement through students' subjective perceptions of resource adequacy and accessibility.

(4) Hierarchical regression analysis revealed that environmental and social-psychological factors contributed significant unique variance ($\Delta R^2=.043$, $p<.001$) beyond course effectiveness dimensions, indicating that context optimization represents a distinct pathway for educational enhancement requiring simultaneous attention to physical infrastructure and interpersonal climate.

(5) The private school context in Guangdong Province demonstrated that resource-intensive environments approaching theoretical ideals of environmental adequacy and social support can achieve exceptional outcomes (overall means 4.37-4.46), though even within optimal conditions, targeted improvements in instructor feedback mechanisms and help-seeking climate warrant consideration for maximizing CS education effectiveness.

(6) This study has three main limitations: First, the research was conducted only at a well-resourced private international school in Guangdong Province, and the specificity of the sample may limit the direct generalization of the research findings to under-resourced public schools or educational environments in other provinces; Second, as a frontrunner region in China's technological innovation and economic development, Guangdong Province's unique industrial ecology, level of technological infrastructure investment, and degree of internationalization may produce specific environmental-social psychological mechanisms that may manifest differently in regions with different educational resources, technological development levels, and cultural contexts; Third, while the cross-sectional research design reveals patterns of associations among variables, it cannot establish causal relationships or capture long-term developmental trajectories. Based on these limitations, we recommend that future research should conduct cross-contextual validation studies across multiple provinces, different types of schools (public/private, urban/rural), and regions with different levels of economic development to test the robustness and boundary conditions of

collaborative learning environments and technological environments as mediation mechanisms, thereby providing more generalizable empirical evidence for computer science education reform in China and internationally.

Conflicts of interest

The authors declare no conflicts of interest.

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