Integrating Scratch into Digital Genetics Courses: The Differential Effects of Simulation and Programming on Students' Learning Emotions and Attitudes toward Scratch

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Abstract: *This study examines the affective impacts of integrating Scratch simulations and programming into secondary genetics education. A quasi-experimental study (N=82) compared three online environments: text-and-graphics (control), simulation, and programming. Paired-samples t-tests and the Johnson-Neyman technique revealed distinct affective outcomes. The programming group showed statistically significant increases in both positive learning emotions and interest in using Scratch. Interaction analyses indicated that for students with lower initial emotional baselines, the control group was more effective, likely due to cognitive load constraints. Conversely, programming significantly enhanced self-efficacy for students with lower initial self-efficacy, highlighting the value of block-based mastery experiences. These findings underscore the necessity of differentiated digital scaffolds that balance cognitive load with affective support to accommodate diverse learner baselines.*
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1. Introduction

Genetics is a complex domain that often imposes substantial cognitive demands on novice learners. To address these affective and cognitive barriers, Scratch, a visual block-based programming language, has emerged as a promising cognitive tool for science education (Koray & Bilgin, 2023). Crucially, rather than treating programming merely as acquiring isolated syntax, this study positions it as an integrated STEM practice. To successfully construct a computational model of inheritance, students must actively understand and apply Mendelian laws, transforming abstract biological concepts into logical programming rules. However, a critical gap remains regarding how the depth of this digital integration (from viewing static text-and-graphics to manipulating simulations, and finally to active programming) differentially impacts students' affective states (Loderer et al., 2020). Furthermore, because educational technology is rarely a "one-size-fits-all" solution, it is essential to understand how students' initial emotional baselines and technological self-efficacy interact with these varying levels of digital interventions.

Therefore, this study aims to investigate the differential impacts of integrating different levels of Scratch applications into secondary-level digital genetics courses. By comparing a text-and-graphics control group, a Scratch simulation group, and a Scratch programming group, this research explores how varying degrees of computational engagement influence seventh graders' learning emotions and attitudes toward Scratch. Specifically, this study utilizes advanced interaction analyses to uncover which level of digital scaffolding is most beneficial for students with different initial affective profiles, thereby providing nuanced insights for designing emotionally supportive, technology-enhanced science education.

2. Methodology

2.1. Research Design and Participants

A quasi-experimental design was adopted to investigate the differential effects of various digital interventions on students' learning emotions and attitudes. The participants consisted of 82 seventh-grade students from a junior high school in central Taiwan. Intact classes were assigned to three different online asynchronous genetics courses: text-and-graphics group (control group), a Scratch simulation group, or a Scratch programming group.

2.2. Learning Interventions

The digital genetics curriculum was aligned with the 112th academic year Nani textbook, covering core concepts including self-pollination in peas, traits, alleles, and Punnett squares. All three groups completed the core online genetics curriculum within a standard 45-minute class period, ensuring equivalent exposure to the primary biological concepts. The interventions differed in their interaction modes (see Figure 1): the control group utilized static text-and-graphics based on the textbook; the simulation group and the programming group interacted with pre-constructed Scratch models replacing static images in the experimental sections; and the programming group participated in an additional Scratch coding curriculum, allowing them to independently construct their own simulation programs. This technical implementation phase required an additional 20-40 minutes for the programming group.

Figure 1

The three digital learning environments: Text-and-graphics control group (left), Scratch simulation group (middle), and Scratch programming group (right).

2.3. Instruments

Affective outcomes were measured using validated scales adapted from Pekrun et al. (2011) and related literature. Both the Learning Emotions Scale and the Attitudes toward Scratch Scale utilized a 5-point Likert format. Reliability analysis indicated high internal consistency. For the Learning Emotions Scale, Cronbach's alpha coefficients were .922 (pre-test) and .940 (post-test). For the Attitudes toward Scratch Scale, Cronbach's alpha coefficients were .918 (pre-test) and .945 (post-test), demonstrating excellent reliability for the study.

2.4. Data Analysis

Quantitative analyses were conducted to evaluate both within-group and between-group differences. Paired-samples t-tests were utilized to assess the significant growth in learning emotions and technological interests within each group from pre-test to post-test. Furthermore, Analysis of Covariance (ANCOVA) was employed to compare the post-test scores among the three groups, utilizing the pre-test scores as covariates to control for students' initial baseline differences. To further explore the nuanced affective outcomes and identify which intervention benefited which specific type of student, the Johnson-Neyman technique was applied to probe the significant interaction effects between the instructional methods and students' initial attitudinal levels.

3. Results

3.1. Within-Group Affective Growth

As summarized in Table 1, paired-samples t-tests were conducted to examine the changes in students' learning emotions and attitudes toward Scratch from pre-test to post-test within each instructional group. The results indicated that the integration of active computational modeling had a profound impact on students' affective states. Specifically, students in the Scratch programming group demonstrated a statistically significant increase in positive learning emotions ($t = 3.306$, $p = .003$). Furthermore, this group also showed a significant enhancement in their interest in using Scratch ($t = 2.581$, $p = .016$). These findings suggest that the cognitive challenge of building genetic models through programming effectively engages students, fostering both positive academic emotions and technological interest.

Table 1

Paired-samples t-test results for learning emotions and Scratch attitudes

Measure	Group	N	Pre-test M (SD)	Post-test M (SD)	*t*	*p*	Effect Size (d)
Emotion	Control	27	3.87 (0.56)	4.18 (0.41)	2.847	.009	0.55
	Simulation	29	3.60 (0.61)	3.69 (0.84)	0.765	.451	0.14
	Programming	26	3.47 (0.60)	3.83 (0.62)	3.306	.003	0.65
Interest in using Scratch	Simulation	29	2.87 (0.61)	3.07 (0.64)	2.00	.055	0.31
	Programming	26	2.91 (0.47)	3.17 (0.55)	2.58	.016	0.50
Scratch Self-efficacy	Simulation	29	2.65 (0.69)	2.62 (0.84)	-0.25	.807	-0.04
	Programming	26	2.52 (0.73)	2.76 (0.50)	1.76	.091	0.35

3.2. Interaction Effects on Learning Emotions

To investigate whether the interventions had differential effects, ANCOVA was utilized. Preliminary results indicated no significant differences in post-test positive emotions when comparing the programming group with either the text-and-graphics group ($F_{(1, 50)} = 1.599$, $p = .212$) or the simulation group ($F_{(1, 52)} = 2.404$, $p = .127$). However, the homogeneity of regression slopes was violated between the control and simulation groups ($F_{(2, 76)} = 3.784$, $p = .027$). Applying the Johnson-Neyman technique revealed that for students with initial positive emotional scores below 4.23, the control group was significantly more effective in boosting positive emotions. This suggests that for learners lacking initial affective readiness, simpler, structured static materials provide a safer environment than interactive simulations.

3.3. Interaction Effects on Scratch Self-Efficacy

Regarding attitudes toward Scratch, paired-samples t-tests indicated that the programming group showed a significant increase in interest ($t = 2.581$, $p = .016$). To investigate self-efficacy, ANCOVA was performed; however, the homogeneity assumption was violated ($F_{(1, 51)} = 5.164$, $p = .027$). The Johnson-Neyman technique revealed a significant interaction: for students with initial self-efficacy scores below 2.99, the Scratch programming group significantly outperformed the simulation group. This indicates that despite the steeper learning curve, the authentic experience of constructing a functional digital model provides a more powerful mastery experience, thereby elevating self-efficacy more effectively than merely manipulating pre-existing simulations.

4. Conclusion & Implications

This study provides compelling empirical evidence that the depth of technology integration in science education significantly influences students' affective outcomes. The findings challenge the assumption that simply adding interactive multimedia automatically enhances learning experiences. While the active construction of genetic models in the Scratch programming group successfully fostered positive learning emotions and technological interest, the nuanced interaction effects revealed by the Johnson-Neyman technique tell a more complex story about learner diversity.

Crucially, the data suggests that interactive simulations are not a universal panacea. For students entering the course with lower positive emotional baselines, the highly structured static text-and-graphics materials were significantly more effective in boosting positive emotions compared to the simulation group. This finding, while diverging from the common expectation that interactive multimedia inherently fosters positive emotions (D'Mello, 2013; Loderer et al., 2020), is well-aligned with Cognitive Load Theory and the broader framework of the Cognitive-Affective Theory of Learning with Media. For learners lacking initial affective readiness, simpler, well-structured static text-and-graphics scaffolding provides a less overwhelming cognitive environment than navigating complex interactive simulations, thereby optimizing cognitive load by minimizing extraneous interference (Mayer, 2021).

Conversely, the programming intervention proved particularly beneficial for students with lower Scratch self-efficacy. Visual block-based programming effectively lowers technical barriers. More importantly, constructing functional genetic models provides meaningful mastery experiences by requiring active application of Mendelian concepts rather than rote coding. This aligns with integrated STEM philosophy, where programming serves as a vehicle for conceptual application. For students with coding anxiety, translating biological rules into computational models elevates self-efficacy more effectively than manipulating pre-built simulations (Koray & Bilgin, 2023; Taslidere, 2024).

These findings highlight a vital implication for instructional designers: it is crucial for educators to carefully scaffold digital integration to support students' varying emotional and attitudinal baselines. Rather than a "one-size-fits-all" technological approach, educators should adopt differentiated digital strategies that balance cognitive load with affective scaffolding to build both science understanding and long-term technological self-efficacy.

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