Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Quantum Computing for Novice Learners: Developing the EduQubit Learning Environment

Haeun Choa
Seoul National University of Education
Dukhoi Koo
dhk@snue.ac.kr

Seoul National University of Education

Research Article

Keywords: Quantum computing education, K–12 education, Novice learners, Quantum program ming, Learning environment

Posted Date: September 18th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10829624/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Quantum Computing for Novice Learners: Developing the EduQubit Learning Environment

Haeun Choa[1] and Dukhoi Koo[1,*]

[1]Department of Computer Education, Seoul National University of Education, Seoul, 06639, Republic of Korea
[*]Correspondence: dhk@snue.ac.kr

Abstract

As quantum computing education expands into K–12 settings, learning environments that help novice learners understand abstract quantum concepts and explore quantum circuits are increasingly needed. This study developed EduQubit, a web-based quantum computing learning environment, and compared it with IBM Quantum Composer. A pretest–posttest study was conducted with 84 sixth-grade students from four intact classrooms at an elementary school in South Korea. The four classrooms were randomly assigned to the EduQubit or IBM Quantum Composer condition. EduQubit structured learning through step-by-step missions and subsequent open-ended exploration, whereas the IBM Quantum Composer condition relied on teacher guidance for the same learning tasks. The results included conceptual understanding of quantum computing, self-efficacy of quantum programming, subjective workload, and user experience; student interviews were also conducted.

Student-level ANCOVA showed significantly higher posttest conceptual understanding in the EduQubit group after controlling for pretest scores ($p = .036$, partial $\eta^2 = .053$). In contrast, quantum programming self-efficacy, subjective workload, and user experience did not differ significantly between the two groups. The exploratory classroom-level analysis showed the same directional pattern for conceptual understanding, although only four classrooms were included. Interviews indicated that both environments supported hands-on circuit exploration, but differed in how that exploration was guided and in the difficulties students encountered.

These findings suggest that quantum computing learning environments for novice learners may benefit from going beyond circuit-manipulation functionality to structure learners' exploration, with greater guidance during initial learning and progressively increasing autonomy.

Given the small number of classrooms and the short intervention, the findings should be interpreted as exploratory rather than definitive evidence of the effects of the learning-environment.

Keywords: Quantum computing education; K–12 education; Novice learners; Quantum programming; Learning environment

1 Introduction

As interest in quantum computing has grown, quantum computing education has expanded beyond specialists in physics and computer science to include a broader range of learners. This expansion has increased the need to provide diverse learners with the knowledge and competencies required to engage with quantum technologies [1–3]. This trend has also been extended to K–12 education, with a growing attention to how students can encounter the core concepts of quantum computing before entering higher education [4–7]. Initiatives such as the National Q–12 Education Partnership and Europe's QTEdu have sought to develop educational resources and competency frameworks for K–12 quantum computing education [8, 9]. At the same time, research on pre-college quantum computing education has increasingly explored approaches involving games, simulations, visualizations, and programming [10–12]. Consequently, the central question in quantum computing education is shifting from whether quantum computing can be taught to novice learners to how instruction can be designed to help them understand and actively explore its core concepts.

Learning quantum computing presents several challenges for novice learners. Core concepts such as superposition, entanglement, and measurement are difficult to understand intuitively because they do not align readily with everyday experience or classical ways of thinking [13–16]. The mathematical formalism used to describe quantum computing may also impose additional learning demands on students who lack sufficient background knowledge. Quantum computing education for novice learners therefore needs approaches that reduce reliance on mathematical representations while making abstract quantum concepts accessible for understanding and exploration [10]. In this regard, visualizations and simulations can represent quantum states and their transformations, which are otherwise difficult to observe directly, in forms that learners can explore [16]. Learning environments that allow students to manipulate quantum circuits and observe the resulting changes in quantum states and measurement outcomes are particularly important because they can connect

abstract concepts with concrete learning experiences.

A range of quantum computing learning environments has been developed to support learners in exploring quantum concepts through quantum circuit construction and execution. Graphical environments such as IBM Quantum Composer, for example, allow learners to construct circuits by placing quantum gates and to examine the resulting execution outcomes. However, these general-purpose environments may provide limited instructional support for novice learners' conceptual understanding and learning processes [17]. Quantum computing learning environments for novice learners may therefore need to provide not only circuit construction and execution capabilities but also instructional support that helps learners carry out activities in relation to learning objectives and connect circuit results with the concepts being studied. However, empirical evidence on the role of instructional support in novice learners' quantum computing learning outcomes and experiences remains insufficient.

Recent reviews highlight this limitation. Studies examining the effects of quantum computing education have primarily involved learners aged 15–22, with even the youngest participants typically at the Grade 6–8 level. Moreover, relatively few studies have evaluated educational materials using both a comparison group and a pretest [18]. Liu et al. [17] similarly noted that empirical evidence on learning outcomes in quantum computing education remains limited relative to work on curriculum and technology development. In particular, little empirical evidence is available on how quantum computing learning environments designed for novice learners differ from existing general-purpose quantum computing environments in terms of both learning outcomes and learning experiences. Thus, K–12 quantum computing education needs to move beyond the development of learning environments alone and empirically examine how their design is reflected in learners' outcomes and experiences.

To address this gap, we designed and developed EduQubit, a web-based quantum computing learning environment for novice learners, and compared it with IBM Quantum Composer, a general-purpose quantum computing environment, in authentic elementary school classrooms. The two conditions addressed the same learning objectives and instructional content. However, in the EduQubit condition, learning activities were structured step by step to support novice learners in constructing quantum circuits in relation to the learning objectives and connecting execution results with the concepts they had learned. We examined differences between the two learning environments

in students' conceptual understanding of quantum computing, quantum programming self-efficacy, subjective workload, and user experience. We also conducted student interviews to examine their learning experiences in each environment. The following research questions guided the study:

RQ1. How does students' conceptual understanding of quantum computing differ between the EduQubit and IBM Quantum Composer conditions?

RQ2. How does students' quantum programming self-efficacy differ between the EduQubit and IBM Quantum Composer conditions?

RQ3. How does students' subjective workload differ between the EduQubit and IBM Quantum Composer conditions?

RQ4. How does students' user experience differ between the EduQubit and IBM Quantum Composer conditions?

This study makes three contributions. First, it presents a design case of a quantum computing learning environment that integrates instructional guidance and support within the environment to connect novice learners' quantum circuit construction and execution with structured learning activities. Second, by directly comparing EduQubit, which was designed for novice learners, with the general-purpose IBM Quantum Composer under the same learning objectives and instructional content in authentic elementary school classrooms, the study provides empirical evidence regarding these two types of learning environments. Third, rather than focusing only on whether quantum computing education is feasible for novice learners, the study empirically examines an instructional design question: how learning activities can be structured and supported to facilitate novice learners' engagement with quantum computing.

2 Related Work

2.1 Quantum computing education for K–12 learners

As quantum computing education has expanded beyond university-level physics and engineering, increasing attention has been given to how fundamental concepts of quantum computing can be introduced to novice learners and K–12 students. Qubits, superposition, measurement, and entan-

glement, in particular, have been identified as core concepts for introductory quantum computing education [19] and have also been proposed as appropriate foundational content at the secondary-school level [20].

Teaching these concepts to novice learners, however, presents several challenges. Quantum phenomena often conflict with learners' everyday experiences and classical intuitions, and students may have difficulty distinguishing classical from quantum concepts [13, 14, 21]. Their counterintuitive nature may also lead students to perceive quantum phenomena as difficult or unfamiliar [22]. In addition, the mathematical representations used to describe quantum computing may impose further learning demands on novice learners who lack sufficient background knowledge [23].

In response to these challenges, K–12 quantum computing education has adopted instructional approaches that reduce reliance on advanced mathematical formalism and enable learners to explore abstract quantum concepts through visual and interactive representations. Prior research has proposed a range of approaches, including simulations and visualizations, games, programming, and unplugged and collaborative activities [24–30]. These approaches have generally focused on representing quantum phenomena that cannot be directly observed and allowing learners to experience them in manipulable forms [10, 13].

This body of work suggests that visual and interactive representations, together with reduced mathematical barriers to entry, can make foundational quantum concepts more accessible to novice learners. Quantum computing education, however, involves more than conceptual understanding alone. It is also important for learners to experience the processes of constructing and executing quantum circuits and interpreting the resulting outcomes. Hands-on programming, for example, has been proposed as a way to bridge theoretical knowledge and practical implementation and to deepen understanding of superposition, entanglement, quantum gates, and algorithms [31]. Quantum computing education for novice learners therefore needs to move beyond simply providing opportunities for circuit construction and execution and structure these activities so that they are connected to learning objectives and the concepts being studied.

2.2 Interactive and programming environments for quantum computing

A variety of programming environments have been used in quantum computing education to enable learners to explore abstract concepts through quantum circuit construction and execution [32].

Through graphical interfaces or code-based approaches, these environments allow users to place quantum gates, construct circuits, and examine execution and measurement results. IBM Quantum Composer and Quirk, for example, provide graphical interfaces that allow users with limited programming experience to construct quantum circuits using drag-and-drop interaction [33]. In contrast, frameworks such as Qiskit support code-based quantum circuit construction and execution on simulators or quantum hardware [34].

The ability to construct and execute quantum circuits alone may not be sufficient to support novice learners' learning. General-purpose quantum programming environments allow users considerable freedom in constructing and executing circuits, but this openness may require novice learners who are unfamiliar with quantum circuits to determine the direction of their exploration on their own. Learners must decide not only which gates to select and how to construct a circuit, but also what the resulting execution outcomes mean and how those outcomes relate to the quantum concepts they are learning. This concern is consistent with observations that existing general-purpose tools have often been designed primarily for expert users or learners in engineering-related contexts, leaving a gap in support for introductory learners' learning processes [17]. Quantum computing learning environments for novice learners therefore need to consider not only ease of circuit manipulation but also instructional features that structure the goals and progression of programming activities and support the interpretation of their results.

In response to this need, recent quantum computing learning environments have begun to integrate features intended to structure and support novice learners' learning activities. CryptoLearn supports middle- and high-school students as well as introductory university learners through a staged sequence of conceptual explanations, visual examples, interactive activities, and feedback [35]. QuantAid combines step-by-step guidance, formative assessment, personalized feedback, and an AI-based tutor to support novice learners' learning processes [36]. Similarly, Spin-Quantum Gate Lab integrates multimedia learning materials, simulations, and programming exercises, emphasizing learners' direct manipulation and exploration of quantum systems [17]. Other approaches have sought to connect theoretical concepts with practical quantum circuit activities through programming exercises and projects [37]. Collectively, these examples indicate that quantum computing learning environments for novice learners are increasingly being designed not only to provide circuit construction and execution capabilities, but also to integrate structured learning activities,

feedback, visual representations, and opportunities for exploration into the learning process.

These developments highlight the growing emphasis on instructional support, including structured learning activities and feedback, in quantum computing learning environments for novice learners. However, empirical research on instructional support for novice learners in quantum computing remains limited. In particular, few studies have directly compared learning environments designed for novice learners with general-purpose quantum programming environments under the same instructional content while examining both learning outcomes and learning experiences.

3 Methods

3.1 Study Design and Participants

This study employed a pretest–posttest design in which intact classrooms were randomly assigned to one of two instructional conditions: EduQubit or IBM Quantum Composer. Outcome variables were measured at the student level.

Participants were 84 sixth-grade students from four intact classrooms at an elementary school in Seoul, South Korea. Following random assignment, two classrooms comprising 40 students participated in the EduQubit condition, while the remaining two classrooms comprising 44 students participated in the IBM Quantum Composer condition. Students participated in the learning condition assigned to their classroom, with no crossover between conditions during the study period. Before the study, an a priori power analysis was conducted using G*Power 3.1.9.7 based on individual-level observations. For an analysis of covariance (ANCOVA) with the posttest score as the dependent variable and the corresponding pretest score as a covariate, assuming an effect size of f = .40, a significance level of $\alpha = .05$, and statistical power of $1 - \beta = .80$, the minimum required sample size was 52. To account for possible attrition and incomplete responses, the study was planned to recruit at least 80 participants.

The study design is presented in Table 1. At pretest, students' conceptual understanding of quantum computing and quantum programming self-efficacy were measured. The two groups then participated in instruction using EduQubit or IBM Quantum Composer under the same learning objectives and instructional content. After the instructional intervention, conceptual understanding of quantum computing and quantum programming self-efficacy were measured again. Students'

subjective workload during the learning activities and their user experience with the respective learning environment were also assessed after the intervention.

Table 1: Research design

Group	Pretest	Intervention	Posttest
EduQubit	O_1	X_1	O_2
IBM Quantum Composer	O_1	X_2	O_2

Note. O = measurement; X = instructional condition.

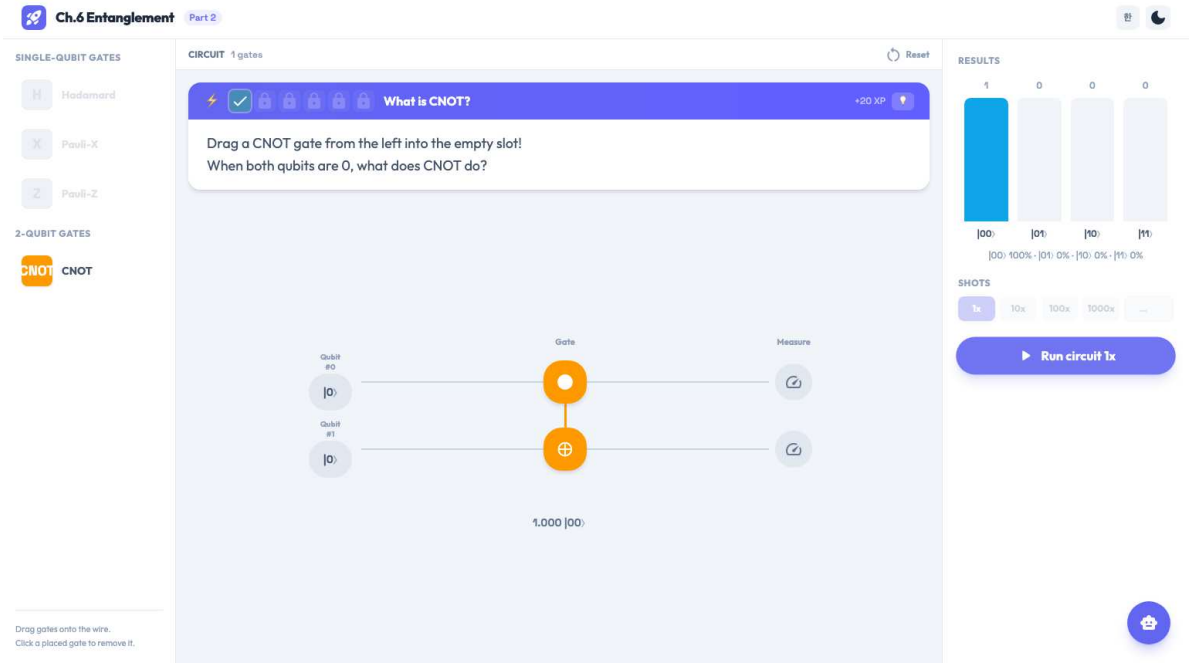
The study protocol was approved by the Institutional Review Board of Seoul National University of Education (SNUEIRB-2026-004). Written informed consent was obtained from the students' legal guardians, and student assent was obtained before participation.

3.2 Learning Environments

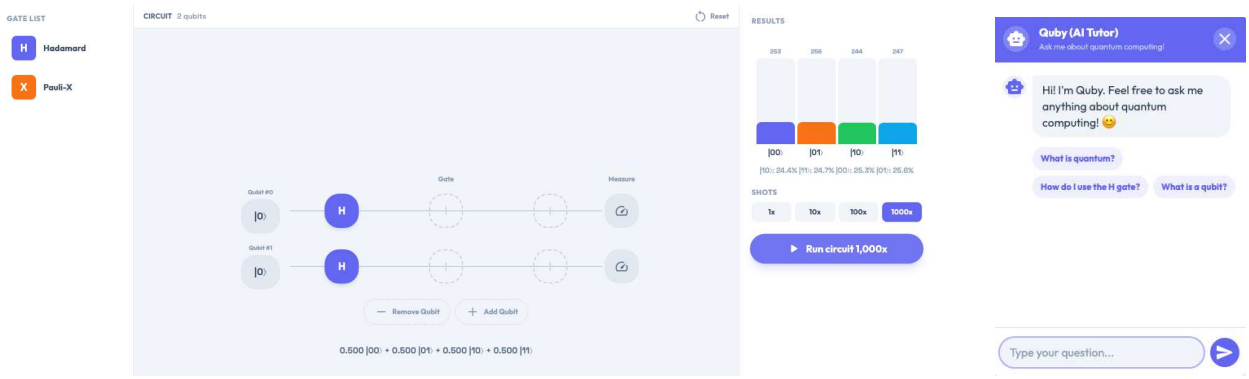
3.2.1 EduQubit

EduQubit is a web-based quantum computing learning environment developed in this study to support novice learners in learning quantum computing. It was designed to integrate quantum concept learning with circuit programming activities within a single environment, allowing learners to construct and execute quantum circuits as they learned the underlying concepts. The EduQubit interface consists of a mission guidance panel, gate palette, circuit workspace, and results visualization panel. Learners can construct quantum circuits by manipulating gates without writing programming code and view the execution results of their circuits within the same interface (Figure 1).

Building on this interface, EduQubit incorporates four key features designed to support novice learners in learning quantum computing. First, EduQubit structures quantum circuit learning activities as step-by-step missions. Each mission presents the objectives and activities to be completed within the learning environment and displays learners' progress and mission completion status before they proceed to the next activity. Learners can therefore construct and execute circuits and examine their results by following the sequence presented in the learning environment without requiring separate external instructions. This mission structure was designed to reduce the need for novice learners to determine for themselves what to do within a quantum circuit environment and



(a)



(b) (c)

Figure 1: EduQubit learning interface. (a) Mission-based learning interface with mission guidance panel, gate palette, circuit workspace, and result visualization panel. (b) Laboratory interface for open-ended circuit exploration. (c) AI tutor "Quby" interface.

to connect conceptual learning and circuit manipulation within a structured learning sequence.

Second, after completing the structured missions, learners can use a separate Lab feature to explore the concepts and gates introduced in the missions through open-ended circuit exploration. In the Lab, learners can freely add or remove quantum gates, change the types and arrangements of gates, and repeatedly execute their circuits. This allows them to observe how quantum states and measurement results change depending on the combinations and sequencing of gates.

Third, learners who need additional assistance during the learning process can use the built-in AI tutor Quby. Quby was designed to respond to questions based on the content of the chapter that the learner was currently studying. Learners could therefore obtain explanations and support for questions about quantum concepts or circuit construction without leaving the learning environment. Rather than providing the same additional explanation to all learners, this feature enabled learners to request support individually when needed.

Fourth, quantum circuits constructed in EduQubit were implemented using Qiskit Statevector-based simulation. The results presented to learners were therefore not predetermined for specific missions but were generated from quantum states calculated from the circuits that learners actually constructed. The simulation results were presented through visual representations, including histograms of measurement outcomes, allowing learners to examine the results produced by their circuits. In this way, EduQubit combined structured instructional support with a quantum circuit exploration environment in which changes to learner-constructed circuits were reflected in the simulation results.

3.2.2 IBM Quantum Composer

IBM Quantum Composer is a graphical quantum programming environment provided through IBM Quantum Platform [32]. It allows users to construct quantum circuits by placing quantum gates and operations and to examine the resulting quantum states and execution results through visualizations. In this study, IBM Quantum Composer was selected as the comparison environment because it provides a general-purpose graphical interface for quantum circuit construction and exploration.

Students used Composer's operations catalog and graphical circuit editor to select quantum gates and place them on qubit wires. They also examined changes in quantum states resulting from their circuit configurations using Composer's probabilities and statevector visualizations. During

the exploration activities, students used Composer's circuit-editing features to add or remove gates, modify circuit configurations, and examine the resulting outcomes.

3.3 Measures

This study compared the two learning environments in terms of learning outcomes and learning experiences. Learning outcomes included conceptual understanding of quantum computing and quantum programming self-efficacy, whereas learning experiences included subjective workload and user experience. Conceptual understanding of quantum computing and quantum programming self-efficacy were measured before and after the intervention, while subjective workload and user experience were measured after the intervention. Semi-structured interviews were also conducted to complement the quantitative findings and provide a more detailed understanding of students' experiences with each learning environment.

3.3.1 Conceptual Understanding of Quantum Computing

Students' conceptual understanding of quantum computing was measured using a 10-item assessment developed to align with the instructional content of this study. Given the limited availability of existing instruments for assessing K–12 learners' understanding of quantum computing concepts, the items were designed to assess understanding of the major concepts covered during instruction, including superposition, entanglement, and quantum gates [38]. The content appropriateness of the developed items was reviewed by two doctoral researchers in computer education.

Each item was scored as 1 for a correct response and 0 for an incorrect response. Students were informed in advance that they could leave an item unanswered if they did not know the answer. In accordance with the prespecified scoring criteria, such nonresponses were treated as failure to provide a correct answer for the corresponding concept and were scored as 0. Scores across the 10 items were summed to produce a total score ranging from 0 to 10, with higher scores indicating greater understanding of the quantum computing concepts covered during instruction.

3.3.2 Quantum Programming Self-Efficacy

Quantum programming self-efficacy was defined as learners' perceived capability to successfully perform programming tasks related to quantum circuit construction and execution. The measure

was intended to assess learners' perceptions of their ability to perform these tasks rather than their actual quantum programming performance. To measure this construct, the Computer Programming Self-Efficacy Scale (CPSES) developed by Kukul et al. [39] was adapted to the context of quantum programming [40].

The original item structure and measurement intent of the CPSES were retained, while expressions referring to general programming activities were modified to reflect the learning activities in this study, such as quantum circuit construction and execution. Thus, rather than developing a new self-efficacy construct, this study contextualized the programming task self-efficacy measured by the original CPSES for quantum programming.

The scale consisted of 31 items rated on a 5-point Likert scale. The mean of the item responses was used as the scale score, with higher scores indicating greater perceived capability to successfully perform quantum programming-related tasks.

3.3.3 Subjective Workload

Subjective workload was measured using the six dimensions of the NASA Task Load Index (NASA-TLX) [41, 42]: mental demand, physical demand, temporal demand, performance, effort, and frustration. In this study, each dimension was assessed on a 7-point scale.

Because a higher raw score on the performance dimension represented a higher level of perceived performance, this dimension was reverse-scored so that its direction was consistent with the other workload dimensions. No dimension-specific weighting was applied. Instead, the unweighted mean of the six dimensions was calculated as the overall subjective workload score. Higher overall scores therefore indicated greater subjective workload. Scores for each of the six dimensions were also analyzed separately.

3.3.4 User Experience

Students' user experience with the two learning environments was measured using the User Experience Questionnaire–Short (UEQ-S) [43]. The UEQ-S consists of eight items assessing two dimensions: pragmatic quality, which concerns aspects such as efficiency, clarity, and ease of use, and hedonic quality, which concerns aspects such as interest and attractiveness.

Students responded to each item on a scale from 1 to 7. For analysis, the direction of each

item was checked in accordance with the standard UEQ-S scoring procedure, and the responses were transformed to a scale ranging from -3 to $+3$. A score of -3 represented the most negative user experience, 0 represented a neutral evaluation, and $+3$ represented the most positive user experience. The transformed scores were used to calculate pragmatic quality and hedonic quality scores separately, and the mean across all eight items was used as a summary measure of overall user experience.

3.3.5 Semi-Structured Interviews

Semi-structured interviews were conducted to provide a more detailed understanding of the learning outcomes and learning experiences observed in the quantitative analyses and to explore students' experiences while using each learning environment. Students interested in participating in the interviews were recruited from each classroom, and two students were randomly selected from among those who volunteered in each classroom. A total of eight students participated in the interviews.

The interviews focused on students' interest and difficulties while using the learning environment, the workload and confidence they experienced while completing the tasks, and the activities or features they perceived as helpful for understanding quantum concepts. The interviews also explored students' experiences with the interface and task-support features of each learning environment while they constructed quantum circuits and solved problems. With consent from both the participating students and their legal guardians, the interviews were audio-recorded, transcribed, and subsequently used for qualitative analysis.

3.4 Instructional Procedure

The classroom activities were conducted across three regular class periods. Both conditions used the same learning objectives, instructional content, and core learning tasks. The primary difference between the conditions was how the learning activities were guided and supported. In the EduQubit condition, step-by-step missions were embedded within the learning environment, allowing students to progress through the activities in a structured sequence and access support from the AI tutor when needed. In the IBM Quantum Composer condition, the teacher presented the same learning tasks and guided students through the progression of the activities. The instructional content and core learning activities for each session are presented in Table 2.

Table 2: Instructional sequence

Session	Learning topic	Core learning tasks
1	Introduction to quantum concepts	Motivation for quantum computing; introduction to the double-slit thought experiment; qubits and measurement.
2	Superposition	Concept and role of superposition; single-qubit preparation; X and H gates; circuit execution and interpretation of measurement outcomes.
3	Entanglement	Concept and role of entanglement; two-qubit preparation; H and CNOT gates; circuit execution and interpretation of measurement outcomes.

In Sessions 2 and 3, students first learned the concepts of superposition and entanglement, respectively, followed by the functions of the relevant quantum gates and how to construct corresponding circuits. During the superposition session, students used the X and H gates to construct basic quantum circuits, whereas during the entanglement session, they used the H and CNOT gates. In both sessions, students repeatedly executed their circuits and examined the measurement outcomes.

The subsequent exploration activities involved target-output circuit tasks in which the teacher specified a target measurement outcome and students explored circuit configurations that could produce it by adding, removing, and rearranging previously introduced gates. For example, in Session 3, after learning about entanglement and the operation of the CNOT gate, students were given a task to construct a circuit that produced $|11\rangle$ as the measurement outcome. This task was intended to allow students to apply the conditional operation of the CNOT gate, in which the state of the target qubit changes depending on the state of the control qubit. Students explored circuit configurations by combining and rearranging the X and CNOT gates while considering the functions and sequencing of the gates until they identified a circuit that produced the target outcome.

The same target-output exploration activities were provided in both conditions. Students in the EduQubit condition completed these activities using the Lab feature within the learning environment, whereas those in the IBM Quantum Composer condition used its circuit-editing features. The overall study procedure consisted of a pretest, three sessions of quantum computing learning activities, a posttest and post-intervention questionnaires, followed by semi-structured interviews

with the selected students.

3.5 Data Analysis

Before analysis, response ranges and patterns of missing data were examined for each item. Cases in which pretest and posttest data could not be matched because a student did not participate at one of the two time points were excluded from the corresponding pretest–posttest analysis. Scale scores for quantum programming self-efficacy, NASA-TLX, and UEQ-S were calculated only when participants responded to at least 80% of the items. For quantum programming self-efficacy, only cases meeting this criterion at both pretest and posttest were included in the analysis.

To assess the internal consistency of the measures, the Kuder–Richardson Formula 20 (KR-20) was calculated for the conceptual understanding of quantum computing assessment, and Cronbach's α was calculated for quantum programming self-efficacy and the UEQ-S [44, 45].

For conceptual understanding of quantum computing (RQ1) and quantum programming self-efficacy (RQ2), analysis of covariance (ANCOVA) was conducted to compare posttest scores between the two learning environments while controlling for pretest levels. The posttest score was specified as the dependent variable, learning environment (EduQubit or IBM Quantum Composer) as the independent variable, and the corresponding pretest score as the covariate. Before conducting the ANCOVA, relevant assumptions were examined, including the normality of residuals, homogeneity of error variances, and homogeneity of regression slopes. Results were reported using the F statistic, p value, and partial η^2, together with adjusted means, standard errors, and 95% confidence intervals for each group. Pretest–posttest changes within each group were described using means and standard deviations.

Because subjective workload (RQ3) and user experience (RQ4) were measured only once after the intervention, scores were compared directly between the two groups. Between-group comparisons were conducted using Welch's independent-samples t-test. When the data did not meet the normality assumption, the Mann–Whitney U test was additionally conducted as a supplementary analysis to determine whether the conclusions differed depending on the analytic method. For the NASA-TLX, results for the six individual dimensions were presented descriptively alongside the overall score. For the UEQ-S, pragmatic quality and hedonic quality were likewise reported descriptively in addition to the overall score.

To explore whether clustering by classroom affected the pattern of the student-level findings, an additional sensitivity analysis was conducted using classroom means. For conceptual understanding of quantum computing and quantum programming self-efficacy, change scores were calculated from the classroom-level pretest and posttest means. For subjective workload and user experience, post-intervention classroom means were used. Because classrooms were the units of random assignment, each classroom was given equal weight, and the pattern and direction of classroom means were compared across learning environments. Given that only four classrooms were included, no separate inferential statistical tests were conducted. This analysis was therefore interpreted as an exploratory sensitivity analysis intended to examine the direction of the student-level findings and their consistency across classrooms. The significance level for all statistical tests was set at $\alpha = .05$. Statistical analyses were conducted using jamovi version 2.7 [46].

The semi-structured interview data were transcribed and reviewed iteratively. Meaningful segments of the transcripts were classified into initial codes, and related codes were subsequently grouped into higher-order categories. The resulting categories were used to complement the quantitative findings and to provide a more detailed understanding of students' learning experiences in each learning environment. The quantitative and qualitative findings were compared and connected during the interpretation stage to develop an integrated understanding of the learning outcomes and learning experiences observed across the two learning environments.

4 Results

4.1 Preliminary Analyses

The primary analyses included data from 84 students for conceptual understanding of quantum computing, subjective workload, and user experience. For quantum programming self-efficacy, data from 82 students who met the response criterion at both pretest and posttest were included.

Regarding the internal consistency of the measures, the KR-20 coefficients for the conceptual understanding of quantum computing assessment were .82 at pretest and .11 at posttest. The overall posttest mean was 8.07 (SD = 1.26), with 41.7% of students scoring 9 or higher and 13.1% obtaining the maximum score. This concentration of scores at the upper end of the scale indicated restricted score variability; accordingly, the low posttest KR-20 was considered in conjunction with

this limited variability. Cronbach's α for quantum programming self-efficacy was .96 at pretest and .98 at posttest, while Cronbach's α for the UEQ-S was .90.

Examination of the ANCOVA assumptions showed that, for conceptual understanding of quantum computing, the assumptions of normality of residuals ($p = .124$) and homogeneity of error variances ($p = .348$) were both satisfied. For quantum programming self-efficacy, the normality assumption was not satisfied ($p = .025$), whereas the assumption of homogeneity of error variances was satisfied ($p = .286$). The assumption of homogeneity of regression slopes was satisfied for both conceptual understanding of quantum computing ($p = .437$) and quantum programming self-efficacy ($p = .838$).

4.2 Conceptual Understanding of Quantum Computing (RQ1)

Both groups showed increases in conceptual understanding of quantum computing after the intervention. In the EduQubit group, the mean score increased from 1.13 (SD = 2.07) at pretest to 8.35 (SD = 1.31) at posttest. In the IBM Quantum Composer group, the mean score increased from 2.34 (SD = 2.45) at pretest to 7.82 (SD = 1.17) at posttest (Figure 2a).

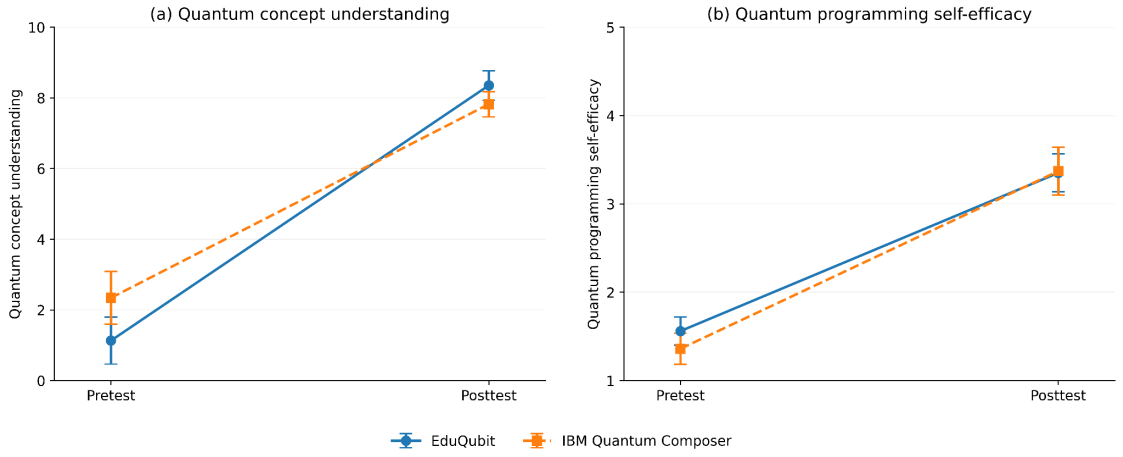


Figure 2: Pretest and posttest scores by learning environment. (a) Quantum concept understanding. (b) Quantum programming self-efficacy. Error bars represent 95% confidence intervals.

ANCOVA controlling for pretest conceptual understanding of quantum computing showed a statistically significant difference in posttest scores between the learning environments, $F(1, 81) = 4.54$, $p = .036$, partial $\eta^2 = .053$. The adjusted mean was 8.38 (SE = 0.20, 95% CI [7.99, 8.78]) for the EduQubit group and 7.79 (SE = 0.19, 95% CI [7.41, 8.16]) for the IBM Quantum Composer

group. The adjusted mean difference was 0.60 points (95% CI [0.04, 1.16]).

4.3 Quantum Programming Self-Efficacy (RQ2)

Both groups showed increases in quantum programming self-efficacy after the intervention. In the EduQubit group, the mean score increased from 1.56 (SD = 0.50) at pretest to 3.35 (SD = 0.67) at posttest. In the IBM Quantum Composer group, the mean score increased from 1.36 (SD = 0.56) at pretest to 3.30 (SD = 0.79) at posttest (Figure 2b).

ANCOVA controlling for pretest quantum programming self-efficacy showed that the difference in posttest self-efficacy between the learning environments was not statistically significant, $F(1, 79) = 0.04$, $p = .850$, partial $\eta^2 < .001$. The adjusted mean was 3.34 (SE = 0.12, 95% CI [3.10, 3.57]) for the EduQubit group and 3.31 (SE = 0.11, 95% CI [3.08, 3.54]) for the IBM Quantum Composer group.

4.4 Subjective Workload (RQ3)

The overall subjective workload measured after the intervention was 2.97 (SD = 0.71) in the EduQubit group and 3.04 (SD = 0.80) in the IBM Quantum Composer group. The between-group difference was not statistically significant, and the effect size was small, Welch's $t(81.97) = -0.42$, $p = .678$, Cohen's $d = -0.09$, 95% CI [−0.52, 0.34]. A supplementary Mann–Whitney U test conducted because of the non-normal distribution of the data likewise showed no statistically significant between-group difference, $U = 849.50$, $p = .787$.

Across the NASA-TLX dimensions, both groups reported relatively higher levels of mental demand and effort, whereas physical demand, temporal demand, and frustration were relatively low (Table 3). Descriptively, the overall level and dimensional pattern of subjective workload were generally similar across the two learning environments.

4.5 User Experience (RQ4)

Using the standard UEQ-S scoring procedure (−3 to +3), the overall user experience score was higher in the EduQubit group (M = 1.91, SD = 0.93) than in the IBM Quantum Composer group (M = 1.48, SD = 1.19). However, the between-group difference was not statistically significant, Welch's $t(80.19) = 1.83$, $p = .071$, Cohen's $d = 0.40$. The mean difference was 0.42 points (95%

Table 3: Subjective workload by learning environment

NASA-TLX dimension	EduQubit M (SD)	IBM Quantum Composer M (SD)
Mental demand	4.42 (1.85)	4.64 (1.54)
Physical demand	1.85 (1.14)	1.95 (1.46)
Temporal demand	1.88 (1.30)	2.12 (1.50)
Performance	2.17 (1.32)	2.43 (1.42)
Effort	5.75 (1.13)	5.41 (1.26)
Frustration	1.75 (1.32)	1.56 (0.83)
Overall	2.97 (0.71)	3.04 (0.80)

Note. Performance was reverse-scored so that higher scores indicate greater subjective workload across all dimensions.

CI [−0.04, 0.89]). A supplementary Mann–Whitney U test conducted because of the non-normal distribution of the data likewise showed no statistically significant between-group difference, U = 705.50, p = .118.

For the UEQ-S subdimensions, pragmatic quality was 1.84 (SD = 1.02) in the EduQubit group and 1.29 (SD = 1.24) in the IBM Quantum Composer group. Hedonic quality was 1.97 (SD = 0.96) and 1.68 (SD = 1.31), respectively (Table 4). The EduQubit group had numerically higher mean scores on both subdimensions.

Table 4: User experience by learning environment

UEQ-S measure	EduQubit M (SD)	IBM Quantum Composer M (SD)
Overall user experience	1.91 (0.93)	1.48 (1.19)
Pragmatic quality	1.84 (1.02)	1.29 (1.24)
Hedonic quality	1.97 (0.96)	1.68 (1.31)

Note. UEQ-S scores range from −3 to +3. Positive scores indicate a more favorable user experience.

4.6 Exploratory Classroom-Level Sensitivity Analysis

To explore the potential influence of classroom-level assignment, student data were aggregated to the four classrooms, and the direction and consistency of the findings across classrooms were examined. For conceptual understanding of quantum computing, the mean gains were 7.21 and 7.25 points in the two EduQubit classrooms, both of which were higher than the gains of 4.78 and 6.24 points in the two IBM Quantum Composer classrooms. When each classroom was weighted equally, the mean gain by condition was 7.23 points for EduQubit and 5.51 points for IBM Quantum Composer,

showing the same directional pattern in favor of EduQubit as observed in the student-level analysis.

For quantum programming self-efficacy, the condition-level averages of the classroom mean gains were similar: 1.78 points for EduQubit and 1.92 points for IBM Quantum Composer. Classroom means for subjective workload were also similar across the two learning environments, at 2.99 and 3.04, respectively. For user experience, the means of the two EduQubit classrooms were 2.01 and 1.76, whereas those of the two IBM Quantum Composer classrooms were 1.33 and 1.65. The corresponding condition-level classroom means were 1.88 and 1.49, respectively, maintaining a directional pattern in favor of EduQubit.

Overall, after aggregating the data to the classroom level, the directional differences observed in the student-level analyses were maintained for conceptual understanding of quantum computing and user experience, whereas quantum programming self-efficacy and subjective workload showed similar patterns across the two learning environments. However, because only four classrooms were included, these findings were not interpreted as evidence for the statistical significance of effects between the learning environments. Rather, the analysis was used exploratorily to examine whether the student-level findings were driven by a particular classroom and how consistently their direction was observed across classrooms.

4.7 Students' Learning Experiences

The semi-structured interview analysis identified three broad categories of students' learning experiences. Students in both learning environments described exploring abstract quantum concepts through direct circuit construction and observation of the resulting outcomes. Differences in how the two environments guided and supported learning activities were also reflected in students' problem-solving experiences. In addition, students in both groups expressed interest and curiosity about learning quantum computing, although the sources of difficulty they encountered during the learning process differed.

First, students described direct gate manipulation and observation of circuit results as helpful for understanding quantum concepts. One student who used EduQubit explained, "If I just listened, I couldn't really understand why it worked that way, but when I put [the gate] into this box myself, I could understand it a little better." Another student similarly commented, "I think I understood it better because I actually got to use it myself." Students using IBM Quantum Composer also found

the process of placing different gates and observing the results engaging. One student explained, "It was fun trying different things, putting them in one by one, and actually experimenting with them." At the same time, students in both environments reported that qubits, superposition, entanglement, and the operating principles of quantum gates were themselves difficult or confusing. These responses suggest that direct circuit manipulation supported students' exploration of the concepts but did not eliminate the inherent difficulty of the quantum concepts themselves.

Second, students' problem-solving experiences differed according to how the learning activities were structured and guided. EduQubit students described the restriction of available gates within missions and the step-by-step presentation of activities as helpful for learning. One student explained, "I think it's easier to understand when things are set. It's limited when you're doing the missions, but once the Lab opens, you can do everything, so I think that's better." Other students similarly reported that these restrictions helped them focus on the instructional content and reduced confusion from having too many options. At the same time, they enjoyed freely combining different gates in the Lab after completing the missions. In contrast, students using IBM Quantum Composer primarily described trial-and-error exploration, repeatedly placing different gates and examining the resulting outcomes when attempting to solve a problem. Some students reported difficulty determining whether the circuits they had constructed were correct and said that they could verify their solutions only after the teacher provided the correct answer. Thus, although both environments supported exploratory activities, EduQubit initially constrained the range of available gates and then expanded learners' options in the Lab, whereas IBM Quantum Composer allowed students to explore a broader range of gates from the outset, often through trial and error.

Third, students in both groups generally found quantum computing interesting, but the sources of perceived difficulty differed. EduQubit students described the learning environment itself as relatively easy to use but reported difficulty with the quantum concepts or with problems posed by the teacher during the Lab activities. One student commented, "The program itself wasn't difficult at all, but the concepts were a little confusing." In contrast, some IBM Quantum Composer students described the interface as complex when they first encountered it because it contained many features and elements. One student recalled thinking, "What am I supposed to do?" upon first seeing the interface, while another simply described the screen as "complicated." Nevertheless, students using IBM Quantum Composer also reported that freely manipulating gates and observing the resulting

outcomes was enjoyable.

5 Discussion

This study developed EduQubit, a web-based quantum computing learning environment for novice learners, and examined differences between learning with EduQubit and IBM Quantum Composer under the same learning objectives and instructional content. Students in both groups constructed circuits by placing quantum gates, repeatedly executed the circuits, and observed the measurement outcomes. During the interviews, students also described manipulating gates and observing the resulting changes as engaging learning experiences. This finding is consistent with previous research suggesting that visual and interactive representations can support novice learners in exploring abstract quantum concepts [17, 32]. The improvements in conceptual understanding and quantum programming self-efficacy observed in both groups may therefore be associated with their shared experience of constructing and executing circuits and observing how changes in gates affected the measurement outcomes.

However, the ways in which students explored quantum circuits differed between the two learning environments. In EduQubit, the mission sequence and the gates available at each stage were restricted, and students reported that this structure helped them understand what to do and focus on the content being learned. After completing the missions, students could freely combine a broader range of gates in the Lab, allowing them to move gradually from guided to more open-ended exploration. In contrast, IBM Quantum Composer provided access to a relatively broad range of gates and features from the outset, and students solved problems through trial and error by placing different gates and examining the resulting outcomes. Although some students found this freedom engaging, others reported difficulty determining whether the circuits they had constructed were correct and had to wait for the teacher to provide the correct solution. Thus, the primary difference between the two environments was not whether students could explore quantum circuits, but how the scope and sequence of that exploration were regulated during the learning process.

This difference provides one possible explanation for the relatively higher conceptual understanding of quantum computing observed in the EduQubit group. In EduQubit, gate selection, circuit construction, and observation of execution results were organized in relation to the concepts

and learning objectives presented in each mission. Rather than exploring a wide range of features independently from the beginning, students could therefore focus on the gates and outcomes relevant to each stage of learning. This approach is consistent with recent quantum computing learning environments that integrate staged conceptual explanations, guided activities, and feedback with quantum circuit manipulation to support novice learners [17, 35, 36]. The findings of this study suggest that supporting novice learners may require not only opportunities to manipulate quantum circuits but also the sequential presentation of available gates and relevant outcomes in relation to specific learning objectives.

Nevertheless, these findings should not be interpreted as definitive evidence that EduQubit was superior in promoting conceptual understanding. The student-level ANCOVA showed a difference in favor of EduQubit, and the exploratory classroom-level analysis showed the same directional pattern, with both EduQubit classrooms demonstrating greater mean gains than the two IBM Quantum Composer classrooms. This pattern suggests that the student-level difference was unlikely to have been driven solely by the results of a single classroom. However, because only four classrooms were included, the study could not reliably separate classroom-specific characteristics from the effects of the learning environment. The conceptual understanding findings should therefore be interpreted as preliminary evidence of the potential of structured instructional support and reexamined in future studies involving a larger number of classrooms. Moreover, EduQubit students still experienced difficulty understanding quantum concepts such as qubits, superposition, and entanglement. Some also found it difficult to independently interpret the functions of multiple gates and their execution results when greater freedom of exploration was introduced in the Lab. Structured exploration may therefore have provided direction regarding what to manipulate and observe during the initial learning process rather than reducing the inherent difficulty of the quantum concepts themselves.

Unlike conceptual understanding, quantum programming self-efficacy did not differ between the two groups after controlling for pretest scores. Students in both conditions constructed and executed quantum circuits for the first time, and some students explained during the interviews that quantum computing was less difficult than they had expected or seemed easier after they had tried it themselves. At this introductory stage, the experience of successfully constructing and executing a circuit and obtaining results may have been more closely related to students' perceptions of their capabilities than the specific form of support provided by the learning environment. In

addition, both conditions involved the same instructional content and tasks, and teacher guidance was also provided in the IBM Quantum Composer condition. There may therefore have been limited opportunity for EduQubit's built-in support to produce an additional difference in self-efficacy. The short duration of the instruction may also have been insufficient for differences in self-efficacy associated with the two forms of support to develop. Future studies should examine whether longer-term learning experiences, through which students accumulate experience in independently designing circuits and solving problems, result in different patterns of self-efficacy across learning environments.

The two groups also did not differ significantly in subjective workload. Based on the quantitative findings alone, EduQubit's step-by-step missions and support features did not result in lower overall subjective workload than IBM Quantum Composer. The interviews, however, suggested that the sources of difficulty differed between the conditions. EduQubit students generally did not find the learning environment itself difficult to use, but they experienced difficulty understanding quantum concepts or solving open-ended problems in the Lab. In contrast, IBM Quantum Composer students described conceptual difficulties as well as difficulty determining what to manipulate when first presented with an interface containing numerous features and elements. When considered alongside the relatively high levels of mental demand and effort in both groups, these findings suggest that a substantial portion of students' workload may have arisen not from basic interface manipulation or time pressure but from understanding superposition and entanglement and reasoning about the relationships between gate combinations and circuit outcomes. EduQubit may therefore have reduced uncertainty about what to do during the initial activities without reducing the mental effort required to understand quantum concepts and gradually solve problems more independently.

A similar pattern was observed for user experience, with no statistically significant between-group differences in overall user experience, pragmatic quality, or hedonic quality. The interviews nevertheless indicated that students in both environments had positive experiences in different ways. EduQubit students reported that the step-by-step missions helped them understand the direction of the activities and that they enjoyed freely combining a broader range of gates in the Lab. Although some IBM Quantum Composer students initially found the interface complex, they also enjoyed freely experimenting with different gates and observing the resulting outcomes. The descriptively larger mean difference in pragmatic quality than in hedonic quality was consistent

with interview accounts suggesting that EduQubit helped students understand the direction of the activities. However, because the between-group differences in the subscales were not statistically significant, this pattern should not be interpreted as evidence of a reliable difference but rather as a possibility to be investigated in future research.

These findings suggest that quantum computing learning environments for novice learners should not emphasize either guidance or open-ended exploration exclusively. Instead, the balance between the two may need to change as learners progress. During the initial stages of learning, clearly presenting activity goals and limiting the available gates may help regulate the scope of exploration. Once students become familiar with basic concepts and circuit operations, expanding the range of available gates and possible problem-solving approaches may be appropriate. From this perspective, the distinctive feature of EduQubit was not simply that it provided more guidance than IBM Quantum Composer, but that it organized the learning experience so that students moved from structured exploration in the missions to more autonomous exploration in the Lab. This study therefore identifies the sequential regulation of guidance and openness as a potential design direction for quantum computing learning environments intended for novice learners.

Students' experiences with EduQubit's AI tutor, Quby, also varied. Some students reported that Quby's explanations were helpful, whereas others indicated that it did not provide the information they needed for the circuits they had constructed or the problems they were attempting to solve. This finding suggests that the mere availability of an AI tutor does not ensure that learners' immediate support needs will be met. Its responses may need to reflect both the circuits learners have constructed and the activities they are currently completing. However, this study did not systematically analyze how frequently students used Quby, the questions they entered, or the content and quality of its responses. The contribution of Quby to learning outcomes and user experience therefore cannot be separated from that of EduQubit's other features. Future research should examine the situations in which learners seek assistance from an AI tutor and the extent to which its responses are appropriately connected to their circuits and problem-solving processes.

Several limitations should be considered when interpreting the findings. First, although the learning environments were assigned at the classroom level, only four classrooms were included in the analysis, making it difficult to estimate classroom-level effects reliably. Second, posttest scores on the conceptual understanding assessment were concentrated at the upper end of the scale, and the

posttest showed low reliability. These measurement limitations reduced the assessment's ability to distinguish precisely between students' conceptual understanding in the two environments. Third, the between-group comparison of subjective workload should be interpreted cautiously because the NASA-TLX showed low internal consistency. Although the NASA-TLX dimensions measure distinct aspects of workload and are not necessarily expected to demonstrate high homogeneity, the low internal consistency limits the measurement precision of the overall workload score used in this study. Fourth, only eight students volunteered to participate in the interviews, and their experiences cannot be assumed to represent all students in either condition. The interview findings should therefore be interpreted as complementary evidence that provides insight into students' exploration processes and difficulties rather than as evidence establishing the causes of the quantitative differences. Fifth, EduQubit provided the mission structure, staged restrictions on available gates, the Lab, result visualizations, and the AI tutor as an integrated environment. The observed findings therefore cannot be attributed to any single feature. Furthermore, because teacher guidance was provided in the IBM Quantum Composer condition, the differences between the conditions may reflect the combined effects of guidance embedded within the platform and guidance provided externally by the teacher.

Future studies should reexamine these findings with a larger number of classrooms and learners from a wider range of age groups. In particular, features such as staged gate restrictions, mission guidance, and the open-ended Lab could be examined separately to determine how each feature relates to conceptual understanding, self-efficacy, subjective workload, and user experience. Analyzing students' circuit construction logs could also reveal their actual exploration behaviors, including how they added and removed gates, how frequently they executed circuits, and how they identified and corrected errors. Such data could provide behavioral evidence for the differences between guided and trial-and-error exploration identified in the interviews. Longer-term studies are also needed to determine when guidance should be reduced and when greater freedom of exploration should be introduced as learners develop their knowledge and circuit construction skills.

Taken together, the most important distinction between the two environments was not whether students could explore quantum circuits, but how that exploration was organized. EduQubit clarified the direction and scope of exploration through its initial missions and subsequently expanded opportunities for more autonomous exploration in the Lab. This structure provides one possible

explanation for the difference in conceptual understanding observed in favor of EduQubit, but it did not produce consistent between-group differences in self-efficacy, subjective workload, or user experience. The findings should therefore be interpreted not as evidence of EduQubit's overall superiority, but as preliminary evidence of the potential value of structuring novice learners' initial exploration while preserving opportunities for more autonomous experimentation at later stages of quantum computing learning.

6 Conclusion

This study developed EduQubit, a web-based quantum computing learning environment for novice learners, and compared learning with EduQubit and IBM Quantum Composer under the same learning objectives and instructional content. In the student-level analysis, the EduQubit group demonstrated higher conceptual understanding of quantum computing after controlling for pretest scores. The exploratory classroom-level analysis showed the same directional pattern, although the small number of classrooms limits the strength of this evidence. No clear between-group differences were found in quantum programming self-efficacy, subjective workload, or user experience. These findings therefore do not indicate the overall superiority of one environment across learning outcomes but provide preliminary evidence that structured instructional support may contribute to novice learners' conceptual understanding.

The student interviews showed that the main distinction between the two environments concerned how circuit exploration was organized. EduQubit initially guided students' exploration through step-by-step missions and restricted gate options and subsequently expanded opportunities for more autonomous exploration in the Lab. In contrast, IBM Quantum Composer allowed students to explore a broader range of gates and features from the outset, often through trial and error. Although students in both environments found circuit manipulation and experimentation engaging, their difficulties differed. EduQubit students primarily described challenges related to understanding quantum concepts and solving open-ended problems, whereas some IBM Quantum Composer students also experienced uncertainty about how to use the interface and determine whether their circuits were correct.

These findings suggest that designing quantum computing learning environments for novice

learners involves more than making quantum circuits accessible for direct manipulation. The scope and sequence of exploration also need to be considered. Providing clear goals and a manageable set of options during initial learning, followed by opportunities for more autonomous experimentation, may help learners engage with quantum circuits without removing the conceptual challenge involved. EduQubit provides one example of this progression from structured to open-ended exploration. Further research involving more classrooms, longer instructional periods, and separate examination of individual design features is needed to determine how and when guidance should be reduced as learners develop their conceptual understanding and circuit construction skills.

References

[1] Aiello CD, Awschalom DD, Bernien H, Brower T, Brown KR, Brun TA. Achieving a quantum smart workforce. Quantum Science and Technology. 2021;6(3):030501.

[2] Hughes C, Isaacson J, Turner J, Perry A, Sun R. Teaching quantum computing to high school students. The Physics Teacher. 2022;60(3):187-189. https://doi.org/10.1119/10.0009686

[3] Greinert F, Müller R, Bitzenbauer P, Ubben MS, Weber K-A. Future quantum workforce: Competences, requirements, and forecasts. Physical Review Physics Education Research. 2023;19(1):010137. https://doi.org/10.1103/PhysRevPhysEducRes.19.010137

[4] Tappert CC, Frank RI, Barabasi I, Leider AM, Evans D, Westfall L. Experience Teaching Quantum Computing. In: Proceedings of the 52nd Annual Conference of the Association Supporting Computer Users in Education (ASCUE); 2019 Jun 9-13; Myrtle Beach, SC. ASCUE; 2019. p. 46-60.

[5] Pashaei P, Amiri H, Haenel R, Lopes PL, Chrostowski L. Educational resources for promoting talent in quantum computing. In: 2020 IEEE International Conference on Quantum Computing and Engineering (QCE). IEEE; 2020. p. 317-322.

[6] Singh C, Levy A, Levy J. Preparing precollege students for the second quantum revolution with core concepts in quantum information science. The Physics Teacher. 2022;60(8):639-641. https://doi.org/10.1119/5.0027661

[7] Ghimire A, Kashyap JS, Edwards E, Franklin D, Singh C. Investigating high school and pre-high school teachers' perceptions and experiences introducing quantum concepts: a survey of QuanTime and other quantum-related activities. EPJ Quantum Technology. 2025;12(1):89. https://doi.org/10.1140/epjqt/s40507-025-00392-9

[8] Kaur M, Venegas-Gomez A. Defining the quantum workforce landscape: A review of global quantum education initiatives. Optical Engineering. 2022;61(8):081806. https://doi.org/10.1117/1.OE.61.8.081806

[9] Oikonomou AV, Savvas IK. Quantum legacy: Quantum literacy for secondary students. In: 2025 IEEE Global Engineering Education Conference (EDUCON). 2025. https://doi.org/10.1109/EDUCON62633.2025.11016576

[10] Dundar-Coecke S, Yeh L, Puca C, Pfaendler SM-L, Waseem MH, Cervoni T, Kissinger A, Gogioso S, Coecke B. Quantum picturalism: Learning quantum theory in high school. In: 2023 IEEE International Conference on Quantum Computing and Engineering (QCE). 2023.

[11] Coban A, Dzsotjan D, Küchemann S, Durst J, Kuhn J, Hoyer C. AI support meets AR visualization for Alice and Bob: personalized learning based on individual ChatGPT feedback in an AR quantum cryptography experiment for physics lab courses. EPJ Quantum Technology. 2025;12(1):15.

[12] Yan Y, Lee JS, Chen K, Wong NH. Enhancing Quantum Computing Education Through Virtual Reality. In: Proceedings of the 20th International Conference on Virtual Reality Continuum and its Applications in Industry. 2025. p. 1-2.

[13] Krijtenburg-Lewerissa K, Pol HJ, Brinkman A, van Joolingen WR. Insights into teaching quantum mechanics in secondary and lower undergraduate education. Physical Review Physics Education Research. 2017;13(1):010109. https://doi.org/10.1103/PhysRevPhysEducRes.13.010109

[14] Bouchée T, de Putter-Smits L, Thurlings M, Pepin B. Towards a better understanding of conceptual difficulties in introductory quantum physics courses. Studies in Science Education. 2022;58(2):183-202. https://doi.org/10.1080/03057267.2021.1963579

[15] Piispanen L, Pfaffhauser M, Wootton J, Togelius J, Kultima A. Defining quantum games. EPJ Quantum Technology. 2025;12(1):7.

[16] Castillo-Salazar D, Thirumuruganandham SP, Lituma González WD, Ortega HC. Scaffolding quantum entanglement in secondary school: from tangible analogy to computational simulation. Frontiers in Education. 2026;10:1729099. https://doi.org/10.3389/feduc.2025.1729099

[17] Liu Z, Song Y, Yang Q, Xing W, Guo J. Board 68: Exploring the impact of a simulation-based learning tool on undergraduate quantum computing education. In: 2025 ASEE Annual Conference & Exposition; 2025 Jun 22-25; Montreal, Canada. Washington, DC: American Society for Engineering Education; 2025. Paper ID #45437.

[18] Folkers B, Castenmiller C, Brinkman A, Stadermann K. An analysis of demonstration materials in quantum physics education. EPJ Quantum Technology. 2026;13(1):6.

[19] Albert C, Förster M, Pospiech G. Developing a quantum physics curriculum for lower secondary education: insights into the design of a Spin First teaching concept and first empirical findings. EPJ Quantum Technology. 2025;12(1):132. https://doi.org/10.1140/epjqt/s40507-025-00436-0

[20] Merzel A, Bitzenbauer P, Krijtenburg-Lewerissa K, Stadermann K, Andreotti E, Anttila D, et al. The core of secondary level quantum education: A multi-stakeholder perspective. EPJ Quantum Technology. 2024;11(1):27. https://doi.org/10.1140/epjqt/s40507-024-00237-x

[21] Bitzenbauer P. Effect of an introductory quantum physics course using experiments with heralded photons on pre-university students' conceptions about quantum physics. Physical Review Physics Education Research. 2021;17(2):020103. https://doi.org/10.1103/PhysRevPhysEducRes.17.020103

[22] Anttila D, Bitzenbauer P, Scheer S, Tartaglia D, Folkers B, Goorney S, Vartak S, Sherson J, Toninelli C. What makes a good quantum outreach video? An evaluation framework for a quantum video playlist. EPJ Quantum Technology. 2026;13(1):40. https://doi.org/10.1140/epjqt/s40507-025-00461-z

[23] Chou Y-H, Jiang Y-C, Kuo S-Y, Kung S-Y. Bridging the quantum education gap: Hands-on visualization projects for quantum search algorithm. In: 2024 IEEE International Conference on Quantum Computing and Engineering (QCE). 2024. https://doi.org/10.1109/QCE60285.2024.20466

[24] Angara PP, Stege U, MacLean A. Quantum computing for high-school students: An experience report. In: 2020 IEEE International Conference on Quantum Computing and Engineering (QCE). 2020. p. 323-329. https://doi.org/10.1109/QCE49297.2020.00047

[25] Economou SE, Rudolph T, Barnes E. Teaching quantum information science to high-school and early undergraduate students. arXiv. 2020. https://doi.org/10.48550/arXiv.2005.07874

[26] Angara PP, Stege U, MacLean A, Müller HA, Markham T. Teaching quantum computing to high-school-aged youth: A hands-on approach. IEEE Transactions on Quantum Engineering. 2021;3:1-15.

[27] Chiofalo ML, Foti C, Michelini M, Santi L, Stefanel A. Games for teaching/learning quantum mechanics: A pilot study with high-school students. Education Sciences. 2022;12(7):446. https://doi.org/10.3390/educsci12070446

[28] Mykhailova M. Developing programming assignments for teaching quantum computing and quantum programming. In: 2022 IEEE International Conference on Quantum Computing and Engineering (QCE). 2022. p. 688-692.

[29] Wootton JR, Harkins F, Bronn NT, Carrera Vazquez A, Phan A, Asfaw AT. Teaching quantum computing with an interactive textbook. In: 2021 IEEE International Conference on Quantum Computing and Engineering (QCE). IEEE; 2021. p. 385-391. https://doi.org/10.1109/QCE52317.2021.00058

[30] Seskir ZC, Migdał P, Weidner C, Anupam A, Case N, Davis N. Quantum games and interactive tools for quantum technologies outreach and education. Optical Engineering. 2022;61(8):081809.

[31] Galetto F, et al. Experience in teaching quantum computing with hands-on programming labs. The Journal of Supercomputing. 2024;80:14029-14056. https://doi.org/10.1007/s11227-024-06001-3

[32] Usmani AA, Thale SS, Menezes NN, Pinto KN, Mahamuni CV. Super POS: An Interactive Web-Based Quantum Simulator with Real-Time 2D and 3D Visualizations. In: 2024 9th International Conference on Communication and Electronics Systems (ICCES). IEEE; 2024. p. 111-120. https://doi.org/10.1109/ICCES63552.2024.10859909

[33] Hannum MS. Introducing quantum computing to high school students with Grover's search algorithm. American Journal of Physics. 2025;93(1):78-87. https://doi.org/10.1119/5.0228847

[34] Orts F. Pedagogical approach for quantum computing in engineering education. Computer Applications in Engineering Education. 2025;33(2):e70004. https://doi.org/10.1002/cae.70004

[35] Abdelhamid S, Bangura J, Jeffers J, Aly M. Designing and implementing CryptoLearn: a web-based platform for cryptography and quantum computing education. In: Proceedings of the 15th International Conference "New Perspectives in Science Education" (NPSE); 2026 Mar 19-20; Florence, Italy. Filodiritto Editore; 2026.

[36] Hernandez K, Patel K, et al. QuantAid: A quiz-based quantum learning platform for high-school and undergraduate students. In: Proceedings of the 57th ACM Technical Symposium on Computer Science Education (SIGCSE TS 2026). 2026. https://doi.org/10.1145/3770762.3772593

[37] Mykhailova M, Svore KM. Teaching quantum computing through a practical software-driven approach: Experience report. In: Proceedings of the 51st ACM technical symposium on computer science education. 2020. p. 1019-1025.

[38] Yusuf A, Román-González M, et al. Development of a quantum literacy test for K-12 students. Education Sciences. 2026;16(1):31. https://doi.org/10.3390/educsci16010031

[39] Kukul V, Gökçearslan Ş, Günbatar MS. Computer programming self-efficacy scale (CPSES) for secondary school students: Development, validation and reliability. Eğitim Teknolojisi Kuram ve Uygulama. 2017;7(1):158-179. https://doi.org/10.17943/etku.288493

[40] Rich PJ, Larsen RA, Mason SL. Measuring teacher beliefs about coding and computational thinking. Journal of Research on Technology in Education. 2021;53(3):296-316.

[41] Hart SG, Staveland LE. Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. In: P. A. Hancock & N. Meshkati (Eds.), Human mental workload. North-Holland; 1988. p. 139-183. https://doi.org/10.1016/S0166-4115(08)62386-9

[42] Hart SG. NASA-Task Load Index (NASA-TLX); 20 years later. Proceedings of the Human Factors and Ergonomics Society Annual Meeting. 2006;50(9):904-908. https://doi.org/10.1177/154193120605000909

[43] Schrepp M, Hinderks A, Thomaschewski J. Design and evaluation of a short version of the user experience questionnaire (UEQ-S). International Journal of Interactive Multimedia and Artificial Intelligence. 2017;4(6):103-108. https://doi.org/10.9781/ijimai.2017.09.001

[44] Cronbach LJ. Coefficient alpha and the internal structure of tests. Psychometrika. 1951;16(3):297-334. https://doi.org/10.1007/BF02310555

[45] Kuder GF, Richardson MW. The theory of the estimation of test reliability. Psychometrika. 1937;2(3):151-160. https://doi.org/10.1007/BF02288391

[46] The jamovi project. jamovi. Version 2.7 [Computer software]. 2025. Available from: https://www.jamovi.org. Accessed 15 Aug 2026.

Abbreviations

AI, Artificial Intelligence; ANCOVA, Analysis of Covariance; CPSES, Computer Programming Self-Efficacy Scale; KR-20, Kuder–Richardson Formula 20; NASA-TLX, NASA Task Load Index; UEQ-S, User Experience Questionnaire–Short.

Declarations

Ethics approval and consent to participate

The study protocol was approved by the Institutional Review Board of Seoul National University of Education (SNUEIRB-2026-004). Written informed consent was obtained from the students' legal guardians, and student assent was obtained prior to participation.

Availability of data and materials

The datasets generated and analyzed during the current study are not publicly available due to ethical and privacy considerations associated with research involving minor participants, and cannot be shared outside the approved research protocol. Requests for further information may be directed to the corresponding author, subject to applicable ethical and institutional restrictions.

Competing interests

The authors declare that they have no competing interests.

Funding

Not applicable.

Authors' contributions

HC conceptualized the study, designed and developed EduQubit, developed the research methodology and instructional materials, conducted the study, collected and analyzed the quantitative and qualitative data, and wrote the original draft of the manuscript. DK supervised the study, contributed to the research design and interpretation of the findings, and critically reviewed and revised the manuscript. Both authors read and approved the final manuscript.

Acknowledgements

The authors thank the students and teachers who participated in this study for their time and participation.