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A model of cyber thinking behaviour using experiential learning in robotics education

Noridayu Adnan [a,*], Siti Norul Huda Sheikh Abdullah [a,**], Raja Jamilah Raja Yusof [b], Noor Faridatul Ainun Zainal [a], Elaheh Yadegaridehkordi [c], Nazrul Anuar Nayan [d,e]

[a] Universiti Kebangsaan Malaysia, Faculty of Technology and Information Science, Bangi, Selangor, 43600, Malaysia
[b] Universiti Malaya, Faculty of Computer Science and Information Science, Kuala Lumpur, Federal Territory of Kuala Lumpur, 50603, Malaysia
[c] College of Information and Communications Technology, School of Engineering and Technology, Central Queensland University, Sydney, NSW, 2000, Australia
[d] Universiti Kebangsaan Malaysia, Faculty of Engineering and Built Environment, Bangi, Selangor, 43600, Malaysia
[e] Universiti Kebangsaan Malaysia, Institut Islam Hadhari, Bangi, Selangor, 43600, Malaysia

A R T I C L E I N F O

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A B S T R A C T

STEM education is growing worldwide, but students often find it hard to engage with because the subjects seem complex. This study introduces a new model to develop students' computational and adversarial thinking skills through hands-on experiences (learning behaviour) and emotion management, based on the Matsuo–Nagata experiential learning approach. After verifying the model's components through focus group discussions with experts, 131 teachers were given a questionnaire to validate the developed model, supported by Partial Least Squares–Structural Equation Modelling analysis. A pilot test was conducted with approximately 116 students and 25 teachers. After expert reviews and surveys with teachers and students, the model, namely the Cyber Thinking Behavioural Model, was tested and comprises four key parts: expected and unexpected experiences, emotion management, cyber thinking, and computational reflection. It promotes learning through robot exploration, reflection, teamwork, curiosity, and problem-solving to suggest short-term cybersecurity skills. The results are consistent with the view that integrating experiential learning with cyber thinking (a combination of computational and adversarial thinking) significantly enhances students' readiness to face cyber-enabled challenges while making STEM learning more engaging and meaningful, positioning the Cyber Thinking Behavioural Model as a practical framework for embedding cybersecurity awareness into school robotics education.

1. Introduction

According to Analytics Insight, drones and robotics cybersecurity are the top 10 Robotics trends and predictions to look out for in 2023 (Aiswarya, 2023). Such high-tech advancement has improved integrated learning, which consists of four domains: science, technology, engineering, and growing up in the conservative era. The new young generation was only willing to choose careers as teachers, police officers, or doctors as their aspirations for the future. However, our new young generation has improved their aspirations and pursued careers as scientists, technologists, or physicists, which are more revolutionary (Adnan et al., 2019). The arts domain has been included, resulting in the acronym STEAM. As stated in the Malaysian Education Development Plan 2013–2025, STEM education must be applied theoretically and practically to prepare youth with a high-performance education system (Musa, 2020).

STEM education is essential to teachers and educators. Our young generation can master multiple skills, especially in digital technology. Based on the study by Thi Nguyet Trang et al. (2025) , Gen Z in Vietnam, mostly between 16 and 27 years old, are very comfortable with technology, use their smartphones a lot for fun and staying informed, and share common traits with global Gen Z, such as having short attention spans and enjoying content that's mostly videos or audio. One of the methods to attract young generations into computational thinking is through game-based learning (Bayaga, 2024) since it can enhance their interest, also elevating their learning experience. A study by (Prem et al., 2025) verified that game-based learning also associated with cybersecurity skills. Teaching adversarial thinking alongside computational

* Corresponding author.
** Corresponding author.
E-mail addresses: p131986@siswa.ukm.edu.my (N. Adnan), snhsabdullah@ukm.edu.my (S.N.H. Sheikh Abdullah).

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thinking from the beginning of computer education is crucial for current software development because it bridges the gap between technical capabilities and cybersecurity awareness (Servin et al., 2018).

Adversarial thinking, a hacker's ability to perform their adversary's work strategically (Hamman et al., 2017), is introduced to increase cybersecurity awareness to handle new and advanced high-tech machines or devices. Computational thinking (CT) has also been introduced to improve problem-solving skills among young generations. CT provides aid in dealing with this increasingly worrying cybersecurity issue. The escalation of various applications and new systems has increased security risks (Priyadarshini, 2017). Therefore, cybersecurity awareness must be implemented from the very beginning. Introducing new thinking concepts, such as the integration of computational and adversarial thinking, to the younger generation would improve their ability to be more critical and creative and provides promising exploratory evidence to their resilience in solving complex problems.

The concepts of computational and adversarial thinking are integrated with the experiential learning model to improve student education; students should be exposed to fresh experiences, encouraged to reflect on their new experiences and draw fresh insights, and assisted in applying their new information with the new practice set (Kang et al., 2022). Educational robotics is widely framed as a form of experiential learning in which students construct, test, and refine solutions through hands-on activities. The Kolb learning model, developed in 1984, is an example of a well-known experiential learning model (cycle) in which a person can feel and learn thoroughly through four phases: concrete experience, reflective observation, abstract conceptualisation, and active experimentation (Kolb, 1984).

Experiential learning gives a natural foundation to design robotics-based activities since it emphasises learning through cycles of action and reflection. Kolb's classical model conceptualises experiential learning as a four-stage process, which has been widely applied in human resource development and higher education (Kolb, 1984). However, it has been criticised for under-specifying second-order learning processes. To address this, Matsuo and Nagata proposed a revised experiential learning model that explicitly distinguishes between expected and unexpected experiences, foregrounds the management of emotions, and adds reflective analysis, abstract conceptualisation, unlearning, and active experimentation, accompanied by a debriefing checklist for experience-based training (Matsuo and Nagata, 2020). Matsuo and Nagata reviewed and improved several learning components of the model, including the concept of unlearning in the abstract conceptualisation phase and the importance of emotion management. The present study has applied the Matsuo–Nagata learning model because it is more holistic than the Kolb learning model.

The Matsuo–Nagata experiential learning model was chosen as the reference model for this study because of its emphasis on a deeper learning phase, including the management of emotion (Matsuo and Nagata, 2020). The model is divided into technical and critical levels, where in-depth learning can be implemented in education, especially robotics. Integrating cyber thinking, which consists of computational and adversarial thinking, is aligned with the STEM experiential learning needs of high school students. Robotics and cyber-physical tasks operationalise these ideas particularly well: learners interact with tangible devices that provide immediate feedback, encounter unanticipated system behaviours and task constraints, and must iteratively debug, adapt, and refine their solutions in authentic, time-pressured situations.

Recent work on robotics experiential learning confirms that such hands-on activities are effective contexts for fostering computational thinking and related higher-order skills, precisely because they require students to cycle repeatedly between doing, reflecting, and re-designing in response to both expected and unexpected outcomes (Adnan et al., 2023). Within this perspective, as shown in Table 1, drone-based cyber-physical tasks become a concrete instantiation of the revised experiential learning model, where expected and unexpected experiences, emotion regulation, and reflective analysis can be systematically orchestrated to cultivate cyber thinking and cybersecurity awareness.

Table 1
Roles of CT, at, and experiential learning.

Construct	Core focus	Role in model
Computational thinking	Structuring and solving technical problems	Enables correct and efficient programming
Adversarial thinking	Anticipating malicious behaviour and defences	Enables security-aware decisions
Experiential components	How learning is experienced	Bind CT and AT into durable cyber thinking

This cybersecurity awareness must be raised to ensure that a society has the skills and knowledge to protect itself if people encounter cyberattacks or cybercrimes (Blueprint, 2021). The definition of CT is to reformulate a complex problem to be easier to solve by using the concepts of reduction, merging, transformation, or simulation (Wing, 2006). CT combines computational techniques into one discipline using problem-solving skills (Echeverría et al., 2019). Adversarial thinking applies the concept of reverse engineering by understanding the hacker's mind (Hamman et al., 2017). The components of CT integrated with adversarial thinking are pattern recognition, decomposition, algorithm and abstraction. The other two components of CT are debugging and generalization, which are in separate phases because they are used for reflection analysis. The characteristics of adversarial thinking are having solid technical ability, being obsessed with doing things to the limit, looking for the various possibilities that ordinary people rarely do, and having the ability to plan, strategize, and face obstacles to achieve their goals (Hamman & Hopkinson, 2016). The present study expects the students to master the basics of composing solutions for every problem using CT and be aware of cybersecurity aspects in modern technology. The understanding level of cyber thinking will be tested pre- and post-test during robotics learning activities.

This study motivates and attracts the interest of young people by training their minds to think critically and creatively by applying computational and adversarial thinking concepts, which can aid teachers during formal learning (class). The concepts of computational and adversarial thinking can be implemented in various subjects(Nurudin Sudin et al., 2026). This learning attraction is vital because augmenting STEM skills among young people faces one challenge: the lack of interest. Low interest in STEM education can cause our future society to lack the ability to think critically and creatively. Critical thinking is essential in preparing the community because it will face many challenges of modernisation (Swaid, 2015). Therefore, teachers are expected to incorporate technology into their lessons to promote the achievement of important educational goals, which may require the teachers to include new content in their classroom or shift the instructional focus (Guggemos & Seufert, 2021). Based on the literature, two research questions were developed.

RQ1. How can experiential learning in robotics be structured into a coherent Cyber Thinking Behavioural Model?

RQ2. How can the validated Cyber Thinking Behavioural Model be used to support the development of students' cybersecurity awareness and readiness within school-based robotics education?

This study proposes the Cyber Thinking Behavioural Model, which integrates computational thinking, adversarial thinking, and experiential learning to strengthen students' problem-solving, cybersecurity awareness, and readiness for technology-driven learning environments (Kucuk & Sisman, 2020). Using drones and robotics as experiential learning tools, the model is intended to help students develop strategic thinking and skills relevant to STEM education (Farr & Light, 2019). At the same time, the study recognizes that implementing technology-rich pedagogy can place added demands on teachers, which can influence teaching motivation and, in turn, student learning experiences (Sailer et al., 2021). The model therefore also emphasises positive behaviour and self-reflection as important elements in supporting students' personal development and learning engagement (Ismail et al., 2018).

To establish the model, the study analyses its underlying factors using Partial Least Squares–Structural Equation Modelling (PLS-SEM), a statistical method used to test relationships among model constructs. This approach supports the validation of the model components and helps determine whether the integrated framework is suitable for educational use (Farr & Light, 2019). The study aims to contribute to knowledge on cyber thinking as a foundational skill, while also highlighting the close connection between computational thinking and cybersecurity. In addition to developing and validating the model, the study further explores its classroom application through a robotics workshop designed to support students' cybersecurity-oriented thinking and preparedness.

2. Hypothesis development on related works

Cyber thinking behaviour in this study is defined as a cybersecurity-oriented form of thinking that integrates computational thinking, adversarial thinking, and regulated emotional responses when working with cyber-physical systems such as educational drones. In comparison to generic computational thinking, problem-solving, or digital literacy, which mainly focus on abstraction, algorithmic reasoning, or tool use, cyber thinking behaviour explicitly emphasises threat anticipation, reverse-engineering potential attacks, and emotion management under cyber-enabled risk during hands-on robotics tasks. In this study, cyber thinking behaviour is operationalised through five dimensions of the Cyber Thinking Behavioural Model: Expected and Unexpected Experience (PDTD), Management of Emotion (E), Computational Thinking (PK), Adversarial Thinking (PT), and Computational Reflection (R), each measured by a set of questionnaires and enacted through the four stages of the robotics workshop. These dimensions capture how students encounter planned and unplanned situations, regulate their emotions, apply computational and adversarial thinking, and reflect on and generalise solutions in authentic robotics activities. Five components of the Matsuo-Nagata learning model were studied with computational and adversarial thinking based on (Adnan et al., 2023). Their learning components were compared to find the limitations in the problem-solving method. The learning components were compared, as shown in Table 2. Several hypotheses were then developed.

2.1. *Expected and unexpected experiences affecting the management of emotion*

Experiential learning suits students because they can feel and learn from the experience themselves. Gaining experience can help them understand the root of the problem in robotic learning. Experience is a feeling where action, emotion, cognition and communication unite (Hohr, 2013). Experience is a subjective and holistic phenomenon in which the person develops the final experience in the environment (Vyas et al., 2005). The Matsuo–Nagata learning model (Matsuo and Nagata, 2020) is an example of experiential learning developed from the Kolb learning model (Kolb, 1984). The Kolb learning model uses experiential learning to help students undergo an active learning process (Isnawati & Jalinus, 2020). Experiential learning also impacts the development of students' metacognitive skills, which can be improved when students can apply their knowledge to real-world situations (Alkan, 2016). Students can experiment with their current or new knowledge gained throughout experiential learning to overcome any simple or complex problem they face.

Experiential learning is frequently an emotional process because metacognitive self-awareness is raised (Morris, 2020). That is, the existence of emotion does influence experiential learning. The Kolb learning model did not introduce the importance of emotion management in experiential learning. Thus, the Matsuo-Nagata learning model discusses the more profound version of concrete experience: expected and unexpected experiences. Through these experiences, students learn to encounter different problems in various situations. Emotion is invariably present in any situation. Therefore, expected and unexpected experiences affect emotion management.

Hypothesis 1. Expected and unexpected experiences have a significant relationship with emotion management.

Table 2
Comparison of learning components.

Experiential learning (Matsuo and Nagata, 2020)	Components of thinking ability (Adnan et al., 2023)	
	Computational thinking	Adversarial thinking
Expected and unexpected experiences	-	-
The management of emotion	-	-
Reflective analysis	Decomposition	Strategic reasoning
	Pattern recognition	Analytics
	Abstraction (Unlearning)	-
Abstract conceptualisation (Unlearning)	Algorithm	Creative
Active experimentation	-	Practical
-	Debugging, Generalization	-

2.2. *Management of emotion*

Good emotional management can help individuals become more confident, optimistic and excellent risk-takers (George & Dane, 2016) in making decisions. The importance of emotion must be considered to ensure that each action can be done rationally and impartially. On the one hand, robotic education helps improve educators' emotions because they are happier working and teaching students how to use the tools (D'Amico & Guastella, 2019). On the other hand, students face difficulties in the new educational environment because they experience changes to use advances in education and technology (Sharma et al., 2019). explained that students enjoy a programming workshop, which suggests short-term gains in their interest in learning. This finding can be linked to the importance of emotions in learning. Emotions are an essential factor. Students who are stressed cannot solve problems optimally (Raj & Vidyaathulasiraman, 2021)Therefore, emotion impacts facing any situation. The emotional management phase can stimulate or hinder a person's learning. For example, feelings of fear, uncertainty and misgivings can enhance a person's learning if managed well. However, if those negative emotions are not controlled, feelings of adversarial or neglect will disturb a person in a problem-solving situation. This reaction can cause important information to be neglected and make problem-solving difficult.

Hypothesis 2. Management of emotion has a significant relationship with CT.

Cyber-attacks can affect an individual's emotions. Anger (due to the feeling of betrayal), fear, and shame, specific flight reactions if the occurrence is related to the person's faults, once they realise they are the victims of cyber-attacks (Searle & Renaud, 2023). Changing one's thoughts or feelings towards stressful circumstances is part of an emotion-focused coping mechanism (Reeves et al., 2021). An individual can anticipate the cybercriminal's action by applying the reverse engineering concept through adversarial thinking (Hamman et al., 2017). However, the emotion must be well-managed first to learn the cyber criminal's behaviour, especially for the victims.

Hypothesis 3. Management of emotion has a significant relationship with adversarial thinking.

2.3. Cyber thinking

Cyber thinking is the integration of computational and adversarial thinking, which will be highlighted as enhanced learning behaviour in this study. The components of CT involved in cyber thinking are pattern recognition, decomposition, abstraction, and algorithm, whereas the components of adversarial thinking included are analytical, creative, and practical. Based on the literature review, CT is one of the beneficial activities to improve students' cognition (Selby, 2013). searched for a definition of CT and explained that CT combines mental tools and computer science, where it can break down large problems into forms that are easier to solve. CT elements include decomposition, abstraction, algorithms, debugging, pattern recognition and generalisation (Shute et al., 2017).

Breaking down data or the processing or breaking down of problems into smaller forms (decomposition); observing patterns, trends, and prevalence in data (pattern recognition); identifying theories or principles used in generating patterns (scaling); developing step-by-step instructions to solve problems (e.g., algorithm design) (Cachero et al., 2020); identifying the types of errors that exist; attempting to solve the error with a trial-and-error method (debugging) (Wong & Jiang, 2019); and adapting a solution that has been formulated to different problems (generalisation) (Cansu & Cansu, 2019). Next, factors such as cooperation in groups, the goal of solving the problem at hand, and the perspective that learning outside the classroom is more fun than learning formally (Nguyen, 2018). explained that this CT activity should be increased and that schools should prioritise having a module that can help their learning sessions.

The CT activity can be implemented in two ways, namely, through activities that do not require technology, such as computers (unplugged activity) or activities that use technology (plugged-in activity) (del Olmo-Muñoz et al., 2020). Several studies have been conducted before, reemphasizing that CT must be applied in recent education (Agbo et al., 2021). found that most previous studies used the approach of designing courses to carry out CT activities. Such course designs consider the importance of having an activity book or module in implementing learning (Thi Nguyet Trang et al., 2025). Appropriate knowledge transfer methods can increase the competitiveness of students so that they can apply it in real life (Harangus & Kátai, 2020). Table 3 presents some of the efforts carried out using various technologies by several researchers to provide exposure to CT activities.

The present study chose the visual programming language Scratch because it uses simple block-based programming, helps cognitive and meta-cognitive development and provides an opportunity to introduce computing principles in a practical and productive method (Duckworth, 2019, pp. 78–82). Most studies for pattern recognition elements involve line-following robots or identifying Bee-Bot map patterns (Angeli & Giannakos, 2020; Pancieri et al., 2019). The pattern recognition-based program is commonly applied in early childhood education because it can provide a fun challenge to those involved in this activity. Decomposition is the second most used element of CT in robotics learning, with a frequency of 35 studies. Based on the assigned task, students must break down the main problem into several manageable problems to understand the situation better.

(Cachero et al., 2020) gave students specific assignments in Python and found that the concept of decomposition helps reduce complex problems (Bakala et al., 2019). agreed that students must divide the main problem into several small problems to facilitate problem-solving (D'Amico & Guastella, 2019). explained that participants use simple programming; that is, they can ignore programming information that is unnecessary in problem-solving or use more profound knowledge. These thinking skills help reduce the problem's difficulty, where students only need to focus on the main task. Focusing on these two elements of CT (Karaahmetoğlu & Korkmaz, 2019), used only basic functions in problem-solving. The algorithm with the highest frequency applied in robotic learning (56 studies) explains that robotic learning participants organise their ideas first when solving problems.

Table 3
Previous computational thinking activities.

Authors	Computational thinking approaches	Observation on participant's involvement
Lin and Shaer (2016)	Using technology games commercial, littleBits	Participants who have used more technology tend to join the activities provided compared to the first time they were involved in such activities.
Pei et al. (2018)	Designing a learning environment computing, Lattice Land	The creativity of the participants has been featured in object construction-mediated mathematics computation. The volunteers are interested in exploring and making important discoveries.
Echeverría et al. (2019)	The Dynamic Geometry tool is used on the Moodle-G platform	The participants were motivated by the Moodle-G platform and gave positive results through the results of the participants' performance after doing polygon building activities.
Rodríguez-garcía (2020)	The use of robots Entry Hamster and Entry platform	Improvement in the aspect of participants' creativity occurs after participating in computational thinking activities
Pérez-Marín et al. (2020)	Scratch programming language used to apply the use of metaphors (MECOPROG)	Students show interest and fun when the activity is carried out. Students also give full attention when completing problems.

(Witherspoon et al., 2017) stated that students learn the elements of computational thought sequencing to repeat several steps several times to develop robotic programming language instructions. The application of algorithmic elements has shown the success of students in developing step-by-step instructions for programming robots in real life (Conde et al., 2019; Pedersen et al., 2018) involved algorithmic elements in improving transportation using mobile robots (Bermúdez, Casado, Fernández, Guijarro, & Olivas, 2019a), also agreed that algorithms are important in designing the movements of drones so that they can take off and land safely at their destination.

Adversarial thinking will be learned along with CT to spread cybersecurity awareness among students. Adversarial thinking can be explained as the ability to anticipate the strategic actions of hackers, useful in cybersecurity using reverse engineering (Hamman et al., 2017). This thinking ability helps to ensure that all information is safe from cyber threats, such as data theft, identity theft and data mining, and can be obtained by learning the thoughts of adversaries (Thah et al., 2019).

(Huang et al., 2020) proposed that a cyber-physical system that uses a game-theoretic approach becomes a standard tool for performing strategic behaviour analysis and can also model the interaction between cyber attackers and their defences. PenQuest is a serious game prototype by (Luh et al., 2020) that exposes the behaviour of intelligent enemies and the defences used against them. Drones, an example of IoT technology, may also provide exposure to the issues of device ownership and stored data, leading to the importance of adversarial thinking knowledge (Kajtazi et al., 2018; Kurakin et al., 2019).

Hypothesis 4. CT has a significant relationship with adversarial thinking.

2.4. Computational reflection

Debugging and generalization from CT were included in computational reflection Students primarily use debugging in school activities. They can identify the errors that exist in the problems in learning activities. Likewise (Rodríguez-Martínez et al., 2020), agreed that students can diagnose programming errors without help from a teacher (Karaahmetoğlu & Korkmaz, 2019), stated that participants could develop various solutions to a problem by identifying multiple possibilities that can occur through elements of CT, such as debugging and generalisation.

Hypothesis 5. CT has a significant relationship with computational reflection.

Online fraudsters and hackers target big companies and people at home. People without knowledge of cybercrime may be the victims of love scams, Macau scams, or even identity theft. Technical knowledge and scientific reasoning are needed to investigate and solve these complex cybercrime situations, which are uncommon for laypersons (Casey et al., 2023). The work or personal life of the cybercrime victim will be disturbed and may lead to depression or suicide. The components of adversarial thinking, including strategic reasoning, can aid people before they fall into cybercrime. Furthermore (Jung et al., 2022), proposed educational aids to elementary students by teaching hacking principles to improve their CT skills. This early approach, chosen as hacking accident graphs, has been worrying escalated over ten years (Agency, 2020).

Hypothesis 6. Adversarial thinking is stated to have a significant relationship with computational reflection.

Computational reflection consists of debugging and generalisation components. Debugging is a skill for testing and fixing errors through logical thinking to predict and verify the results (Aminah & Maat, 2023), while generalisation will apply the solution knowledge from debugging to different situations (Wan Ali & Wan Yahaya, 2022). More knowledge can be developed and applied to different situations (expected and unexpected experiences) using these two components.

Hypothesis 7. Computational reflection has a significant relationship with expected and unexpected experiences.

2.5. Conceptual framework

The conceptual framework for this study shows the relationship between five components of experiential learning from the integration of the Matsuo-Nagata learning model and cyber thinking elements. Some of the model components of the Matsuo-Nagata learning model have been improved with the cyber thinking elements to give an in-depth application of the learning model. Seven hypotheses have been constructed, showing the components' relationship. Previously, the Matsuo-Nagata learning model was in the cyclic form, where an individual must undergo the whole cycle to complete experiential learning. However, the elements of this Cyber Thinking Behavioural Model are connected. Several research hypotheses were developed during the model development session. The development of this hypothesis is significant because it is the study's basis, where critical elements can be studied and conclusions can be made (Toledo et al., 2011). Table 4 lists initial hypotheses based on integrating the Matsuo–Nagata learning model with computational and adversarial thinking from the literature review. Fig. 1 illustrates the relationship between research hypotheses and experiential learning integrated with computational and adversarial thinking.

As shown in Fig. 1, the stages of experiential learning are directly mapped onto the Cyber Thinking Behavioural Model: concrete experience is represented by students' expected and unexpected experiences with the drone, reflective observation by computational reflection (debugging and generalisation), abstract conceptualisation by the integration of computational and adversarial thinking into cyber thinking, and active experimentation by the iterative programming and testing of drone solutions in response to emerging problems. Taken together, the constructs form a Cyber Thinking Behavioural Model in which learners move from expected and unexpected cyber experiences, through emotion regulation and computational problem-solving, into adversarial reasoning and, finally, reflective debugging and generalisation. In this cycle, experiences trigger emotional and cognitive responses, emotion management supports sustained engagement, computational thinking provides structured strategies, adversarial thinking orients learners to hostile actors and attack surfaces, and computational reflection consolidates and extends learning. This model is adopted to explain how cyber-focused workshops can systematically cultivate cyber thinking behaviour rather than isolated technical skills.

Table 4
Initial hypotheses of the study.

No.	Hypotheses
H1	Expected and unexpected experiences have a significant relationship with the management of emotion.
H2	Management of emotion has a significant relationship with computational thinking.
H3	Management of emotion has a significant relationship with adversarial thinking.
H4	Computational thinking has a significant relationship with adversarial thinking.
H5	Computational reflection has a significant relationship with expected and unexpected experiences.
H6	Computational thinking has a significant relationship with computational reflection.
H7	Adversarial thinking has a significant relationship with computational reflection.

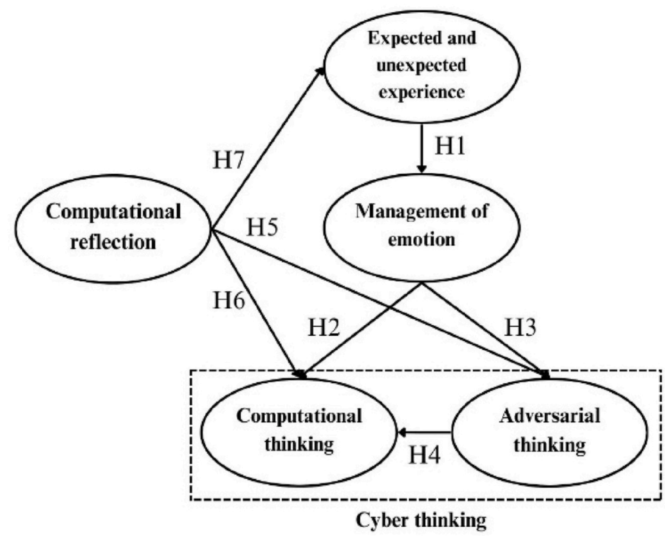

Fig. 1. The proposed conceptual model of cyber thinking.

3. Methodology

3.1. Research procedure

Fig. 2 summarises the overall research procedure adopted in this study, which comprised four sequential steps. Step 1 (Factors extraction) involved identifying the key components of cyber thinking through a systematic literature review and focus group discussions with experts, leading to the formulation of seven hypotheses underpinning the conceptual model. Step 2 (Instrument development and validation) focused on constructing a questionnaire based on the identified factors; this instrument was subsequently reviewed and validated by domain experts before pilot testing with teachers. In Step 3 (Model Development and

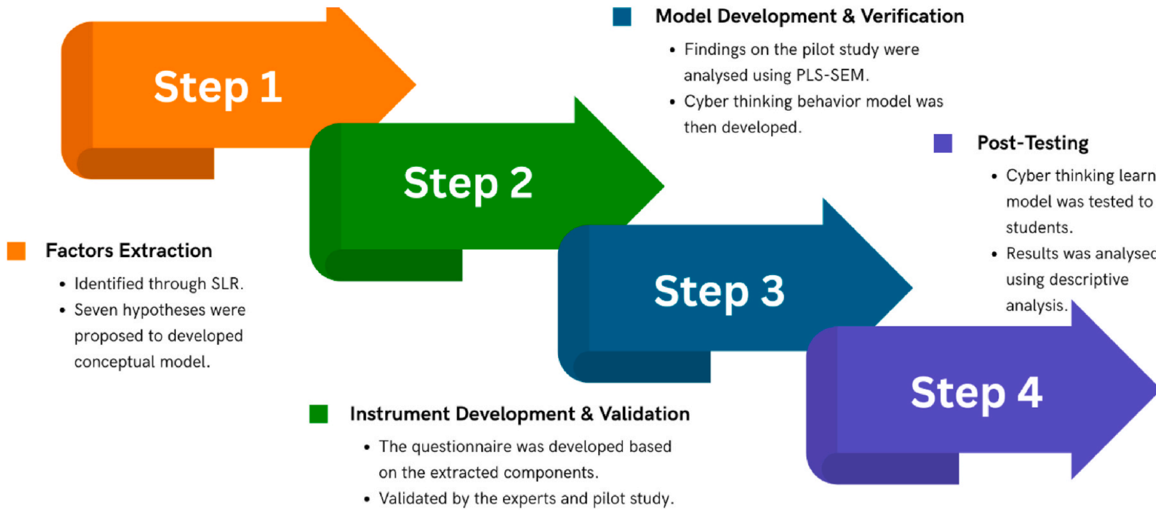

Fig. 2. Research methodology.

Verification), data from the teacher pilot study were used to analyse the measurement and structural model using PLS-SEM and to obtain the final Cyber Thinking Behavioural Model. The post-test data were analysed descriptively to examine the effectiveness of the finalised model in a real classroom robotics context. Then, the model was finally applied with students.

The Cyber Thinking Behavioural Model was subjected to post-testing with lower secondary school pupils from Form 1 to Form 3 selected from mixed-ability classes (high medium low achievers) which reflect the normal classroom. The model was implemented through a one-day workshop comprising an introductory briefing and pre-test, group-based robotics activities designed around expected and unexpected experiences, guided reflection on emotions and problem-solving, and a concluding post-test and debriefing. Before the workshop, teachers and facilitators attended a training session on the model's five components, the robotics tools, and strategies for eliciting computational and adversarial thinking while supporting students' emotions and ensuring inclusive participation.

3.2. Questionanaire instruments

Questionnaire instruments allow researchers to make conclusions or generalisations about a large population by only studying a small part, applying a systematic procedure that includes scientific sample survey research (Rea & Parker, 2014). In this study, the questionnaire was designed to measure the five main components of the Cyber Thinking Behavioural Model: (i) expected and unexpected experience, (ii) Management of emotion, (iii) Computational thinking, (iv) Adversarial thinking, and (v) Computational reflection. To ensure content validity and strengthen the reliability of the instrument, a panel of experts specialising in experiential learning, computational thinking and adversarial thinking reviewed all items. These experts evaluated each item for clarity, relevance and alignment with the underlying constructs, and revisions were made based on their feedback before the pilot administration (refer to Table 5) (Tong, 2024) and analysed using PLS-SEM analysis (Gorai et al., 2024). The resulting instrument was then analysed using PLS-SEM to examine its internal consistency and construct validity (Gorai et al., 2024). Subsequently, the final model of cyber thinking was validated with students to assess its significance in real-world situations, with student data analysed using SPSS. Fig. 2 summarises the methodology for this study.

Table 5
Questionnaire instruments.

Components	Items
PDTD: Expected and Unexpected Experience	PDTD1: I am always prepared to encounter any problems. PDTD2: I know the consequences of my actions. PDTD3: I easily get anxious if I am in a new situation.
E: Management of emotion	E1: I am good at expressing my emotions. E2: I can think well when I am in a positive emotion. E3: I can be rational in every situation or problem.
PK: Computational thinking (Cyber thinking)	PK1: I can decompose the problem to make it easy to solve. PK2: I can identify ways to solve problems. PK3: I can generally identify the concept of a solution. PK4: I can design the solution in an orderly manner. PK5: I learn strategic reasoning through drone activity.
PT: Adversarial thinking (Cyber thinking)	PT1: I can think critically during problem-solving. PT2: I am good at thinking creatively. PT3: I clearly understand the purpose of the solution. PT4: I know the importance of programming as one of the ways to keep drones safe from being hacked. PT5: I know the importance of maintaining data privacy when using drones. PT6: I understand the bad effect if a drone falls into a criminal's hands.
R: Computational reflection	R1: I understand the weakness of the designed solution. R2: I understand the usage of the designed solution in daily life. R3: I understand the importance of reflection-making at activities.

3.3. Instructional procedures

In implementing the Cyber Thinking Behavioural Model, the robotics workshop was structured into four stages that correspond to the experiential learning components: expected and unexpected experiences, management of emotion, cyber thinking (computational and adversarial thinking), and computational reflection.

1. Expected and unexpected experiences (Concrete experience)

At the beginning of the workshop, students were introduced to a programmable drone and its control interface, which many of them were experiencing for the first time. After a short briefing on basic computational thinking concepts (decomposition, pattern recognition, abstraction, and algorithm), students engaged in hands-on drone programming tasks, such as designing simple flight paths (take-off, hovering, and landing) and basic manoeuvres. Subsequent tasks deliberately introduced unexpected conditions, for example, navigating maze-like flight routes, responding to virtual no-fly zones, and avoiding obstacles detected by sensors, so that students had to handle both planned and unplanned situations during the activities.

2. Management of emotion (Guided emotional regulation during tasks)

The teachers and facilitators drew students' attention to their feelings (e.g. excitement, frustration, anxiety) during the drone programming and flying when the flight plan didn't work, when the drone didn't follow the expected route, or when groups didn't do as well in the flying challenges. Facilitators encouraged students to talk about their feelings, normalised errors and crashes as part of the learning process, and redirected their attention back to problem solving rather than giving up. For example, they were led through a discussion on improving their flight paths or safety strategies after an unsuccessful attempt. This process exemplified the emotional management component, which students were assisted in employing to remain rational and resilient in the face of difficulties during the drone operations.

3. Cyber thinking stage (computational and adversarial thinking with drones)

In the cyber thinking stage, students applied computational and adversarial thinking to organized drone tasks. Students applied computational thinking to break down the complex missions of the drone (e.g., take-off, waypoint navigation, altitude change, landing) into smaller steps; identify patterns in successful and unsuccessful flight paths; and devise algorithms to code the drone with a sequence of steps. Role-play activities took place in which one student was the “programmer” and another was the “drone”, which only acted according to the instructions given to them, to show the necessity of accurate, unambiguous commands. For the adversarial thinking activity, the students discussed and strategized scenarios related to drone security. Some points consisted of understanding how strong a connection needs to be, what happens if a drone were to be hijacked or used for crime, how coding poor coding or weak security settings could be exploited and extensively more similar points. These procedures necessitated students' predictions of possible attacks or failures along with strategically reasoning towards protecting drones, data and people.

4. Computational reflection (debugging and generalisation in drone flights)

After the completion of each drone activity, students were asked to observe the drone's behaviour, recognize the errors in the drone's flight program, and debug by changing the parameters or modifying the code and testing it again. The facilitators prompted participants to state what went wrong and how they fixed it. Furthermore, they also asked how the same solution would be applied to other flight scenarios. For example, adapting a successful obstacle avoidance strategy for a different route, or reusing a stable take-off/landing sequence for a complex mission. The students also considered the strengths and weaknesses of their flight plans and the real-life possible applications for safe and secure drones. The computational reflection stage in experience-based activities of drone-based activities was completed via this structured debrief.

3.4. Statistical analysis

The data from the teacher (pilot study) questionnaire were analysed using Partial Least Squares–Structural Equation Modelling (PLS-SEM), while the student (post-testing) data were analysed using SPSS. The PLS-SEM analysis is proposed to be reported using the report style by (Salah et al., 2021). The PLS-SEM procedure followed a two-step approach: first, the measurement model was assessed by examining indicator loadings, Cronbach's alpha, composite reliability, average variance extracted (AVE), and discriminant validity for each construct of the Cyber Thinking Behaviour Model (expected and unexpected experience, management of emotion, computational thinking, adversarial thinking, and computational reflection). Second, the structural model was evaluated by estimating path coefficients for hypotheses H1–H7 and testing their statistical significance.

Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed to develop and evaluate the Cyber Thinking Behavioural Model, given the moderate sample size and the presence of multiple latent constructs and indicators. The analysis followed a two-step procedure in which we first assessed the measurement model (indicator reliability, internal consistency, convergent validity, and discriminant validity) and then examined the structural model by estimating standardized path coefficients, testing their statistical significance using bootstrapping, and reporting the explained variance (R^2) of the endogenous constructs. A descriptive statistics would be examined for all questionnaire items and components (means and standard deviation). The principal reliability and validity indices are summarised in Table 7. A hypothesis testing (bootstrapping) results are presented in the Results Section.

3.5. Sampling and participants

This study used a purposive sampling method to recruit teachers and students engaged in school-based robotics or STEM activities. In collaboration with the district education office, we are identifying lower-secondary schools that offer robotics co-curricular programmes and are willing to work on the cyber thinking workshop. The inclusion criteria for teachers were: (i) teachers presently teaching ICT, science, maths or robotics-related subjects; (ii) teachers who had at least one year of experience in supervising robotics or technology-enriched activities. The selection of students was done using the following criteria. As mentioned, students from Form 1 to Form 3 were chosen from mixed-ability classes (i.e. high, moderate and low achievers) to reflect typical classroom composition. Also, students who have severe learning or behavioural difficulties would be excluded. Most importantly, this will prevent the students from participating in group-based robotics work.

A total of 131 teachers were involved in the phase of model development and validation, while participating in post testing workshop were 116 students (that was supported by 25 teachers/facilitators). The sample of teachers surveyed is sufficient for PLS SEM analysis due to the complexity of the Cyber Thinking Behavioural Model involving more than one significant construct of the model and its structural paths. Current recommendations for PLS SEM models suggest that the sample size should not only depend on the rules of thumb, such as the “10 times rule,” but also on the complexity of the models, the number of parameters, and the necessary statistical power (Hair & Alamer, 2022). Recent methodological work notes that PLS-SEM is particularly suitable when the research objective is prediction and theory development and when data characteristics (e.g., non-normality, moderate samples) would challenge covariance-based SEM (Hair & Alamer, 2022). In this study, the teacher sample (N = 131) comfortably exceeds the minimum sample size estimates suggested for models of similar complexity, targeting a power level of approximately 0.80, which is considered acceptable for hypothesis testing in behavioural and educational research (Haji-Othman et al., 2024).

4. Result

4.1. Pilot study

The first statement in the aspect of expected and unexpected experience refers to the component of the expected experience. Based on the average cumulative score for the expected experience component, as shown in Table 5, most experts agree that students must be prepared before facing various problems. The experts also agreed that students knew the consequences of their actions. However, most experts also agreed that students often experience anxiety when facing problems. Emotional management refers to how we handle our emotions well, either on our own or with the help of others. Table 5 shows positive feedback, where most experts agree that students can express their emotions instead of just sitting in silence. This feedback shows the importance of emotions when solving problems. Teachers also agree that students can solve various problems when in a rational state. Table 6 shows the research findings for aspects of CT, one of the elements found in the cyber thinking component. Four components of CT and one element of adversarial thinking were included. Table 6 shows the relationship between those questions developed based on CT elements (Adnan et al., 2026).

The findings in Table 7 show that decomposition, pattern recognition, scaling, and algorithm components have high average scores for Moderately Agree (5) and Agree (6). The scores explain that the students can apply the components to the problem-solving session. The average score for the strategic reasoning component is highest for Neutral (4). This neutral agreement may be due to the confusing statement for item 5. The teacher suggested changing the word 'strategic reasoning' to a term easier for students to understand. In this section, aspects of cybersecurity are questioned through adversarial thinking. The use of adversarial thinking elements for each item is as follows: analytical (item 1), creative (item 2), practical (item 3), technological capability (item 4), unconventional perspective (item 5), and cybersecurity (item 6). Overall, the highest average score is a score of 5 (Moderately Agree) and a score of 6 (Agree), as shown in Table 5. The scores indicate that teachers accept the aspect of adversarial thinking in improving aspects of cybersecurity among students. The computational reflection component is the final part of the questionnaire. This component is intended to help students conclude at the end of problem-solving activities. Two elements of CT, namely, debugging and generalisation, are applied in this section.

4.2. PLS-SEM analysis

The constructs of computational thinking (PK), adversarial thinking (PT), expected and unexpected experiences (PDTD), emotional management (E), and computational reflection (R) are measured. A reliability test was done by measuring Cronbach's alpha. Based on (George & Dane, 2016). Construct reliability is required to evaluate the consistency of the indicators comprehensively. The α value higher than or equal to 0.90 has excellent reliability, while an α value higher than or equal to 0.80 means good reliability. Reliability is still acceptable if the value of α is higher than or equal to 0.7. An α value below 0.50 is considered weak and needs evaluation.

As shown in Table 8, all constructs showed high Cronbach's alpha values. Convergent validity explains the importance of a construct based on its indicators. The AVE value must be at least 0.5 to be considered a good measure of convergent validity (Purwanto & Sudargini, 2021). All four constructs shown in Table 8 are accepted because they have at least a 0.535 AVE value. As shown in Table 8, all square root values of AVE indicate no overlap between the constructs and emphasize that the constructs are unique. The Expected and Unexpected Experience (PDTD) construct used three items with both positively and negatively worded statements to reduce acquiescence bias and capture confidence as well as discomfort in new situations. This mixed wording made the items less homogeneous, which lowered Cronbach's alpha (α = 0.469), even though composite reliability (CR = 0.766) and AVE (0.535) met recommended thresholds (Barnette, 2000). This pattern suggests that the items still reflect a common latent factor with acceptable reliability and convergent validity, but the wording mix attenuated inter-item correlations and yielded a conservative alpha estimate (Salazar, 2015). Given the theoretical importance of covering both expected and unexpected experiences, and the acceptable CR and AVE, all three PDTD items were retained, with the acknowledgement that alpha likely underestimates their true reliability.

Discriminant validity is essential in introducing a construct by testing the combination of those constructs into a new theory (Matthes & Ball, 2019). HTMT results in Table 9 indicate that most of the correlations between constructs were below the conservative threshold of 0.85, indicating adequate discriminant validity of the latent variables. The relationships between Adversarial Thinking (PT) and Computational Reflection (R) (HTMT = 0.906) and Adversarial Thinking (PT) and Computational Thinking (PK) (HTMT = 0.908) are slightly above the threshold, so they might be conceptually close. Given that both adversarial reasoning and computational reasoning use some form of analysis and problem solving, such overlap might be possible. The other construct pairs are evidently separated as the emotional and experiential dimensions of the model can be distinguished (see Table 10).

The Fornell-Larcker criterion further confirms discriminant validity. Construct values are greater than inter-construct correlation values. Value of PT is 0.792, R is 0.919, CT is 0.867, E is 0.786 and PDTD is 0.894. All constructs meet this requirement, as shown by the correlation value where the highest correlation is noted at PT and CT (0.832) while not exceeding CT (0.867). This almost-threshold relationship indicates a substantial theoretical connection between adversarial and computational thinking, which are both higher-order cognitions. Moderate correlations between R, E, and PDTD (0.413–0.570) suggest that this emotional and experiential construct are not a purely cognitive one. Together, the HTMT and Fornell–Larcker results confirm the measurement model has strong discriminant validity.

According to (Mitchell & Jolley, 2013), such R^2 values are small when they range from 0.01 to 0.09, moderate from 0.09 to 0.25, and substantial if they are from 0.25 to 1. Table 11 presents the R^2 and adjusted R^2 values of the endogenous constructs, Adversarial Thinking (PT), Computational Thinking (PK), the Management of Emotion (E), and Expected and Unexpected Experience (PDTD), indicating the explanatory power of our structural model. The R^2 values for PT, PK, and E at 0.786, 0.646, and 0.325, respectively, indicate that the exogenous variables explain significant portions of variance in these variables. Specifically, the excellent R^2 value of Adversarial Thinking (0.786) suggests that the predictors greatly explain the variance in Adversarial Thinking and the model offers a good capture of the cognitive mechanisms involved in Adversarial Thinking. Computational Thinking has an excellent explanatory power value of 0.646, indicating that the model is

Table 6
Correlate the questionnaire items with cyber thinking (computational and adversarial thinking).

No.	Item	Elements of Computational Thinking
1.	I can decompose the problem to make it easy to solve.	Decomposition
2.	I can identify the way to solve the problem.	Pattern recognition
3.	I can generally identify the concept of a solution.	Abstraction
4.	I can design the solution in an orderly manner.	Algorithm
		Elements of adversarial thinking
5.	I learn strategic reasoning through drone activity.	Strategic reasoning

Table 7
Cumulative score data for each component.

Components	Items	Strongly Disagree	Disagree	Moderately Disagree	Neutral	Moderately Agree	Agree	Strongly Agree	Mean	SD
Expected and Unexpected Experience (PDTD)	PDTD1	-	1	10	20	33	57	11	5.27	1.11
	PDTD2	-	-	4	12	31	71	14	5.60	0.91
	PDTD3	-	4	8	31	35	38	16	5.08	1.24
	Total (%)	-	5 (1%)	22 (6%)	63 (16%)	99 (25%)	166 (42%)	41 (10%)		
Management of Emotion (E)	E1	-	2	8	27	29	49	14	5.22	1.17
	E2	-	1	2	12	23	65	25	5.75	0.98
	E3	-	-	7	18	47	46	11	5.28	0.99
	Total (%)	-	3 (1%)	17 (4%)	57 (15%)	99 (26%)	160 (41%)	50 (13%)		
Computational Thinking (PK)	PK1	1	-	7	11	53	47	6	5.24	0.98
	PK2	1	-	6	13	49	50	6	5.26	0.98
	PK3	1	-	4	11	57	48	4	5.26	0.89
	PK4	1	-	5	17	52	48	2	5.17	0.92
	PK5	3	1	9	41	36	31	4	4.72	1.18
	Total (%)	7 (1%)	1 (0%)	31 (5%)	93 (15%)	247 (40%)	224 (36%)	22 (4%)		
Adversarial Thinking (PT)	PT1	1	-	6	23	50	46	5	5.13	0.99
	PT2	1	-	11	22	53	38	6	5.02	1.05
	PT3	-	1	6	16	46	56	6	5.28	0.95
	PT4	2	2	14	22	36	43	12	5.02	1.30
	AT5	2	3	5	23	33	40	25	5.31	1.33
	PT6	-	2	2	21	25	48	33	5.63	1.16
	Total (%)	6 (1%)	8 (1%)	44 (6%)	127 (16%)	243 (31%)	271 (34%)	87 (11%)		
Computational Reflection (R)	R1	1	2	8	32	43	39	5	4.93	1.10
	R2	1	3	7	23	48	40	8	5.05	1.13
	R3	1	2	4	11	34	54	24	5.56	1.15
	Total (%)	3 (1%)	7 (2%)	19 (5%)	66 (17%)	125 (32%)	133 (34%)	37 (9%)		

Table 8
Reliability and validity.

Construct	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
Expected and unexpected experience, PDTD	0.752	0.888	0.799
Management of emotion, E	0.692	0.829	0.618
Computational thinking, PK	0.916	0.938	0.752
Adversarial thinking, PT	0.881	0.910	0.628
Computational reflection, R	0.908	0.942	0.844

Table 9
Heterotrait-Monotrait Ratio of Correlations (HTMT) criteria.

	PT	R	PK	E	PDTD
Adversarial Thinking, PT					
Computational Reflection, R	0.906				
Computational Thinking, PK	0.908	0.835			
Management of Emotion, E	0.713	0.514	0.667		
Experience and Unexpected Experience, PDTD	0.551	0.504	0.525	0.773	

Table 10
Fornell-Larcker criteria.

Construct	PT	R	CT	E	PDTD
Adversarial Thinking, PT	0.792				
Computational Reflection, R	0.810	0.919			
Computational Thinking, CT	0.832	0.764	0.867		
Management of Emotion, E	0.572	0.413	0.542	0.786	
Experience and Unexpected Experience, PDTD	0.455	0.424	0.444	0.570	0.894

Table 11
R^2 values.

	R-square	R-square adjusted
Adversarial thinking, PT	0.786	0.781
Computational thinking, PK	0.646	0.640
Management of emotion, E	0.325	0.319
Expected and unexpected experience, PDTD	0.180	0.173

adequate in specifying the relationships among the cognitive and emotional dimensions affecting this construct.

On the other hand, Management of Emotion predicts a moderate R^2 (0.325), which indicates that the predictors seem to work, but there are other reasons as well. The R^2 value of Expected and Unexpected Experience (PDTD) is the lowest among the structures reported here (0.180). The weak explanatory power, characteristic of a dependent variable, is owing to the indirect effect through Management of Emotion. The adjusted R^2 values are close to the unadjusted R^2 value of the model, which confirms a stable and non-overfitted model. All in all, these findings show that the structural model has a strong predictive relevance for the main cognitive constructs and moderate explanatory power for the experiential dimension.

Table 12 presents the f^2 effect size values, which quantify the contribution of each exogenous construct to the explanatory power of the endogenous variables. According to Cohen's (1988) guidelines, f^2

Table 12
f^2 values.

Construct	PDTD	E	PK	PT	R
Experience and Unexpected Experience, **PDTD**		0.482			
Emotion Management, **E**			0.175	0.098	
Computational Thinking, **PK**				0.288	
Adversarial Thinking, **PT**					
Computational Reflection, **R**	0.219		0.993	0.344	

values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively. Findings showed that the influence of the constructs varies in magnitude and there are relationships present in the structural model. The most significant outcome is seen between the reflection during the computational phase (R) and the knowledge in the computational phase (PK). Thus, computational reflection significantly boosts computational thinking and validates the theoretical relationship between metacognitive reasoning and problem-solving capability. Correspondingly, R → Adversarial Thinking (PT) ($f^2 = 0.344$) shows a large effect, suggesting that reflective thinking is an important factor for developing adversarial thinking.

The effects of Experience and Unexpected Experience (PDTD)→ Emotion Management (E) ($f^2 = 0.482$), Computation Thinking (PK)→ Adversarial Thinking (PT) ($f^2 = 0.288$) moderate meaningful (but not dominating) effects. The use of experiential learning and cognition for emotional regulation and capacity to act adversarially are positively related. The relationship of E → PK ($f^2 = 0.175$) and E → PT ($f^2 = 0.098$) denotes the limited but essential impact of emotional management on cognitive constructs. Ultimately, R for Computational Reflection and E for Emotion Management $f2$ of 0.219 manifests a moderate effect, which means reflective processes affect the regulation of emotions moderately. Overall, the pattern of values of f^2 indicates that Computational Reflection is the most significant variable in the model and acts as a central driver of the cognitive as well as emotional dimension. The outcomes indicate that the model's theoretical framework is validated, revealing strong relationships between reflection, cognition, and emotion.

As shown in Table 13, the cross-loading matrices of all indicators and constructs. Overall, each of the indicators shows its maximum loading to the construct being measured, which supports item-level discriminant validity of the reflective measurement model. However, Experience and Unexpected Experience and Management of Emotion cross-loadings indicate that these construct are more related to each other, compared, relative to the other dimensions. E3 has relatively strong loading on Management of Emotion and high loading on Computational Thinking, indicating conceptual proximity rather than real violations of discriminant validity. Since the loadings of no indicator on the non-target constructs are stronger than their own, the cross-loading pattern does not suggest problematic overlap. Instead, it indicates theoretically meaningful relationships between closely related constructs.

The Variance Inflation Factor (VIF) values presented in Table 14 assess the degree of multicollinearity among the constructs in the model. Multicollinearity exists where two or more predictor variables are correlated and, therefore, contains information not available to the other predictor(s). In a regression model, this condition inflates variance of the regression coefficient, which must affect other estimates. A VIF value lower than 5 is acceptable, suggesting that the predictor variables are adequately different. In this analysis, the VIF values for all constructs range from 1.319 to 4.277, indicating that no multicollinearity exists among the constructs. Items E1, E2, E3, and PDTD1 to PDTD2 have very small values of VIF which are highly independent. Value of VIF for items PK and PT is slightly higher but they are still within acceptable limits. In general, the findings indicate that the model's predictors are well specified and that path coefficient estimates are not adversely affected by multicollinearity.

The model fit results in Table 15 evaluate how well the estimated structural model represents the observed data compared to the saturated model, which assumes perfect fit. A value of 0.102 is marginally acceptable as a value of below 0.10 is considered good. Values of d_ULS

Table 14
Variance Inflation Factor (VIF) values.

Construct	VIF
PDTD1	1.571
PDTD2	1.571
E1	1.326
E2	1.319
E3	1.423
PK1	3.143
PK2	3.775
PK3	3.391
PK4	3.847
PK5	1.710
PT1	3.451
PT2	3.691
PT3	3.779
PT4	3.230
PT5	4.038
PT6	2.192
R1	3.138
R2	4.277
R3	2.657

Table 15
Model fit.

	Saturated model	Estimated model
SRMR	0.094	0.102
d_ULS	1.674	1.959
d_G	0.891	0.958
Chi-square	601.14	594.922
NFI	0.701	0.704

Table 13
Cross loading values.

Construct	Experience and Unexpected Experience	Management of Emotion	Computational Thinking	Adversarial Thinking	Computational Reflection
PDTD1	0.868	0.446	0.334	0.381	0.332
PDTD2	0.919	0.563	0.450	0.429	0.418
E1	0.457	0.766	0.423	0.367	0.235
E2	0.359	0.747	0.332	0.465	0.349
E3	0.514	0.842	0.506	0.512	0.384
PK1	0.415	0.480	0.878	0.692	0.617
PK2	0.446	0.579	0.893	0.757	0.628
PK3	0.404	0.458	0.896	0.716	0.667
PK4	0.412	0.532	0.915	0.762	0.725
PK5	0.236	0.28	0.741	0.672	0.672
PT1	0.411	0.592	0.800	0.830	0.633
PT2	0.375	0.537	0.742	0.817	0.585
PT3	0.439	0.547	0.790	0.866	0.704
PT4	0.236	0.288	0.565	0.772	0.636
PT5	0.283	0.297	0.565	0.779	0.681
PT6	0.399	0.399	0.410	0.677	0.631
R1	0.343	0.363	0.648	0.700	0.904
R2	0.403	0.345	0.692	0.710	0.944
R3	0.416	0.425	0.757	0.813	0.908

and d_G discrepancy measures of 1.959 and 0.958 are low, thus indicating that estimated model is close to saturated model. The Chi square statistic for the estimated model (594.922 vs. 601.14) is slightly lower, indicating little improvement in fit. In conclusion, the NFI value of 0.704 is also greater than the minimum acceptable value of 0.70. Thus, this shows that the model achieves a satisfactory level of adequacy. The overall results indicate that the estimated model meets a fair model fit, with a minor deviation that remains within the conventional limit for PLS SEM analysis.

In the structural model, the standardized path coefficient β represents the strength and direction of the relationship between each exogenous and endogenous construct. Values of β range from -1 to $+1$, where coefficients approaching $+1$ indicate a strong positive relationship and those approaching -1 indicate a strong negative relationship (Hair et al., 2017). As shown in Table 16, all estimated path coefficients are positive ($\beta = 0.172$ to 0.651), demonstrating that increases in the exogenous constructs are associated with increases in their respective endogenous constructs. The statistical significance of these relationships was assessed using bootstrapping, and all paths yield p-values below 0.05 and y-values well above the 1.96 threshold, indicating that each relationship is significant at the 5% level. Consequently, all seven hypotheses (H1–H7) are accepted, confirming that the proposed directional effects between the constructs are empirically supported in the structural model. Hypothesis support for each construct is explained in Table 16. Based on the final model in Fig. 3, the path model of the Cyber Thinking Behavioural Model has been developed, which is then illustrated for the final model as shown in Fig. 4. This Cyber Thinking Behavioural Model includes experiential learning components that can influence robotics learning such: (1) expected and unexpected experiences, (2) management of emotion, (3) cyber thinking (computational and adversarial thinking) and (4) computational reflection.

4.3. Post-testing

Based on the developed Cyber Thinking Behavioural Model, the model was then tested on actual students. As shown in Table 17, the robotics workshop was implemented as a structured one-day intervention designed to enact all components of the Cyber Thinking Behavioural Model in the classroom setting.

The day begins with an introductory briefing and pre-test, which orients students to the activities and captures baseline scores for expected/unexpected experiences (PDTD), emotion management (E), computational thinking (PK), adversarial thinking (PT), and related behaviours. The subsequent drone familiarisation session provides initial, expected experiences and focuses on basic pattern-related aspects of computational thinking as students learn to control the drones and observe their responses. In the next session, students encounter unexpected tasks such as obstacles, failures, and errors, which are deliberately designed to trigger both cognitive and emotional challenges. This session targets unexpected experiences, emotion management, and debugging within computational thinking, with facilitators guiding students to document errors and reflect on their emotional reactions. The midday adversarial scenarios then shift attention to adversarial thinking, using privacy and misuse discussions to raise cyber-physical risk awareness; students work as a whole class to identify threats and articulate attacker perspectives, linking these insights back to PT.

The afternoon challenge tasks integrate computational and adversarial thinking in more complex missions, operationalising cyber thinking as students plan, program, and execute drone solutions that must be both functionally correct and security-aware. The reflection and generalisation session then foregrounds computational reflection (R), using worksheets to help students analyse their strategies, debug conceptually, and generalise lessons to future expected and unexpected situations. Finally, the post-test and closing segment reassesses PDTD, E, PK, PT, and R, allowing the model's dimensions to be compared against baseline and giving students space to provide feedback on their experiences.

Fig. 5 illustrates the demographic distribution of students by gender, age, and race. The chart shows that male students (64) slightly outnumber female students (49). In terms of age, the largest group is 15-year-olds (50), followed by 13-year-olds (25), 14-year-olds (21), and 16-year-olds (17), indicating that most participants are mid-teen students. Regarding race, the majority are Malay (100), with smaller representations of Chinese (11) and Indian (2) students. Overall, the figure highlights a predominantly Malay student population, balanced gender representation, and concentration around the age of 15. Fig. 6 shows students actively participating in a drone-related learning activity, involving teamwork, hands-on assembly, and outdoor practice in operating drones.

The students also have chosen their most liked and disliked school subject, as shown in Table 18. Based on the findings, Mathematics has been the favourite subject of the students. It can be said that having Mathematics as their favourite subject does give interest in drone activity, where they can learn numbers (such as measurement and scale) and increase their problem-solving skills by playing with drones (Pergantis & Drigas, 2024). This study applied a paired *t*-test to compare the students' scores before and after the workshop, which is the recommended approach for one-group pre-test/post-test designs (Ross & Willson, 2017).

Table 19 shows that the robotics workshop is associated with modest but meaningful short-term gains in students' self-reported cyber-thinking constructs. Scores for Expected and Unexpected Experience (PDTD) and Management of Emotion (E) increase only slightly, with small effect sizes and non-significant t-tests, suggesting that these foundational perceptions did not change substantially over the brief intervention. In contrast, Computational Thinking (PK), Adversarial Thinking (PT), and Computational Reflection (R) show small-to-moderate, statistically significant improvements, indicating that students felt more capable of applying computational strategies, thinking from an adversarial perspective, and engaging in debugging and generalisation after the workshop. When all items are considered together, the overall mean rises from 3.42 to 3.74, yielding a small-to-moderate, significant effect, consistent with the view that the Cyber Thinking Behavioural Model supports short-term enhancement of cyber-oriented thinking and reflective problem-solving during drone-based experiential activities.

5. Discussion

The Cyber Thinking Behavioural Model is intended to help teachers

Table 16
Bootstrapping result.

Hypothesis (H)	Relationship of constructs	β	t-value	p-value	Hypothesis Result	Supported By
H1	PDTD→PE	0.570	7.623	0.000	Accepted	Myyry et al. (2020)
H2	PE→PK	0.273	2.047	0.042	Accepted	Sun et al. (2020)
H3	PE→PT	0.172	3.104	0.002	Accepted	Uddin and Rahman (2022)
H4	PK→PT	0.417	4.805	0.000	Accepted	Hamman et al. (2017)
H5	R→PDTD	0.424	3.933	0.000	Accepted	Jones et al. (2020)
H6	R→PK	0.651	5.585	0.000	Accepted	(Bermúdez et al., 2019a)
H7	R→PT	0.420	5.390	0.000	Accepted	Hart et al. (2020)

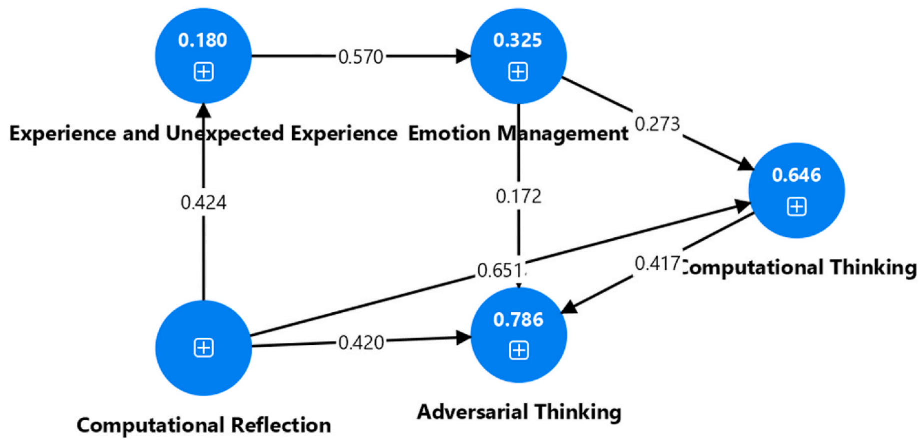

Fig. 3. Final path model.

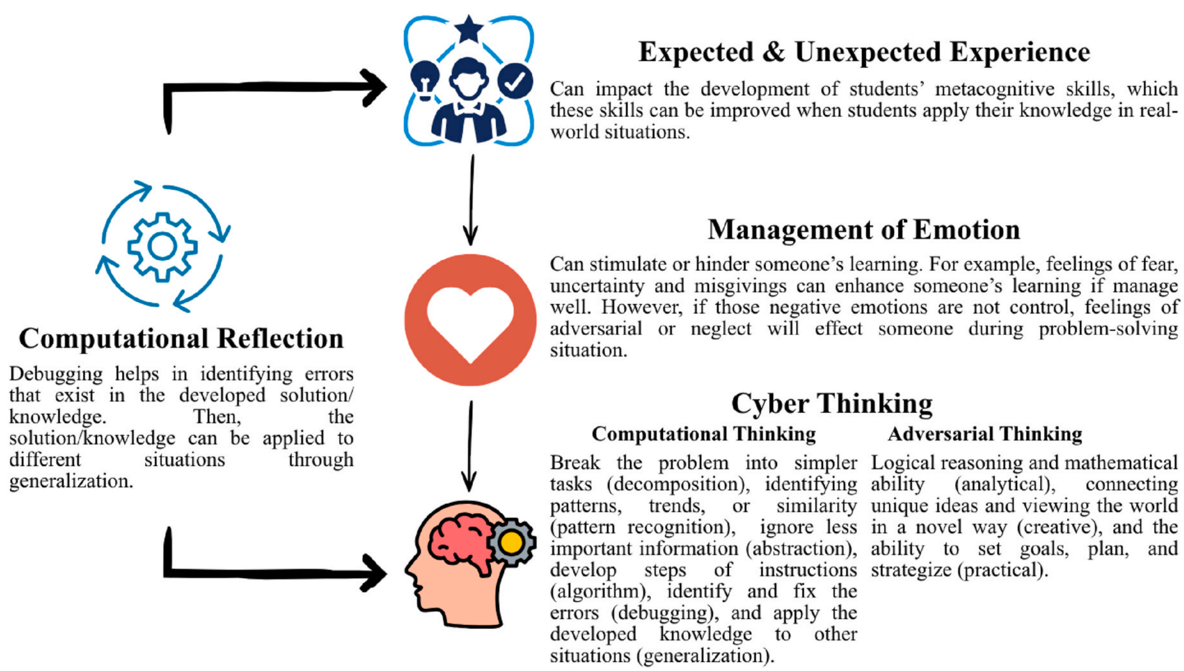

Fig. 4. Cyber thinking behavioural model.

Table 17
Robotics workshop schedule and mapping to Cyber Thinking Behavioural Model.

Session time	Activity description	Learning objectives (constructs)	Group size/facilitator	Materials and tools	Student assessment
9.00am – 9.30am	Introduction, briefing, pre-test	Orient students; baseline (PDTD, E, PK, PT)	Whole class; 1 teacher, 1 facilitator	Pre-test questionnaire; slides	Completed pre-test, initial questions
9.30am – 10:30am	Drone familiarisation	Expected experiences (PK-pattern)	Groups of 5; 1 facilitator	Drones	Working basic flight programs, observations
10.30am – 11.30am	Unexpected tasks (obstacles, failures, errors)	Unexpected experiences; emotion management (E); PK (debugging)	Groups of 5; guided by facilitators	Drones, obstacle markers	Logs of errors, emotion notes
11.30am −12.30pm	Adversarial scenarios (privacy/misuse discussion)	Adversarial thinking (PT); cyber-physical risk awareness	Whole class; facilitator leads	Scenario prompts, discussion sheets	Group answers, threat lists
2.30pm – 3.30pm	Challenge tasks (integrated CT + AT problem)	Integrated PK and PT (cyber thinking)	Groups of 5	Drones, coding environment, task sheet	Complete mission plan, performance notes
3.30pm – 4.00pm	Reflection and generalisation	Computational reflection (R); linking PDTD to future situations	Whole class	Reflection worksheet	Written reflections
4.00pm – 4.30pm	Post-test and closing	Measure changes in PDTD, E, PK, PT, R	Whole class	Post-test questionnaire	Completed post-test, feedback

sharpen students' problem-solving abilities while making STEM learning more engaging and relevant to modern cybersecurity challenges. Cyber thinking, as conceptualised in this study, links computational thinking with adversarial thinking and emotion

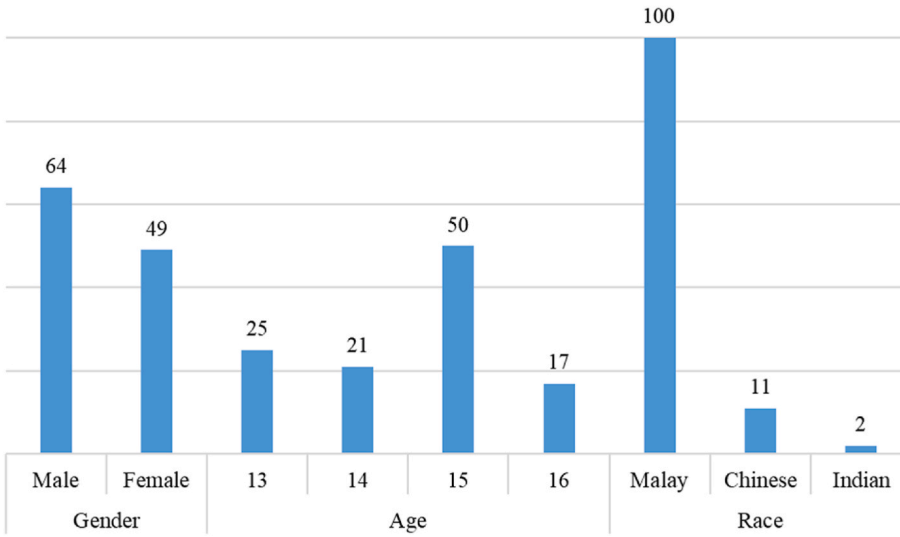

Fig. 5. Demographic of students.

Fig. 6. Drone's activity.

management to prepare students for cyber-enabled risks such as data manipulation or adversarial examples in machine learning systems (Kurakin et al., 2019). Within this framework, experiential learning factors were examined to understand how hands-on robotics activities can support problem-solving, cybersecurity awareness, and interest in using modern technology.

The model was developed by extending the Matsuo–Nagata experiential learning model into a cyber-physical robotics context. Computational and adversarial thinking components were integrated into the revised experiential learning cycle and operationalised through five dimensions: expected and unexpected experiences (PDTD), management of emotion (E), computational thinking (PK), adversarial thinking (PT), and computational reflection (R). The present findings provide empirical support that these components can be combined into a coherent Cyber Thinking Behavioural Model in the context of school-based robotics education. At the same time, because the student intervention used a one-group pre–post design without a comparison class, changes in student scores should be interpreted as short-term associations rather than definitive evidence that the model alone caused improvement; other influences such as maturation, novelty effects, and teacher enthusiasm may also have played a role.

Methodologically, the use of Partial Least Squares–Structural Equation Modelling (PLS-SEM) to validate the Cyber Thinking Behavioural Model aligns with recent work that applies PLS-SEM to complex learning frameworks involving computational constructs, cognitive engagement, and performance (Hsia et al., 2025). The measurement model showed good reliability and convergent validity for all five dimensions, and the structural paths H1–H7 were consistent with the hypothesised relationships between expected and unexpected experiences, emotion management, computational thinking, adversarial thinking, and

Table 18
School subjects.

Like	School Subject	Dislike
39	Mathematics	68
25	Computer Science	12
12	Science	7
1	History	16
7	English Language	2
3	Geography	2
1	Arabic Language	1
11	Malay Language	-
-	Additional Mathematics	3
3	Arts	-
2	Accounting	-
1	Islamic Studies	-
1	Sport Science	-
1	Robotics	-
-	Moral Studies	1
3	Others	-

computational reflection. The addition of computational reflection as a distinct component, focusing on debugging and generalisation, appears particularly valuable, as it links cyber thinking back to expected and unexpected experience by encouraging learners to adapt solutions to new situations.

At the level of classroom practice, the Cyber Thinking Behavioural Model serves as a design blueprint for teachers seeking to integrate robotics and cybersecurity awareness into mixed-ability lower-secondary classes. The workshop schedule and activities demonstrate how theoretical components can be translated into programmable drone tasks and guided reflections that are feasible within a one-day school context. Teachers' and students' high agreement with items related to decomposition, pattern recognition, algorithm design, strategic reasoning, and cybersecurity awareness suggests that the model can help structure robotics lessons in a way that foregrounds cyber-oriented thinking rather than isolated technical skills (Hsia et al., 2024). Experiential drone activities thus become a context not only for problem-solving, but also for anticipating and responding to cyber-enabled risks.

The student pre–post descriptive results show that mean scores on items related to expected and unexpected experiences, emotion management, computational thinking, adversarial thinking, and computational reflection (Bermúdez et al., 2019b; Klaška et al., 2020; Sattar & Nawaz, 2023) are generally higher after the workshop than before. These short-term gains are consistent with increased engagement in experiential robotics tasks and more frequent use of cyber-thinking strategies such as pattern recognition, strategic reasoning, and reflective debugging during drone missions. However, given the one-group design, reliance on self-report questionnaires, and limited intervention duration, these changes should be viewed as preliminary and exploratory rather than as proof of lasting competency development. Future studies should complement self-report data with objective indicators such as programming artefacts, error-handling behaviours, and security-aware design decisions.

The discussion of prior work on technology-supported reflection and feedback in education underscores the importance of structured opportunities for students to analyse their actions and receive guidance. In our model, this is operationalised through computational reflection, where debugging and generalisation after robotics activities help consolidate cyber thinking skills by encouraging students to examine errors, test alternative strategies, and apply solutions to new problems. Implementing the Cyber Thinking Behavioural Model in drone programming activities appears to have provided such reflective opportunities, with students drawing on prior experiences to handle new constraints and unexpected outcomes in the workshop.

By engaging in increasingly complex drone tasks, students were invited to practise managing emotions under time pressure, collaborate with peers, and make decisions in situations that simulate real-world cyber-physical challenges. These experiences are consistent with the notion that experiential robotics activities can contribute to both cognitive and affective development (Hsia & Hwang, 2021), supporting self-efficacy, motivation, and emotional regulation, although our evidence in this study is limited to short-term self-report measures. Overall, the Cyber Thinking Behavioural Model emerges from this work as a promising exploratory framework for integrating experiential learning, computational thinking, adversarial thinking, and emotion management in school robotics education.

5.1. *Theoretical implications*

This study contributes to the body of knowledge on CT, where CT is highlighted as an important skill to be used as a societal skill foundation. The Cyber Thinking Behavioural Model includes all aspects of cybersecurity's cognitive, emotional, and knowledge aspects. The components of the model, consisting of expected and unexpected experiences, emotional management, cyber thinking (computational and adversarial thinking) and computational reflection, provide a method for how a situation needs to be managed to obtain the best and rational solution. Using the Cyber Thinking Behavioural Model will help form a society that reasons when facing any problem. Building on evidence that self-reflection, belief systems, social relations, technology, and governance jointly strengthen adolescents' self-control and positive behaviours (Sudin et al., 2026), the Cyber Thinking Behavioural Model translates these protective factors into experiential robotics activities to foster cybersecurity-oriented cyber thinking in schools. Moreover, this Cyber Thinking Behavioural Model can impact the country in dealing with cybersecurity threats through adversarial thinking.

5.2. *Practical implication*

The Cyber Thinking Behavioural Model's application to robotics activities provides several advantages that significantly improve students' learning experiences and outcomes. Robotics fundamentally encompasses problem-solving, logical reasoning, and repeated testing, rendering it an optimal medium for developing the essential elements of the Cyber Thinking Behavioural Model, specifically computational thinking and adversarial thinking. In robotics, students frequently encounter unforeseen problems, like environmental variations, unanticipated inputs, or task limitations that reflect real-world problem-solving under duress. The Cyber Thinking Behavioural Model fosters adversarial thinking by equipping students to foresee challenges,

Table 19
Paired *t*-test results.

Construct	Average Mean		Mean Difference	Std. Dev.		t-value	p-value	Cohen's d	Result
	Pre	Post		Pre	Post				
Expected & Unexpected Experience, **PDTD**	3.62	3.76	0.14	0.88	0.91	1.2	0.23	0.14	Small, not significant
Management of Emotion, **E**	3.62	3.74	0.13	0.81	0.84	1.2	0.23	0.13	Small, not significant
Computational Thinking, **PK**	3.32	3.64	0.32	0.76	0.81	2.9	0.004	0.29	Small-to-moderate, significant
Adversarial Thinking, **PT**	3.49	3.87	0.38	0.82	0.87	3.5	0.001	0.34	Moderate, highly significant
Computational Reflection, **R**	3.34	3.71	0.37	0.74	0.84	3.4	0.001	0.33	Moderate, highly significant
Overall	**3.42**	**3.74**	**0.32**	**0.82**	**0.85**	**2.9**	**0.004**	**0.29**	**Small-to-moderate, significant**

evaluate alternative methods, and execute strategic judgments in reaction to evolving scenarios where these skills are directly utilised in robotic contests or missions. For example, from December 2022 until February 2023, one robotic learning program was held in Simunjan, Sarawak. This program was participated in by 116 students and 25 teachers with the accompaniment of six facilitators, as shown in Fig. 7. This robotic learning program consists of four modules: expected and unexpected experience, management of emotion, cyber thinking, and computational reflection.

1. Expected and unexpected experiences

    Simunjan, Sarawak students were first introduced to the module activity before they proceeded to hands-on learning. They have never experienced any robotic technology, which made this robotic learning program their first time experiencing it. Two learning tools were used in this robotic learning program: the Scratch application and the mBlock application. Scratch is a simple programming language introduced by the Massachusetts Institute of Technology, USA, while mBlock application is Scratch-based program blocks combined into a complete program that instructs 'sprite' the objects found in mBlock. Accordingly, the mBlock application will systematically guide participants in producing a computer game.

    The students were also taught CT concepts before they started the activity. The main CT components taught to the students are decomposition, pattern recognition, abstraction and algorithm. This CT concept is crucial to teach students the process needed to solve complex problems by breaking them into smaller problems, identifying similarities and differences, focusing on the important ones, and arranging the steps to solve the problem. Once the students' CT concepts have been grasped, they can apply them using image-based computer programming (Scratch) to develop computer games. CT concepts aid the students in producing a flow chart to draw up a plan using mBlock.
2. Management of emotion

    This robotic learning program includes emotion management in the Cyber Thinking Behavioural Model. For example, students must present their developed computer games. The presentation score of the developed computer game was based on the students' creativity, positive peer feedback and presentation skills. The group with a lower score could accept the evaluation result and continue the robotic activity without feeling devastated. The emotion management component in this activity shows the importance of emotion management for problem-solving.
3. Cyber thinking

    After learning the basics of CT, the students were asked to solve programming tasks. The first activity required the students to do addition operations from 1 to 200. After they succeeded, their difficulty level increased, and they needed to solve problems from 1 to 1000 immediately. In the following activity, the students identified the similarity in the set of numbers and applied the CT concept to obtain the value of 'N'. Then, the students needed to sit with their partners for the next task. This activity taught students the importance of true, clear, and comprehensible information. One student acted as a 'programmer', and the other as a 'computer'. The 'programmer' gives instructions and positions shapes for the 'computer'. The 'computer' draws and follows the 'programmer's' instructions. Lastly, the drawings of the programmer and computer were compared.

    In the robotics learning program, the mBot2 robot was also introduced to the students. The mBot2 activity is related to the adversarial thinking element. The mBot2 robot consists of a brain (CyberPi), a motor that moves the robot's tires, an ultrasonic sensor to detect obstacles and a Quad RGB sensor to detect colours and lines.

Fig. 7. Robotic programming activity in Sarawak.

At the end of the program, a competition was held to find the team with the best instructions for mBot2. This activity trained the students to be proficient in basic mBot2 movements. The instructions for mBot2 are given through the mBlock application in the students' notebooks. The students need to confirm whether the connection of the mBot2 is correct and secure. Wi-fi connectivity used during the activity also needs to be secured. This activity taught students the importance of a secure mBot2 connection because an unsecured connection and incorrect port may cause issues for the mBot2 robot.

4. Computational reflection

The computational reflection component is present in four sub-activities of the robotic learning program: line tracker (activity 1), colour recognition (activity 2), ultrasonic sensor (activity 3) and robot dance (activity 4). In activity 1, the Quad RGB sensor helps the mBot2 detect the black line on the line tracker circuit. The students were guided to develop a program that ensures the mBot2 stays above the black line. Once the programming was completed, the students placed the mBot2 on the circuit to observe the movement. For activity 2, mBot2 uses the Quad RGB sensors for blue, green, yellow and red coloured lines. The same goes for how the students observe the movement of the black and coloured lines. Then, CyberPi's LED lights light up based on the colour detected by the sensor and are displayed on the LCD screen that the students observe. Lastly, the students must develop a program combining the instruction of line tracking and colour recognition for mBot2.

In activity 3, ultrasonic sensors are used to avoid obstacles. mBot2 continued to move forward when no obstacles were within the detector distance range set by the participant. mBot2 turned when it detected an obstacle. The mBot2 challenge for this activity is a maze. The maze consists of a black line that mBot2 must follow while avoiding obstacles. As for the final activity, the robot dance applies an art element, one of the STEAM branches. The students were guided beforehand to develop a program to produce a nursery rhyme. Based on their creativity, the students must program the robot to dance to a different song. The students used the generalisation skill of CT by applying the knowledge from previous activities to complete their tasks. They also applied the debugging element to create a variety of solutions.

The findings of implementing the Cyber Thinking Behavioural Model are consistent with the robotic programming activity. The ability of the students to utilise their previous experience in new situations is shown through the component of expected and unexpected experiences (Morris, 2020). The importance of emotion management in robotic programming activity is portrayed to ensure that the students develop the best programming steps (Sharma et al., 2019). Conclusively, the Cyber Thinking Behavioural Model is a useful problem-solving method. The model is suggested to be applied to other problems such as cybercrime, agriculture, or mental health issues. Table 20 explains the structure of the one-day robotics workshop.

Table 20
Structure of the one-day robotics workshop and alignment with Cyber Thinking Behavioural Model components.

Stage	Tools	Key tasks	Assessed components
Expected and unexpected experiences	Scratch, mBlock, drone/mBot2	Intro to CT concepts; basic flight/robot paths; maze with unexpected constraints	Expected and Unexpected Experience (PDTD)
Emotion management	Group debrief, facilitator prompts	Sharing challenges and successes; discussing frustration, anxiety, and coping strategies	Emotion/ Management of Emotion
Cyber thinking (CT + AT)	Scratch, mBlock, mBot2, Wi-Fi	Solving programming tasks, anticipating failures or attacks, designing robust routes and responses	Computational Thinking; Adversarial Thinking
Computational reflection	mBot2, worksheets, group discussion	Observing robot performance, debugging programs, and generalising solutions to new tracks or missions	Computational Reflection
Integration and competition	mBot2, mBlock	Team challenge combining line tracking, colour recognition, and obstacle avoidance under time pressure	All cyber thinking components in applied form

5.3. Limitations and future study

This study has several limitations that should be acknowledged. First, the sample of 131 teachers and the pilot group of approximately 116 students and 25 teachers were drawn from a specific robotics education context with purposively selected schools and teachers who were willing and able to implement a drone-based workshop. This may limit the generalisability of the Cyber Thinking Behavioural Model to other regions, school types, age groups, or educational systems, particularly those with different levels of STEM and cybersecurity readiness. Second, the student component used a one-group pre–post design with a single day of activities and short-term post-testing. The observed improvements in descriptive pre- and post-test scores should therefore be interpreted as short-term gains rather than definitive evidence of sustained change. Without a control or comparison group, changes over time cannot be attributed solely to the Cyber Thinking Behavioural Model and may partly reflect teacher effects, prior experiences, or the novelty of working with educational drones.

Third, the study relied primarily on self-reported questionnaire data from teachers and students. Such data are vulnerable to social desirability bias and subjective interpretation, and participants may have overestimated their preparedness, emotion management, or cyber thinking skills relative to their actual behaviour. The Expected and Unexpected Experience (PDTD) scale used a small number of items with mixed positive and negative wording to reduce acquiescence bias and capture both confidence and discomfort in unfamiliar situations. While composite reliability and AVE for PDTD were acceptable, the low Cronbach's alpha indicates attenuated inter-item correlations, so this construct should be interpreted cautiously and further refined in future studies with an expanded, better-matched item pool. Fourth, although Partial Least Squares–Structural Equation Modelling was used to validate the measurement and structural model, the analysis remains exploratory. The structural evaluation focuses mainly on path coefficients, significance levels, and R^2 values, and does not include a full set of diagnostics such as path-specific effect sizes, predictive relevance indices, and cross-validated redundancy measures. Future replications should compute and report these additional indicators to provide a more comprehensive picture of effect magnitude and predictive power.

Finally, the present study mainly captured cyber thinking behaviour through questionnaire scores and short written reflections rather than detailed performance measures. Future research could strengthen the evidence base by incorporating objective indicators (for example, students' programming artefacts, error-handling strategies, and security-aware design decisions), longitudinal follow-up, and comparisons between classes that implement the Cyber Thinking Behavioural Model and those using more conventional robotics or STEM instruction.

6. Conclusion

The present study developed and validated a Cyber Thinking Behavioural Model that integrates experiential learning, computational thinking, and adversarial thinking into a coherent framework for cybersecurity-oriented robotics education in lower-secondary schools, connecting expected and unexpected experiences, management of emotion, cyber thinking, and computational reflection within a drone-based learning cycle supported by PLS-SEM evidence from 131 teachers and post-test data from students which the findings justified cyber thinking behaviour as a distinct construct that goes beyond generic problem-solving and digital literacy by emphasising threat anticipation, reverse-engineering perspectives, and emotional regulation in cyber-physical contexts, and offer teachers a practical design framework for robotics lessons that simultaneously build STEM competencies and early cybersecurity awareness, while acknowledging limitations related to the single national setting, specific drone platform, and short-term student intervention, and recommending future research that tests the model across diverse educational systems, employs longitudinal or experimental designs, and extends its application to teacher professional development and other cyber-physical tools such as IoT kits or autonomous vehicles.

CRediT authorship contribution statement

Noridayu Adnan: Conceptualization, Data curation, Formal analysis, Methodology, Validation, Writing – original draft, Writing – review & editing. **Siti Norul Huda Sheikh Abdullah:** Conceptualization, Data curation, Funding acquisition, Software, Supervision, Writing – original draft, Writing – review & editing. **Raja Jamilah Raja Yusof:** Writing – review & editing. **Noor Faridatul Ainun Zainal:** Data curation. **Elaheh Yadegaridehkordi:** Writing – review & editing. **Nazrul Anuar Nayan:** Data curation, Writing – review & editing.

Ethics declaration

Written informed consent to take part in the study and to publish the article has been obtained from all participants or their legal representatives. The privacy rights of participants have been observed.

This study was performed in compliance with relevant laws, regulatory frameworks and guidelines where the research took place. This study was approved by the Ministry of Education Malaysia. (Approval No. KPM.600-3/2/3-ERAS (9263))

Ethics approval statement

All procedures performed in studies involving human participants were in accordance with the Ministry of Education Malaysia (KPM.600-3/2/3-eras (12499)).

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this manuscript, the author used ChatGPT for language refinement and drafting support. The author reviewed, edited, and takes full responsibility for the final content of the manuscript.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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