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Personalised Learning through Context-Based Adaptation in the Serious Games with Gating Mechanism

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Abstract

When the traditional "one size fits all" approach is used in designing educational games, the game context is usually arranged in a fixed sequence. However, the designated content may not effectively support the diversity of players. The player's ability and characteristics should be considered and supported with an appropriate learning context embedded in the game to facilitate personalised experiences. Adapting game scenarios to a player's characteristics can boost motivation and ultimately improve learning outcomes. This research applies a context-aware design approach and the Learner-Centered Design approach to establish a personalised adaptation framework for designing educational serious games and enhancing personalised knowledge delivery. The proposed framework decouples the game logic implementation and adaptation mechanism. It dynamically adapts the designed game objects and activities to personal learning objectives, learning levels and learning progress to achieve a non-linear learning sequence. Through synchronous real-time xAPI message exchange mechanisms, system components and learning content adaptation are enabled. The adaptation aims to fit personal learning objectives and provide a non-linear learning sequence in a game environment. The framework provides students with personalised learning experiences. A game named GhostCoder is implemented and used to evaluate the framework. Based on the externalised adaptive mechanism, the game content is adapted to the player's performance by adjusting the difficulty of the learning content within the game. Testing of the game in the lab environment has been performed. At the next stage, an evaluation will be conducted with the target groups of students.

Keywords Games Based Learning · Educational Games · Serious Games · Personalised Learning · Context-Based Adaptation

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1 Introduction

Games, in general, are designed for entertainment purposes. Serious games provide an engaging environment for knowledge acquisition, improvement in interest, motivation, and the enhancement of the student's learning achievements (Arias-Calderón et al., 2022; Dörner et al., 2016). Serious games focus on the problem-solving aspect and learning components (Govender & Arnedo-Moreno, 2021) and are designed for students to learn and practice various skills through playing games (Priyaadharshini et al., 2020), leading players to achieve the planned educational goal through different interactive challenges (Sørensen, 2011) and endeavouring to transform the learner from a passive receptor of information to a collaborator in the educational process (Darwesh, 2016b). Players usually assimilate the learning content and construct their knowledge through conscious decision-making (Govender & Arnedo-Moreno, 2021), by finding solutions and organising concepts (Rajeh, 2020). Serious games can be an alternative method for assessing student learning, revalidating concepts, and reinforcing learning by presenting personalised scenarios adaptive to the need of students (Arias-Calderón et al., 2022).

Serious games integrate a broad range of game mechanics with game objects to facilitate the learning process (Altay, 2014) and deliver interactive learning content in a fun and interactive way. Game mechanics should align with learning objectives (Kalmpourtzis & Romero, 2020). Dynamic game mechanics and the interactivity of game objects create not only engaging gameplay but also immersive learning opportunities. Game scenarios, learning, interactivity, user trace, and player engagement are the core elements in designing meaningful learning activities in serious games (Darwesh, 2016a). Game elements can be designed and customised to support personalised learning objectives through dynamic player modelling (Paraschos & Koulouriotis, 2023). Interactive user traces are the keys to emulating cognitive behaviour, motivation, identifying the type of Learners (Priyaadharshini et al., 2020), and evaluating player experiences and engagement levels (Arias-Calderón et al., 2022). Personalised game activities can enhance motivation and learning performance through adaptive learning technologies (Taylor et al., 2021), tailoring game scenarios to individual goals.

Game Learning Analytics (GLA) framework collects, processes and analyse game interaction data in order to provide an overview of the user learning experience, from an individualised assessment to a collective perspective (Cano et al., 2017; Freire et al., 2016), supporting personal and contextualising personalise learning activities in the game world context.

Learning begins with the acquisition of declarative knowledge. With the help of repeated practices of declarative knowledge in different tasks, learners will enable them to achieve procedural knowledge. (Tavakoli et al., 2016). Designing gameplay as a set of activities containing different learning patterns with scaffolding makes the games exciting and challenging (Oliver, 2018). Aligning tasks to performance engages learners' natural abilities for acquiring knowledge (Robinson, 2011). Personalising and adaptively changing the player's learning content in the same game scenario is a possible training strategy that sustains and enhances players' motivation through gameplay. i.e. repeating or substituting various scenarios composed of similar learning concepts.

Learning, gaming, and learner aspects are three interrelated constraints in combining meaningful learning activities within a video game (Dorça et al., 2016). Educationalists and game designers have different focuses and concerns during the development of serious games. Educationalists are primarily concerned with what learning contexts have been embedded in the game scenarios. The learning aspect should be composed of different learner parameters, including specific characteristics of the learning audience, specific learning objectives, sequence of activities and the evaluation approach. These elements can be used to evaluate both pedagogical purposes and learning effectiveness.

Meanwhile, game designers are focused on creating fun and engaging gameplay mechanisms. Players can learn hidden concepts through game interactions while having fun. However, their learning objectives and game goals may be aligned or conflict.

This research extends the Game Learning Analytic framework (GLA) with a decoupling game design approach (Bellotti et al., 2009) to enhance the design of serious adaptive games. The decoupling design approach separates the game content from the content delivery strategy. The game engine delivers the game content, while the GLA analyses the player's performance and provides mechanisms for adapting to provide a meaningful player experience.

This research integrates serious games with Game Learning Analytics, monitors learners' learning progress based on assessment results, determines learners' knowledge level and provides adaptive learning support. A framework is proposed to separate game design, player attribute evaluation and adaptation for adaptive games. The developed framework acts as an intelligent agent for serious games using the Experience API (xAPI) protocol and game learning analytics.

The paper is structured as follows. Section 2 presents related work, and Sect. 3 describes the contextual adaptive design approach. Sections 4 and 5 discuss adaptation framework design and implementation. Sections 6 and 7 present the evaluation outcomes, conclusion and future work.

2 Related work

The section discusses Learning-Centred Design (LCD) and Adaptive Serious Games. It then discusses the notions in Context-Aware Serious games and Game Adaptation. It also discusses the Game Learning Analytics Framework and Experience API (xAPI) Standard adopted in this research.

2.1 *Game adaptation and personalisation*

Adaptation refers to the continuous adjustment of the game based on the user's actions and performance and the game's current state towards the desired state

(Bontchev et al., 2021; Göbel & Wendel, 2016; Khudhair Abbas Ahmed, 2016; Paraschos & Koulouriotis, 2023; Zhu & Ontañón, 2020). Personalization in serious games can be established through adjustments in the game content and support adapted to a player's personal abilities or needs (Paraschos & Koulouriotis, 2023). The game activities such as game scenarios are the key elements that can be adapted. Learning adaptation in serious games can be adaptive and interactive storytelling (Lester et al., 2013; Rowe et al., 2010; Chen et al., 2018), motivational interventions, adaptive presentation, adaptive curriculum sequencing (David et al., 2016), as well as navigation support (Guerra et al., 2018).

Adaptive learning is a technique using a data-driven approach to establish instruction and remediation in serious games, by providing efficient, effective, and customized learning paths to engage each student based on learning from student interactions and then adjusting the path and pace of learning (Patsy Moskal et al., 2017). The adaptation algorithm responds to unwanted player behaviour and then chooses the appropriate adaptations to achieve the desired mode (Carron & Marty, 2013). An adaptation engine uses a player model and learner model to manipulate the game tasks in order to optimise the player behaviour (e.g. sequences of tasks according to the player's need or player styles. (Bellotti et al., 2009). The design of adaptation should consider constructively aligning (Biggs, 2007) learner engagement through the activity with learning goals and outcomes (Romero & Kalmpourtzis, 2020). Game learning activities engage players to build their knowledge and game training activities can personally adjust and adapt to fit the player's proficiency, based on intended learning outcomes. The constructively aligned game activity can reduce player cognitive load and achieve the intended learning outcomes through learning adaptivity in-game.

The adaptation design should consider what to adapt, when to adapt, how and to what degree, and why something should be adapted (Zhu & Ontañón, 2020). The learner is one of the key dimensions in design adaptation in serious games. The adaptation mechanism measures learner proficiency and adjusts the game accordingly (Zohaib, 2018). The learner model and adaptation mechanism are usually fixed at the early stage of game design. However, the pre-defined models may not support the diversity of learners. The pre-defined models are difficult to update once the game has been implemented and deployed. This study aims to enhance the flexibility of adaptivity in serious games by extending the Game Learning Analytic framework (GLA) with a decoupling game design approach.

2.2 *Learning-Centred Design (LCD)*

The Learner-Centered Design (LCD) is the pedagogical approach (Guzdial et al., 1997) that considers learners as the core element in designing software, enhancing learning motivation, academic performance, and persistence in task completion (Brent et al., 2021). The needs of learners are the core elements in creating adaptive mechanisms in education software. The adaptive content supports individual needs and establishes a unique learner experience. i.e. changing the content according to what the learner needs in any learning moment. In designing adaptive educational software, context, tasks, tools, and interface are four essential interlinking elements that constitute an effective educational software, facilitating learner engagement, motivation, and metacognition that support enhanced learning achievement.

- **Context** is the goal, purpose, and audience of the software. It represents its audience, how it will be used and the environment where the software will be placed.
- **Interfaces** represent the front end and aesthetics of the software that learners interact with.
- **Tasks** are the features that are supported by the software. i.e. What will the learner do with the software?
- **Tools** are the adaptable features that support a learner's growth in expertise. These can be software scaffolds.

When Serious Games designs with The Learning-Centered Design (LCD) approach, game elements represent four interlinking elements. Educational goals embedded in the serious game are considered as the Context. The virtual game environment where players interact with is the Interface. The game activities that are embedded in the educational goal are the Tasks. The game mechanics designed to support the learners are the Tools.

2.3 *Context-Aware approach and adaptive mechanism*

The Context-Aware Approach takes players as the core element. This approach continuously adjusts the learning content or curriculum to fit the level of the learner, intending to optimise learning efficiency, increase student engagement, and address each learner's specific needs, interests, or preferences (Hsiao et al., 2010). The context-aware serious game takes players as the core elements. It evaluates player statuses and adapts to their needs. The player's actions are evaluated for creating adjustment game content and establishing personalised adaptive learning through a dynamic game context (Darwesh, 2016b), attempting to keep the player motivated by providing the right level of challenge. This is closely related to the self-determination theory (Deci & Ryan, 2015).

Context-aware learning games provide personalised resources and services related to the learning situation. Context-specific supports can guide the users through challenging tasks and support students in progressing through the level that the player cannot complete by themselves. The supports are established by arranging the personalised game content structure based on the individual user's context. Adaptive learning scaffolds motivate students toward the target academic content and establish a personalised learning experience.

Both the static and dynamic information of the users can be modelled to adjust the context in the system to support the needs of users. The architecture of an adaptive context-aware system comprises a learner, domain, adaptation, and context model, as shown in Fig. 1. The adaptive mechanism is responsible for providing users with personalised content that fits their individual needs. It is based on the

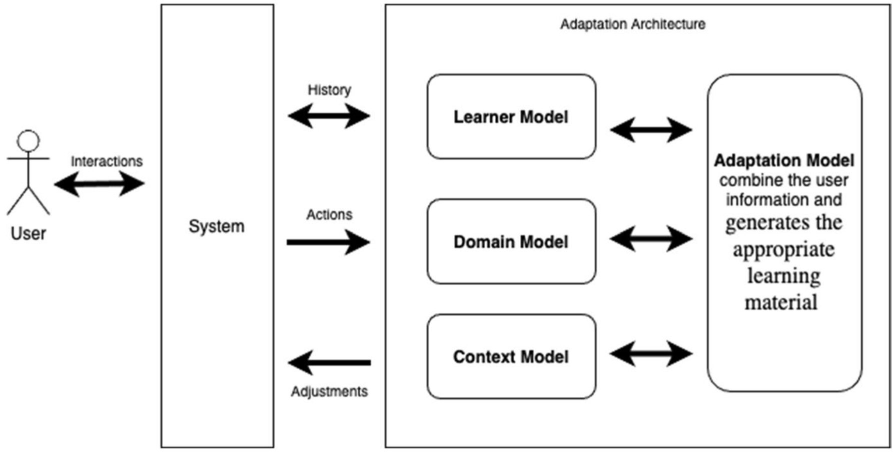


Fig. 1 The Conceptual view of Adaptive Learning Architecture

process of collecting contextual information to adjust the content for users. Each model is described below as follows:

- The learner model represents the significant characteristics of the learners. The learner profile in the model stores static information of the learners, such as learning styles, knowledge levels, interactions with the system, preferences, learning progress, and academic and personal information.
- The domain model represents a structured representation of all learning materials. These resources are stored in the database and can be updated by the administrator or educationalists.
- The adaptation model uses the rules and functions to generate the appropriate learning material imported from the domain model, based on the data collected from the learner model. The model is responsible for designing and implementing adaptivity. The data analysis component collects and processes information on adaptivity. The adaptation mechanism tweaks the content without informing the player.
- The context model is the core model to support the development of personalised adaptation. The context model collects the dynamic individual context information (i.e. user actions, location) detected in real-time execution from the environment. The collected context predicts the learner's current situation and determines contextual adaptation. The context model relies on the adaptation engine to establish personalised adjustment.

Context awareness contextualised learning experience through passively framing or constraining activities in the environment (Glahn & Gruber, 2020). The context-awareness mechanism identifies the personalised knowledge structure or needs in a game learning environment, aiming to drive individual users to the virtual world. The adaptive mechanism automatically generates game content or provides dynamic game mechanic adjustments. i.e. suggesting different levels for different players with the same objective but with different time spent playing the different levels. The adaptive mechanism also provides learners with learning materials that fit individual learning styles and needs (Lu et al., 2014). The learning experience is tailored to the learner by matching appropriate contextual dimensions in the game learning environment (Glahn & Gruber, 2020).

The adaptive mechanism is the core component that creates and establishes a unique player experience. However, the implementation of adaptive mechanisms in serious games is mainly developed under the hood of the game engine. The player learning assessments usually are not transparent to the educators, and assessment data is difficult to obtain. The adaptive mechanisms also can be difficult to modify and personalise to the need of the individual learners.

2.4 Game learning analytics framework

Game Learning Analytics (GLA) is the combination of both Game Analytics (GA) and Learning Analytics (LA), allowing both game designers and educators to design serious games in a collaborative way (Perez-Colado et al., 2017). GLA analyses player/learner interactions to evaluate player behaviour, categorise players and define player models (Reardon et al., 2022), provides insight on players' prior domain knowledge (Liu et al., 2013) and improves the use of the games in the education aspects (Freire et al., 2016). GLA is a powerful analytic tool, that depicts and measures the growth of player skills in educational games (Owen & Baker, 2019) through analytics visualisation i.e. dashboard and establishes predictive modelling to optimise for learning (Owen & Baker, 2020; v. Elizabeth Owen, 2015) by providing user-adaptive, engaging gameplay. GLA has shown positive impacts on learning, skill enhancement and engagements in knowledge acquisition/content understanding, and affective and motivational outcomes (Boyle et al., 2012, 2016; Connolly et al., 2012). GLA facilitates serious game usage in the classroom setting (Calvo-Morata et al., 2019).

Game Learning Analytics (GLA) framework establishes a systematic approach in analysing serious games. GLA is therefore essential for assessing student performance since the most relevant variables on the predictions model obtained were related to GLA information Player models can be established to provide adequate adaptive instructions.

GLA framework takes the role of educational analysis for the game. Player analytics and learning assessment can be decoupled from the game and performed in the remote Game Learning Analytics (GLA) server. The Experience API (xAPI) model is used as a communication channel.

The abstract overview of GLA Architecture shown in Fig. 2 is adapted from (Alonso-Fernandez et al., 2017). The adapted architecture focuses on adaptivity between the game engine and the game learning analytics system. The game engine sends player interactions to the collector for player data aggregation. The aggregator is based on the interaction data analyses and evaluates player status. Based on the aggregated data, the player model is generated. The adapter in the system evaluates

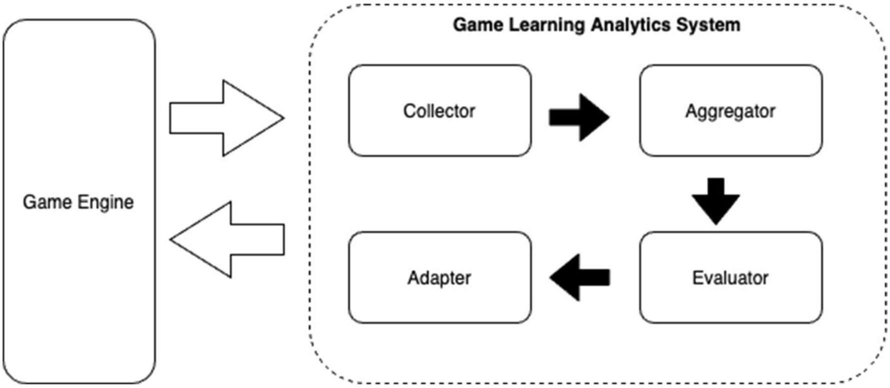


Fig. 2 Abstract Overview for Game Learning Analytics Architecture

player statuses and provides adaptive instructions that send back to the game. This adaptivity enables personalised gameplay adaptation. The GLA Architecture facilitates the externalised game adaptivity to the attached game.

2.5 Experience API (xAPI) standard

The Experience API (xAPI) is an open-source e-learning specification for learning technology managed by Advanced Distributed Learning Initiative (ADL) and applies the Activity Streams concept to e-learning (Xapi.com, 2014). The xAPI specification enables tracking and communicating learning experiences using JavaScript Object Notation (JSON). The specification's objective is to define a data and communication model to track user activities within a learning environment.

The independent format xAPI statement tracks game activities and establishes interoperable game adaptivity. The adaptivity is established through data exchange between systems such as Learning Management Systems (LMS), game engines, computer simulators and analytics systems. The xAPI-SG model (Serrano-Laguna et al., 2017) enables online and offline game-based assessments and student knowledge evaluation through their gameplays (Streicher & Roller, 2015). The collected players' interactions within the game can be used to establish personalised game adaptivity for enhancing the users' engagement, motivation, and ultimately learning outcome. Experience API (xAPI) provides the communication channel between GLA and attached games.

3 Summary

Serious games provide interactive content and gain the attention of the learners to enhance learners' motivations. The context-aware approach establishes personalised learning assistance based on the learners' context to enhance the learning experience. Game mechanics, game events, learning objectives and assessment points are contextual information that can be considered and used to create a personalised game learning environment.

The context-aware approach can be made adaptive, where games can be designed to improve the academic performances of learners by providing an efficient learning context. The dynamic knowledge level of players is required to be tested progressively to ensure the appropriate context is provided. In addition, the adaptive game learning objects can tailor learning styles and preferences according to the player's activities.

GLA architecture facilitates the development of serious adaptive games (Freire et al., 2016). GLA enables the measurement and evaluation of player knowledge level according to the performance and progress of a game scenario. and allows real-time knowledge evaluation of what players are doing and the prediction of player knowledge (Alonso-Fernández et al., 2019).

Current efforts in developing games using the adaptive context-aware approach do not typically provide the flexibility where educators can be involved in the game usage after the game has been implemented. Using the GLA architecture, there is an opportunity to enable more involvement of educators in the game usage regarding learning objectives, assessment points and game content. The aim of this research is to develop a framework where GLA is integrated with the design of the serious adaptive game. A prototype is developed to demonstrate how the processes involved.

4 Context-aware serious game and game adaptation

Context-aware learning systems are systems which adapt to the learner's context, providing tailored learning for a particular learning environment (Tortorella et al., 2018), detecting the learner's context, evaluating their status or abilities, and adapting learning materials to their needs (Glahn & Gruber, 2020; Hasanov et al., 2019; van Engelenburg et al., 2019) and use contextual framing to guide learners through learning.

Context-aware serious games interpret contextual information and adapt game behaviour and functionalities to the current player context. Game scenarios integrate with learning resources that contribute to the learning outcomes used for knowledge assessment. Game scenarios are considered as the learning context. Aggregated contextual information facilitates the development of content adaptation mechanisms for delivering educational resources and optimising the attainment of learning goals. Figure 3 shows.elements that determine the information about the player should be collected and how it will be used to provide the desired adaptation in a game learning environment (Vandewaetere et al., 2011).

According to the methodology for the context-aware design (van Engelenburg et al., 2019), the following steps should consider for establishing a context-aware game-based learning environment.

(1) Identify the learning components in the game environment that are relevant to the learning goal.
(2) Determine the components needed to sense and evaluate.

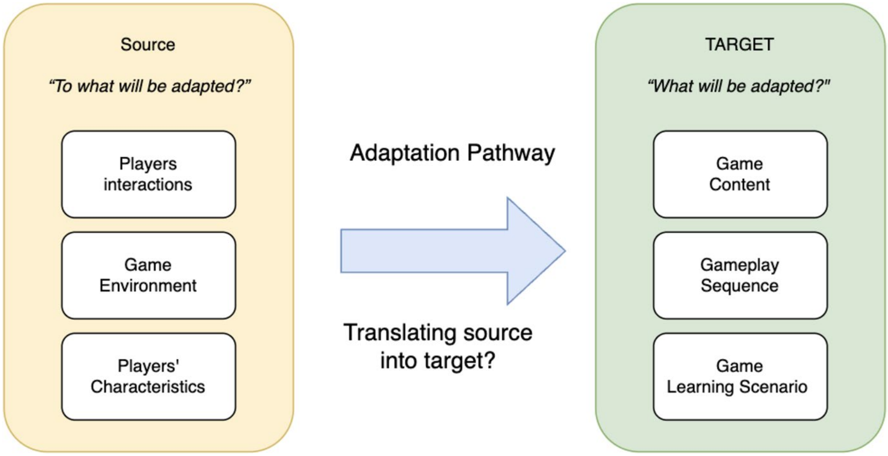


Fig. 3 The tripartite structure of adaptive instruction

(3) Determine the necessary components to adapt to the learning goal.
(4) Determine the strategies for how the system should adapt to different situations.

By integrating dynamic challenge adjustments (Blatsios & Refanidis, 2019; Hsiao et al., 2010; Patsy Moskal et al., 2017), concerning the progression of the learner skills, adaptive challenges create an immersive learning experience.

Game tasks consider context elements and guide the players through the learning process. Taking the competency-based learning approach, the game scenarios tailor to their unique needs based on the evaluated learning efficiency. While players interact with the game tasks, the individual knowledge structures are evaluated. The identified individual knowledge structures are used to determine the subsequent personalised guidance messages, directing individual learners to move around the virtual world or adjusting challenge levels. Personalised learning opportunities are tailored by alternating the game scenarios. The context-aware design applied for this research is shown in Fig. 4.

However, the integration into context-aware educational games presents unique challenges. It includes.

- Collecting the player/learner attributes such as knowledge, skills, motivation, and meta-cognitive skills
- Evaluation of the dynamic player status
- Preservation of the gaming experience

This research study applied the context-aware approach with the Game Learning Analytics framework to support player data collection, evaluate the player status, and provide a better learning experience. The proposed adaptive framework aims to decouple game adaptivity components from the game, decentralising the

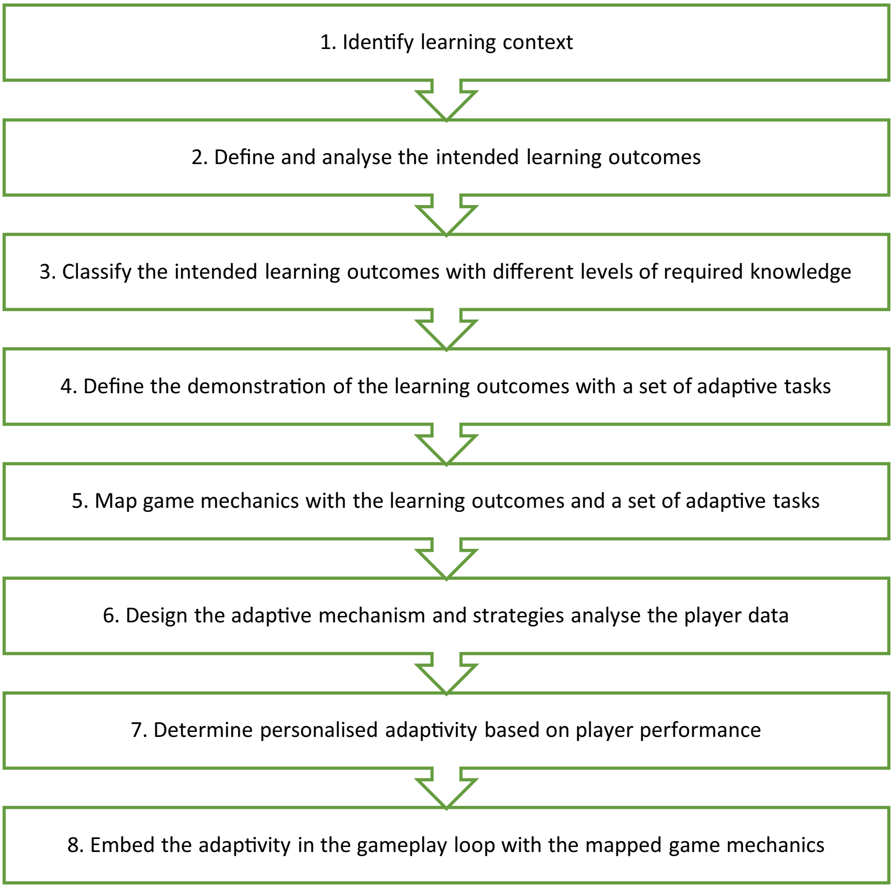


Fig. 4 Context-aware design approach applied for this research

data analysis engine as the core part of an analytic system and leaving the adaptivity part to be utilised by the game via the designed interfaces.

In this study, we propose a framework adapted from the Game Learning Analytics framework that will integrate the following:

(1) The design of Interoperable game objects to support the personalised adaptation process (described in Sect. 4.2).
(2) Provision of system-embedded synchronous real-time message exchange mechanisms for collecting player events and providing game context adaptation (described in Sect. 4.3).
(3) Player context evaluation with the Game Learning Analytic System (described in Sect. 4.4).
(4) Adaptive mechanisms establish system components and learning contents adaptation, utilising both real-time and long-term data (described in Sect. 4.4).

This research has applied a decentralised approach to achieve interoperable game content adaptivity by extending the Game Learning Analytic framework (Freire et al., 2016) and the game interaction model (Serrano-Laguna et al., 2017). Context-aware serious games are the games that infuse pedagogy and instructions inside digital game scenarios and provide personalised adaptive contents, which contextualises the player experience. The adaptive content could be modified game mechanics to match the user's needs or new content that better fits the user's current situation. (de Gloria et al., 2014).

The proposed framework follows the Learner-Centered Design (LCD) approach to establish the adaptive serious game framework with the Interoperable Adaptation Mechanism. It focuses on the quality of individual learning progress and highlights the unique learners' growth and motivational performance support in serious games.

5 Interoperable Personalised Learning with Adaptive Training Object Framework (I-PLATO)

The Interoperable Personalised Learning with Adaptive Training Object Framework (I-PLATO) is proposed, aiming to establish personalised game experiences by adapting the game contents to individual players' interactions and behaviours. The dynamic learning adaptation is established through bi-directional communication between the game engine and the analytic server. In addition, the I-PLATO also aims to enable educators to participate in the design of serious games, monitoring the users' progress and making customised adaptations concerning player behaviours.

The I-PLATO supports the designs of the adaptive training objects, interaction protocol and adaptation mechanism. The interoperability features are the externalisation of the adaptation module from the game engine to the adaptation module in the game learning analytic platform by bi-directional data exchange between game engines and the GLA Platform. The adaptation mechanism captures the player events and establishes game content adaptivity by exchanging player actions from the game engine with adaptive training content through the interaction protocol.

In the next few sections, a system overview of the framework is presented, showing the major components in Sect. 4.1. The integration of adaptive training objects is described in Sect. 4.2. The Player Events for Game Content Adaptivity is described in Sect. 4.3. Game Object Adaptor is described in Sect. 4.4. Section 4.5 presents the Interoperable Adaptation Mechanism.

5.1 System overview

The proposed architecture diagram is shown in Fig. 5. It comprises several modules that work together to analyse player data and establish game object adaptation.

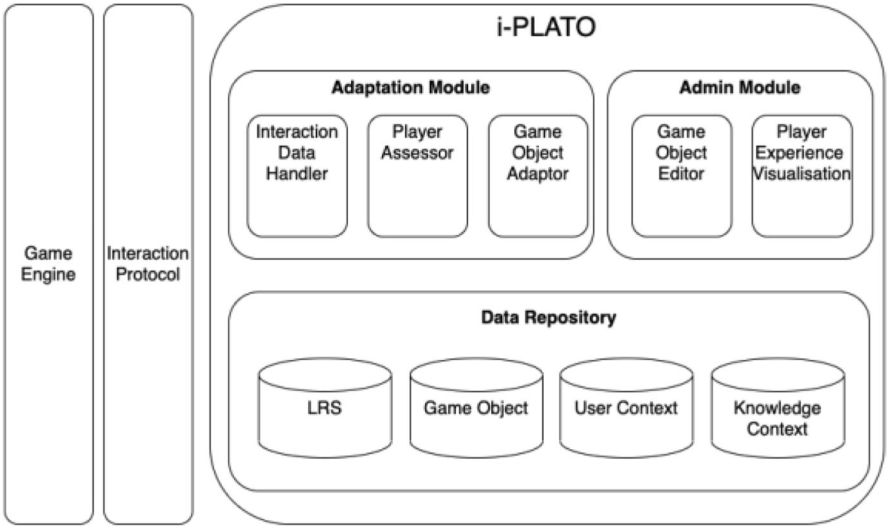


Fig. 5 The I-PLATO Architecture is presented for establishing Interoperable Training Object Adaptivity

5.1.1 Game Engine

The **Game Engine** is attached to the GLA platform. The role of the game engine is an environment to display interactive content for players to have fun, learn or acquire skills, driving the whole human–computer interaction while responding to user inputs. The game engine mainly focuses on displaying game scenarios to the player and maintaining the game flow. The game engine tracks and sends player actions to the GLA platform. Then, it collects and executes adaptive game instructions.

5.1.2 *Interaction protocol*

The **Interaction Protocol** is the communication layer between the game engine and the Game Learning Analytic platform (GLA). The Interaction Protocol maps the player interactions data and adaptive instructions with Experience API (xAPI-SG). The Interaction Protocol captures and delivers the players' interactions to the GLA. i.e. the attempts of the game objects and retrieves the adaptive instructions from the GLA.

The **I-PLATO** manages the game object adaptivity. It comprises of adaptation module, data module and admin module.

5.1.3 Adaptation module

The **Adaptation Module** is responsible for the adaptation evaluation and execution. It applies the adaptation strategy and determines the adaptive game scenarios based on the player knowledge estimation. It exchanges player actions and game content adaptation through **the interaction data handler.** The handler manages and stores game interactions in the player profile in the user context repository. The handler replies the suitable game content to the game engine. **The player Assessor** evaluates the player status based on the collected player interaction, e.g., attempts on a game object, user context and knowledge base information and evaluates the real time player knowledge rating and supposes the suitable difficulty rating in the game objects. **Game Object Adaptor** executes the predefined adaptation strategy, applying the adaptation rules based on the estimated player knowledge, which is the result of the player assessor. It constantly monitors the player's status and maintains the content that fits the player and the learning objectives. The adaptation strategy considers the target level of knowledge and the current knowledge level of the users and decides and selects in-game modification. e.g., personalised sets of game objects.

5.1.4 *Admin module*

Admin Module supports the teacher in applying and monitoring the designed game in educational situations.

The **Game Scenario Editor** enable teachers and developers to work together to design serious games. It is an authoring tool for managing the componentry model of the game task.

The **Player Experience visualisation** provides analytics results for the player experience, performance and progress during the game.

5.1.5 *Data repository*

Data Repository stores scenario information, user profile, player data and pedagogical information.

Game Objects Repository stores the metadata of scenarios and the associated competency model. It stores the adaptive game objects that can be applied at the run time and other metadata such as limits and boundaries that can be adjusted and pedagogical information. The competency model, which the domain experts and educators identify, is applied to evaluate player status. Scenarios are classified according to the difficulty level and the type of training goals (e.g., to enhance practice on domain topics). The metadata of the scenarios and competency model can be composed with the authoring tools.

Learning Record Store (LRS) is a player action database that stores the player action history generated by the game. It allows authenticated and authorized users to save and query traces.

The **User Context Repository** stores information about user preferences, personal characteristics, user experiences, and the knowledge level of registered game objects. It aims to support adaptation strategies on the learning experience.

The **Knowledge Context Repository** stores the pedagogical information implemented in the game object. It links the game object with the pedagogical evaluation and supports the knowledge estimated on the game objects.

5.2 Design of interoperable game learning objects

The educational context embeds game scenarios to support players in acquiring knowledge in a game learning environment, and the game scenarios also enable learning performance evaluation. The same learning goal can be designed in different scenarios. The different scenarios with the same learning goal provide alternative ways for players to learn in different ways. The design of alternative scenarios in the educational context can be achieved at the designing stage by adjusting the variables or conditions in the game scenario (Hendrix et al., 2013).

Alternative scenarios can be designed by varying compositions of the game objects within the scenario as illustrated in Fig. 6. The scenario-1 provides game object z for task x whereas the scenario-2 provides object x and object y for task x. Both scenarios serve the same goal and can be applied for adaptation. The variations can also be made in terms of the number of resources or supports, different challenges levels or tasks. The different scenarios consider interoperable game objects to support learning adaptivity. The metadata of scenarios and competency information is stored in the I-Plato.

5.3 Player event for game content adaptivity

Game Adaptivity is achieved by tracking player actions, evaluating performance during a game scenario, and adjusting the content in the following scenarios (Serrano-Laguna et al., 2017). The major events are the Session event, Progression event and Completion event. When the registered event has occurred in the game, the game engine sends the corresponding player actions to the I-PLATO server, which assesses player status, analyses their behaviours with the established player model and adapts game scenarios.

- **Session Events** occur when the game starts or ends. The game captures the player information and sends a trace to the GLA server for initialising the game session.
- **Progression Events** occur when the player has attempted but not completed a level in a game. The game captures player completion status in the scenario and sends a trace to the GLA server.

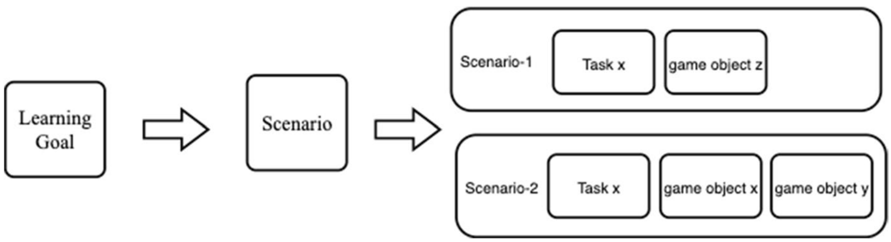


Fig. 6 Two adaptive scenarios, which are variations of the same scenario, are shown. Task x is the core task in the scenario. The variation of game objects creates alternative scenarios for the same objective

- **Completion Events** occur when the player has completed a game scenario. The game captures player performance in the scenario and sends a trace to the GLA server for retrieving the adaptive instructions in the next game stage. The events establish personal game content adaptivity from the GLA.

5.4 Player context evaluation and adaptation with GOA

Game Object Adaptor (GOA) provides alternative game content adaptation concerning player learning goals and status based on communication between game engines and Game Object Adaptor GOA. The implementation of interoperable micro adaptivity is supported by the preparation of alternative scenarios in games and the adaptation pipelines Game Object Adaptor (GOA).

The Game Object Adaptor (GOA) makes up the core of the adaptation process. It is responsible for real-time adaptive control of the games, based on the metadata of alternative scenarios and the competency model registered in the repositories. GOA assesses the player interactions in the adaptive scenarios and evaluates the current player status with the competency models. GOA then determines the adaptive, personalised scenario for the next game phrase and generates adaptive instructions at run time for the game engine. The game scenarios are adaptively selected based on user needs. It results in establishing the micro adaptivity in the game.

5.5 Interoperable adaptation mechanism with game object

An interoperable adaptation mechanism is distributed process between the game and an analytic platform. The overall adaptation process is externalised from the game, which is typically built within the game engine. The pipeline in the game adaptation mechanism examines the player status, identifies the need for adjustments, and provides adaptive instructions on the adaptive elements and/or generates adaptive content. The game adaptation is an iterative process that continues making player evaluations and adjustments throughout the game based on the adaptation strategy.

(1) Games initialise the adaptation process by sending player interactions to I-Plato
(2) Player evaluation is performed at run time at I-Plato.
(3) Based on the adaptation strategy, GLA platform evaluates the player status and intelligently returns adaptation instructions to the games.
(4) Games present adaptive content to players.

The interoperable adaption mechanism enables real-time personalisation of game adaptation and offline player model establishment with the collected player data.

Figure 7 depicts the interoperable adaption mechanism. The adaptation mechanism starts with a player playing the game. The game presents the game scenario to the player. The game task tracker maps the player events to the xAPI statement and sends it to the GLA server. The player events represent the player experience and store them in the LRS for offline batch analysis and player experience visualisation. Real-time assessment is made on the series of player interactions. The player status

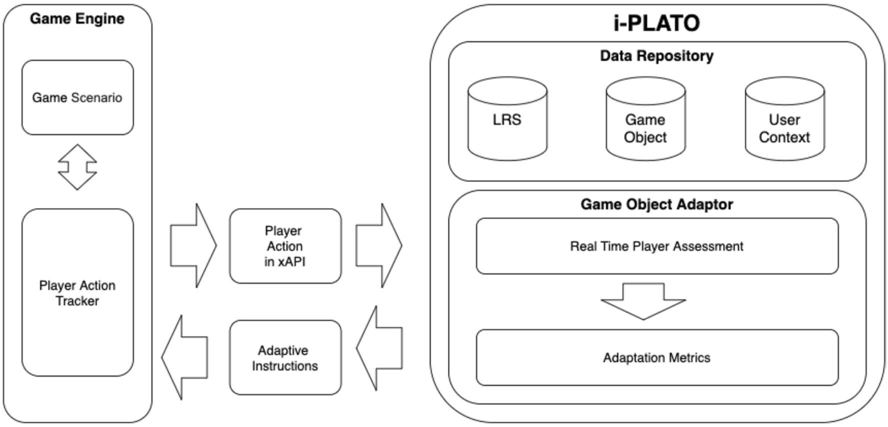


Fig. 7 Illustrates the exchange of player information and adaptive instruction during adaptation

is evaluated and updated in the user profile. Based on the defined adaptation metric and the evaluated player's current status, the game object adaptor intelligently selects the next appropriate tasks from the game object (GO) repository. Adaptive instructions are returned to the game engine, which presents the adapted content in the next suitable phase. The player continues to play with the adapted content.

6 Framework implementation—GhostCoder

The proposed framework is evaluated with the educational content adaptation to learners' capacity through personalised learning scenarios in a serious game, GhostCoder. The GhostCoder is an adaptive game based on the game's difficulty faced by the player and mastery of programming concepts. It adapts the learning content to the player knowledge status. The design is supported by a set of adapted elements that are aligned to the individual capacity and establish motivational structures gameplay experiences.

6.1 Contextual game design

The GhostCoder aims to contextualise the player's programming learning experience during their gameplay. The game aims to encourage novice programmers to practise programming syntax during the game. The game cards are the contextualised tasks that guide the player's programming learning process, aligning the game challenges with the player's programming knowledge/performance to engage their motivation to learn. The contextual approach as described in Fig. 4 is applied as follows:

- The learning context is Fundamental Programming Concepts

- The intended learning outcome aims to enhance procedural knowledge in programming when solving problems in programming scenarios.
- Each intended learning outcome is designed with learning game tasks and classified into levels of context difficulty for personalised knowledge level adaptivity.
- The learning outcome is embedded in the card game mechanic.
- The adaptive mechanism in GLA is defined as a pedagogic agent that determines the next personalised learning context based on the player interaction data collected in xAPI. The gating mechanism is used to determine the adaptivity.
- Game show with the adaptive content based on selected adaptivity task specified in the response of xAPI.

6.2 Gameplay design

GhosterCoder, shown in Fig. 8, is our serious game designed for novice programmers to familiarise themselves with computer programming concepts such as variables, if-statements and loops, algorithmic logic, etc. It aims to engage programmers to practise programming syntax while fighting the opponent. The gameplay requires the player to battle with the computer opponent by completing the programming tasks embedded in the card. Each card comprises programming tasks associated with a specific learning concept and a difficulty rating. The game's main goal is to eliminate the computer opponent's health points (HP) by issuing as many attacks as possible and maintaining the player's HP at the same time. Incorrect answers have no negative impact on the score, but skipping the card will lose the chance of attacking the opponent or recovering HP. The hidden goal of the game is to practise the programming concept specified in the card while playing the game.

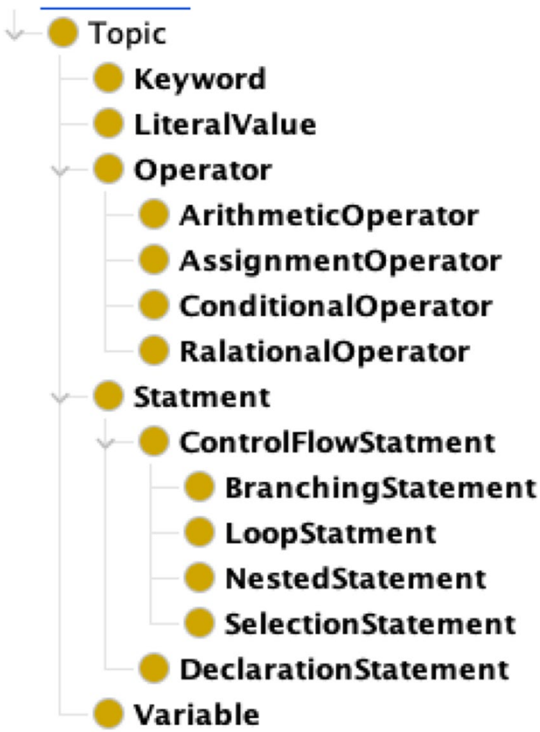
Fig. 8 Shows the game scenario that requests players to complete the programming task and fight with the component

The hidden learning goal is designed with context adaptation. The contexts of cards are adapted to the player's performance regarding the knowledge status on the embedded programming concepts. The level of context difficulty of the cards is adjusted in proportion to the growth of the player's knowledge. The context adaptation provides players with tasks that are not too hard or not too easy to complete. i.e. keeping the challenge at their level of programming mastery. The main aim is to keep them in the immersive state and zone of practice. The performance adaptation establishes their sense of completion and maintains the motivation to play and practise.

6.3 Game scenario design with java ontology

The game cards are the game scenarios designed to support players in practising Fundamental Programming Concepts, including syntax and semantics, variables, primitive data types, expressions and assignments, conditionals and iterative as well as functions and parameters (ACM/IEEE-CS Joint Task Force on Computing Curricula, 2013). The game cards embed the learning objective and metadata to measure the mastery of the programming knowledge status of the player. Different game cards are designed using the ontology approach Field (Raies et al. 2014) to automate training scenarios. The game scenarios are embedded with educational

Fig. 9 The class hierarchy of the Java ontology



context and learning outcomes. The game scenarios organise the educational context with difficulty levels. They are described with an appropriate set of metadata applied to evaluate the mastery of the knowledge, such as time required, click expected and difficulty level. The primary programming topics are shown in Fig. 9.

6.4 Context adaptive model design

GhostCoder extracts player actions and interprets current knowledge status in designing a context-aware adaptive system. It adapts the game content to suit the player's needs by providing additional support, hints and different level of difficulty. The context-aware adaptive model determines the suitable level of training material to provide personalised training material in the game. To ascertain the feasibility of a context-adaptive training model, GhostCoder has been designed and implemented to.

- Utilise player action and performance history to learn the patterns of the user's behaviour and knowledge level in the virtual environment; and
- Support context-adaptive training adaptations through adjustment of the content of the practising material. (i.e. increase or decrease the level of difficulty in training material)

Balancing skills and challenges is an essential factor that constitutes a flow experience in serious games. The balance factor is not only determined by the difficulty of the game but also by the player's abilities. Balancing game challenge to players' skills leads them toward the flow state and helps them into the immersive zone of the game (Cox et al., 2012). Flow state experience positively influences performance enhancement, learning, and engagement (Perttula et al., 2017).

GhostCoder follows the concept of gating, a level design technique that unlocks the scenarios when players are ready and adjusts the content difficulty provided in the game scenarios. The game's difficulty is adjusted by varying the number of the selection options presented or the scenario content. These adaptive features adjust the difficulty level to match individual players' skills. The intention is to improve and prolong the player experience by allowing the player to have the feeling of challenge without it being overwhelming and leading to repeated failure and frustration. The game provides personalised training question content adapted to fit the concept mastery of players. The personalised content on the practising card is presented.

The following presents an exemplary educational scenario on how learners' contextual information can be used for adapting its learning flow through implementing game object adaptivity in I-PLATO.

6.5 The design of adaptive game scenario in GhostCoder

Cards, shown in Fig. 10, illustrate the programming task to be completed by players. The goal is to fight with the opponent. The cards are associated with a

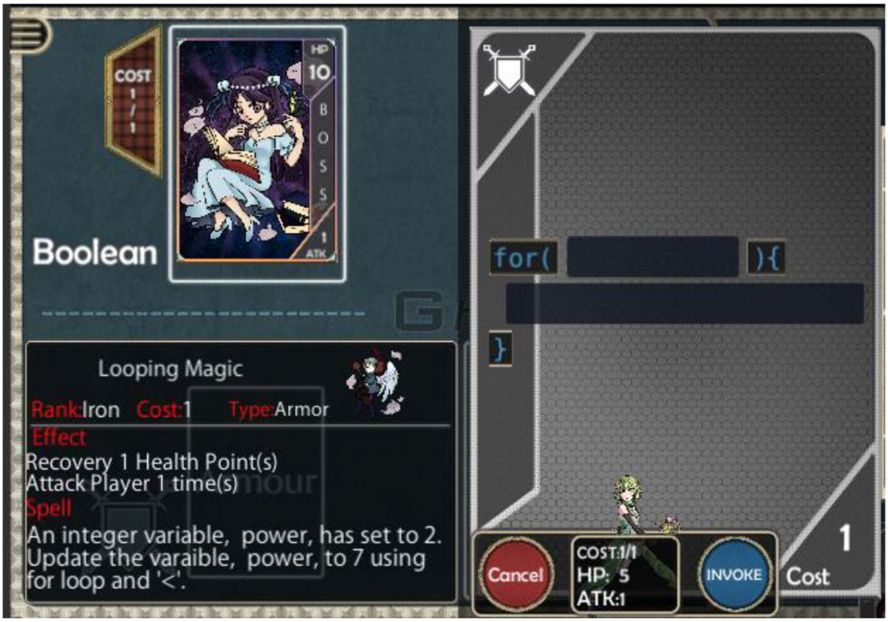


Fig. 10 Shows the scenario embedded with the programming task on the iteration topic.

specific learning objective and identified by the domain experts. The gameplay scenarios help players to practise programming constructs. Players drag the tiles and drop them to the appropriate options to complete a specified programming task. The successful completion of the job executes the card effect for attacking

(a) Easy Level (b) Medium level (c) Hard Level

Fig. 11 A, (b) and (c) shows the easy, medium and difficulty levels of tasks, respectively. They are served as the adaptive components the opponent and obtaining the health points. Playing cards are scenarios where players build their domain knowledge or practice skills.

Each card scenario can be modified and appended with a set of adaptive scenarios. The adaptive methods create variations and can enhance motivation in practice and play. Adaptive scenarios are defined with the same objective but vary with the number of operations required. The number of actions needed for the scenario is the factors measuring of the difficulty level. Figure 10 Shows the scenario that embedded the programming task on a topic about the programming loop.

Implementing adaptive scenarios shown in Fig. 11 enables dynamic difficulty adjustment and provides adapted scenarios to the player's needs. The scenarios presented to players at run-time can be adapted to support the player's needs (e.g., increase player success rate by reducing content difficulty).

6.6 Gamescenarioadaptivity

The sequence diagram shown in Fig. 12 illustrates the overall adaptation process in the proposed framework.

When a player starts playing a serious game, the serious game sends login information to the Interaction Data Handler in GLA to retrieve the reference of registered game scenarios. The game object adaptor retrieves the game objects based on the existing knowledge record stored in the player profile. The registered game objects are the game objects displayed in the serious game and are also the media used to analyse the player's knowledge. Once the game has started, the player interacts with the serious game. When the player attempts the registered game scenarios, the

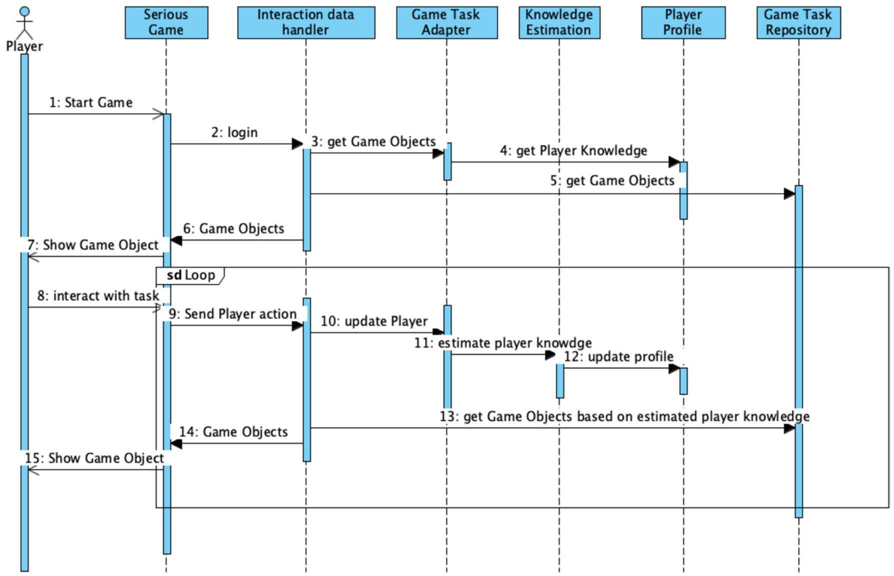


Fig. 12 Sequence Diagram for Game Object Interoperability Adaptivity based on player performance

```
{
 "actor": { "name": "Alan"     },
  "verb": { "name": "completed"},
  "object": { "name": "quest",
              "definition": { "name": "/scenarios/name/001" },
  },
  "result": {
    "name": "completed",
    "extensions": [
      { "name": "Select", "value": "2"  },
      { "name": "Drag", "value": "6"},
      { "name": "Attempt", "value": "1"},
      { "name": "Time Taken", "value": "57934" }
    ]}
 }
```


Fig. 13 Shows the xAPI statement of a completion event of a game scenario

Fig. 14 The adaptive responses from GLA System indicate the possible scenarios in the next stage


```
[
  { "scenarioID": "BasicCardTrim_Iron",
    "prefabName": "BasicCardTrim"
    "game_attribute": {"timeLimit": 25000}
  },
  { "scenarioID": "BasicCardLength_Iron",
    "prefabName": "BasicCardLength",
    "game_attribute": {"timeLimit": 25000}
  }
]
```

serious game sends the attempt result of the game scenario via the xAPI statement to the Interaction data handler. Figure 13 shows a sample of the xAPI statement. The handler analyses the performance result and estimates the current player knowledge based on the knowledge tracing algorithm in the game object adaptor. Finally, the adaptor selects the game objects based on the adaption rules. Figure 14 shows the sample of adaptive instructions. The adaptation strategy continuously monitors player interaction and provides personality adaptation, which is done by giving a game scenario with a suitable difficulty level. Figure 14 illustrates adaptive responses from GLA. It indicates adaptive scenarios and related attributes for the next stage. The scenarios are "BasicCardTrim_Iron" and "BasicCardLength_Iron".

6.7 Game object adapter

The game object adapter is the intelligent component in the framework that interprets the collected data, including user interaction data on the game objects, to determine the adaptive game's context. The captured player data is stored in the Game Object repository and used to determine the adapted content. The game object adapter used the metadata associated with pedagogical and domain knowledge to identify suitable game objects with an appropriate level of difficulty and the expected competency. Table 1 illustrates a sample metadata of a card game scenario (Loop Magic), which supports players to practise the iteration process in learning programming.

The metadata establishes the competency model in the attached game. The metadata facilitates the scenario adaptation mechanism. Based on the player status and metadata, the scenario can be adjusted to fine-tune the personalised learning experience of the player.

The scenario adaptation mechanism breaks down into two steps, player estimation and scenario adjustment. Player estimation can apply rule-based heuristics to determine the player learning's state Western (Nyamsuren et al., 2017). As player performance indirectly indicates their knowledge level, knowledge estimation of a player can be based on the accuracy of the game scenario and the response time taken. The knowledge rating of the player for each card is calculated as follows:

$$Knowledge\ Rating = \frac{no.\ of\ successful\ attempts}{total\ number\ of\ attempts}$$

where:

*Knowledge Rating is also a proportion of the response time.

Table 1 Game Task Information Registered in the GLA System

Card Name	Difficulty Rate	Time Limit(s)	No. Of Clicks	No. Of Drags	Learning Objective
Loop Magic	0.7	300	20	14	Practise for iteration
Loop Magic	0.6	150	6	7	Practise for iteration
Loop Magic	0.4	60	3	2	Practise for iteration

Response time is the duration that the player spent playing the scenario. There are three different types of attempts: (i) skipping the card without completion, (ii) completing the card within the time limit, and (iii) completing the card exceeded the time limit. The number of successful attempts is only considered for completing the card within the time limit. Accuracy and response time are used to measure their knowledge rating.

The knowledge rating supports the scenario adaptivity in the adaptation component. Adjustment strategies can be designed to support different learning purposes. For example, a practice mode situation aims to keep the player practising the various scenarios at their level of difficulty level. The adaptation strategy continuously monitors the individual actions, estimates knowledge ratings, and personally adapts the game scenario to maintain the learning and game flow with a suitable difficulty level. The adaptation criterion is to keep the difficulty level ideal for the player. The adaptor interprets the player's knowledge status and selects personalised scenarios. e.g., the difficulty ratings are within the range of the estimated knowledge rating. Even though player knowledge or skill has grown during the game, the player knowledge rating is continuously evaluated, and adapted scenarios can be maintained.

7 Evaluation

I-PLATO's adaptive framework provides personalised adaptivity for the serious game described. The personalised adaptivity has been designed and implemented as an external component to the game engine using the GLA server. It enhances the game-based adaptivity and provides a way for non-technical users (e.g., educationalists) to customise the personalised learning content to the individual players during different scenarios. It also reveals the individual players' game activities and performance during the game session. The revelation of individual status provides educators with additional feedback and allows them to make custom adjustments.

The I-PLATO has enhanced the development of externalised game adaptivity. The adaptivity is set up by initialising the adaptive game objects and adaptive mechanisms in the GLA server during the development phase. During game sessions, individual players' adaptation is established through game object adjustments by collecting player data and using the built-in adaptive mechanism. The framework implementation is evaluated with the game GhostCoder. GhostCoder has established personalised adaptivity through personalised adjustments of game objects during the game session. GhostCoder is an educational game for practising computing programming syntax. The programming practices are embedded in the game mechanic and objects. GhostCoder has been designed to adapt the programming practises to the individual students through adjusting the appropriate game object to suit their individual needs. The presentation of the programming tasks is designed with a personalised difficulty adaptation and spaced repetition approach. i.e., if a player gets an answer correct, there will be a longer delay before it is represented than if the player gets the answer wrong. It also adapts the player's performance over time by adjusting the presentation of the game objects.

Data captured from the player's interaction impacts both the repetition of scenarios and it also manipulates the adaptation features. The player's performance on the programming task influences the order and the frequency with which individual items are presented to them. It tries to find the optimal interval between presentations of the items to be learned and adapted to the player's performance to establish personalised gaming and learning experience. I-PLATO continuously monitors the player's performance and adjusts game scenario repetitions. The result shows personalised game-based adaptivity.

The game-based adaptivity motivates learning through the sense of achievement. The GhostCoder supports the practice sessions of programming constructs for novice programmers. The scenario adaptation mechanism adapts the player's performance to the scenario's difficulty. The current adjustment strategy applied in the GhostCoder uses a 75% success rate. It means that players have a 75% chance to complete the given scenario. The difficulty level of selected scenarios is slightly lower than the individual knowledge rating. This strategy aims to maintain players' flow in playing by aligning the knowledge status with the difficulty rating. This adaptive strategy offers a more personalised learning experience.

The I-PLATO also provides detailed data about learners' interactions with the attached game. It shows the learner's mastery on the particular scenarios. It provides an insight for the educationalists about remedial actions that could be taken in the class when they interact with students face-to-face.

The implementation of GhostCoder shows that the I-PLATO is feasible to establish the personalised adaptation mechanism. The I-PLATO demonstrate an approach to facilitate personalised learning support while playing the game.

The initial evaluation of the scenario adaptation mechanism successfully has been made within the lab settings with the developers, game designers and related teaching staff. Initial feedback on the game adaptation was positive. The next phase will be conducting tests with the learners and collecting more learner data.

8 Discussion and conclusion

Educational serious games can positively impact learning, but various improvements are still required to present serious games in an academic setting. Promoting the application of games in actual educational settings is necessary to simplify the design, development and application of games for educators.

Game Learning Analytics (GLA) are data science techniques that validate and deploy serious games. Freire (2016) presented an overview of a Game Learning Analytics (GLA) system and described analytic process starts when the game sends data to a collector. The data collected is aggregated to generate information to feed reports and visualisations (in real-time or offline) and assess students. The process ends in the adapter component, which provides feedback to adapt the game to players.

Research on GLA has advanced the development of serious adaptive games. GLA facilities to relate gameplay with learning, providing a more evidence-based measure of players' performance (Alonso-Fernández et al., 2021), and also enables real-time knowledge evaluation of what players are doing and the prediction of player knowledge (Alonso-Fernández et al., 2019). Support Content Analysis, Temporal Analysis and Social Network Analysis can be visualised through data collected from the serious game (Bakharia et al., 2016). xAPI-SG enables standardisation of the common interactions that can be tracked in serious games, providing meaningful aggregated and visualised information to educators and standardising Learning Analytics solutions (Serrano-Laguna et al., 2017). T-Mon has further simplified the analysis and visualisation of interaction data from serious games (Alonso-Fernández et al., 2021). In addition, research applied GLA to validate and improve the serious game design (Calvo-Morata et al., 2020). However, only a few research has explored the adaptor component in GLA to provide content intervention or feedback in the game adapted to players' needs. Collected data from players' interactions provide insights regarding players' learning and information on where players have problems with educational objectives indicating those game mechanics or game contents could be adapted to achieve their needs.

I-PLATO framework is established based on the Learning-Centred Design (LCD) approach. The I-PLATO supports the liaison between educators and developers. It allows educators to participate in designing the game objects and game content. It enhances their understanding of the operations of the game logic and mechanics. Participation enables the alignment of game mechanics with learning objectives and enables educators to effectively use the game contents in their real-time classroom. In addition, actual in-game actions directly reflect the behaviour and status of the player.

The collections of player interaction data support learning assessment in the remote server. The game learning analytics helps educators monitor players' progress effortlessly and unobtrusively through dashboard visualisation. Besides, prediction models developed based on player interaction data can automatically evaluates students' knowledge mastery after playing the game and thus provide real-time adaptive adjustments on the game objects while playing the game to establish personalised learning experiences.

The I-PLATO framework has extended the GLA framework by decoupling the content adaptation and delivery approach. The PLATO shows an Interoperable Adaptation Mechanism by designing interoperable game objects and decoupling content adaptation from the game engine to the remote analytics server. This approach isolates the player knowledge evaluation mechanism from the game engine to the remote analytics server and supports adaptive content delivery with the xAPI communication. It aims to optimise the content delivery in the game engine and establish personalised adaptation in serious games through the support of game analytics. Player interaction data from games is collected through the x-API model. Game Learning Analytics has been implemented in the remote server to estimate student knowledge mastery and recommend personalised learning content. Based on the adaptive instructions, the game engine dynamically scheduled and delivered the personalised learning material to match students who needed help. The approach can enhance the design collaboration between educators and game designers but separates the design game tasks from learning objectives, adaptation evaluation and the content delivery of different game mechanics in serious games. The framework supports the integration of game interaction data sources to create a customised content adaptation.

The PLATO demonstrated the concept of extracting learning patterns from raw game data and automating the game content adjustments through player knowledge classification, prediction, and detection. However, this adaptation framework for serious games presents certain limitations and requirements that need improvement. Although the knowledge prediction and adjustment models have been created and evaluated at the development setting, further testing and evaluation in the classroom settings are required. A pilot study will be conducted. Questionnaires and associated statistical analysis will be employed to gather students' attitudes toward the game.

Future work will include developing other methods for identifying students' skills, predicting student performance, and improving decision-making with the other machine learning approach. Evaluations are also planned to evaluate the additional game content adjustment and content difficulties and understand what influences students' attitudes or experiences towards using such educational games.

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Declarations

Conflict of interest None
The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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