A Privacy-Preserving Framework Enhancing University Student Engagement Using Machine Learning and Gamification

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Abstract. Student disengagement and high attrition continue to be a major problem in higher education, particularly in intensive disciplines like computer science. These challenges are often compounded by problems such as academic stress, mental health issues and the particular adjustment difficulties of international students. Traditional teaching methods often lack the flexibility and responsiveness required to meet the diverse and evolving needs of learners. In response, this paper presents a comprehensive conceptual framework that combines machine learning techniques with a structured gamification design to improve student engagement. The proposed model consists of three interrelated layers: The first involves systematic data collection and feature engineering of virtual learning environments, capturing behavioural indicators such as interaction with content and activity on the platform. The second layer applies unsupervised machine learning algorithms to create dynamic engagement profiles that enable continuous monitoring and identification of student engagement patterns. The third layer uses the Web-Agon framework to design and adapt gamification strategies based on these profiles and offer personalised interventions tailored to individual engagement. The framework also incorporates privacy-preserving technologies, including federated learning and differential privacy, to ensure ethical handling of sensitive data. This approach aims to create an adaptive and student-centred learning environment that promotes sustained engagement and academic success.

Keywords: Gamification · Machine Learning · Student Engagement

1 Introduction

Innovative and adaptive approaches are needed to address the growing problem of student dropout, particularly in challenging fields such as computer science [2].

While factors such as mental health, stress, previous educational experiences and self-motivation significantly influence engagement, international students face additional difficulties such as language barriers, cultural adaptation and unfamiliar educational practices. Conventional university strategies, even if well intentioned, often struggle to recognise and respond effectively to these diverse and changing student needs. This leads to increased disengagement, poorer academic performance and higher dropout rates.

Building on fundamental research in student engagement and machine learning (ML) [2,9], our previous work has successfully used ML techniques, specifically unsupervised clustering algorithms such as K-means, to analyse student behavioural data and categorise them into different engagement profiles: highly engaged, moderately engaged and disengaged. In addition, the first-year computer science curriculum, which won the AdvanceHE Collaborative Award for Teaching Excellence in 2019, uses the concept of student observable behaviours (SOBs), which lends itself very well to being further supported by the integration of gaming elements, as demonstrated by the integration of robotic systems [5]. These previous studies have shown correlations between levels of engagement and academic outcomes and provide a solid methodological foundation for further research. While previous implementations offered valuable insights into the analysis of student behaviour, in practice they were limited in their ability to dynamically adapt pedagogical strategies to the individual and changing needs of students, especially in real-time learning contexts.

Given these limitations, this paper proposes an entirely new and comprehensive conceptual framework specifically designed to significantly improve student engagement in computer science modules. Our model uniquely integrates and extends the previously developed ML-based behaviour analysis frameworks by embedding them in a sophisticated gamification engineering context. Specifically, our approach leverages the robust and user-centred Web-Agon framework [1,4,6] to systematically match ML-based insights with tailored gamification strategies to proactively and continuously engage students. This integration not only ensures initial categorisation of students based on observed behaviour, but also enables continuous adaptation of gamification strategies in response to evolving student interactions.

The proposed conceptual framework includes three distinct but interconnected layers designed to enable a continuous cycle of student engagement. The first level, data acquisition and feature engineering, systematically collects, processes and refines behavioural data from virtual learning environments (VLEs) such as Moodle or Canvas. This data includes detailed metrics such as login frequency, total time spent online, video tutorial completion rates, interactive experiments and forum participation. In addition, student reactions to the initial gamification interventions are recorded to provide continuous real-time feedback that feeds into subsequent analysis processes.

The second layer, machine learning for dynamic student profiles, serves as the analytical core of the framework. Using advanced ML techniques such as K-Means clustering, this layer dynamically groups students into clearly defined engagement profiles: highly engaged, moderately engaged and not engaged. This categorisation is constantly updated based on student behaviour captured in the

first layer, ensuring a real-time response to changes in student engagement. In addition, the model is able to adapt the cluster creation process as it provides the opportunity to change the clustering algorithm based on new behavioural data (which may be extracted by the learning platforms by considering coefficients such as attendance, activities and results), selecting the most performant one for a given dataset. The dataset, indeed, may change with the iterations and the model is able to maximise the assignment of the students to the related cluster. This enables instructors to continuously monitor student engagement during the module and creates a virtuous cycle aimed at understanding students' needs and improving their learning experience. Robust ethical considerations are addressed in this layer through privacy-preserving methods such as Differential Privacy, which anonymises individual data, and Federated Learning, which enables secure, decentralised data analysis [3].

At the third layer, gamification design and dynamic adaptation, ML-driven insights are translated into actionable and personalised gamification strategies using the Web-Agon framework. Customised interventions such as advanced challenges for highly engaged students, collaborative activities and incremental rewards for moderately engaged students, and gentle nudges and simpler interactive tasks for disengaged students are implemented dynamically. This adaptive mechanism continuously refines and optimises the gamification strategies in direct response to the evolving student profiles provided by the analytical layer.

Consequently, our proposed framework represents a significant advance that goes beyond incremental improvements and offers a holistic, dynamic and ethically responsible solution. By integrating advanced ML analytics with sophisticated gamification methods, we aim to sustainably improve student engagement and academic success, effectively addressing the multiple challenges associated with student disengagement and dropout.

2 Background

2.1 Student Engagement and ML

Proper engagement during teaching activities is crucial for students as it increases satisfaction, enhances motivation to learn, reduces isolation and improves performance [32]. Student engagement is a key indicator of the quality of the learning experience, reflecting students' intrinsic, cognitive and emotional involvement in their learning [33]. Low engagement has been shown to have a negative impact on student motivation [34] and can also have negative consequences on academic performance [35].

During the period of the pandemic, when teaching sessions were moved online, it was observed that several students faced challenges in terms of engagement, which had a negative impact on their performance [36]. Researchers have noted that students are responsible for their own engagement, and instructors must provide a better learning environment to help overcome the challenges students face [37]. However, a better learning environment is not always enough to overcome low engagement. Sometimes, a lack of engagement can be caused by

students' emotions, which can negatively impact motivation and performance [38]. In the worst-case scenario, low motivation can affect not only student performance, but also lead to dropout. Interrupting their studies can lead students to experience dangerous emotional states such as depression and a sense of inadequacy, which constitute actual psychological trauma [39]. Despite universities taking action to provide students with the best approach to their studies, aimed at promoting academic success and preventing dropout, they sometimes fail to achieve the expected results [40]. Indeed, it is a very challenging task for universities to detect engagement indicators, particularly those that identify students who are more likely to drop out [41].

However, machine learning predictive models have been developed to provide solutions to prevent dropout based on various features, such as demographic information, academic performance, learning behaviours, financial situation, technological self-efficacy, and family situation [42–44]. Although these models support institutions in taking action to help students find the motivation to avoid dropping out, students' engagement during teaching activities could persist. Researchers identified features that can be used to categorise students' behaviours based on presence, study activities, results, social social and tutor coefficients [45].
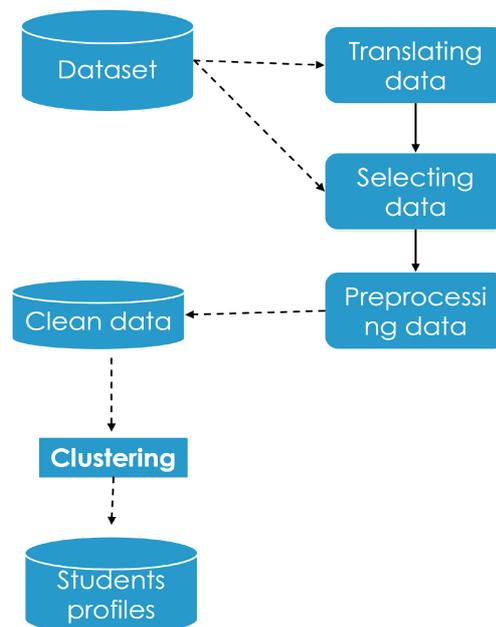

Fig. 1. Flow of the step required for the identification of the students' profiles.

These features were processed using ML models to identify different levels of student engagement, demonstrating also their impact on the students' performance [2]. The model adopted in [2] involved collecting students' learning analytics from e-learning platforms used to access teaching materials and complete

activities provided by module leaders. The dataset included all the behavioural features accessible from the platform, such as login frequency, last login time, total time spent online, the number of video tutorials and experiments viewed, the frequency with which video tutorials and experiments were viewed, the number of web pages viewed, the number of PDF files downloaded, and the number of exercises performed. However, the dataset required preliminary data preprocessing, cleaning and normalisation to prepare it for ML processing (see Fig. 1). As the dataset was not provided with labelled data, a clustering model was adopted to profile the students based on their engagement. The clustering step involved a comparative analysis of three different algorithms, evaluated using Silhouette analysis, which identified K-means as the most effective. This important step was necessary to ensure better identification. The effectiveness of the model was also confirmed by a correspondence between different levels of engagement (high, moderate or not engaged) and the final grade in the module that demonstrated the impact of the engagement on the performance. Highly engaged students obtained the highest scores, while those with lower engagement obtained the lowest grades [2].

The use of ML to have an early identification of the student's level of engagement can be a crucial support for the instructor to identify the students at risk and provide some useful actions to tailor the teaching activities. This can be done in various ways, such as providing collaborative activities based on work groups, which can increase student engagement, motivation and effort, maximising performance and enhancing knowledge and skills.

2.2 Gamification, Gamification Engineering, Acceptance Requirements, and the Web-Agon Framework

In recent years, gamification, which has been properly defined by Deterding et al. as "The use of game design elements in non-game contexts", has gained traction as a strategy for improving user engagement across different domains such as education [7,14,20,25–27], software testing [13], software engineering [11], public services [12], data privacy and compliance with GDPR [22], procedural change on air traffic management [21], privacy and security [24]. Unlike entertainment-driven systems, gamified environments aim to encourage user behavior aligned with specific functional or learning goals [15,16]. In education, and particularly in computing education, especially after the COVID-19 pandemic, the role of gamification has become even more relevant, as students often disengage from theory-heavy content and gravitate toward hands-on, practical tasks [7,17]. Gamification, through mechanisms like points, badges, and leaderboards can create more interactive and rewarding learning experiences [25–27].

To systematically design and implement gamified systems, the concept of Gamification Engineering has been introduced [6]. This emerging discipline encompasses languages, models, engines, and design tools aimed at embedding game mechanics into software systems in a structured way [14,18]. Within this context, Goal-Oriented Requirements Engineering (GORE) has shown promise in enabling designers to consider gamification from the early stages

of system development. However, simply adding game elements is not sufficient: designers must also factor in user characteristics, contextual constraints, and behavioral theories from psychology, sociology, and organizational studies [1,10,19]. To support such multifaceted analysis, the Agon Framework was developed [4,18]. It extends traditional GORE techniques by introducing Acceptance Requirements [4, 23]: a set of considerations that encompass psychological and social factors critical to user adoption and engagement. This framework has been successfully applied in multiple EU-funded research projects and has demonstrated its capacity to improve how gamified components are planned and aligned with user needs [4,21–24].

Agon is a multi-layered conceptual modeling framework encapsulating meta-models related to acceptance requirements and gamification requirements. Furthermore, Agon can be used via the web thanks to its Web-Agon tool [1], which is available online [8]. The tool was created as a web-based environment that automates part of the gamification design process [1]. It provides structured support for requirements analysts, helping them to identify which system functionalities are best suited for gamification and how to gamify them effectively. This automation can reduce the likelihood of design errors, and can accelerate the development of engaging systems [1]. Agon and its tool enable analysts to model gamification strategies systematically, based on Acceptance Requirements, and have shown effectiveness in heterogeneous case studies (also within EU Projects) and domains such as air traffic management and university-level web development courses [4,7,21–24]. In educational settings, particularly in computing modules, such gamified tools have proven valuable in bridging the gap between theoretical knowledge and practical application [7]. By fostering intrinsic motivation through selected gamification design patterns, appropriate for the users to engage, well-design mechanisms based on gamification concepts (e.g., points, badges, leaderboards, gamified avatars, tours, quizzes and challenges) can create more interactive and rewarding learning experiences [7]. In summary, the evidence from the literature suggests that a well-structured design process, anchored in both engineering and human behavioral analysis, can significantly enhance the user participation, engagement and collaboration with other professionals [4,21–24], and, in particular for the education settings, can foster student engagement and learning outcomes [7,17,20,28].

The Agon framework (and web tool available online [8] encapsulates, in its method and models, exactly this concept and approach supporting a well-structured design process, anchored in both engineering and human behavioral analysis. Figure 2 conceptualises the layers and models of Agon, and their interactions.

For the sake of clarity, we henceforth refer to the Agon Framework and its accompanying tool available online [8] as the Web-Agon Framework [1,4]. The Web-Agon Framework offers a structured, meta-modelling approach aimed at guiding the design of user-adaptive and engagement-driven software systems. Its central contribution is to bridge theoretical models of technology acceptance with practical gamification strategies through a set of interconnected meta-models
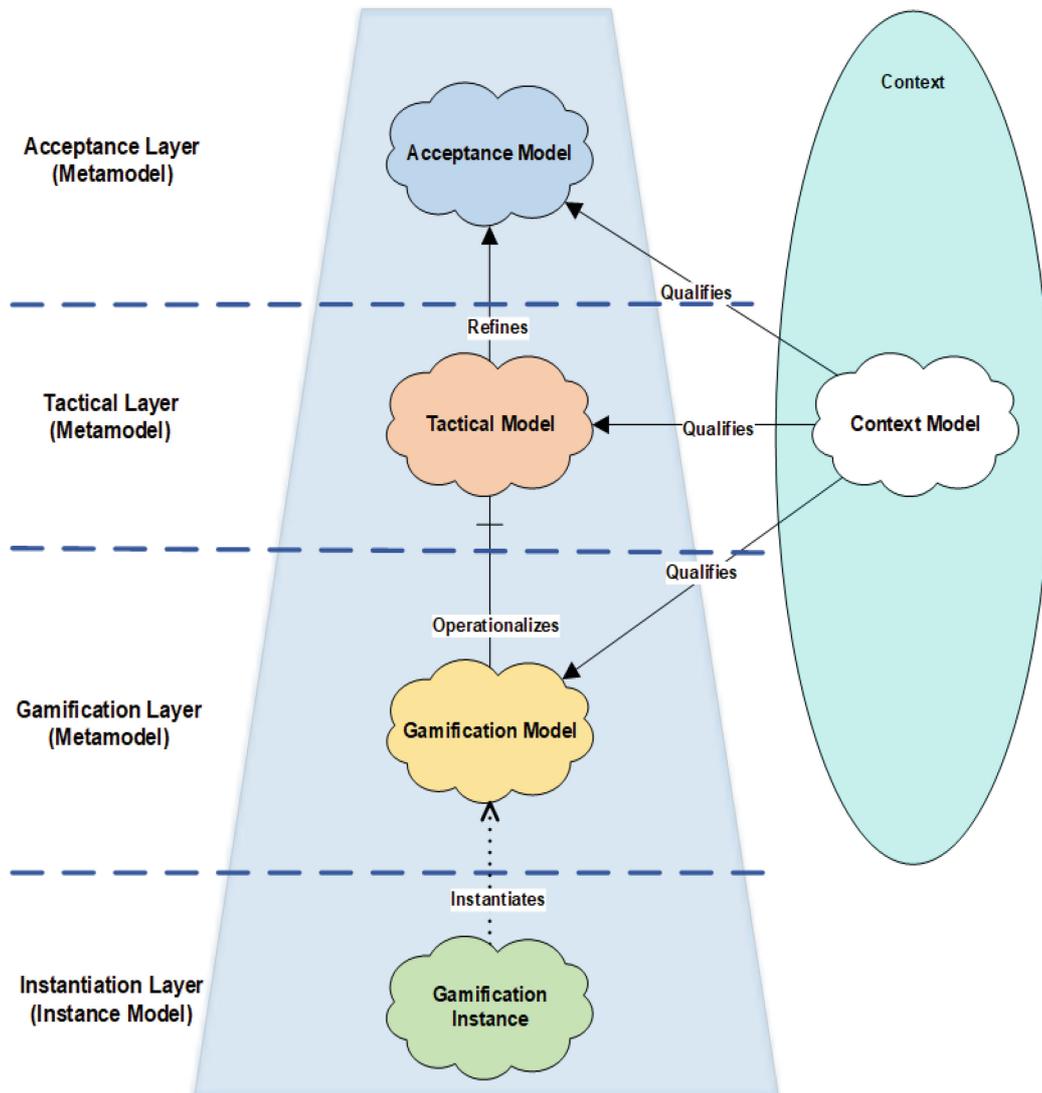
Fig. 2. Conceptualisation of Agon, a multi-layered modeling framework encapsulating meta-models related to acceptance requirements and gamification requirements [4,6, 18,21]

(Fig. 2). Such meta-models form a layered architecture, moving from abstract user needs to context-sensitive gamification elements. In the next, we will outline such meta-models, and those are fully available online at [31].

As shown in Fig. 2, as its foundation, the Acceptance Meta-Model (AMM) conceptualises user motivation and behavioural intentions by incorporating constructs from established models such as UTAUT [29] and TAM2 [30]. Within this model, key constructs like "Effort Expectancy", "Performance Expectancy", and "Social Influence" are represented as goals [4]. These goals are then logically

refined through contribution relations that help identify which system qualities are necessary to foster user acceptance.

To translate these high-level psychological goals into actionable qualities, the framework employs a second layer (Fig. 2): the Tactical Meta-Model (TMM). TMM introduces a set of abstract tactics, such as "Foster Feedback", "Promote Collaboration", or "Support Personalisation", which act as design-level responses to acceptance needs [4]. This model serves as the functional intermediary between the acceptance concerns of users and the concrete mechanisms provided by gamification.

As depicted in Fig. 2, gamification mechanisms are captured within the Gamification Meta-Model (GMM). GMM presents a structured catalogue of gamification strategies derived from both academic literature and industry practices [4,21]. These include familiar concepts like Badges, Leaderboards, Challenges, Avatars, and Progression Paths, all modeled as goals. Tactics from TMM are operationalised in this layer by linking them to one or more gamification techniques. For example, the tactic "Promote Collaboration" may be fulfilled by mechanisms such as "Team Challenges", "Team Leader boards" or "Set Team Roles".

Furthermore, to ensure the relevance of these models to real-world users, the User Context Model (UCM) provides a framework for representing individual user characteristics (Fig. 2). These characteristics are organized using Context Dimension Trees, which include facets like Player Type, Age Group, Employment Status, Gender, Acceptance Goal, Acceptance Task, Social Structure, and Nature of Good Being Produced [4,6]. Context-Dependent Rules (CDRs) are used to associate specific model elements with user contexts, and used for making automatic analysis and filtering in the other other models (AMM, TMM, GMM), in order to individuate the most suitable gamification solution per the group of users to engage [4,21]. For instance, a rule may specify that users identified as "Explorers" are better supported through features like "Unlockable Content" or "Progressive Disclosure". To connect all the above models, the Integration Model (IM) facilitates formal relationships between their elements. It ensures consistency and traceability across layers, from psychological constructs to gamification techniques, while incorporating contextual annotations. This comprehensive traceability allows analysts to explain and validate the choices made during system design [4,21].

The Web-Agon Framework thus supports the engineering of software systems that are both user-aware and engagement-oriented. Its modular structure and formal semantics enable scalability and extensibility. By linking user motivation, design tactics, and gamification in a coherent and context-sensitive manner, it provides a principled approach to designing interactive systems that foster sustained user engagement [4,7,21–24].

3   A Conceptual Framework for Engaging University Students via ML and Gamification

The increasing problem of students dropping out of university [44], especially in demanding fields such as computer science, requires innovative and adaptable solutions. Factors such as mental health, stress, prior learning experiences and the need for self-motivation have a significant impact on students' ability to stay engaged. International students face additional challenges such as adapting to a new culture, language barriers and different educational practices that make it difficult for them to stay motivated and engaged. While universities try to create a supportive learning environment, traditional methods are often unable to dynamically recognise and address the differentiated and changing needs of individual students, leading to potential disengagement, reduced academic performance and even dropout. To comprehensively address this multifaceted problem, we propose a novel conceptual framework that synergistically combines advanced machine learning (ML) techniques with sophisticated gamification engineering methods. Our framework proactively identifies different profiles of student engagement, dynamically adapts gamification strategies, and continuously adjusts to evolving student behaviour while maintaining critical human oversight by the instructor. This innovative approach builds on our previous research in ML-driven student behaviour analysis [2,9] and strategically leverages the powerful Web-Agon framework for the systematic design of gamification [1,4,6]. Our framework, illustrated in Fig. 3, consists of three interconnected layers that enable a continuous, data-driven feedback loop to optimise student engagement.

Layer 1: Data Acquisition and Feature Engineering (The Observational Foundation). This fundamental layer systematically collects, processes and refines various data on student behaviour and provides the essential inputs for our analytical models, as also shown in Fig. 3. The effectiveness of the subsequent profiling and gamification strategies depends heavily on the quality and scope of this data. Based on previous research [5], this first step (**Step 1**) identifies a robust set of observable student behaviours (SOBs) that signal different levels of engagement. Data from virtual learning environments (VLEs) such as Moodle and Canvas provide instructive examples [2], including frequency of logging in, which indicates routine participation, and total time actively spent with online materials, which reflects engagement with coursework. In addition, we track interactions such as video tutorial views and completion rates, engagement with hands-on experiments and virtual simulations, and interactions with course content such as web page views and document downloads. Exercise performance data, such as the number of quizzes completed and points earned, provide direct measures of student academic understanding and interaction. Forum participation, which includes both active contributions and passive views, demonstrates students' willingness to collaborate with others, seek help or contribute to learning. Assignment submission behaviour also reflects consistency and academic
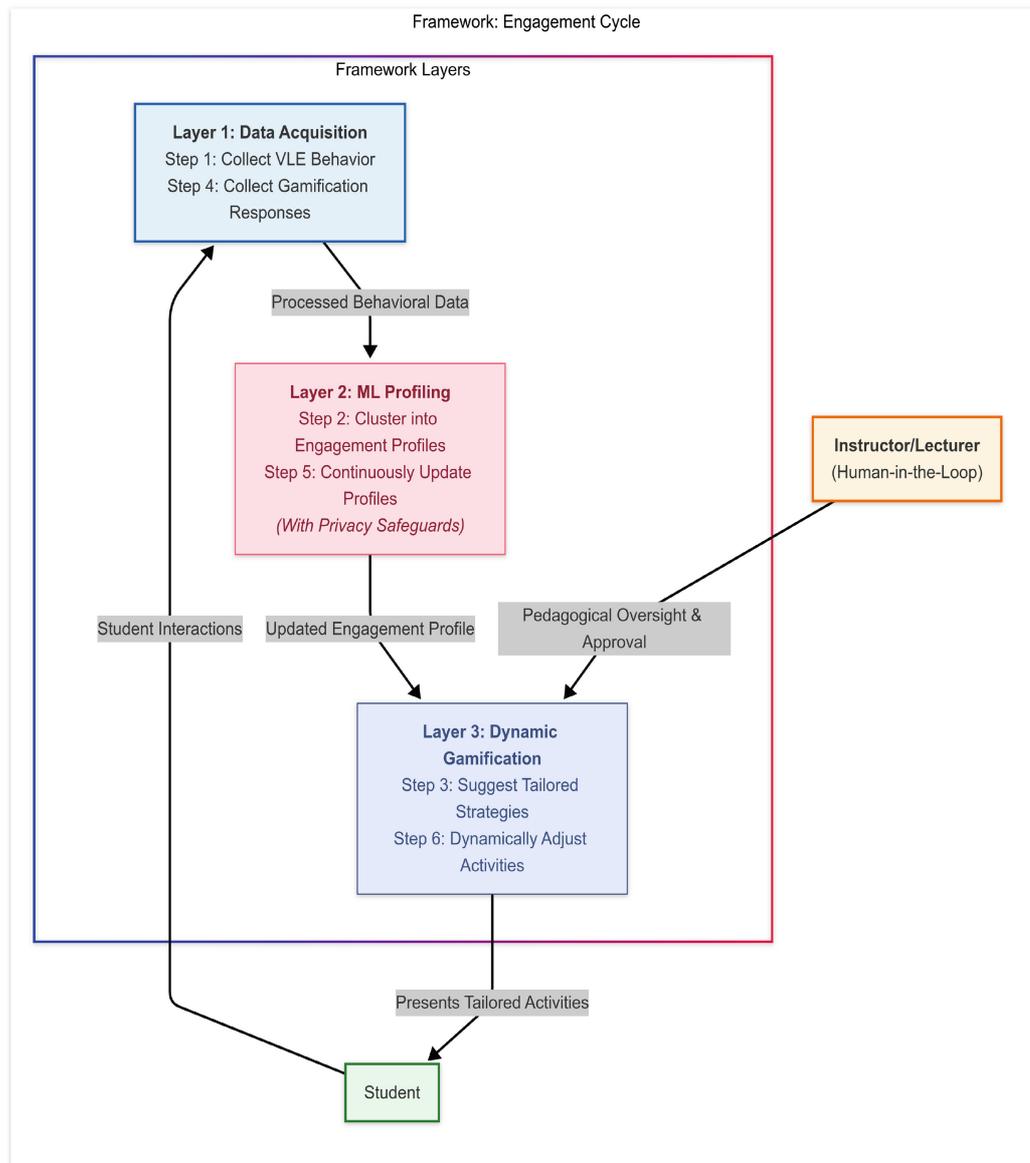
Fig. 3. Conceptual framework illustrating the interaction among data acquisition, machine learning, and gamification layers to support a continuous and adaptive student engagement cycle.

responsibility. Raw data undergoes basic pre-processing, cleaning and normalisation to mitigate inconsistencies and effectively manage missing information so that it is carefully prepared for accurate analysis. Response data on student participation in game-based activities is also collected at this level (**Step 4**). Metrics include participation frequency, performance scores, badges earned, leaderboard rankings, and interaction specifics such as engagement with game-based prompts or optional challenges. This continuous feedback mechanism enables real-time

evaluation of the effectiveness of gamification, allowing the framework to empirically track student engagement and adjust strategies as needed.

Layer 2: Machine Learning for Dynamic Student Profiling (The Analytical Core). This layer serves as the analytical centre of our framework and uses advanced ML algorithms to categorise students based on the behaviour observed in Layer 1 (**Step 2**). Using unsupervised clustering methods such as K-means, students are categorised into different engagement profiles: "highly engaged", "moderately engaged" or "not engaged" [2,9]. These profiles dynamically reflect their current level of interaction with the learning content. Highly engaged students consistently interact positively with all educational elements, while moderately engaged students show selective or sporadic interaction patterns. Not-engaged students often show minimal interactions and inconsistent patterns of activity. Continuous monitoring of student behaviour through ML enables timely detection and reclassification of student engagement profiles (**Step 5**). For example, a student initially categorised as "highly engaged" may shift over time towards "moderately engaged" or "not engaged", leading to necessary adjustments to gamification approaches. Conversely, improved engagement observed in previously less engaged students may improve their categorisation. This proactive, ongoing analytical approach ensures responsive and tailored educational interventions that significantly increase the potential for effective student re-engagement. Given the sensitive nature of student data, our framework incorporates robust data privacy mechanisms. While confidentiality is of paramount importance, advanced solutions are required to enable meaningful ML analyses for diverse student populations (e.g. students from different cultural and educational backgrounds at institutions such as Middlesex University). We propose the integration of differential privacy into federated learning systems [3]. Differential privacy adds a controlled level of noise to data or query results that makes it statistically difficult to infer information about an individual person, even when the data is aggregated. This ensures that the behaviour of individual students cannot be identified, so their privacy is protected, but collective insights into engagement patterns are still possible [3]. For example, instead of knowing exactly how many times Student A has logged in, the system could learn that "students in this cluster have logged in between 10–12 times, with some noise added to protect individual exact counts." Federated learning enables the collaborative training of models in decentralised datasets (e.g. on individual university servers) without the need to centralise students' raw data. This significantly reduces the privacy risks associated with data transfer and storage, as only the model updates (and not the raw data) are shared [3]. For example, Middlesex University's system could train a local model with the student data and then send only the learnt model parameters (not the raw data) to a central server, which aggregates these updates from multiple institutions to create a more robust global model. This combined approach provides a robust and principled solution to ensure data privacy while supporting collaborative,

data-driven insights while strictly adhering to GDPR and other relevant data privacy regulations.

Layer 3: Gamification Design and Dynamic Adaptation (The Engagement Engine). In Layer 3, the analytical findings from Layer 2 are translated into realisable gamification strategies with the help of the structured, psychology-based web agon framework. The student engagement profiles created in Layer 2 initially serve as the basis for the User Context Model (UCM) in Web-Agon and guide the tailored development of gamification elements (**Step 3**). For highly engaged students, advanced gamification strategies such as "Expert Quests" or "Bonus Labs" provide intellectual stimulation and deeper exploration opportunities, while "Peer Mentor" badges or leadership roles provide meaningful tasks that leverage their intrinsic motivation. Moderately engaged students benefit from structured collaborative activities such as "Team Challenges" or "Group Quizzes" that encourage peer interaction and shared responsibility. Progress tracking tools, including visual "progress bars" for milestones and personalised feedback systems, reinforce incremental success and boost confidence. For students deemed disengaged, simpler, low-stakes gamification elements such as introductory quizzes with immediate feedback, guided virtual tours, and strategically timed gentle nudges can effectively reignite engagement and gradually build confidence. The adaptive nature of our framework ensures that gamification strategies evolve dynamically in response to updated student profiles and behaviours (**Step 6**). Each time Layer 2 generates updated student clusters (indicating shifts in engagement), Web-Agon responds by updating the UCM characteristics accordingly. This leads to a re-analysis and elaboration of an updated gamification design. For example, if a student initially categorised as "moderately engaged" responds exceptionally well to the tailored gamification elements (e.g. by regularly answering optional quiz questions or actively participating in team challenges) and is subsequently re-clustered as "highly engaged" by Layer 2, Web-Agon will dynamically adjusts the challenges so that they become slightly more demanding to ensure continuous motivation and progression. Conversely, if a "highly engaged" student shows signs of disengagement, the system can introduce supportive or basic gamification elements to help them regain momentum. This iterative process of continuously refining gamification strategies based on real-time student behaviour continues throughout the module until it is complete. During this iterative cycle, human supervision by the instructor remains essential. Web-Agon supports semi-automated phases of gamification design. This means that the instructor can review the gamification designs proposed by the system, make informed decisions and adapt them to the specific pedagogical goals of the module or other didactic constraints. For example, a lecturer can override a suggestion from the system if they know that a particular student is facing external personal challenges or if a suggested gamification activity does not align with a specific learning outcome. This human oversight ensures that the technological interventions are pedagogically sound and aligned with the overall educational goals. The interaction between Layer 2

and Layer 3 is facilitated by a precise mapping between student clusters and Web-Agon's User Context Model (UCM) characteristics, ensuring that gamification strategies are always contextualised. Ultimately, our comprehensive, iterative and ethically-driven framework systematically supports sustained student engagement by dynamically responding to evolving behaviours and significantly improving academic outcomes in the higher education context.

4 Conclusions

This study has presented a conceptual framework that combines machine learning-based behavioural analytics with adaptive gamification techniques to improve student engagement in higher education. By utilising learning analytics data and applying clustering algorithms, the framework enables the identification of different levels of student engagement in real time. These insights are then used to develop targeted gamification strategies that dynamically adapt to changing student behaviour and motivational needs. The integration of the Web-Agon framework provides a structured methodology for designing these gamified interventions that takes into account both psychological and contextual factors. A key strength of the approach lies in its ability to continuously and individually address the needs of students and support those at risk of disengaging, while challenging highly engaged learners. The privacy-friendly design of the framework ensures compliance with ethical standards and enables meaningful data analysis without jeopardising individual confidentiality. In addition, it plays an important role for educators who can refine or override the suggestions generated by the system depending on pedagogical goals or contextual factors. Overall, the framework represents an adaptable model for promoting student engagement that has the potential to reduce dropout rates and improve academic performance.

Future research will focus on implementing the framework in real classrooms, evaluating its impact using empirical data, and expanding its application to other disciplines and institutional contexts. Gamification of student engagement may also allow us to use proper tools from game theory in future work. Analysing the game theoretical equilibria of gamified student engagement to compute the most optimised output for all parties involved remains an interesting problem. Furthermore, designing gamification models inspired by well-studied games, such as prisoners' dilemma and Bayesian Stackelberg game, promises future research directions. This allows us seeing learning and teaching as a multi-agent strategic game.

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