One Size Does Not Fit All: Global Trends in Personalised Gamification Research

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ABSTRACT

The rise of personalised gamification has gained more attention as researchers begin to realise that a one-size-fits-all approach is not necessarily effective, especially when the user has different characteristics, motivations, and preferences. Hence, this study aims to map the global contributions, citation impact, and emerging research directions in personalised gamification research. Using performance indicators and science mapping techniques, publications that were retrieved from Scopus between 2016 and 2026 were used as the bibliographic data. To conduct bibliographic coupling, author-keyword co-occurrence, and overlay visualisation, VOSviewer 1.6.20 was employed, while publication output, country productivity, and citation counts were examined descriptively. Publications activity increased evidently after 2022 and peaked in 2025, showing that academic interest in personalised and adaptive gamification systems is growing. The most productive country was the United States, followed by China, Spain, and India, indicating strong contributions from North America, Europe, and Asia. Klock et al. (2020) emerged as the most highly cited publication, confirming the influence of research on tailored gamification and user-modelling. Based on keyword co-occurrence analysis, five dominant thematic clusters were identified: Digital Learning Innovation and Analytics, Gamification Design and User Characteristics, AI-Driven Adaptive Learning, Player-Type-Based Motivational Tailoring, and Personalisation and User Modelling. Recent themes involving artificial intelligence, learning analytics, self-determination theory, student engagement, and tailored gamification were indicated by the overlay analysis. The study reveals that personalised gamification is evolving towards more intelligent, theoretically grounded, and data-driven forms of adaptation. Future research should prioritise empirical testing of how personalised game elements drive motivation, engagement, and performance across diverse contexts.

Keywords: Bibliometric analysis, personalised gamification, gamification, research trends

INTRODUCTION

Background

Gamification has emerged as a powerful approach to enhance motivation, engagement, and behavioural outcomes across multiple domains, including education, health, and enterprise systems. By integrating game design elements into non-game contexts, gamification seeks to foster user involvement through elements such as points, badges, leaderboards, and rewards (Hamari et al., 2014; Sailer et al., 2017; Yusoff et al., 2024). Recent advances have shifted focus from uniform one-size-fits-all designs toward personalised and adaptive gamification, where users' individual preferences, behaviours, and learning needs are tailored based on their experiences (Klock, Gasparini, & Pimenta, 2020; Tondello et al., 2016). The design of gamified experiences should be influenced by individual differences, such as cognitive styles, player types, prior knowledge, and motivational drivers, which is the basis of personalised gamification (Mekler et al., 2017; Tondello et al., 2019).

Evidence has increasingly shown that such tailored systems not only improve engagement and satisfaction but also positively influence learning outcomes and long-term participation (Hassan et al., 2021a; Oliveira et al., 2023). Learners' motivation can be enhanced through the implementation of personalisation in the learning process, as it enables learners to engage in an autonomous learning experience without the need for supervision or control from others (Saputro et al., 2019). As a result, this field has gained momentum across disciplines, prompting the need for a comprehensive synthesis of its intellectual and conceptual development.

A systematic method for examining the evolution of research domains can be done through bibliometric analysis by evaluating publication trends, citation networks, and co-occurrence of thematic keywords (Donthu et al., 2021; van Eck & Waltman, 2010). Moreover, a systematic approach is required in bibliometric analysis to ensure a comprehensive collection and analysis of relevant literature (Sahri & Janom, 2025). Although previous reviews have addressed general trends in gamification, few have focused specifically on the personalised or adaptive dimensions. In addition, there is limited synthesis of how these themes have evolved across regions, authors, and institutions. Addressing this gap is critical not only for consolidating existing knowledge but also for guiding future research and practice in personalised gamification. The aim of this study is to investigate the global development, intellectual influence and thematic structure of personalised gamification research between 2016 and 2026.

This study has two complementary analytical purposes. It evaluates the performance and geographical distribution by examining annual publication output, country contributions and citation impact. Next, through bibliographic coupling and keyword co-occurrence analysis, it maps the conceptual and intellectual organisation of personalised gamification research. Bibliographic coupling is used to determine how contemporary publications are intellectually related through their shared references, thereby revealing current research fronts and clusters of scholarship. Keyword co-occurrence analysis is used to identify dominant concepts, research hotspots and thematic relationships, while the temporal interpretation of keywords indicates emerging research directions and shifts in scholarly attention. Accordingly, the study addresses the following research questions:

RQ1: How has research on personalised gamification evolved in terms of annual publication output from 2016 to 2026?

RQ2: Which countries have contributed most significantly to the global research output on personalised gamification?

RQ3: Which publications have had the greatest citation impact in personalised gamification research?

RQ4: What are the dominant research hotspots and thematic clusters in personalised gamification research, as revealed through keyword co-occurrence analysis?

The study provides a consolidated account of how personalised gamification has developed as a research field, where its principal scholarly contributions originate, which publications have shaped its intellectual development, and which thematic areas describe its present research agenda. It is expected to assist researchers in positioning future studies, identifying underexplored themes, establishing opportunities for international collaboration and developing more theoretically grounded approaches to personalised gameful design as resulting evidence.

Related Work

From Generic to Personalised Gamification

Gamification has been widely adopted as a motivational design tool in various domains, including education (Coelho et al., 2025; Hamari et al., 2014; Sailer et al., 2017; Su et al., 2025), healthcare (Al-Rayes et al., 2022; Nishi et al., 2024), and business (Keshmiri, 2025; Musyaffi et al., 2025). Its core premise lies in incorporating game elements such as points, badges, and leaderboards into non-game contexts to enhance user engagement. However, growing evidence suggests that generic gamification designs often yield inconsistent outcomes due to individual differences in user behaviour, motivation, and learning preferences (Mekler et al., 2017; Sailer et al., 2017). As a result, researchers have advocated a shift from uniform designs to personalised gamification, in which game elements are tailored to user profiles, cognitive traits, and contextual needs (Klock, Gasparini, Pimenta, et al., 2020; Tondello et al., 2016).

Theoretical Foundations of Personalisation

Several frameworks, such as Self-Determination Theory (SDT) (Ryan & Deci, 2020), Big Five Personality Traits (Soto, 2018), and player typologies like HEXAD (Tondello et al., 2016), serve as the foundation of the personalisation. These theories underpinned the design of user-centred gamification that explains how intrinsic and extrinsic motivation differ among individuals. SDT posits that autonomy, competence, and relatedness must be supported to sustain motivation, a principle that aligns well with adaptive gamified interventions (Ryan & Deci, 2020). Meanwhile, the HEXAD framework enables designers to categorise users into player types and match them with game elements that align with their motivations (Tondello et al., 2016). However, few studies integrate these theoretical models cohesively into adaptive systems, suggesting a gap between theory and applied gamification design (Toda et al., 2019).

Empirical Evidence and Limitations in Current Research

Tailored gamification has been empirically shown to improve learning outcomes, flow experience, and engagement levels more effectively than static gamified systems (Hassan et al., 2021; Oliveira et al., 2023). For instance, learning styles have been found to increase cognitive performance and satisfaction in e-learning environments through adaptive gamification (Hassan et al., 2021). Likewise, Oliveira et al. (2023) demonstrated that flow and enjoyment were enhanced through dynamic adaptation of gamified learning paths. However, these studies often differ in design rigour, sample size, and contextual application, with many relying on short-term interventions or single-platform testing, limiting generalisability. Moreover, the inconsistency in evaluation metrics and validation methods used across studies makes it difficult to compare outcomes or synthesise findings meaningfully. In addition, most empirical studies are scattered across different fields and lack a single framework that shows personalised gamification has changed globally. Many publications focus on isolated case studies in education or health without considering cross-disciplinary patterns or longitudinal trends. Therefore, a macro-level synthesis is urgently needed to map publication trajectories, research networks, and intellectual foundations of the field. Approach like bibliometric analysis offers a solution by providing a data-driven overview of how personalised and adaptive gamification has progressed over time, across countries, and among influential scholars (Donthu et al., 2021).

Identified Research Gaps

While the conceptual and empirical basis of personalised gamification is expanding, several research gaps remain. Firstly, there is a lack of cross-platform and scalable implementations of adaptive gamification models, particularly those integrating real-time analytics and machine learning (Shukla & Merikapudi, 2025). Secondly, the underlying psychological and behavioural mechanisms driving personalised engagement are often under-theorised or oversimplified. Thirdly, despite a growing body of literature, a limited bibliometric synthesis has not yet mapped the development, dissemination, and global collaboration patterns specific to personalised gamification. Without such analysis, it is difficult to understand the maturity, fragmentation, or emerging directions within this field. Addressing these gaps would not only enrich theoretical understanding but also inform the design of future adaptive systems in education, healthcare, and beyond.

The present study consequently extends previous work in three respects. First, it isolates personalised gamification as the principal unit of analysis while incorporating its major terminological variants, including adaptive, tailored, customised, individualised, user-adaptive and player-adaptive gamification. Second, it adopts a global and cross-domain perspective rather than restricting the analysis to education, healthcare or another individual application context. Third, it integrates performance indicators with bibliographic coupling and keyword co-occurrence mapping to examine not only the volume and influence of research but also its current intellectual structure and thematic development.

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METHODOLOGY

This study employed a quantitative, descriptive, and exploratory bibliometric research design to systematically examine the global development of personalised gamification research. Bibliometric analysis provides an objective and reproducible approach for evaluating the scientific landscape of a research field through publication, citation, authorship, and keyword metadata. Accordingly, this study integrates performance analysis and science mapping techniques to identify publication trends, geographical research contributions, citation impact, and thematic structures within the personalised gamification literature. The methodological framework consists of two components: bibliometric analysis and procedural analysis, which describes the systematic processes of data collection, screening, preprocessing, and software implementation.

Bibliometric Analysis

The bibliometric analysis provides a comprehensive review of personalised gamification research by addressing the research objectives through science mapping and performance metrics. Through an evaluation of annual publication output, country contributions, and citation performance, the performance analysis identifies the scholarly influence and productivity of the research field. Publication output was analysed between 2016 and 2026, while country productivity analysis identified the ten most productive countries contributing to personalised gamification research. In addition, citation analysis was conducted to identify the ten most influential publications based on their citation counts, thereby revealing the intellectual foundations of the field. Accordingly, to enhance the performance metrics, science mapping techniques were implemented to reveal the conceptual framework of personalised gamification research. Keyword co-occurrence analysis was performed to identify relationships among frequently occurring author keywords, dominant research themes, conceptual clusters, and research hotspots. The thematic evolution of personalised gamification over time is revealed by the resulting keyword networks, which provide insights into the interconnections of major research topics. Therefore, these analyses address the four research questions by describing the publication landscape, geographical distribution, citation influence, and conceptual development of the research domain.

Procedural Analysis

The procedural analysis describes the systematic workflow used to retrieve and prepare bibliographic data, as well as the tools required for analysis. The overall methodology follows internationally recognised bibliometric practices to ensure transparency, reproducibility, and methodological rigour. Scopus was selected as a single bibliographic database for its extensive coverage of high-quality peer-reviewed literature across multiple disciplines, including computer science, information systems, education, healthcare, engineering, and the social sciences. Its compatibility and comprehensive metadata with bibliometric software make it particularly suitable for large-scale science mapping studies. The literature search was conducted using the following search string applied to the “personalisation”, “adaptation”, “tailor”, “customisation”, “individual”, "user-adaptive", "player-adaptive”, “gamification” and “gameful”. The wildcard operators were used to capture variations of relevant terminology associated with personalised gamification. This search strategy encompasses studies on personalised, adaptive, tailored, customised, individualised, user-adaptive, and player-adaptive gamification while ensuring that the retrieved literature explicitly relates to gamification or gameful design. To ensure the relevance and quality of the retrieved literature, several inclusion criteria were applied. Only documents published in English were considered to maintain consistency during bibliometric analysis. Furthermore, the study included only journal articles and review articles, as these publication types represent mature and peer-reviewed scientific contributions. The analysis was restricted to publications from 2016 to 2026, reflecting the development of personalised gamification research. The complete dataset was retrieved from Scopus on 27 July 2026, ensuring the reproducibility of the search results.

Study Screening and Data Preparation

The initial database search identified 651 publications. Duplicate records, irrelevant studies, and publications that did not explicitly investigate personalised gamification were subsequently excluded through title, abstract, and keyword screening based on the predefined eligibility criteria. Through the screening process, 425 records were removed, resulting in a final dataset of 226 publications for bibliometric analysis. For each eligible

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publication, bibliographic metadata were exported directly from Scopus. The exported information included publication title, abstract, author names, affiliations, publication year, source title, author keywords, index keywords, Digital Object Identifier (DOI), and citation count. These metadata served as the basis for subsequent performance analysis and science mapping. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework is used for the literature selection process, as shown in Figure 1, to ensure a transparent and reproducible screening procedure.

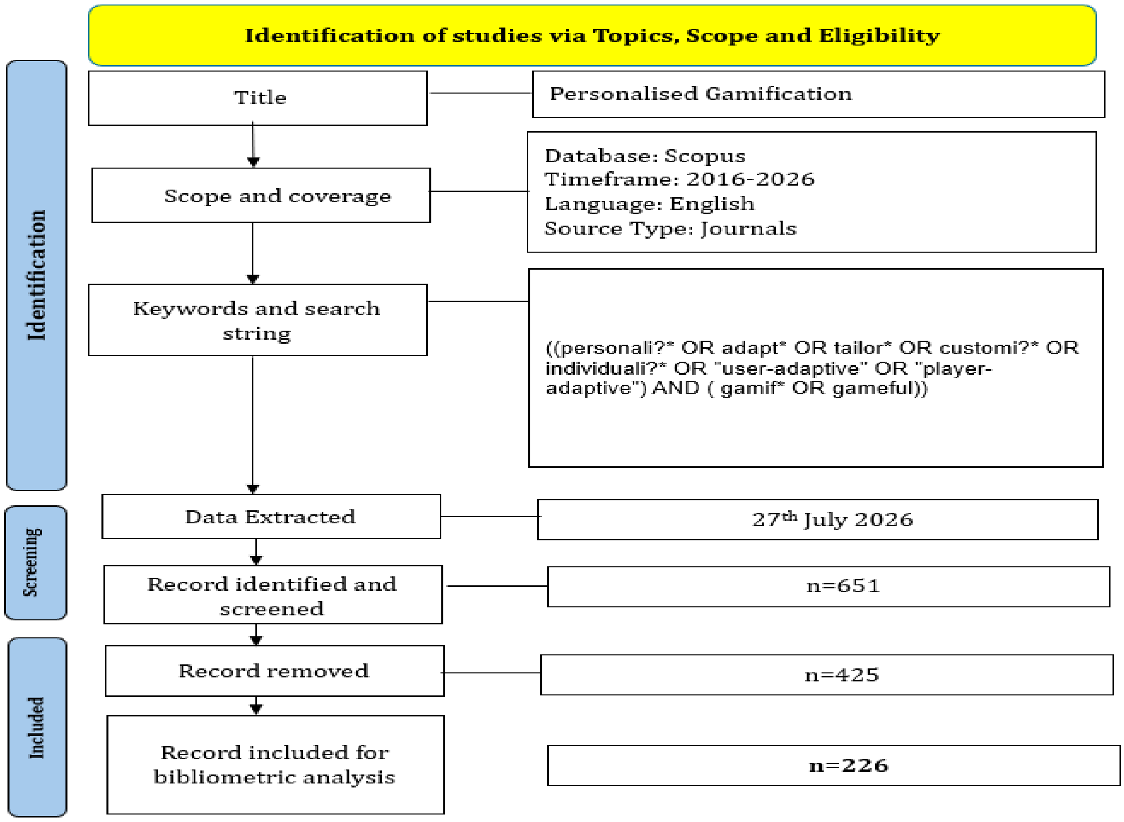

Figure. 1. The Study Flowchart

RESULTS

In this section, the findings of the bibliometric analysis are discussed in relation to the four research questions that underpinned it. It addresses publication patterns over time, the most productive countries in the field, the most frequently cited works and their thematic focus, and the crucial research hotspots identified using keyword co-occurrence and overlay visualisations. Each subsection provides a focused analysis, offering a comprehensive overview of the evolution of personalised gamification from 2016 to 2026, supported through visual data.

Publication Trends (RQ 1)

Figure 2 shows the annual publication trends that research on personalised gamification experienced from 2016 to 2026. Publication activity remained limited and relatively stable during 2016 to 2018. Only three publications were recorded in 2016, followed by two publications in both 2017 and 2018. With relatively limited scholarly attention and few established research streams, this was a period when personalised and adaptive gamification was still in an emerging phase. Expansion growth began in 2019, when annual publication output increased sharply from two to 14 publications. This represented the initial significant period of expansion in the field. Publication output consequently rose to 21 in 2020 and remained at that level in 2021. Although no further increase occurred between 2020 and 2021, the sustained output indicates that research interest had become more established compared with the earlier stage.

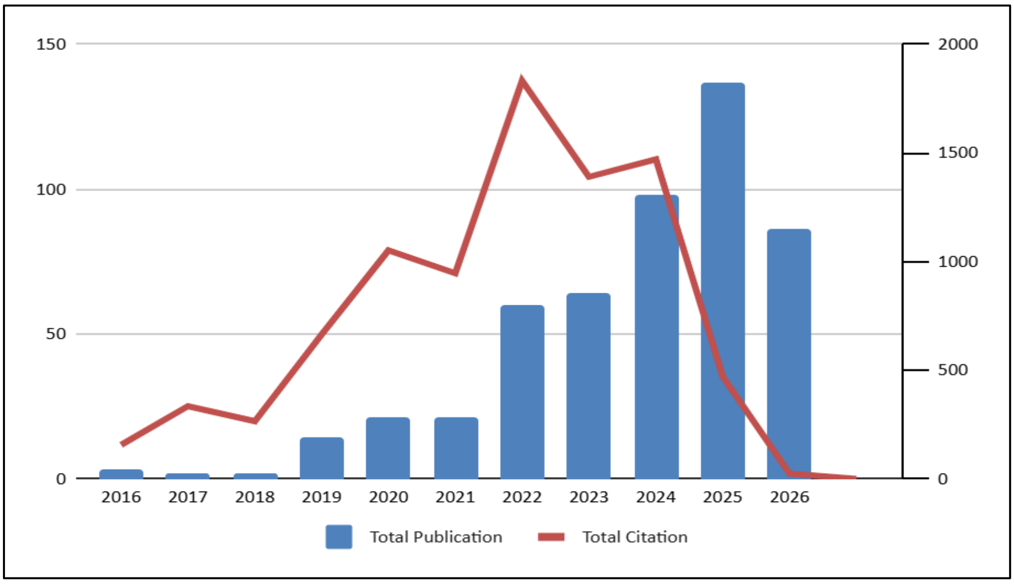

Figure 2. Total Publication and Total Citation

The most significant escalation was reported from 2022 onwards. The number of publications increased from 21 in 2021 to 60 in 2022, representing an increase of approximately 185.7%. Output then rose to 64 publications in 2023, followed by a stronger expansion to 98 publications in 2024. The highest annual publication output was recorded in 2025, with 137 publications. From 2019 to 2025, annual output increased from 14 to 137 publications, corresponding to an approximate compound annual growth rate of 46.3%. The results further show that approximately 70.7% of all publications in the dataset were published between 2022 and 2025. This concentration of recent publications confirms that personalised gamification has gained considerable scholarly momentum in the past several years. The growth may reflect increasing recognition that uniform gamification designs do not adequately address differences in user preferences, player types, motivational characteristics and behavioural patterns. It may also correspond with the growing use of artificial intelligence, machine learning, learner analytics and adaptive technologies to support more personalised gameful experiences.

Although publication output declined from 137 publications in 2025 to 86 publications in 2026, this reduction should not be interpreted as evidence of declining research interest. The Scopus data were retrieved on 27 July 2026, meaning that the 2026 publication count represents only a partial publication year. Additional publications may still be indexed before the end of the year. Therefore, a direct comparison between the complete 2025 output and the incomplete 2026 output would be misleading. The citation trends also provide additional context for the development of the field. In general, publications from earlier years received more citations due to the extended period, as they had more time in which they had to be discovered and cited. The highest annual citation total was recorded at 1,831 citations in 2022, followed by 1,470 citations in 2024 and 1,389 in 2023. By contrast, publications from 2025 and 2026 received 471 and 24 citations, respectively. These lower totals are mostly due to citation-window effects rather than implying lesser scholarly quality or influence. Recent publications have had considerably less time to accumulate citations. Overall, the findings reveal three stages in the development of personalised gamification research: an emergence stage from 2016 to 2018, a gradual development stage from 2019 to 2021, and a rapid expansion stage beginning in 2022. The steep rise in publication output, particularly between 2022 and 2025, demonstrates that personalised gamification has evolved into a prominent and increasingly mature research domain. This trend supports the idea that researchers are moving beyond "one-size-fits-all" gamification and toward more flexible, user-centred, and aware of the situation.

Global Research Contributions by Country (RQ 2)

As shown in Table 1, the United States (33) was the leading contributor to personalised gamification research, followed by China (21), Spain (20), and India (19). Indonesia ranked fifth with 16 publications, while Germany (13), Canada (12), Malaysia (12), Brazil (10), and France (10) completed the top ten most productive countries. The research activity is distributed across several nations rather than concentrated in a single region, as indicated by the relatively small differences among second to fifth-ranked countries. As illustrated in Figure 3, the global

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distribution map shows that research on personalised gamification is focused on North America, Europe, and Asia. The United States demonstrates the highest publication output, while China and India represent robust research activity in Asia, and Spain leads European contributions. Southeast Asia is also represented by Indonesia and Malaysia, reflecting the growing interest in personalised gamification within the region. Conversely, limited contributions are observed from Africa, the Middle East, and most parts of South America, suggesting opportunities for future research and broader international collaboration in underrepresented regions.

Table 1. Total publication by country

Country	Total Publication
United States	33
China	21
Spain	20
India	19
Indonesia	16
Germany	13
Canada	12
Malaysia	12
Brazil	10
France	10

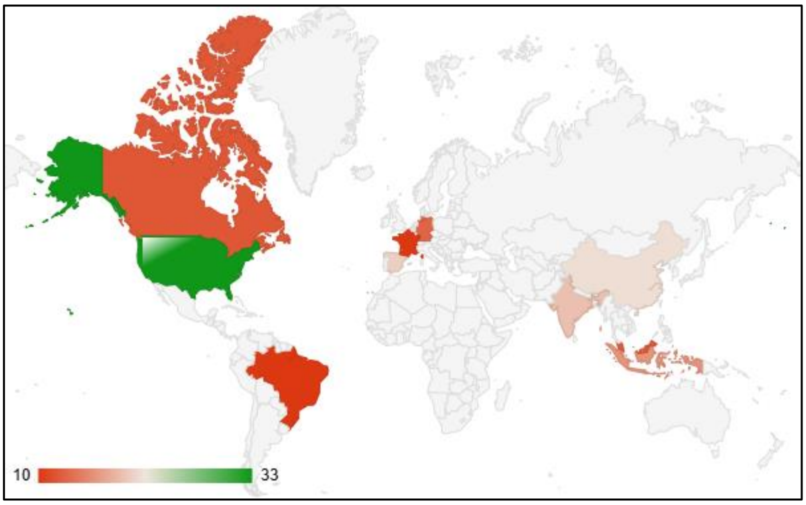

Figure 3. Global Distribution Map

Citation Impact of Influential Publications (RQ 3)

Table 2 presents the top ten most cited publications in the domain of personalised gamification between 2016 and 2026. The analysis of the most highly cited publications from 2016 to 2026 reveals a rich diversity perspectives on personalised gamification. The most-cited publication was Klock et al. (2020) with 351 citations, followed by Oliveira et al. (2023) with 292 citations and Buckley and Doyle (2017) with 289 citations. Hassan et al. (2021) ranked fourth with 224 citations, while Jagušt et al. (2018) received 198 citations. The remaining

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highly cited publications were Lavoué et al. (2019) with 177 citations, Bennani et al. (2022) with 150 citations, Lopez and Tucker (2019) with 136 citations, Oliveira et al. (2022) with 133 citations, and Zourmpakis et al. (2023) with 116 citations. Collectively, these highly cited publications reveal the intellectual evolution of personalised gamification research. Early influential studies primarily established the theoretical justification for personalisation by demonstrating that individual differences, such as personality, learning styles, and player types, significantly influence users' responses to gamification (Buckley & Doyle, 2017; Lopez & Tucker, 2019). Subsequent research shifted towards the development of adaptive frameworks and player-modelling approaches (Hassan et al., 2021; Lavoué et al., 2019), while more recent studies have increasingly explored artificial intelligence and intelligent adaptive systems to enable dynamic and context-aware personalisation (Bennani et al., 2022; Zourmpakis et al., 2022). This progression reflects the field's transition from static, one-size-fits-all gamification towards more sophisticated, user-centred, and adaptive gamification paradigms.

Table 2. Top ten most cited publications

Authors & Year	Citations	Insights	Themes
(Klock, Gasparini, Pimenta, et al., 2020)	351	This study relied on user modelling, particularly player types, to personalise game elements. It also identified key research gaps, including the need for dynamic user modelling and multi-dimensional personalisation.	User experience; Educational settings; Individual Differences; Multiple characteristics; Personalizations; User Modeling; Gamification
(Oliveira et al., 2023)	292	Highlighted that personalised gamification in education remains dominated by player-type matching, while empirical evidence for improving learning performance is still limited.	Adaptive learning; Game-based learning; Gamification; Tailoring
(Buckley et al., 2018)	289	Identified that learners with different personality traits and learning styles respond differently to gamified environments, challenging the effectiveness of a one-size-fits-all approach to gamification.	Gamification; Higher level pedagogy; Learning styles; Millennials; Personality traits
(Hassan et al., 2021)	224	Presents an adaptive gamification framework that automatically identifies learners' learning styles and personalises game elements accordingly.	Adaptive learning; e-learning; Gamification; learning dimensions; motivation
(Jagušt et al., 2018)	198	Examining competitive, collaborative, and adaptive gamified learning activities, and showed that adaptive gamification produced superior learning performance when combined with appropriate game mechanics.	Gamification; Learning technologies; Mobile learning; Primary school; Student performance
(Lavoué et al., 2019)	177	Provides empirical evidence that adapting gaming features according to learner profiles significantly increases user engagement while reducing amotivation.	Adaptation to user profiles; adaptive and intelligent educational systems; Educational games
(Bennani et al., 2022)	150	Exploring the growing integration of artificial intelligence and machine learning into adaptive gamified learning environments.	Adaptive gamification; artificial intelligence; E-learning; gamification; machine learning

(Lopez & Tucker, 2018)	136	Investigate how Hexad player types influence both users' perceptions of game elements and their performance within gamified applications.	Game elements; Gamification; Hexad scale; Performance; Player types
(Oliveira et al., 2022)	133	Investigate whether personalised gamification based on BrainHex gamer types enhances learners' flow experience and motivation.	Experimental study; Flow experience; Gamified education; Personalised gamification; User modelling
(Zourmpakis et al., 2022)	116	Developed a multidimensional adaptive gamification environment incorporating motivational and psychological frameworks in science education.	Adapted game elements; Adaptive gamification; students' motivation

Research Hotspots and Thematic Structure (RQ 4)

To explore the conceptual framework and thematic evolution of research on personalised gamification, a keyword co-occurrence analysis was conducted. This method reveals latent topic clusters and new research hotspots by determining the frequency and degree of co-occurrence between terms throughout the literature. To enable visual mapping of semantic relationships within a dataset, VOSviewer software is chosen for the data review. From 725 unique keywords, a minimum occurrence threshold of five was applied to ensure analytical relevance and reduce semantic noise. The findings show that 36 keywords met the threshold for inclusion in the final map generation. It shows the most actively discussed keywords and conceptually significant topics within the field between 2016 and 2026. The co-occurrence network visualisation is structured into distinct clusters, each representing a thematic focus area such as gamification design and user characteristics: digital learning innovation and analytics; AI-driven adaptive learning; player-type-based motivational tailoring and personalisation; and user modelling. These clusters are visualised in Figure 4 and reflect the underlying conceptual framework of the field between 2016 and 2026.

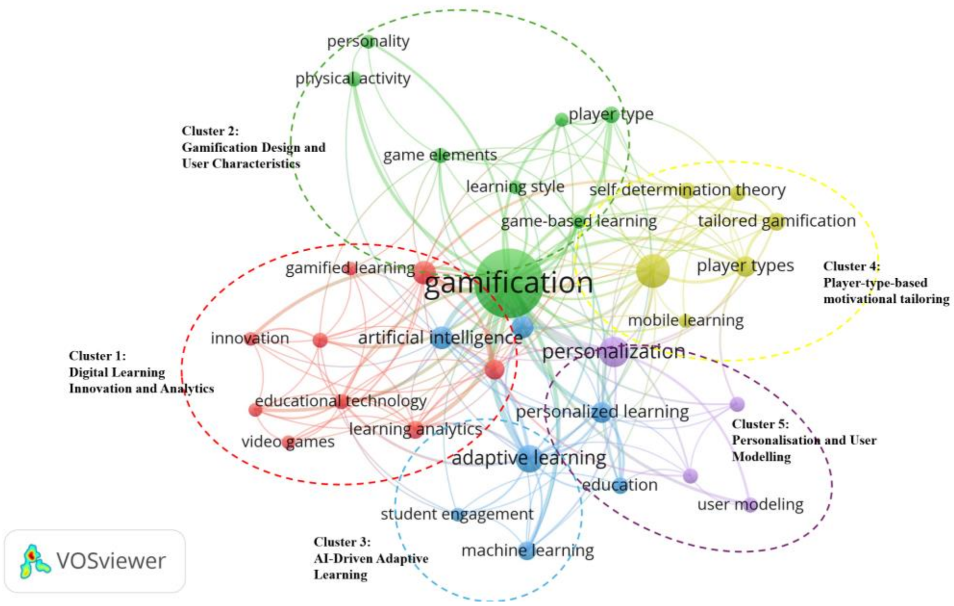

Figure 4. Co-occurrence network visualisation by cluster

The first cluster, represented in red, is on digital learning innovation and analytics includes the term such as "educational technology", "learning analytics", "gamified learning" "innovation", and "video games" indicates that personalised gamification is commonly embedded within digitally mediated learning environments. Learning analytics potentially allows designers to observe participation, task completion, interaction patterns, and performance, thereby providing data for evaluating or adapting gamified experiences. Jagušt et al. (2018)

found that gamification effectiveness depended on the balanced combination of competitive, narrative, adaptive, and individual-performance elements rather than on isolated features. Consequently, this cluster suggests that future work should use learning analytics not merely as an evaluation mechanism, but also as an input for theoretically informed, iterative gamification design.

The second cluster, represented in green, is classified as gamification design and user characteristics, which connect gamification with “game elements”, “player type”, “learning style”, “personality”, “game-based learning", and “physical activity”, showing that individual differences from a central foundation of personalised gamification research. However, much of this work appears to classify users according to relatively stable categories and then associate those categories with preferred game elements. Klock et al. (2020) observed that tailored gamification studies predominantly relied on player-type-based user models and called for dynamic modelling and the simultaneous consideration of multiple user characteristics. Similarly, Buckley and Doyle (2017) showed that personality and learning styles produce different responses to gamification, but such differences do not necessarily justify fixed or deterministic design rules. Therefore, the cluster reveals strong recognition of user heterogeneity, while also exposing the need to move beyond static profiles towards behavioural, contextual, and continuously updated representations of users.

The third cluster, in blue, integrates “artificial intelligence”, “machine learning”, “adaptive learning”, “personalised learning”, “education”, and “student engagement”, representing the technological development of personalised gamification. Bennani et al. (2022) identified artificial intelligence as an important enabler of intelligent adaptive gamification, while Hassan et al. (2021) stated that after adapting gamification to inferred learning styles, there was an increased motivation and reduced dropout rate. Nevertheless, technological adaptation remains conceptually ambiguous when systems personalise learning content or assessment but leave the game elements unchanged. Recent research also identifies data privacy, algorithmic bias, scalability, and ethical governance as continuing concerns in AI-driven adaptive gamification.

Next, the fourth cluster in yellow, focusing on player-type-based motivational tailoring. The occurrence of “player types”, “tailored gamification”, “self-determination theory”, and “mobile learning” reflects attempts to connect user profiling with psychological explanations of motivation. This cluster theoretically important because it moves beyond asking which elements may support autonomy, competence, or relatedness. Lavoué et al. (2019) found that learners receiving adapted gaming features spent more time in the learning environment, whereas poorly matched features were associated with greater amotivation. Lopez and Tucker (2019) also reported relationships between Hexad player types, perceptions of game elements, and performance. Nevertheless, Oliveira et al. (2022) found no general main effect of personalised over non-personalised gamification, while Oliveira et al. (2023) concluded that evidence remains contradictory and frequently lacks sufficient statistical support. These mixed findings suggest that player-type matching alone is insufficient and that motivational processes, situational preferences, and changes in user behaviour should be examined alongside player profiles.

The last cluster in purple, centred on “personalisation”, “personalised learning”, and “user modelling”, represents the underlying mechanism through which user information is converted into adaptive system decisions. User modelling functions as the technical and conceptual bridge between individual differences and the delivery of tailored game elements. However, outdated profiles, inaccurate or incomplete profiles may result in poor adaptation and may produce the limitations of one-size-fits-all gamification. Klock et al. (2020) specifically highlighted the need for dynamic user modelling and the integration of multiple characteristics.

As shown in Figure 5, the temporal dynamics of these clusters were overlaid in a visualisation. This visualisation depicts the keywords in colours based on their average publication year. This allows a thematic evaluation between 2016 and 2026. The overlay visualisation indicates a temporal shift from earlier topics such as personality, physical activity, educational technology, machine learning, and user modelling towards more recent topics including artificial intelligence, tailored gamification, self-determination theory, player types, learning analytics, and student engagement. This progression suggests that the field is moving from identifying stable individual differences and developing basic user models towards designing dynamic, data-driven, and psychologically informed adaptation mechanisms. However, the emergence of AI-related and tailored

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gamification keywords should not automatically be interpreted as evidence that the field has achieved effective personalisation. The available reviews report contradictory outcomes, limited statistical evidence, and continuing dependence on player types as the principal basis for tailoring. The overlay, therefore, reflects increasing technological and theoretical sophistication, but also highlights a gap between the development of adaptive systems and rigorous evidence that these systems consistently improve motivation, engagement, or learning outcomes across users and contexts.

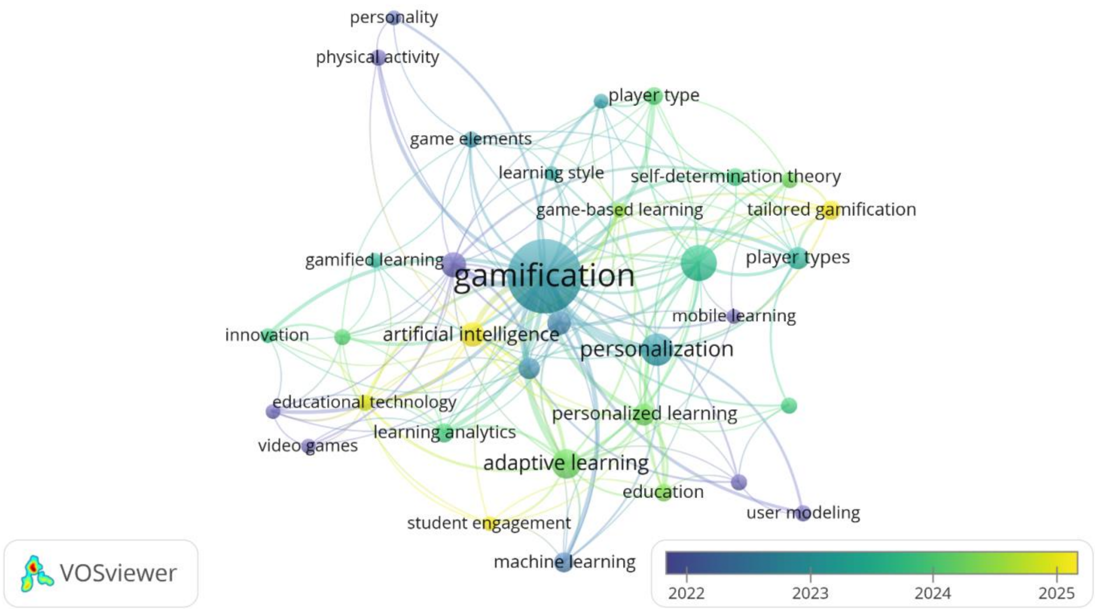

Figure 5. Overlay Visualisation

DISCUSSIONS

In this study, data were collected through the Scopus database to map patterns in publications of personalised gamification over the last decade (2016-2026). This bibliometric analysis provides a comprehensive understanding of prior studies and potential directions for further research in this field. Findings show that during the early years of the analysis, the publication output remained limited but grew substantially from 2022 onwards, reaching its highest level in 2025. This indicates increasing scholarly attention to the limitations of uniform gamification designs and the need to adapt with the differences in users' characteristics, preferences, motivations, and behaviours. However, the lower publication count recorded in 2026 should not be interpreted as a decline in research because the data were retrieved on 27th July 2026 and thus represent an incomplete publication year.

Despite sustained growth in publication output, personalised gamification does not necessarily reflect corresponding theoretical or empirical maturity. The inconsistent results on whether personalised designs outperform non-personalised gamification are still being debated. Some studies have reported increased motivation, engagement, or persistence after adapting game elements to learner profiles. Hassan et al. (2021) reported higher motivation and a lower dropout rate following learning-style-based adaptation, while Lavoué et al. (2022) found that learners who received adapted gaming features spent more time in the learning environment and exhibited lower amotivation. On the other hand, Oliveira et al. (2022) found there are no differences between personalised and non-personalised conditions in flow, motivation, enjoyment, and perceptions of gamification. Their subsequent literature review similarly concluded that existing results remain contradictory and that many studies provide insufficient statistical evidence, particularly concerning learning performance. The finding indicates that, despite the substantial increase in research activity, the empirical evidence confirming the universal efficacy of personalised gamification is relatively scarce. By identifying publications that are connected through shared reference bases, bibliographic coupling analysis reveals the current intellectual structure of the field. The coupled literature appears to converge around several interconnected issues: user profiling and player typologies, adaptive and tailored gamification systems, educational engagement and motivation, artificial intelligence and learning analytics, and the psychological mechanisms underlying users'

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responses to game elements. This structure indicates that personalised gamification is not a single, methodologically uniform research area. Instead, it represents an interdisciplinary domain situated at the intersection of human–computer interaction, educational technology, motivational psychology, user modelling, and intelligent adaptive systems.

Theoretical Contributions

Integrating bibliographic coupling, keyword co-occurrence, and overlay visualisation within a single analytical framework contributes to bibliometric research. Publications that share common reference foundations and map the current intellectual organisation are identified by the bibliographic coupling. Keyword co-occurrence reveals the principal concepts that structure the research domain, while overlay analysis adds a temporal dimension by showing which concepts are more prominent in recent publications. The integration of these methods provides a more comprehensive perspective than relying on publication counts or citation rankings alone. In addition, the results provide evidence of a process-oriented comprehension of personalised gamification. According to the thematic analysis, it involves five connected stages: identifying individual differences, constructing a user model, selecting or adapting game elements, supporting psychological and motivational processes, and evaluating behavioural or experiential outcomes. Existing studies frequently focus on only one or two of these stages. Classification and preferences of player-type research can be examined without explaining the adaptation process, whereas AI-based studies may prioritise prediction and automation without establishing the underlying motivational mechanisms. The present bibliometric synthesis connects these fragmented streams and demonstrates that effective personalised gamification requires theoretical and methodological integration across the entire process. The field is evolving conceptually from static user classification towards dynamic, multidimensional personalisation. Methodologically, it is progressing from preference surveys and cross-sectional studies towards experiments, behavioural analytics, longitudinal observation, and AI-supported adaptation. However, the literature also indicates that technological development has advanced more rapidly than theoretical and causal validation. Therefore, future research should investigate the consequences, the conditions under which personalised gamification produces positive outcomes and the motivational mechanisms under which those outcomes occur.

Practical Implications

For researchers, the findings identify several promising areas for further investigation, including dynamic user modelling, AI-supported adaptation, motivationally informed tailoring, longitudinal engagement, and the integration of multiple user characteristics. The country and citation analyses can also help researchers identify influential research communities, potential international collaborators, and leading publications that form the intellectual foundation of the domain. The thematic findings may further guide the selection of journals and publication outlets associated with human–computer interaction, educational technology, adaptive learning, user modelling, and artificial intelligence. For policymakers and funding bodies, the results highlight personalised gamification as an interdisciplinary research area requiring collaboration across computing, education, psychology, data science, and design. Before making a strategic investment, a project should demonstrate strong evidence of its efficiency, fairness, usability, and long-term effects, not just technically advanced prototypes. Support may also be directed towards underrepresented geographical regions to broaden the contextual and cultural diversity of the evidence base.

CONCLUSION

This bibliometric study demonstrates that personalised gamification has evolved from a specialised research topic into a rapidly expanding interdisciplinary field, with substantial growth in publication output, particularly since 2022. The findings show that the domain is conceptually organised around five major themes: gamification design and user characteristics, digital learning innovation and analytics, AI-driven adaptive learning, player-type-based motivational tailoring, and personalisation and user modelling. The keyword co-occurrence and overlay analyses further reveal a shift from static user classification and general gamification applications towards more dynamic, theoretically informed, and data-driven approaches involving artificial intelligence, learning analytics, self-determination theory, and tailored gamification. However, the literature continues to

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report mixed empirical findings, indicating that the growth of the field has not yet been matched by equally strong evidence regarding the consistent effectiveness of personalised gamification. The results suggest that future research should prioritise dynamic and multidimensional user modelling, transparent adaptation mechanisms, longitudinal evaluation, and stronger theoretical explanations of how personalised game elements influence motivation, engagement, and performance. The study contributes methodologically by integrating bibliographic coupling, keyword co-occurrence, and overlay visualisation to provide a comprehensive view of the field's current intellectual structure and emerging research directions. The findings also offer practical value for researchers and funding bodies by identifying influential themes, potential areas for collaboration, and strategic topics for future investment and publication.

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