AD EDUXIAN JOURNAL
A Quarterly Multidisciplinary Blind Peer Reviewed & Refereed Online International Journal
Google Scholar Indexing PIF: 1.048(I2OR), 3.125 (IIFS) & 3.8(SJIF)
Vol (3), Issue (2), April-June 2026 *ISSN: 3048-7951*

Behaviourism in MOOCs: A Systematic Literature Review

Mr. Abhishek Kumar Maurya[1]; Dr. Anjali Bajpai[2]

DOI: http://doi.org/10.5281/zenodo.21185732
Review: 18/06/2026 **Acceptance: 16/06/2026** **Publication: 04/07/2026**

Abstract

Massive Open Online Courses (MOOCs) have expanded access to higher education through scalable, flexible, and technology-mediated learning environments. However, persistent concerns regarding learner engagement, motivation and low completion rates continue to challenge their effectiveness. This systematic literature review examines the behavioural principles and learning theories underpinning MOOC research, with particular emphasis on behaviourism and its contemporary extensions. Guided by the PRISMA 2020 framework, a structured search was conducted using Google Scholar as the primary database by publish or Perish 8 app. A total of 280 records were identified, of which sixteen peer-reviewed studies meeting predefined inclusion criteria were selected for qualitative analysis. The findings generated thirteen behavioural codes organised into five major themes: (1) behaviourist and reinforcement-driven learning, (2) self-regulated and self-directed learning behaviour, (3) social and constructivist learning behaviour, (4) motivational behaviour and engagement dynamics and (5) behavioural analytics and ethical behaviour. The review indicates that operant conditioning mechanisms such as immediate feedback, quizzes, badges and certification remain foundational in xMOOC design. At the same time, learner success is strongly associated with self-regulation, autonomy, intrinsic motivation and networked participation. Alignment with India's SWAYAM platform reveals a predominance of reinforcement-driven and certification-oriented structures, with limited integration of social and adaptive learning analytics. The study concludes that MOOCs function as hybrid, multi-theoretical ecosystems requiring contextual adaptation to enhance engagement and retention.

Keywords: Behaviourism; MOOCs; SWAYAM; Self-Regulated Learning; Learning Analytics.

Introduction

Massive Open Online Courses (MOOCs) represent a significant transformation in digital education, characterized by accessibility, scalability, and flexibility that enable learning for vast global audiences (Rehfeldt et al., 2016). The term "massive" refers to large enrolments, "open" highlights unrestricted access, and "online" underscores their digital and often asynchronous delivery (de Maura et al., 2021). First introduced in 2008 by Stephen Downes and George Siemens of University of Manitoba (Baturay, 2015), MOOCs gained prominence through platforms like Coursera, edX, Udacity and many more, which partnered with leading universities to democratize higher education (Zhu, 2022). Their success lies in low-cost, scalable learning models supported by short video lectures, online peer interaction and automated assessments that promote self-paced learning (Egloffstein et al., 2023). However, despite expanded access, MOOCs face challenges of low engagement and completion, often below 10% (Kahan et al., 2017). Engagement reflects learners' behavioural, cognitive and emotional investment but remains difficult to sustain in voluntary, self-directed environments (Wu & Zhang, 2016).

[1] Junior Research Fellow, Faculty of Education, Banaras Hindu University, Varanasi, Uttar Pradesh India.
[2] Professor, Faculty of Education, Banaras Hindu University, Varanasi, Uttar Pradesh India.

Behaviourism, pioneered in the early twentieth century by John B. Watson, reshaped educational psychology by prioritizing observable behaviour over internal mental processes. Two foundational contributions define this tradition. First is Ivan Pavlov's classical conditioning and second is B. F. Skinner's operant conditioning. Pavlov demonstrated that learning occurs when a neutral stimulus is repeatedly paired with an unconditioned stimulus, eventually producing a conditioned response (Clark, 2004). In educational contexts, this principle supports the use of repeated associations between learning tasks and positive outcomes to encourage habitual engagement. Skinner advanced behaviourism through operant conditioning, arguing that behaviour is shaped by its consequences. Reinforcement, both positive and negative increases the choice of doing repetition, while punishment reduces particular undesired behaviour (Zheng et. el., 2018). Skinner's idea is translated into practice by MOOCs through programmed instruction and teaching machines, which delivered content in small, sequential steps, required correct responses before progression and provide immediate feedback. This structured and feedback-driven approach improves learning efficiency and laid the conceptual groundwork for many features of contemporary digital learning systems (Rehfeldt et al., 2016).

Behaviourist principles are applicable to Massive Open Online Courses (MOOCs), where learning interactions are mediated entirely through technology. MOOCs routinely employ repetitive tasks like small videos, automated assessments and measurable performance indicators such as points or badges that align closely with stimulus–response models of learning (Wang et. el., 2022). Tools such as micro-quizzes, progress dashboards and digital badges function as positive reinforcers that encourage continued participation and persistence (Zhu, 2022) in massive open online courses. Immediate grading and progress tracking mirror Skinner's emphasis on timely reinforcement, strengthening learning through rapid feedback loops (Rehfeldt et al., 2016). Segmenting content into micro-learning units reflects the "small steps" principle, enabling self-paced progression, reducing cognitive load, and fostering incremental mastery. MOOCs generate extensive behavioural data, including learner actions like clicks, quiz attempts and discussion posts to be analysed as observable behaviours (Egloffstein et al., 2023). This data-driven monitoring supports evidence-based interventions, echoing Skinner's experimental in reinforcement conditions. However, challenges persist, particularly the limited capacity for personalized and social reinforcement at scale. While automated systems provide efficiency, they often lack the motivational depth of human feedback and peer interaction (Wu & Zhang, 2016). Consequently, integrating behaviourist mechanisms with social learning elements may enhance engagement and retention, reaffirming behaviourism as a valuable framework for optimizing MOOC design in contemporary digital education.

Need of the Study

The emergence of Massive Open Online Courses has revolutionized access to higher education by providing free and flexible learning opportunities to millions of learners globally. MOOCs have become an integral component of digital pedagogy, combining multimedia content, peer discussion and self-paced assessments (Tseng et al., 2016). Despite their global reach, MOOCs continue to face critical challenges, particularly in learner engagement, motivation and retention (de Freitas et. el., 2015). Scholars have observed continuously very high dropout rates often exceeding 80% and limited evidence of sustained learning behaviours (Gamage et al., 2020).

Behaviourism, grounded in stimulus–response (S–R) theory, gives valuable insights into observable behaviours and the reinforcement mechanisms of learners. In traditional classrooms, reinforcement occurs through feedback, grading and teacher acknowledgment where MOOCs rely on automated systems such as quizzes, progress badges and peer reviews. Although these mechanisms generate large amount of behavioural data, most existing studies focus on descriptive analytics rather than interpretive or theory-driven understanding of these behaviours. Quantitative models dominate in MOOC researches, often reducing learner engagement to measurable metrics such as click counts, video views, or quiz submissions (Hu et al., 2016).

Tseng et al. (2016) analysed over 1,400 MOOC learners and identified behavioural clusters such as *active learners*, *passive learners* and *bystanders*. While their study effectively classified behavioural types, it lacked a theoretical grounding in operant conditioning, which could have explained how reinforcement and feedback cycles influence transitions between these behavioural states. Similarly, Zhong et al. (2017) used computational modelling to categorize learning styles in a computer science MOOC, finding that learners' interaction frequency predicted their course performance. However, these analyses were quantitative and correlational, offering little interpretation about *why* specific behaviours occurred or persisted. Thus, while MOOC platforms generate rich behavioural datasets, there remains a theoretical gap in linking observable behaviour patterns to core behaviourist principles such as reinforcement schedules and stimulus control.

Recent efforts have begun to move toward qualitative examinations of learner behaviour in MOOCs. Gamage et al. (2020) employed ethnographic methods including diary studies and interviews to explore why some learners persist while others disengage. They discovered four behavioural archetypes based on learners' intrinsic and extrinsic motivations. Despite this qualitative depth, their work primarily emphasized motivational psychology rather than behavioural reinforcement. Moreover, qualitative studies like this often adopt constructivist or socio-cognitive frameworks, prioritizing learner perception over behaviour observation. Consequently, behaviourist interpretations of qualitative learner data such as how feedback or reinforcement cues condition learner responses remain scarce in MOOC literature.

A related concern lies in the fragmentation between learning analytics and pedagogical theory. As Hu et al. (2016) point out from the behavioural data collected through MOOC platforms are often used for predictive modelling (e.g., predicting dropout or success rates) without theoretical integration. Behaviourism offers an ideal bridge between data and pedagogy by linking observed digital actions (stimuli and responses) with instructional interventions (reinforcements). Yet, qualitative research that interprets such data through behaviourist constructs for instance, identifying how immediate feedback shapes participation or how lack of reinforcement leads to attrition remains virtually absent. This underutilization of behaviourist theory in qualitative MOOC research represents a critical theoretical gap.

Therefore, the need for this study arises from a confluence of theoretical and methodological gaps. While MOOCs are inherently rich in behavioural data, the interpretation of this data through a qualitative behaviourist lens remains unexplored. Much of the current literature prioritizes predictive analytics and performance metrics, overlooking the qualitative nuances of learner reinforcement, motivation and behavioural conditioning. Finally, given that behaviourism focuses on observable and measurable learning acts, it aligns naturally with the digital footprints generated in MOOCs, making it a promising but underused framework for qualitative inquiry. This study aims to address these gaps by systematically reviewing and qualitatively analysing secondary data on learner behaviour in MOOCs using a behaviourist framework. This study also seeks to understand that how

MOOC designers can behaviourist principles such as immediate feedback, positive reinforcement and repeated practice can be effectively integrated to improve engagement and retention.

Research Question: What behavioural principals or theories are documented in existing studies related to the Massive Open Online Courses?

Materials and methods:

To answer the research question, a systematic review was conducted by using Preferred Reporting Items for Systematic Reviews and Meta-Analyses 2020 (PRISMA 2020) statement (Page et al., 2021). The PRISMA 2020 statement comprises:

- A 27-item checklist address the introduction, methods, results and discussion sections of a systematic review report. This study strictly follows the above contents.
- A flow diagram depicts the flow of information through the different phases of a systematic review, it is shown in the following diagram.

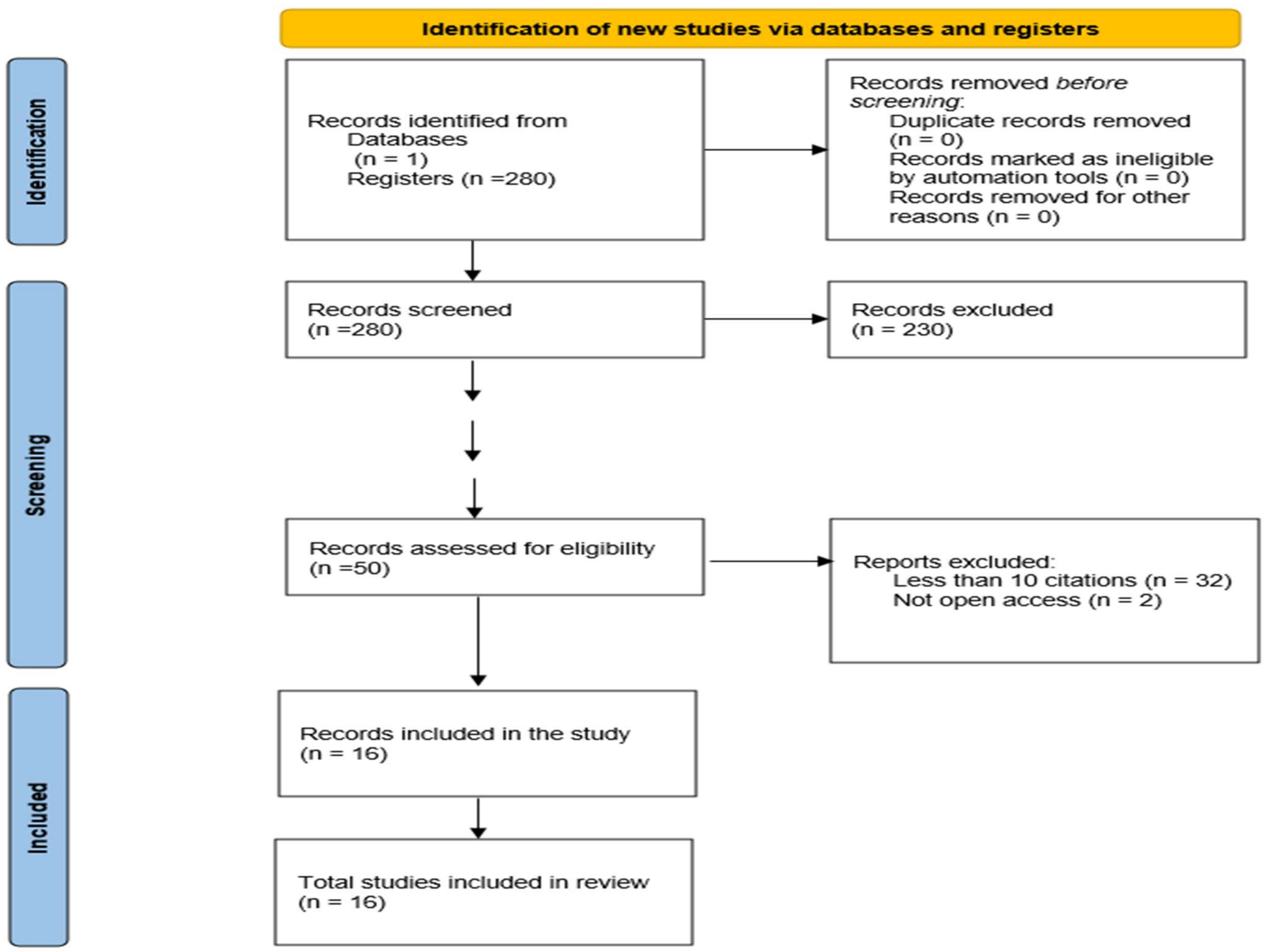

Figure 1: PRISMA flow diagram

AD EDUXIAN JOURNAL
A Quarterly Multidisciplinary Blind Peer Reviewed & Refereed Online International Journal
Google Scholar Indexing PIF: 1.048(I2OR), 3.125 (IIFS) & 3.8(SJIF)
Vol (3), Issue (2), April-June 2026 ISSN: 3048-7951

Search Strategy-

One database (Google Scholar) was searched for the relevant studies using the keywords given in the Table 1. The search was focused to find the articles in which keywords match in the title, keyword and abstract field. The search was conducted on January 03, 2026.

Table 1: Keyword combinations used for search in database by Publish and Perish 8 app

Search terms
MOOC learner behaviour
reinforcement in MOOCs
behavioural engagement patterns
behaviourism in online learning

Article selection-

Total 280 article were retrieved from the specific database. Figure 1 illustrate the article selection process, the number of articles retained at each stage and reasons for article exclusion. Sixteen articles that met the selection criteria were included in the final analysis.

Data distribution

Figure 2: Year-wise distribution of studies

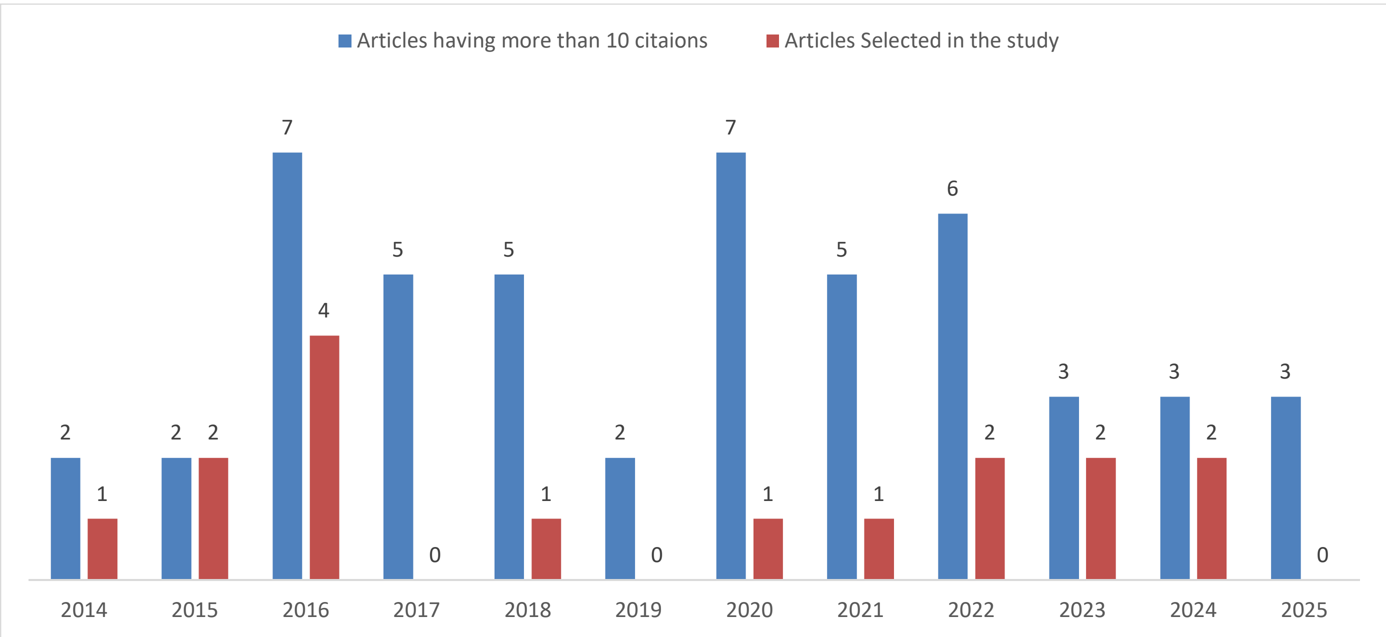

Figure 2 shows the distribution of the articles having more than 10 citations as it was one of the purpose and selected articles by year. Table 2 discusses the behaviouristic principles or theories in the selected papers.

Table 2: Overview of the studies having the behaviourist principle or theories

Author, Year	Title	Methodology	Major behaviouristic principle or theories discussed
Knox, 2014	Digital culture clash: “massive” education in the Elearning and Digital Cultures MOOC	Thematic analysis of student-created content, user statistics, and survey data.	Contrasts Instructionism, which seeks to scale and standardize education, with Connectivism and its focus on distributed expertise.
Dubosson & Emad, 2015	The Forum Community, the Connectivist Element of an xMOOC	Netnographic analysis of 2,219 forum posts using textual discourse observation.	Evaluates the forum as a Connectivist element within a Behaviorist xMOOC, introducing the Mixed MOOC (mMOOC) model.
Dron & Ostashewski, 2015	Seeking Connectivist Freedom and Instructivist Safety in a MOOC	Technical implementation report and case study evaluation.	Discusses Connectivism (learning as a network) versus Instructivism (top-down transmission) and utilizes Social Capital through badging.
Hew, 2016	Promoting engagement in online courses: What strategies can we learn from three highly rated MOOCs	Qualitative multiple case study using a grounded approach to analyze reflection data.	Utilizes Self-Determination Theory (SDT), specifically focusing on the psychological needs for autonomy, relatedness, and competence.
Petronzi & Hadi, 2016	EXPLORING THE FACTORS ASSOCIATED WITH MOOC ENGAGEMENT, RETENTION AND THE WIDER BENEFITS FOR LEARNERS	Qualitative thematic analysis of open feedback matched with categorical survey responses.	Discusses Behaviorist pedagogy in xMOOCs versus Collaborative learning and explores Intrinsic vs. Extrinsic motivation.
Celina, et al., 2016	SOLE meets MOOC: Designing Infrastructure for Online Self-organised Learning with a Social Mission	Mixed methods design, deployment, and evaluation of three pilot course configurations.	Based on Self-Organised Learning Environments (SOLE) and Connectivism, emphasizing learner agency and co-creation.
Rehfeldt, et al., 2016	Beginning the Dialogue on the e-Transformation: Behavior	Descriptive survey and case analysis of a 10-week behavior analysis course.	Directly parallels MOOCs with B.F. Skinner’s Teaching Machines, highlighting immediate reinforcement and self-pacing.

	Analysis' First Massive Open Online Course (MOOC)		
Knox, 2018	Beyond the ''c'' and the ''x'': Learning with algorithms in massive open online courses (MOOCs)	Theoretical and descriptive review using a sociomaterial lens.	Examines Algorithmic Culture and critiques the xMOOC/cMOOC binary, proposing a move toward more-than-human agency.
Agonács, et al., 2020	Are you ready? Self-determined learning readiness of language MOOC learners	Quantitative correlational study using validated instruments (SDLRS, SRIS, NGSES, ISS).	Focuses on Heutagogy (Self-Determined Learning), which extends andragogy through double-loop learning and capability.
Banihashem & Macfadyen, 2021	Pedagogical Design: Bridging Learning Theory and Learning Analytics	Conceptual framework review mapping learning theories to analytics.	Bridges Behaviorism (BLA), Constructivism (CsLA), and Connectivism (ConLA) with specific pedagogical design goals.
Li, et al., 2022	Unfolding the learning behaviour patterns of MOOC learners with different levels of achievement	Learning analytics using statistical analysis and Lag Sequential Analysis (LSA) on log data.	Investigates Self-Regulated Learning (SRL) strategies and their impact on different levels of academic achievement.
Chiang, et al., 2022	A systematic review of academic dishonesty in online learning environments	Systematic literature review and content analysis of 59 empirical articles.	Utilizes Gilbert's Behavior Engineering Model (BEM), which is rooted in behaviorist principles of stimulus, response, and reinforcement.
Xia & Qi, 2023	Learning Behavior Interest Propagation Strategy of MOOCs Based on Multi Entity Knowledge Graph	Deep learning analytics (LBB-DL model) using a multi-entity knowledge graph.	Distinguishes between cMOOCs (Connectivism) and xMOOCs (Behaviorism) based on data labeling and prediction requirements.
Bai & Xiao, 2023	The impact of cMOOC learners' interaction on content production	Linear regression analysis of 45,166 real-time behavioral data points.	Grounded in Connectivism, exploring how social interaction drives knowledge creation and content production.
Meng, et al., 2024	Investigating the impact of gamification	Mixed methods study using the Online Student	Discusses Self-Determination Theory (SDT) and Operant Conditioning (Positive

	components on online learners' engagement	Engagement (OSE) scale and textual analysis.	Reinforcement) through gamification components.
Shi, et al., 2024	From unsuccessful to successful learning: profiling behavior patterns and student clusters in Massive Open Online Courses	Data mining (Random Forest, PCA, and K-means clustering) of 26,862 student records.	Integrates Self-Regulated Learning (SRL) and Online Participation Theory to profile successful and unsuccessful learners.

Result

R.Q. What behavioural principals or theories are documented in existing studies related to the Massive Open Online Courses?

To answer this research question, the findings of the selected papers is coded into the following codes-

C1: Reinforcement through Feedback and Rewards follows Behavioural principle of Operant conditioning (Skinner) which describes that learner's behaviour is shaped by immediate feedback, quizzes, badges, certificates, and progress indicators.

C2: Stimulus–Response Learning Design follows Classical behaviourism in which learning tasks are structured as a flow like content → task → response → feedback cycles.

C3: Goal Setting and Persistence includes Self-Regulated Learning in which learners plan, monitor and evaluate their own learning behaviour.

C4: Effort Regulation and Time Management includes the metacognitive behavioural control in the learners.

C5: Learning through Social Interaction includes social constructivism of Vygotsky that means knowledge construction occurs through discussion, peer feedback and collaboration among the learners.

C6: Community Participation and Identity Formation include the Communities of Practice principle in which learning is defined fundamentally as social process occurring through participation in shared practices, rather than the acquisition of abstract knowledge.

C7: Networked Knowledge Construction follows the Siemens connectivism principle in which learning emerges from forming and traversing networks between the learners of the same level.

C8: Autonomy and Choice depend upon the principle of self-determined learning (Heutagogy) in which more emphasize is on learner autonomy, capability development and non-linear learning pathways.

C9: Intrinsic Motivation follows the **principle of** Self-Determination Theory that means the learners intrinsic motivation is more important for learning.

C10: Extrinsic Motivation follows the principle of Incentive-based behaviour which focus on the incentives for successful completion of any task or completion of the courses.

C11: Behavioural Profiling and Clustering includes the data-driven behaviourism that predict the learner behaviour on the basis of his/her login data into a platform.

C12: Predictive Behaviour Modelling focus on algorithmic learning behaviour that uses the learning analytics to predict the completion and drop-out risks in any course.

C13: Academic Dishonesty includes the moral disengagement theory which says that learner rationalised the cheating due to anonymity and low perceived consequences.

Table 3: Categorization of the codes into the themes

THEME	CODE
Behaviourist and Reinforcement-Driven Learning in MOOCs	1. Reinforcement through Feedback and Rewards
	2. Stimulus–Response Learning Design
Self-Regulated and Self-Directed Learning Behaviour	3. Goal Setting and Persistence
	4. Effort Regulation and Time Management
	5. Autonomy and Choice
Social and Constructivist Learning Behaviour	6. Learning through Social Interaction
	7. Community Participation and Identity Formation
	8. Networked Knowledge Construction
Motivational Behaviour and Engagement Dynamics	9. Intrinsic Motivation
	10. Extrinsic Motivation
Behavioural Analytics, Profiling and Ethical Behaviour	11. Behavioural Profiling and Clustering
	12. Predictive Behaviour Modelling
	13. Academic Dishonesty and Moral Behaviour

Discussion

This systematic review analysed sixteen peer-reviewed studies to identify behavioural principles/learning theories underlying learner participation in Massive Open Online Courses (MOOCs). Through thematic analysis, thirteen codes were generated and organised into five major themes- (1) Behaviourist and Reinforcement-Driven Learning, (2) Self-Regulated and Self-Directed Learning, (3) Social and Constructivist Learning, (4) Motivational

Behaviour and Engagement, and (5) Behavioural Analytics and Ethical Behaviour. The results reflect consistent patterns in how learner behaviour is shaped, sustained, and regulated in MOOC environments.

Theme 1: Behaviourist and Reinforcement-Driven Learning

(Codes 1&2: Reinforcement through Feedback and Rewards; Stimulus–Response Learning Design)

In multiple studies, behaviourist learning principles were found that strongly influence instructional design in MOOCs. Hew (2016) reported that highly rated MOOCs consistently employed frequent quizzes, automated feedback and certification mechanisms to reinforce learner participation. These elements functioned as positive reinforcers that promoted course persistence. Similarly, Petronzi and Hadi (2016) observed that graded assessments and formal certification significantly influenced learner retention. Rehfeldt et al. (2016) explicitly compared MOOC structures with Skinner's teaching machines, highlighting the use of micro-lectures and automated assessments as behaviour-shaping tools. Banihashem and Macfadyen (2021) further identified stimulus–response patterns in xMOOC design, where video lectures were systematically followed by quizzes and immediate feedback. Xia and Qi (2023) confirmed that instructor-controlled learning pathways and structured feedback mechanisms remain central features of many xMOOCs.

Theme 2: Self-Regulated and Self-Directed Learning Behaviour

(Codes 3–5: Goal Setting and Persistence; Effort Regulation and Time Management; Autonomy and Choice)

Self-regulated learning behaviours emerged as key predictors of learner success. Agonács and Matos (2020) demonstrated that learners with strong goal-setting and self-monitoring skills exhibited higher completion rates. Their findings emphasized the importance of readiness for autonomous learning in open online environments. Shi et al. (2023) identified effort regulation as the most significant predictor of academic achievement, with persistence and self-assessment distinguishing successful learners from non-completers. Their clustering analysis revealed that high-performing learners-maintained engagement despite experiencing procrastination. Petronzi and Hadi (2016) reported that inadequate time management and competing professional or personal commitments were primary causes of dropout, underscoring the importance of behavioural control strategies. Autonomy was particularly evident in connectivist and self-organised learning contexts. Celina et al. (2016) found that learner-controlled pathways and community-based learning structures enhanced self-directed behaviour. Dron and Ostashewski (2015) similarly observed that cMOOCs enabled learners to design personalised learning trajectories.

Theme 3: Social and Constructivist Learning Behaviour

(Codes 6–8: Learning through Social Interaction; Community Participation and Identity Formation; Networked Knowledge Construction)

Social interaction and collaborative knowledge construction were consistently identified as critical learning mechanisms. Bai and Xiao (2023) found that high-level learner interactions had a significant positive effect on content production in cMOOCs, whereas superficial interactions showed limited impact. Knox (2014) documented how learners gradually transitioned from passive participants to active contributors, highlighting processes of identity formation within digital learning communities. Celina et al. (2016) further reported that strong communities of practice promoted sustained engagement and collective learning. Dron and Ostashewski (2015) demonstrated that networked learning environments enabled learners to generate knowledge through blogs, social media, and shared digital artefacts. Bai and Xiao (2023) supported this finding by showing that knowledge production increased through interaction among distributed network nodes.

These results confirm that learning in many MOOCs is socially situated and constructed through participation in communities and networks.

Theme 4: Motivational Behaviour and Engagement Dynamics

(Codes 9–10: Intrinsic Motivation; Extrinsic Motivation)

Motivational factors were found to play a central role in shaping learner engagement. Petronzi and Hadi (2016) reported that personal interest, professional development goals, and curiosity were primary intrinsic motivators influencing sustained participation. Hew (2016) similarly found that intrinsically motivated learners demonstrated deeper cognitive engagement. Extrinsic motivation was also highly influential. Meng et al. (2024) showed that gamification elements such as points and badges significantly improved participation and performance engagement. Hew (2016) noted that certification opportunities attracted large numbers of learners and encouraged task completion. Shi et al. (2023) further observed that performance-oriented learners were more likely to regulate effort and complete assessments, reflecting extrinsically driven engagement patterns. These findings indicate that MOOC participation is driven by an interaction between intrinsic interests and external incentives.

Theme 5: Behavioural Analytics, Profiling, and Ethical Behaviour

(Codes 11–13: Behavioural Profiling and Clustering; Predictive Behaviour Modelling; Academic Dishonesty and Moral Behaviour)

Several studies employed learning analytics to examine and regulate learner behaviour. Shi et al. (2023) identified distinct behavioural clusters, including Persistence Achievers and Disengagers, based on patterns of effort, participation and self-assessment. Li et al. (2022) similarly distinguished achievement groups using engagement and activity trajectories. Predictive modelling techniques were widely used to forecast learner outcomes. Banihashem and Macfadyen (2021) demonstrated that early engagement indicators could reliably predict dropout risk. Xia and Qi (2023) applied knowledge graph–based models to track interest propagation and support personalised interventions. Ethical behaviour was primarily addressed by Chiang et al. (2022), who reported that anonymity, limited monitoring and performance pressure contributed to academic dishonesty. Their review highlighted moral disengagement and rationalisation as recurring behavioural patterns in online environments.

These findings show that MOOCs increasingly rely on data-driven approaches to understand learner behaviour, while ethical challenges remain unresolved.

Alignment with SWAYAM Platform

This study, when interpreted in the context of Indian MOOCs, particularly for SWAYAM platform; highlights that the behavioural principles and learning theories identified in international researches are highly relevant to India's digital higher education ecosystem. However, their application is shaped by local socio-economic, institutional and technological conditions.

First, behaviourist principles are strongly embedded in SWAYAM course design. Most SWAYAM courses follow structured modules consisting of video lectures, weekly quizzes, assignments and proctored examinations referred as the four quadrants of the SWAYAM(*Swayam Central*, n.d.). These features reflect operant conditioning and stimulus–response models, where certification, credits and assessment scores function as primary reinforcers. In the Indian context, where formal credentials remain crucial for employability and academic progression, extrinsic rewards play a dominant motivational role. Consequently, learner participation on SWAYAM is largely driven by examination requirements and university credit transfer policies (*Swayam Central*, n.d.-b) rather than intrinsic interest alone.

Second, the importance of self-regulated and self-directed learning is particularly pronounced in India. SWAYAM learners often balance online study with full-time employment, conventional university programmes and family responsibilities. As indicated by the reviewed studies, effort regulation, time management and persistence are decisive for success. In India, limited access to learning support systems, digital literacy gaps and inconsistent internet connectivity further intensify the need for strong self-regulation skills. Without adequate scaffolding, many learners struggle to sustain engagement, contributing to high dropout rates observed in Indian MOOCs (PTI, 2025).

Third, social constructivist learning and community participation remain underutilised in the SWAYAM ecosystem. While discussion forums and peer-interaction tools exist, learner participation is generally low. Cultural factors, language diversity, academic hierarchies and limited moderation often restrict meaningful dialogue. In contrast to the active communities reported in connectivist MOOCs, SWAYAM learners tend to adopt passive consumption patterns. This limits opportunities for collaborative knowledge construction and weakens the development of learning communities. Strengthening peer facilitation, multilingual support and mentor presence could enhance social learning in Indian MOOCs.

Fourth, connectivist learning principles are only partially realised on SWAYAM. Most Indian MOOCs are predominantly xMOOC-oriented, emphasising content delivery over networked learning. Although learners increasingly use external platforms such as WhatsApp, Telegram and YouTube for informal peer support, these networks remain disconnected from official course structures. Integrating such learner-generated networks into formal learning designs could enhance knowledge sharing and reflective practice in Indian MOOCs.

Fifth, motivational dynamics in Indian MOOCs are largely shaped by extrinsic factors. Certificates, academic credits, government recognition and career advancement are primary drivers of enrolment. While intrinsic motivation exists, especially among lifelong learners and teacher-educators, institutional incentives remain the dominant influence. The literature suggests that sustained engagement requires balancing these extrinsic motivators with meaningful learning experiences, relevance to local contexts and opportunities for personal growth.

Sixth, learning analytics and data-driven governance are emerging but remain underdeveloped in the SWAYAM ecosystem. Although the platform collects large-scale learner data, its systematic use for personalised feedback, early intervention, and adaptive learning is limited. Studies reviewed in this SLR demonstrate the potential of behavioural profiling and predictive modelling to improve retention and achievement. In India, deploying such tools responsibly could support first-generation learners and rural students, provided ethical safeguards and transparency mechanisms are established.

Finally, issues of academic integrity and ethical behaviour are particularly salient in Indian MOOCs. Proctored examinations, identity verification and assessment monitoring are central to SWAYAM's credibility. However, disparities in digital access and technical infrastructure sometimes create unintended barriers, increasing stress and non-compliance. Strengthening academic ethics education and designing assessment systems that emphasise learning over surveillance are essential for long-term sustainability.

Conclusion

The analysis reveals that contemporary MOOCs are not grounded in a single pedagogical paradigm; rather, they represent hybrid learning ecosystems in which multiple behavioural and cognitive theories coexist and interact.

- **First**, behaviourist principles remain central to MOOC design, particularly in xMOOC environments. Reinforcement mechanisms such as automated feedback, quizzes, certificates, and gamified rewards are widely used to regulate learner behaviour and sustain participation (Hew, 2016; Rehfeldt et al., 2016; Meng et al., 2024). These features reflect operant conditioning and stimulus–response models, where learning is structured through repetition, assessment, and external reinforcement.
- **Second,** self-regulated learning and heutagogical theories strongly underpin learner success in MOOCs. Across the reviewed studies, goal setting, effort regulation, persistence, time management, and self-monitoring emerged as the most consistent predictors of achievement (Agonács & Matos, 2020; Shi et al., 2023; Petronzi & Hadi, 2016). MOOCs therefore operate as highly autonomous learning environments that require learners to function as self-managers of their learning processes, aligning with Zimmerman's self-regulation framework and principles of self-determined learning.
- **Third**, constructivist and social learning theories play a crucial role in facilitating deep learning. Studies focusing on interaction, community participation, and collaborative content creation demonstrate that knowledge is co-constructed through dialogue and shared practices (Knox, 2014; Celina et al., 2016; Bai & Xiao, 2023). These findings support Vygotskian social constructivism and communities of practice theory, highlighting the importance of peer engagement and identity formation in online learning contexts.
- **Fourth**, the literature consistently reflects the influence of connectivist theory, particularly in cMOOCs. Learners construct knowledge through distributed networks, digital platforms, and external resources, extending learning beyond institutional boundaries (Dron & Ostashewski, 2015; Bai & Xiao, 2023). Connectivism explains how learning occurs through the formation, maintenance, and navigation of knowledge networks in digitally mediated environments.
- **Fifth**, motivation theories, especially Self-Determination Theory, provide a strong explanatory framework for learner engagement. Intrinsic motivation driven by interest and personal development coexists with extrinsic motivation driven by certification, career advancement, and assessment (Hew, 2016; Petronzi & Hadi, 2016;

Meng et al., 2024). Successful MOOCs strategically integrate both motivational orientations to sustain long-term participation.

Finally, recent studies demonstrate the growing role of learning analytics and algorithmic behaviour modelling in shaping learner experiences (Li et al., 2022; Shi et al., 2023; Xia & Qi, 2023). These approaches reflect a data-driven extension of behavioural and cognitive theories, enabling predictive intervention and personalization. However, they also introduce ethical challenges, particularly related to academic integrity and surveillance (Chiang et al., 2022). In general, the reviewed literature indicates that MOOCs are theoretically grounded in an integrated framework combining-

- Behaviourism (reinforcement and feedback systems),
- Self-regulated learning and heutagogy (learner autonomy and persistence),
- Social constructivism (collaborative knowledge building),
- Connectivism (networked learning),
- Self-determination theory (motivation) and
- Learning analytics and algorithmic pedagogy (data-driven regulation).

This convergence suggests that effective MOOCs function as multi-theoretical learning environments, where instructional design, learner behaviour, social interaction, motivation and technological mediation are dynamically interconnected.

References

Agonács, N., & Matos, J. F. (2020). Are you ready? Exploring self-directed learning readiness in MOOCs. *Education and Information Technologies, 25*(3), 1–20. https://doi.org/10.1007/s10639-019-10054-1

Bai, Y.-Q., & Xiao, J.-J. (2023). The impact of cMOOC learners' interaction on content production. *Interactive Learning Environments, 31*(7), 4464–4475. https://doi.org/10.1080/10494820.2021.1969955

Banihashem, S. K., & Macfadyen, L. P. (2021). Pedagogical design: Bridging learning theory and learning analytics. *Canadian Journal of Learning and Technology, 47*(1), 1–23.

Baturay, M. H. (2015). An overview of the world of MOOCs. *Procedia-Social and Behavioral Sciences*, *174*, 427-433.

Chiang, F. K., Zhu, D., & Yu, W. (2022). A systematic review of academic dishonesty in online learning environments. *Journal of Academic Ethics, 20*(3), 1–23. https://doi.org/10.1007/s10805-021-09413-3

Clark, R. E. (2004). The classical origins of Pavlov's conditioning. *Integrative Physiological & Behavioral Science*, *39*(4), 279-294.

Celina, H., Kharrufa, A., Preston, A., Comber, R., & Olivier, P. (2016). SOLE meets MOOC: Designing infrastructure for online self-organised learning with a social mission. In *Proceedings of the 2016 ACM Conference on Designing Interactive Systems* (pp. 484–496). ACM. https://doi.org/10.1145/2901790.2901848

de Freitas, S. I., Morgan, J., & Gibson, D. (2015). Will MOOCs transform learning and teaching in higher education? Engagement and course retention in online learning provision. *British journal of educational technology*, *46*(3), 455-471.

de Moura, V. F., de Souza, C. A., & Viana, A. B. N. (2021). The use of Massive Open Online Courses (MOOCs) in blended learning courses and the functional value perceived by students. *Computers & Education*, *161*, 104077.

Dubosson, M., & Emad, S. (2015). The forum community, the connectivist element of an xMOOC. *Universal Journal of Educational Research, 3*(10), 680–690. https://doi.org/10.13189/ujer.2015.031004

Dron, J., & Ostashewski, N. (2015). Seeking connectivist freedom and instructivist safety in a MOOC. *Educación XX1, 18*(2), 51–76. https://doi.org/10.5944/educXX1.18.2.13464

Egloffstein, M., Sahin, M., & Ifenthaler, D. (2023). Course Design Approaches and Behavioral Patterns in Massive Open Online Courses for Professional Learning. *Online Learning*, *27*(4), 48-68.

Gamage, D., Perera, I., & Fernando, S. (2020). Exploring MOOC user behaviours beyond platforms. *International Journal of Emerging Technologies in Learning, 15*(8), 45–58. https://doi.org/10.3991/IJET.V15I08.12493

Hew, K. F. (2016). Promoting engagement in online courses: What strategies can we learn from three highly rated MOOCs. *British Journal of Educational Technology, 47*(2), 320–341. https://doi.org/10.1111/bjet.12235

Hu, X., Liu, S., Xu, Z., & Xiao, G. (2016, September). Learning behaviour analytics and learning effect evaluation for learners based on MOOCs. In *2016 International Conference on Educational Innovation through Technology (EITT)* (pp. 1-5). IEEE.

Kahan, T., Soffer, T., & Nachmias, R. (2017). *Types of participant behaviour in a massive open online course.* The International Review of Research in Open and Distributed Learning, 18(6), 55–77. https://doi.org/10.19173/IRRODL.V18I6.3087

Knox, J. (2014). Digital culture clash: "Massive" education in the e-learning and digital cultures MOOC. *Distance Education, 35*(2), 164–177. https://doi.org/10.1080/01587919.2014.917704

Knox, J. (2018). *Learning with algorithms: From coding to the platform*. Palgrave Macmillan. https://doi.org/10.1007/978-3-319-91911-0

Li, S., Du, J., & Sun, J. (2022). Unfolding the learning behaviour patterns of MOOC learners with different levels of achievement. *International Journal of Educational Technology in Higher Education, 19*(22), 1–20. https://doi.org/10.1186/s41239-022-00328-8

Meng, C., Zhao, M., Pan, Z., Pan, Q., & Bonk, C. J. (2024). Investigating the impact of gamification components on online learners' engagement. *Smart Learning Environments, 11*(47), 1–28. https://doi.org/10.1186/s40561-024-00336-3

Page, M. J., Moher, D., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., et al. (2021a). PRISMA 2020 explanation and elaboration: updated guidance and exemplars for reporting systematic reviews. *BMJ* 372, n160. doi:10.1136/bmj.n160

Petronzi, D., & Hadi, M. (2016). Exploring the factors associated with MOOC engagement, retention and the wider benefits for learners. *International Review of Research in Open and Distributed Learning, 17*(4), 1–19. https://doi.org/10.19173/irrodl.v17i4.2331

PTI. (2025, May 2). Less than 4% students completed SWAYAM courses since 2017, reveals Parliamentary panel report; flags outdated content | Hindustan Times. *Hindustan Times*.

https://www.hindustantimes.com/education/admissions/less-than-4-students-completed-swayam-courses-since-2017-reveals-parliamentary-panel-report-flags-outdated-content-101738752673459.

Rehfeldt, R. A., Jung, H. L., Aguirre, A. A., Nichols, J. L., & Root, W. B. (2016). *Beginning the dialogue on the e-transformation: Behavior analysis' first massive open online course (MOOC).* Behavior Analysis in Practice, 9(1), 101–110. https://doi.org/10.1007/S40617-015-0102-Z

Shi, H., Zhou, Y., Dennen, V. P., & Hur, J. (2023). From unsuccessful to successful learning: Profiling behavior patterns and student clusters in massive open online courses. *Education and Information Technologies, 29*, 5509–5540. https://doi.org/10.1007/s10639-023-12010-1

Swayam Central. (n.d.-a). About SWAYAM. Retrieved September 19, 2025, from https://swayam.gov.in/about

Swayam Central. (n.d.-b). Framework for Universities to Conduct Examinations for SWAYAM Courses. Retrieved September 24, 2025, from https://swayam.gov.in/about_university

Tseng, S. F., Tsao, Y. W., Yu, L. C., Chan, C. L., & Lai, K. R. (2016). Who will pass? Analysing learner behaviours in MOOCs. *Research and Practice in Technology Enhanced Learning, 11*(1), 1–11. https://doi.org/10.1186/S41039-016-0033-5

Wang, R., Cao, J., Xu, Y., & Li, Y. (2022, December). Learning engagement in massive open online courses: A systematic review. In *Frontiers in Education* (Vol. 7, p. 1074435). Frontiers Media SA

Wu, B., & Zhang, C. (2016). *Behavior and intention in MOOCs research.* Proceedings of the International Conference on Artificial Intelligence, 119–124. https://doi.org/10.2991/AIIE-16.2016.119

Xia, X., & Qi, W. (2023). Learning behavior interest propagation strategy of MOOCs based on multi-entity knowledge graph. *Education and Information Technologies, 28*, 13349–13377. https://doi.org/10.1007/s10639-023-11719-3

Xie, L., & Wang, C. (2022). Why did they come back? Analysis of learning behaviour and motivation of repeat learners in cMOOCs. *Interactive Learning Environments*. https://doi.org/10.1080/10494820.2022.2115079

Zheng, Q., Chen, L., Burgos, D. (2018). Innovative and Revolutionary Potential of MOOCs. In: The Development of MOOCs in China. Lecture Notes in Educational Technology. Springer, Singapore. https://doi.org/10.1007/978-981-10-6586-6_3

Zhong, S. H., Li, Y., Liu, Y., & Wang, Z. (2017). A computational investigation of learning behaviours in MOOCs. *Computer Applications in Engineering Education*, *25*(5), 693-705.

Zhu, J. (2022). *How behaviorism can help provide insight into MOOCs in the Chinese education market.* Journal of Contemporary Educational Research, 6(8), 1–5. https://doi.org/10.26689/jcer.v6i8.4281