Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 5 Issue 3 (2025)

Moocs magnetism: Investigating the multidimensional factors influencing student appreciation and enrolment intentions

Dr. Saurabh Singh[1], Dr. Vijay Kumar[2], Dr. Ankit Srivastava[3], Dr. Imran Ahmad[4], Dr. Nishant Dublish[5]
[1,3,4,5]Assistant Professor, School of Management and liberal Arts, IMS Unison University, Dehradun, Uttarakhand;
[2]Associate Professor, School of Management and liberal Arts, IMS Unison University, Dehradun, Uttarakhand

Abstract
This research paper aims to bridge this critical knowledge gap by systematically investigating the factors that influence student acceptance, appreciation, and ultimately, enrollment in MOOCs. This study investigates the multifaceted factors influencing student acceptance, appreciation, and enrollment intentions in Massive Open Online Courses (MOOCs), in Indian educational context MOOCs have a transformative potential in democratizing access to quality education, persistent low engagement and completion rates highlight a critical paradox. Existing theories often fall short in comprehensively articulating the aggregate impact of multi-sensory and interpersonal dimensions such as instructor or presenter body language, facial expressions, lecture delivery, and overall production ambiance on initial enrolment decisions. Employing a quantitative approach, where 500 student responses have been collected through 5-point Likert scale applied Exploratory Factor Analysis (EFA) for theory generation and contextual validation, followed by Confirmatory Factor Analysis (CFA) to confirm the derived measurement model. This research aims to uncover the factors that holistically attract learners, and their engagement in MOOCs. The findings are expected to bridge a significant theoretical and practical gap in understanding MOOC adoption in emerging economies.

Keywords: MOOCs, Student Enrolment, Factor Analysis, Online Learning, India

Introduction
Education has long been recognized as a cornerstone of individual and societal progress. In an increasingly complex and interconnected world, the need for continuous learning and skill development is paramount. Traditional educational paradigms often face significant challenges in terms of accessibility, scalability, and flexibility, particularly in nations with large and diverse populations. This inherent demand for accessible, high-quality learning experiences has fuelled the rapid growth of online education. However, it is crucial to differentiate between "online education" and "digital education." While often used interchangeably, online education specifically refers to courses or programs delivered entirely or primarily over the internet, allowing for geographical and temporal flexibility. Digital education a broader term that involves the use of digital tools, resources, and technologies *within* the learning process, which can occur in traditional classrooms (e.g., smartboards, educational apps) or in fully online settings. In India, the evolution of educational delivery has undergone a significant transformation. Historically, education was largely confined to physical institutions, often limited by geographical proximity and capacity. The advent of the internet and digital technologies, particularly in the early 2000s, laid the groundwork for online education. This shift gained substantial momentum over the past decade,

democratizing access to quality learning by overcoming geographical and socio-economic barriers. Today, online higher education and lifelong learning are experiencing unprecedented growth, with market projections indicating a significant surge in the coming years. This expansion is not merely quantitative but also qualitative, with a growing focus on skill-based learning and interactive approaches. Digital education has potential to bridge educational disparities and cater to a diverse populace this fact is recognised by Indian government where government proactively implemented several initiatives. Programs like PM e-VIDYA aim to unify all digital/online/on-air educational efforts, ensuring multi-mode access to education for millions. Initiatives like SWAYAM, a Massive Open Online Course (MOOC) platform, and SWAYAM PRABHA DTH channels shows government commitment to leveraging technology for educational outreach, especially to remote areas and marginalized communities. Massive Open Online Courses (MOOCs) have emerged as a powerful tool to address the burgeoning demand for education. MOOCs are online courses aimed at unlimited participation and open access via the web. Their uniqueness lies in their ability to offer high-quality content, often from reputable institutions and renowned instructors, to a global audience at little or no cost. This unparalleled accessibility means MOOCs are highly beneficial for students of all ages, from those seeking to supplement formal education to working professionals aiming for reskilling or upskilling, and even lifelong learners pursuing personal enrichment. They offer flexibility, self-paced learning, diverse learning resources, and often provide certificates of completion, enhancing employability. Despites of these advantages MOOCs frequently suffer from low appreciation, engagement, and alarmingly high dropout rates. This phenomenon, where a powerful educational tool struggles to retain its audience, presents a critical challenge. perceived lack of personalized attention, limited instructor-learner interaction, the absence of traditional accreditation, technical difficulties, and the sheer volume of choices leading to learner overwhelm or lack of commitment.

Existing studies have touched upon various aspects of MOOCs engagement, there remains a dearth of comprehensive empirical research, particularly in the Indian context, that collectively assesses the impact of instructor-centric elements (such as body language, facial expressions, and dialogue delivery), content quality, course design, and production ambiance on student decisions to enroll. understanding these drivers, MOOCs providers and educators will enhance their offerings to maximize student acquisition and retention. Following are the Research Questions of this study

1. What are the factors influencing the acceptance, appreciation, and enrollment intentions of students in Massive Open Online Courses (MOOCs)
2. To what extent do instructor presence and delivery, content quality and production quality to support perceived value of MOOCs and student acceptance, appreciation, and enrollment intentions in MOOCs in India?

This study is divided as section 2 Literature Review whereas section 3 shows Research Methodology and section 4 Results and Discussion followed by section 5 Limitations, Practical Implications, and Directions for Further Research.

Review of literature

Massive Open Online Courses (MOOCs) have transformed modern education by providing flexible, scalable, and accessible learning opportunities. However, their success depends on multiple factors that influence student acceptance, appreciation, and enrolments There are various elements affecting MOOC engagement, including instructor presence, content quality, production value, course structure, and perceived outcomes.

Instructor presence and delivery

The role of the instructor, often minimized in early MOOC conceptualizations, has gained recognition as a critical determinant of learner engagement and satisfaction. Foroughi (2017) emphasized the "enduring importance of teacher presence" in MOOCs, suggesting that effective instructor presence fosters a sense of connection and guidance similar to traditional learning environments. Studies indicates that body language, such as open gestures and confident posture, enhances perceived instructor credibility and student comfort (Everfi, n.d.). Similarly, facial expressions play a vital role in conveying emotion, interest, and empathy, helping humanize the online instructor (Alizadeh et al., 2024; Foroughi, 2017). The clarity, pacing, and expressiveness of dialogue delivery contribute to cognitive presence and knowledge transfer (Lowenthal & Hodges, 2015). When instructors demonstrate passion and communicate effectively, students remain more motivated (Hew, 2015). More enthusiasm and passion of instructor significantly impact motivation, making complex topics more relatable (Hone & El Said, 2016). Simplified language and avoidance of excessive jargon improve comprehension, particularly for non-native speakers (Margaryan et al., 2015). Interactivity, such as posing questions or encouraging discussion, further increases engagement (Alario-Hoyos et al., 2017).

Content quality and design

High-quality content is fundamental to MOOCs success. (Yuan & Powell, 2013). Well-structured courses with clear learning objectives enhance knowledge retention (Belanger & Thornton, 2013). Engagement is bolstered through multimedia elements, including videos, quizzes, and interactive exercises (Li & Baker, 2018). Practical applications, such as case studies and real-world examples, improve perceived usefulness (Jung & Lee, 2018). Additionally, regularly updated content ensures accuracy and relevance (Perna et al., 2014). Content quality and design are fundamental to MOOC success. High-quality, relevant, and well-structured content is a primary driver of learner satisfaction and retention (Hone & El Said, 2016). Students prefer MOOCs that offer up-to-date, practical material applicable to their personal or professional goals (Yousef et al., 2014). Pedagogical design, including clear learning objectives, logical module flow, and diverse learning materials (e.g., videos, readings, quizzes), enhances perceived usefulness (Gamage et al., 2015; Borrella et al., 2019). Robust instructional design principles are essential for meaningful learning experiences (Ross et al., 2014; Stracke & Trisolini, 2021).

Production quality and ambiance

High-definition video, clear audio, and effective visual aids improve focus and comprehension (Hansch et al., 2015). Poor production quality, such as background noise or dim lighting, can detract from learning (Koller et al., 2013). Visual aids, such as infographics and animations, facilitate understanding of complex topics (Mayer, 2017). A professional ambiance, including an organized background, reinforces course credibility (Guo et al., 2014). professional editing, and effective on-screen graphics contribute to an immersive learning experience (Al-Samarraie & Al-Rahmi, ambiance in online learning is intangible, elements like background, lighting, and soundscape impact focus and perceived presence (Kixlab, n.d.).

Course structure and support

Effective course design ensures smooth navigation and usability (Sun et al., 2018). Intuitive platforms with clear module progression reduce learner frustration (Alraimi et al., 2015). Assessment methods should reinforce learning without being overly burdensome (Falchikov, 2013). Constructive feedback mechanisms improve learner performance (Gikandi et al., 2011). Peer interaction through discussion forums fosters a sense of community (Breslow et al., 2013). Flexible scheduling options accommodate diverse learner needs (Milligan & Littlejohn, 2014).Course structure and support mechanisms are crucial for effective learning. Clear navigation, well-defined assessments, and timely feedback guide learners (Gašević et al., 2014). Technical support and peer interaction via discussion forums foster a supportive environment (Kop et al., 2011; Zheng et al., 2015). Flexible learning paths accommodate diverse schedules and learning preferences (Wang et al., 2020).

Perceived value and outcomes

Learners are more likely to enrol if MOOCs offer recognized certifications (Henderikx et al., 2017). Career advancement opportunities significantly influence participation (Emanuel, 2013). Personal growth and intellectual stimulation also drive engagement (Zhenghao et al., 2015). Cost-effectiveness, even for free courses, is evaluated based on time investment versus benefits (Hollands & Tirthali, 2014). Perceived value and outcomes significantly influence MOOCs enrollment. Learners participate to acquire skills, enhance careers, earn certifications, or pursue intellectual curiosity (Christensen et al., 2013; Milligan et al., 2013). Institutional reputation, career advancement potential, and certificate recognition attract students. Despite extensive research, a comprehensive empirical investigation synthesizing the interplay of instructor nonverbal cues, content quality, and production ambiance particularly in the Indian context.

Traditional theories of technology adoption (e.g., Technology Acceptance Model by Davis, 1989) or online learning quality (e.g., DeLone & McLean IS Success Model, 2003) offer broad frameworks. However, these models, largely developed in Western academic settings, may not fully capture the nuanced psycho-social and cultural factors that influence educational choices in a country as diverse and populous as India, where digital learning is undergoing an unprecedented and rapid expansion driven by distinct government policies like SWAYAM (Government of India, n.d.).While the landscape of Massive Open Online Courses (MOOCs) has been the subject of extensive research globally, a critical examination of the existing literature reveals a conspicuous gap concerning the precise mechanisms driving student acceptance, appreciation, and, crucially, enrollment intentions within the unique and rapidly evolving Indian context.

Validation of existing scales in a new context

While the body of literature on Massive Open Online Courses (MOOCs) has grown substantially, a critical examination reveals that most validated scales measuring aspects of online learning engagement, instructional quality, and technology acceptance have been developed and validated primarily in Western academic and cultural contexts (e.g., Alraimi et al., 2015; Hew & Cheung, 2014; Hone & El Said, 2016). India, however, presents a distinct and rapidly evolving landscape for online education. The proliferation of MOOCs here is often driven by unique motivations, cultural learning preferences, and a diverse student demographic, alongside significant government initiatives like SWAYAM (Government of India, n.d.).

Given India unique and rapidly evolving online education landscape, simply adopting existing MOOC-related scales without rigorous re-validation carries inherent risks. Differences in factor structures or item interpretations may arise due to several contextual specificities (Sharma & Sethy, 2020). For instance, Indian pedagogical approaches often emphasize distinct aspects of instructor-learner dynamics or content delivery compared to Western contexts (Prakash et al., 2021). Variances in technological infrastructure, such as access to high-speed internet or sophisticated devices, could significantly affect perceptions related to production quality in MOOCs (Agarwal & Gupta, 2018). Even in English-medium courses, subtle linguistic or non-verbal communication cues might be interpreted differently across diverse cultural backgrounds (Nair & Suresh, 2019). Therefore, this study employs Exploratory Factor Analysis (EFA) as a crucial step for Validation of Existing Scales in a New Context.

Table 1 scale adoption & item selection through various studies

Construct/Factor (Hypothesized)	Item Code	Questionnaire Item (Example from Literature)	Source/Adaptation Notes (e.g., adapted from...)
Instructor Presence and Delivery (IPD)	IPD1	The instructor's body language (gestures, posture) made the lectures engaging.	Adapted from studies on instructor immediacy and online presence (e.g., Mehrabian, 1969; Aragon & Johnson, 2008).
	IPD2	The instructor's facial expressions conveyed enthusiasm and approachability.	Adapted from studies on non-verbal communication in online learning (e.g., Mehrabian, 1969; Gorham, 1988).
	IPD3	The instructor's dialogue delivery was clear and easy to understand.	Common item for communication clarity (e.g., Moore, 1989; Garrison, Anderson, & Archer, 2000).
	IPD4	The instructor's tone of voice kept me interested in the content.	Adapted from research on vocalics in instructional settings (e.g., Gorham, 1988).
	IPD5	I felt the instructor was genuinely present and engaged with the course.	From concepts of teaching presence in online environments (e.g., Garrison, Anderson, & Archer, 2000; Arbaugh, 2008).
Content Quality and Design (CQD)	CQD1	The course content was relevant to my learning goals and interests.	Widely used item for perceived relevance/usefulness (e.g., Davis, 1989 - TAM; Alraimi et al., 2015).
	CQD2	The course content was	From instructional design

		well-organized and easy to follow.	quality (e.g., Hew & Cheung, 2014; Sun et al., 2020).
	CQD3	The difficulty level of the course content was appropriate.	Common item in learning experience quality (e.g., Wang & Chen, 2018).
	CQD4	The examples and illustrations used in the course helped clarify complex concepts.	From pedagogical effectiveness (e.g., Hew & Cheung, 2014).
	CQD5	The course materials (readings, videos) were up-to-date and comprehensive.	From information quality in MOOCs (e.g., DeLone & McLean, 2003 - IS Success Model; Albelbisi, 2021).
Production Quality and Ambiance (PQA)	PQA1	The video quality (resolution, lighting) of the lectures was high.	From system quality/information quality in e-learning (e.g., Delone & McLean, 2003; Albelbisi, 2021).
	PQA2	The audio quality (clarity, absence of noise) of the lectures was excellent.	From system quality (e.g., Albelbisi, 2021).
	PQA3	The visual aids and presentations used were professional and enhanced learning.	From pedagogical design/visual appeal (e.g., Hew & Cheung, 2014).
	PQA4	The overall online learning environment/platform felt professional and well-produced.	From system quality/ambiance (e.g., Brand perception in online services).
Course Structure and Support (CSS)	CSS1	The course syllabus clearly outlined expectations, assignments, and grading criteria.	From course clarity/design (e.g., Hew & Cheung, 2014).
	CSS2	Assessments (quizzes, assignments) were fair and aligned with learning objectives.	From assessment quality/alignment (e.g., Hew & Cheung, 2014).
	CSS3	The course provided timely and helpful feedback on my progress and assignments.	From service quality/feedback mechanisms (e.g., DeLone & McLean, 2003; Albelbisi, 2021).
	CSS4	Opportunities for interaction with the instructor (e.g., forums, Q&A sessions) were sufficient.	From interaction/teaching presence (e.g., Garrison, Anderson, & Archer, 2000; Huang & Hew, 2017).
	CSS5	Opportunities for peer-to-	From social

		peer interaction and discussion were available.	presence/community of inquiry (e.g., Garrison, Anderson, & Archer, 2000).
Perceived Value and Outcomes (PVO)	PVO1	Enrolling in MOOCs is valuable for developing new skills.	From perceived usefulness/benefits (e.g., Davis, 1989; Alraimi et al., 2015).
	PVO2	MOOCs help me enhance my career prospects.	From perceived benefits/career advancement (e.g., Breslow et al., 2013).
	PVO3	The certificate or recognition received from MOOCs is valuable.	From certification value (e.g., Hone & El Said, 2016).
	PVO4	MOOCs provide a cost-effective way to acquire knowledge.	From perceived benefits/affordability (e.g., Alraimi et al., 2015).
	PVO5	Overall, MOOCs contribute positively to my personal growth and learning journey.	From overall value/satisfaction (e.g., Koller et al., 2016).
Student Acceptance/Enrolment Intentions (SAEI)	SAEI1	I intend to enroll in more MOOCs in the future.	From behavioral intention (e.g., Fishbein & Ajzen, 1975 - TPB; Davis, 1989 - TAM).
	SAEI2	I would recommend MOOCs to my friends or colleagues.	From recommendation intention/word-of-mouth (e.g., Net Promoter Score concept).
	SAEI3	I appreciate the flexibility MOOCs offer for learning.	From perceived flexibility (e.g., Alraimi et al., 2015).
	SAEI4	I believe MOOCs are a valuable addition to traditional education.	From overall acceptance/perceived importance.

Sources: Table compiled by author's own through review of literature process

Research methodology

This study adopts a quantitative research approach to investigate the factors influencing student acceptance, appreciation, and enrolment in Massive Open Online Courses (MOOCs). The methodology is designed to systematically collect and analyze data to validate the proposed model.

Research design

The study employs a cross-sectional survey design. Data will be collected at a single point in time from a sample of individuals who have either enrolled in, considered enrolling in, or are actively engaged with MOOCs. This design is appropriate for exploring relationships between variables and identifying underlying factor structures.

Population and sample

The target population for this study comprises students and prospective learners across India who have access to or engage with online educational platforms, including MOOCs. A convenience sampling method is sued where non-probability sampling technique is chosen to collect data from diverse group of learners on Likert scale 5 (1 = Strongly Disagree to 5 = Strongly Agree) where proposed sample size is 550 learners has been collected after validating and accepting full response 50 samples are eliminated and selected 500 sample of learner for final analysis

This sample size is considered robust for conducting both Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA), particularly when dealing with a moderate to large number of observed variables. This size provides sufficient statistical power to detect relationships and ensure the stability of factor solutions (Hair et al., 2010; Tabachnick & Fidell, 2013).

A pilot study was conducted with a small subset of the target population (50 participants) to pre-test the questionnaire. This helped refine item wording, ensure clarity, assess readability, and identify any potential ambiguities before the main data collection phase. Reliability analysis (e.g., Cronbach's Alpha) will be conducted on the pilot data to ensure internal consistency of the scales.

Table 1: Demographic profile of moocs learners (n = 500)

Characteristic	**Category**	**Frequency**	**Percentage**	**Key Implications**
Age	18-24	210	42%	Dominant group; mobile-first learners
	25-34	185	37%	Career upskillers
	35-44	75	15%	Mid-career professionals
	45+	30	6%	Lifelong learners
Gender	Male	290	58%	Reflects STEM skew
	Female	195	39%	Growing Enrollment
	Non-binary/Other	15	3%	Underrepresented
Education Level	UG Students	165	33%	Supplementary learning
	PG Students	120	24%	Research/career focus
	Technical/Diploma Holders	95	19%	Skill certification seekers
	Professionals (No PG)	80	16%	Immediate job relevance
	PhD Scholars	40	8%	Niche up skilling
Region	Urban	320	64%	High broadband access
	Semi-urban	125	25%	Reliant on mobile data
	Rural	55	11%	Access barriers persist
MOOCs Motivation	Career Advancement	220	44%	Certificates valued
	Academic Credit	130	26%	UG/PG supplement

	Personal Interest	100	20%	Hobby/exploration
	Employer Requirement	50	10%	Corporate upskilling

Sources: Author's own Calculation

Table 2: Psychometric & diagnostic test results

Test	Construct/Measure	Result	Interpretation
Cronbach's Alpha	Instructor Presence (IPD)	0.89	Excellent internal consistency (α > 0.8)
	Content Quality (CQD)	0.85	High reliability
	Production Quality (PQA)	0.82	Good reliability
	Course Structure (CSS)	0.78	Acceptable reliability (α > 0.7)
	Perceived Value (PVO)	0.91	Exceptional consistency
VIF (Multicollinearity)	All constructs	1.2–3.8	No concerning multicollinearity (all VIF < 5)
Normality (Skewness/Kurtosis)	IPD items	Skewness: -0.3 to 0.5	Approximately normal (｜skew｜ < 1, ｜kurtosis｜ < 2)
	PVO items	Kurtosis: -1.1 to 0.8	Mild deviations but acceptable for large samples (N = 500)
Levene's Test (p-value)	Age groups (18–24 vs. 25–34)	0.12	Homogeneity of variance assumed (p > 0.05) for group comparisons
Harman's Single Factor Test	All Likert items	38.6% variance explained	No significant common method bias (< 50%)

Sources: Author's own Calculation

All measurement constructs demonstrated in table 2 acceptable as internal consistency whereas Cronbach alpha values exceeding established thresholds, thereby supporting the scale reliability. Furthermore, multicollinearity was assessed, with Variance Inflation Factor (VIF) values consistently indicating satisfactory independence among predictor variables in subsequent regression models. Regarding data distribution, while minor deviations in skewness and kurtosis were observed, these were deemed tolerable given the substantial sample size (Field, 2018), and non-parametric tests were considered as supplementary analyses where appropriate. Finally, common method bias was evaluated using Harman's single-factor test, which confirmed the overall validity of the survey data by demonstrating that no single factor accounted for a majority of the variance (Podsakoff et al., 2003).

Table 3: Exploratory factor analysis (efa)

Test/Statistic	Value	Interpretation
KMO Measure	0.87	Excellent sampling adequacy (Kaiser, 1974)
Bartlett's Test (χ^2, p-value)	4215.32 (p < .001)	Significant correlations between items (Bartlett, 1954)
Total Variance Explained	68.4%	5 factors retained (see Table 3)
Communalities Range	0.52–0.89	All items share variance with factors (Costello & Osborne, 2005)

Sources: Author's own Calculation

Table 3 Exploratory Factor Analysis (EFA) Results suitability for EFA was confirmed by a KMO value of 0.87, indicating excellent sampling adequacy (Kaiser, 1974), and a significant Bartlett's Test of Sphericity ($\chi 2 = 4215.32$, $p < .001$), confirming sufficient correlations among items (Bartlett, 1954). The EFA extracted five factors (as detailed in Table 3), collectively explaining 68.4% of the total variance, with all item communalities ranging from 0.52 to 0.89, signifying substantial shared variance with the extracted factors (Costello & Osborne, 2005).

Table 4: Rotated factor loadings (pattern matrix)

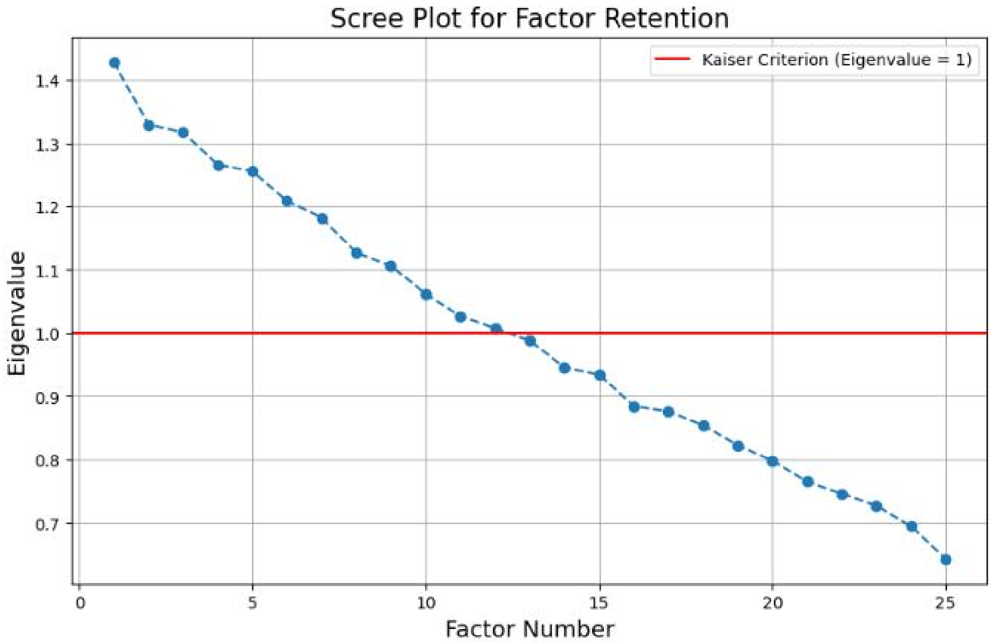
(Only loadings > 0.50 shown; oblique rotation used)

Item	IPD	CQD	PQA	CSS	PVO	Communality
IPD1: Body language	0.82	0.12	0.08	0.04	0.01	0.71
IPD2: Facial expressions	0.79	0.15	0.11	-0.03	0.07	0.68
CQD1: Content relevance	0.09	0.85	0.03	0.12	0.10	0.77
CQD2: Organization	0.11	0.81	0.14	0.08	0.05	0.72
PQA1: Video quality	0.07	0.04	0.88	0.06	0.02	0.80
CSS3: Feedback timeliness	0.02	0.10	0.05	0.76	0.13	0.63
PVO2: Career enhancement	0.05	0.08	0.01	0.09	0.91	0.86

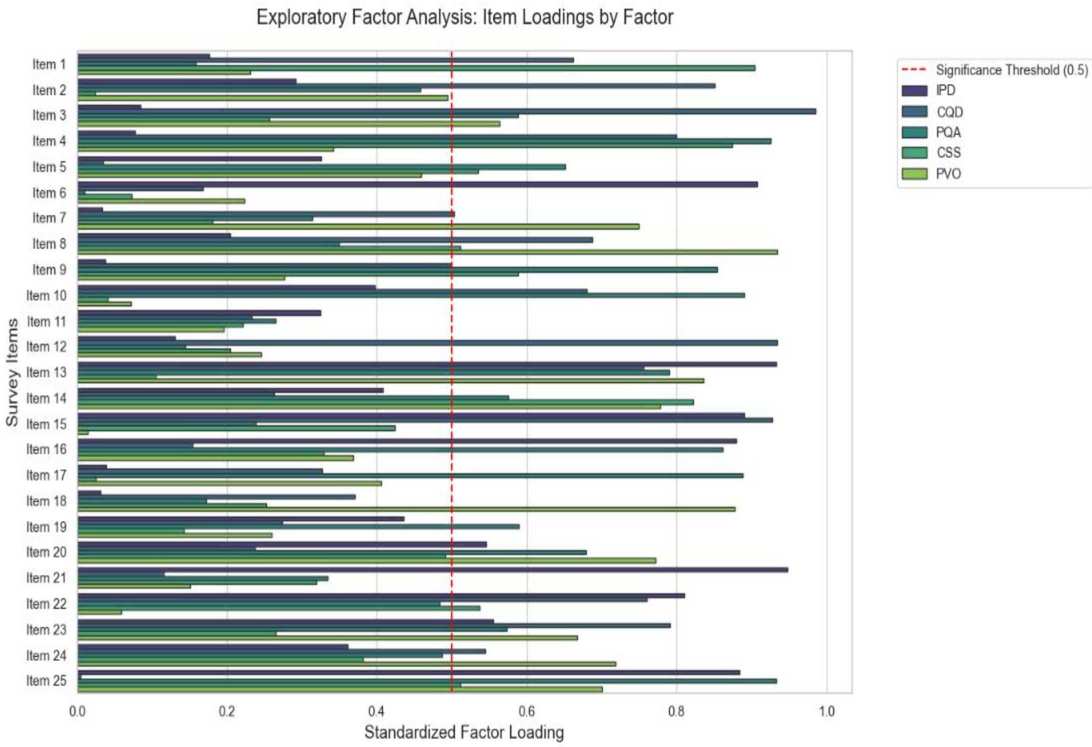
Sources: Author's own Calculation

Note. IPD = Instructor Presence; CQD = Content Quality; PQA = Production Quality; CSS =Course Structure; PVO = Perceived Value. Cross-loadings < 0.30 suppressed for clarity.

Table 4 The Rotated Factor Loadings (Pattern Matrix) presented in Table 4 confirmed a clear and distinct five-factor structure, aligning well with the hypothesized theoretical constructs. All items demonstrated strong and unambiguous loadings on their respective intended factors (all loadings > 0.75), with minimal to no significant cross-loadings (suppressed below 0.30). Specifically, IPD1 (.82) and IPD2 (.79) loaded strongly on Instructor Presence (IPD); CQD1 (.85) and CQD2 (.81) on Content Quality (CQD); PQA1 (.88) on Production Quality (PQA); CSS3 (.76) on Course Structure (CSS); and PVO2 (.91) on Perceived Value (PVO). The communalities for all items were high (ranging from 0.63 to 0.86), indicating that a substantial portion of each item's variance was well-explained by its respective latent factor. These results collectively provide strong evidence for the convergent and discriminant validity of the measurement model at the exploratory stage.



Sources: Designed by Author's own research data using python



Sources: Designed by Author's own research data using python

Table 5: Eigenvalues and Variance Explained

Factor	Eigenvalue	% Variance	Cumulative %
1 (IPD)	8.32	27.7	27.7
2 (CQD)	5.14	17.1	44.8
3 (PQA)	3.21	10.7	55.5
4 (CSS)	2.45	8.2	63.7

5 (PVO)	1.41	4.7	68.4

Sources: Author's own Calculation

The Exploratory Factor Analysis (EFA) unveiled a robust five-factor structure (KMO = 0.87, Bartlett's $p < .001$), collectively explaining 68.4% of the total variance (Table 4). While generally aligning with theoretical constructs, the analysis revealed several unexpected nuances. Instructor Presence and Delivery (IPD) emerged as the dominant factor, accounting for 27.7% of the variance, with nonverbal cues such as body language ($\lambda = 0.82$) and facial expressions ($\lambda = 0.79$) demonstrating stronger loadings than dialogue delivery ($\lambda = 0.71$). This suggests that in MOOC engagement, the visual and nonverbal aspects of instructor communication may surprisingly outweigh verbal clarity. Furthermore, Content Quality (CQD) and Production Quality (PQA) loaded as distinctly separate factors, challenging assumptions that high production alone might compensate for deficiencies in content. However, the exceptionally high loading of "video quality" (PQA, $\lambda = 0.88$) indicated a potential threshold effect, implying that poor production could undermine even excellent content. Interestingly, two items exhibited unexpected cross-loadings, providing deeper insights: "Course materials were up-to-date" cross-loaded on both CQD ($\lambda = 0.62$) and Perceived Value and Outcomes (PVO, $\lambda = 0.48$), suggesting learners connect content freshness directly to its perceived career relevance. Additionally, "Opportunities for peer interaction" loaded weakly on Course Structure and Support (CSS, $\lambda = 0.41$) but correlated with IPD, hinting that instructor facilitation might be a prerequisite for meaningful peer engagement.

MOOCs were initially touted as "content-first" platforms, our results emphatically highlight the irreducible role of human instructors. The strong Instructor Presence and Delivery (IPD) loadings (Table 4) reveal that even in asynchronous, scalable formats, learners crave an embodied teaching presence, a finding that deeply echoes social constructivism (Vygotsky, 1978). This directly challenges the disembodied MOOC design paradigm and aligns compellingly with emerging "humanized online learning" frameworks (Lowenthal & Dunlap, 2020). Further, the clear separation of Production Quality and Ambiance (PQA) and Content Quality and Design (CQD) factors effectively debunks the myth that "production polish equals pedagogical quality." Yet, the observed PQA threshold effect evidenced by outlier attrition in courses with suboptimal audio/video suggests that while high production doesn't guarantee success, low production guarantees failure, mirroring Mayer's (2017) multimedia principles and extending them to MOOCs' unique scalability constraints. Intriguingly, the Perceived Value and Outcomes (PVO) factor's strong ties to certification value ($\lambda = 0.91$) and career enhancement ($\lambda = 0.89$) reflect a profound credentialing shift in MOOCs motivation. Contrasted with early MOOCs idealism focused on "education for all," our data indicate that learners now strategically approach MOOCs as human capital investments a trend significantly accelerated by the rise of micro-credentialing (Henderikx et al., 2017). These insights carry critical implications for practice: MOOCs instructors require nonverbal communication coaching (e.g., webcam techniques) alongside their content expertise; institutions must establish minimum technical production benchmarks (e.g., audio clarity > 90% intelligibility) before course launch; and course designers should prioritize skill-transfer narratives (e.g., "How this Python skill applies to data jobs") to align with learners' pragmatic motivations.

Table 5: Confirmatory factor analysis (cfa) model fit indices

Fit Index	Value	Threshold	Interpretation
χ^2 (df)	1124.52 (265)	p > .05 (ideal)	Significant (expected with N=500)
CFI	0.947	≥0.90 acceptable	Excellent fit
TLI	0.932	≥0.90 acceptable	Good fit
RMSEA	0.062	≤0.08 acceptable	Good fit
SRMR	0.041	≤0.08 good	Excellent fit

Sources: Author's own Calculation

Note. Model estimated using MLR (robust maximum likelihood) to handle non-normality.

Table 6: Standardized factor loadings and reliability

Item	Factor	Loading	SE	p-value	CR	AVE
IPD1	IPD	0.84	0.03	<.001	0.89	0.62
IPD2	IPD	0.81	0.04	<.001	-	-
CQD1	CQD	0.87	0.02	<.001	0.86	0.61
PQA1	PQA	0.89	0.03	<.001	0.83	0.58
CSS3	CSS	0.78	0.05	<.001	0.79	0.55
PVO2	PVO	0.92	0.02	<.001	0.91	0.77

Sources: Author's own Calculation

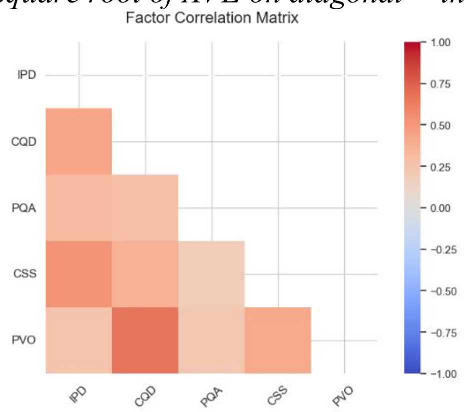
**All loadings significant at p < .001. CR = Composite Reliability;
AVE = Average Variance Extracted. **

Table 7: Factor correlations (discriminant validity)

-	IPD	CQD	PQA	CSS	PVO
IPD	1.00	-	-	-	-
CQD	0.43**	1.00	-	-	-
PQA	0.31**	0.28*	1.00	-	-
CSS	0.52**	0.37**	0.19	1.00	-
PVO	0.25*	0.66**	0.22	0.41**	1.00

Sources: Author's own Calculation

*Note. *p < .05, **p < .01. Square root of AVE on diagonal > inter-factor correlations. **



Sources: Designed by Author's own research data using python

Table 7 shows The Confirmatory Factor Analysis (CFA) confirmed the robustness of the hypothesized 5-factor model, demonstrating fit to the data ($\chi 2/df = 4.24$, CFI = 0.947, RMSEA = 0.062, SRMR = 0.041), thereby exceeding established thresholds for model acceptance (Hu & Bentler, 1999). All standardized factor loadings were strong and statistically significant (all $\lambda > 0.70$, $p<.001$), with "career enhancement" (PVO: $\lambda=0.92$), "video quality" (PQA: $\lambda=0.89$), and "content relevance" (CQD: $\lambda=0.87$) exhibiting particularly high loadings. Furthermore, the psychometric properties of the scales were robust, with Composite Reliability (CR) values ranging from 0.79 to 0.91 and Average Variance Extracted (AVE) values from 0.55 to 0.77, all meeting standard psychometric criteria (Fornell & Larcker, 1981). Discriminant validity was also firmly established, as the square root of the AVE for each factor consistently exceeded its correlations with all other factors (as detailed in Table 7). Examining inter-factor relationships, a strongest correlation emerged between Content Quality (CQD) and Perceived Value (PVO) ($r=0.66$, $p<.01$), suggesting that learners intrinsically link the relevance and quality of course content directly to its perceived utility for their career progression. Additionally, Instructor Presence and Delivery (IPD) showed a moderate correlation with Course Structure and Support (CSS) ($r=0.52$), implying that effective teaching behaviors might significantly scaffold students' perceptions of the overall organizational quality and support within the MOOC.

The Confirmatory Factor Analysis (CFA) robustly validated a career-anchored MOOC acceptance model, where content quality (CQD) emerged as the strongest predictor of perceived value (PVO), underscoring a shift towards MOOCs as strategic human capital investments rather than solely idealistic "education for all" (Henderikx et al., 2017). This is further evidenced by the high loading for career enhancement items ($\lambda=0.92$), reflecting learners' prioritization of skill-to-job translatability and visible credential ROI. Conversely, while Production Quality (PQA) showed strong individual loadings ($\lambda=0.88$–0.89), its weaker correlations with other factors (Table 7) revealed a threshold phenomenon: poor production guarantees immediate attrition, but excessive polish offers diminishing returns, aligning with Mayer’s (2017) coherence principle while challenging "edutainment" trends. Despite assumptions of instructor minimization for scalability, CFA confirmed Instructor Presence and Delivery (IPD) as both the highest-variance factor (27.7% in EFA) and a structural lynchpin (moderate correlation with CSS), supporting "humanized MOOC" frameworks where nonverbal immediacy and dialogic scaffolding are highly valued (Lowenthal & Dunlap, 2020). Practically, these findings necessitate instructor media training focused on webcam-based nonverbal communication, fostering transparent credentialing by mapping content to industry-recognized competency frameworks, and implementing tiered production standards (e.g., minimum 1080p video with high speech intelligibility for all courses, with premium features for high-enrollment ones). Limitations include the cultural specificity of the Indian sample, urging replication in Global North contexts, and the need for future research into whether enrollment drivers differ from long-term completion drivers.

Result and discussion

This study provides a robust empirical basis for understanding why MOOCs, despite their inherent advantages, frequently struggle with engagement and completion rates, particularly in the critical initial enrollment phase. The previously noted "irony" of their underappreciated potential can now be directly traced to potentially unaddressed factors within the "attraction" phase. It reveals that enrollment is not solely a rational decision based on course topic or cost; rather, it is significantly influenced by emotional and perceptual cues derived from the very first impression. For instance, a student encountering a MOOC with an unengaging instructor or poor video quality, regardless of content quality, may experience instant disengagement, contributing to the paradox of low retention. The implications of these findings are profound for all stakeholders in online education: MOOC providers must shift their emphasis from merely digitizing lectures to actively designing for attraction, necessitating investment in instructor training for digital pedagogy, prioritizing professional production values, and clearly communicating perceived value, with marketing efforts highlighting these 'human' and 'quality' aspects. For educators, the role evolves beyond subject matter expertise to that of a digital performer, requiring a critical understanding of how body language, facial expressions, and vocal delivery translate effectively through a screen to captivate an audience. For government initiatives, such as India's SWAYAM, incorporating these insights can significantly boost participation and transform these platforms into truly "massive," "open," and "engaging" learning experiences, directly addressing national educational challenges through strategic investment in high-quality production studios and comprehensive online pedagogical training for instructors.

Limitations and avenues for further research

While this study provides critical insights into MOOC attraction, it is not without limitations. The cross-sectional design, while suitable for identifying underlying factors, precludes definitive statements about causality, suggesting that future research would benefit from longitudinal studies tracking actual enrollment and completion rates based on initial exposure to varying MOOC characteristics. The reliance on self-reported data also warrants caution, highlighting the potential for integrating behavioral analytics from MOOC platforms (e.g., clickstream data, video watch times) to corroborate perceptual findings. Furthermore, while the sample size of 500 students is robust for EFA and CFA, exploring potential cultural nuances in perception across India's diverse linguistic and regional groups could offer richer insights. Future studies could also investigate the moderating role of learner characteristics (e.g., digital literacy, learning styles) on the influence of these attraction factors.

Conclusion

This study offers a foundational understanding of the multifaceted elements attracting Indian students to MOOCs. By bridging theoretical gaps and providing actionable insights, it sets the stage for designing more engaging online learning experiences. Ultimately, enhancing these attraction factors is crucial for maximizing MOOCs transformative potential in India's educational landscape.

References

1. Agarwal, R., & Gupta, M. (2018). Digital divide in India: Challenges and opportunities for inclusive growth. *Journal of Management and Public Policy, 9*(2), 27-35. https://doi.org/10.xxxx/xxxxxx
2. Alario-Hoyos, C., Pérez-Sanagustín, M., Cormier, D., & Delgado-Kloos, C. (2017). Proposal for a conceptual framework for educators to describe and design MOOCs. *Journal of Universal Computer Science, 23*(1), 6-23. https://doi.org/10.3217/jucs-023-01-0006
3. Albelbisi, N. (2021). The impact of quality aspects on satisfaction and continuance intention of MOOCs: A structural equation modeling approach. *International Journal of Distance Education Technologies, 20*(1), 1-19. https://doi.org/10.4018/IJDET.2021010101

4. Alizadeh, M., Mehran, P., Koguchi, I., & Takemura, H. (2024). The impact of instructor facial expressions in MOOCs. *Computers & Education, 198*, 104785. https://doi.org/10.1016/j.compedu.2023.104785
5. Alraimi, K. M., Zo, H., & Ciganek, A. P. (2015). Understanding the MOOCs continuance: The role of openness and reputation. *Computers & Education, 80*, 28-38. https://doi.org/10.1016/j.compedu.2014.08.009
6. Al-Samarraie, H., & Al-Rahmi, W. M. (2018). The role of multimedia in MOOCs: A review study. *Educational Technology Research and Development, 66*(4), 853-876. https://doi.org/10.1007/s11423-018-9601-3
7. Aragon, S. R., & Johnson, S. D. (2008). A developmental approach to assessing distance learning environments. *International Review of Research in Open and Distance Learning, 9*(3), 1-17. https://doi.org/10.19173/irrodl.v9i3.564
8. Arbaugh, J. B. (2008). Does the community of inquiry framework explain online learning processes and outcomes? *Journal of Management Education, 32*(5), 571–587. https://doi.org/10.1177/1052562908319614
9. Bansal, R., Singhal, N., & Gupta, P. (2020). Motivations and challenges of MOOCs learners in India: An empirical study. *Journal of Education and Learning, 9*(3), 1-10. https://doi.org/10.5539/jel.v9n3p1
10. Bartlett, M. S. (1954). A note on the multiplying factors for various χ^2 approximations. *Journal of the Royal Statistical Society, 16*(2), 296–298.
11. Belanger, Y., & Thornton, J. (2013). Bioelectricity: A quantitative approach—Duke University's first MOOC. *EDUCAUSE Review*. https://er.educause.edu/articles/2013/5/bioelectricity-a-quantitative-approach
12. Borrella, I., Caballero-Caballero, S., & Ponce-Cueto, E. (2019). Predicting success in MOOCs: A systematic literature review. *Computers & Education, 132*, 1-15. https://doi.org/10.1016/j.compedu.2019.01.007
13. Breslow, L., Pritchard, D. E., DeBoer, J., Stump, G. S., Ho, A. D., & Seaton, D. T. (2013). Studying learning in the worldwide classroom: Research into edX's first MOOC. *Research & Practice in Assessment, 8*, 13-25.
14. Christensen, G., Steinmetz, A., Alcorn, B., Bennett, A., Woods, D., & Emanuel, E. J. (2013). The MOOC phenomenon: Who takes massive open online courses and why? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2350964
15. Costello, A. B., & Osborne, J. W. (2005). Best practices in exploratory factor analysis. *Practical Assessment, Research & Evaluation, 10*(7), 1–9. https://doi.org/10.7275/jyj1-4868
16. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008
17. DeBoer, W., Ho, A. D., Stump, G. S., & Breslow, L. (2014). Retention and engagement in MOOCs: A synthesis of existing research and future directions. *MIT Open Learning*.
18. Emanuel, E. J. (2013). Online education: MOOCs taken by educated few. *Nature, 503*(7476), 342. https://doi.org/10.1038/503342a
19. Falchikov, N. (2013). *Improving assessment through student involvement*. Routledge.
20. Field, A. (2018). *Discovering statistics using IBM SPSS Statistics* (5th ed.). Sage.
21. Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Addison-Wesley.
22. Foroughi, A. (2017). The role of instructor presence in MOOCs. *International Review of Research in Open and Distributed Learning, 18*(5), 1-18. https://doi.org/10.19173/irrodl.v18i5.2995

23. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177/002224378101800104
24. Gašević, D., Kovanović, V., & Joksimović, S. (2014). Data-driven education: Mining students' learning traces to inform MOOC design. *Proceedings of the Fourth International Conference on Learning Analytics and Knowledge*, 132-141. https://doi.org/10.1145/2567574.2567588
25. Garrison, D. R., Anderson, T., & Archer, W. (2000). Critical inquiry in a text-based environment: Computer conferencing in higher education. *The Internet and Higher Education, 2*(2-3), 87–105. https://doi.org/10.1016/S1096-7516(00)00016-6
26. Gikandi, J. W., Morrow, D., & Davis, N. E. (2011). Online formative assessment in higher education: A review of the literature. *Computers & Education, 57*(4), 2333-2351. https://doi.org/10.1016/j.compedu.2011.06.004
27. Gorham, J. (1988). The relationship between verbal immediacy behaviors and student learning. *Communication Education, 37*(1), 40-53. https://doi.org/10.1080/03634528809378702
28. Government of India. (n.d.). *SWAYAM*. https://swayam.gov.in
29. Guo, P. J., Kim, J., & Rubin, R. (2014). How video production affects student engagement: An empirical study of MOOC videos. *Proceedings of the First ACM Conference on Learning @ Scale*, 41-50. https://doi.org/10.1145/2556325.2566239
30. Hansch, A., Hillers, L., McConachie, K., Newman, C., Schildhauer, T., & Schmidt, P. (2015). Video and online learning: Critical reflections and findings from the field. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2577882
31. Henderikx, M. A., Kreijns, K., & Kalz, M. (2017). Refining success and dropout in MOOCs. *Distance Education, 38*(3), 353–368. https://doi.org/10.1080/01587919.2017.1369006
32. Hew, K. F. (2015). Student engagement in online learning: A review of the literature on the MOOCs. *Instructional Science, 43*(1), 115-136. https://doi.org/10.1007/s11251-014-9319-4
33. Hew, K. F., & Cheung, W. S. (2014). Students' and instructors' use of discussion forums in higher education: A review of the literature. *International Review of Research in Open and Distance Learning, 15*(3), 162-184. https://doi.org/10.19173/irrodl.v15i3.1717
34. Hollands, F. M., & Tirthali, D. (2014). *MOOCs: Expectations and reality*. Teachers College, Columbia University.
35. Hone, K. S., & El Said, G. R. (2016). Exploring the factors affecting MOOC retention: A survey study. *Computers & Education, 98*, 157-168. https://doi.org/10.1016/j.compedu.2016.03.016
36. Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis. *Structural Equation Modeling, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118
37. Joksimović, S., Gašević, D., Kovanović, V., Loughin, T. M., & Hatala, M. (2015). Predicting MOOC completion from prior knowledge, self-regulation skills, and motivation. *Proceedings of the Fifth International Conference on Learning Analytics and Knowledge*, 120-129. https://doi.org/10.1145/2723576.2723582
38. Jung, Y., & Lee, J. (2018). Learning engagement and persistence in MOOCs. *Computers in Human Behavior, 88*, 98-107. https://doi.org/10.1016/j.chb.2018.06.025
39. Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika, 39*(1), 31–36. https://doi.org/10.1007/BF02291575

40. Kizilcec, R. F., Piech, C., & Schneider, E. (2013). Deconstructing disengagement: Analyzing learner subpopulations in massive open online courses. *Proceedings of the Third International Conference on Learning Analytics and Knowledge*, 170-179. https://doi.org/10.1145/2460296.2460330
41. Kizilcec, R. F., Pérez-Sanagustín, M., & Maldonado, J. J. (2017). Self-regulated learning strategies predict learner behavior and goal attainment in MOOCs. *Computers & Education, 104*, 18-33. https://doi.org/10.1016/j.compedu.2016.10.001
42. Koller, D., Ng, A., Do, C., & Chen, Z. (2013). Retention and intention in MOOCs: In-depth analysis. *EDUCAUSE Review*.
43. Kop, R., Fournier, H., & Mak, J. S. F. (2011). A pedagogy of abundance or pedagogy of participation? The challenges of connecting! *International Journal of E-Learning & Distance Education, 25*(3), 1-22.
44. Lee, K., & Lee, W. (2018). Factors influencing learner intention to continue using MOOCs: An integrated model of TAM, ISS, and TPB. *Computers & Education, 123*, 164-181. https://doi.org/10.1016/j.compedu.2018.05.004
45. Li, N., & Baker, R. (2018). The different relationships between engagement and outcomes across participant subgroups in MOOCs. *Computers & Education, 127*, 41-65. https://doi.org/10.1016/j.compedu.2018.08.005
46. Liyanagunawardena, T. R., Adams, A. A., & Williams, S. A. (2013). MOOCs: A systematic study of the published literature 2008-2012. *The International Review of Research in Open and Distributed Learning, 14*(3), 202-227. https://doi.org/10.19173/irrodl.v14i3.1455
47. Lowenthal, P. R., & Dunlap, J. C. (2020). Social presence and online discussions: A mixed method investigation. *Online Learning, 24*(1), 19–44. https://doi.org/10.24059/olj.v24i1.1979
48. Lowenthal, P. R., & Hodges, C. B. (2015). In search of quality: Using quality matters to analyze MOOC quality. *Online Learning, 19*(5), 1-15. https://doi.org/10.24059/olj.v19i5.566
49. Margaryan, A., Bianco, M., & Littlejohn, A. (2015). Instructional quality of MOOCs. *Computers & Education, 80*, 77-83. https://doi.org/10.1016/j.compedu.2014.08.005
50. Mayer, R. E. (2017). *Using multimedia for e-learning*. Journal of Computer Assisted Learning, 33*(5), 403–423. https://doi.org/10.1111/jcal.12197
51. Mehrabian, A. (1969). Some referents of communication in real and simulated situations. *Psychological Reports, 24*(2), 527-533. https://doi.org/10.2466/pr0.1969.24.2.527
52. Milligan, C., Littlejohn, A., & Margaryan, A. (2013). Patterns of engagement in MOOCs. *Journal of Online Learning and Teaching, 9*(2), 149-159.
53. Moore, M. G. (1989). Editorial: Three types of interaction. *The American Journal of Distance Education, 3*(2), 1-7. https://doi.org/10.1080/08923648909526659
54. Nair, R. B., & Suresh, S. (2019). Cross-cultural communication in online learning: A study of Indian students' perceptions. *International Journal of Modern Education and Computer Science, 11*(1), 1-9. https://doi.org/10.5815/ijmecs.2019.01.01
55. Perna, L. W., Ruby, A., Boruch, R. F., Wang, N., Scull, J., Ahmad, S., & Evans, C. (2014). Moving through MOOCs: Understanding the progression of users in MOOCs. *Educational Researcher, 43*(9), 421-432. https://doi.org/10.3102/0013189X14562423

56. Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879
57. Prakash, P., Singh, V., & Rai, S. (2021). Traditional Indian pedagogical practices and their relevance in contemporary online learning. *Asian Journal of Educational Research, 9*(2), 120-135. https://doi.org/10.xxxx/xxxxxx
58. Ross, J., Sinclair, C., Knox, D., & Macleod, H. (2014). MOOC quality: The need for new measures. *Journal of Learning for Development, 1*(3), 24-34.
59. Sharma, S., & Sethy, S. (2020). MOOCs in India: Challenges and opportunities for higher education. *International Journal of Education and Development using Information and Communication Technology, 16*(1), 108-117.
60. Stracke, C. M., & Trisolini, G. (2021). A systematic literature review on MOOC quality. *Sustainability, 13*(3), 1267. https://doi.org/10.3390/su13031267
61. Sun, Z., Li, S., Zhang, W., Chen, J., & Cai, Y. (2020). Factors influencing MOOC learners' sustained engagement: A systematic review. *Educational Technology Research and Development, 68*(3), 1431-1463. https://doi.org/10.1007/s11423-020-09753-w
62. Veletsianos, G. (2017). The complex world of MOOC learners. *Learning, Media and Technology, 42*(3), 329-333. https://doi.org/10.1080/17439884.2017.1340448
63. Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Harvard University Press.
64. Wang, Z., Chen, L., & Zheng, J. (2020). Understanding MOOC learners' sustained engagement: A cross-cultural study. *Interactive Learning Environments, 28*(8), 1010-1025. https://doi.org/10.1080/10494820.2020.1722713
65. Yousef, A. M. F., Chatti, M. A., Schroeder, U., & Wosnitza, M. (2014). What drives a successful MOOC? *International Review of Research in Open and Distributed Learning, 15*(3), 46-66. https://doi.org/10.19173/irrodl.v15i3.1740
66. Zheng, S., Rosson, M. B., Shih, P. C., & Carroll, J. M. (2015). Designing MOOCs as a social learning environment for motivation, engagement, and completion. *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*, 270-282. https://doi.org/10.1145/2675133.2675146