Do Learning Patterns Differ by Gender in MOOCs? Exploring Gender-Based Differences Through Learning Analytics

Ali N. Alshammari

Curriculm and Instruction, Education and Arts, University of Tabuk, Tabuk, Saudi Arabia
Email: aalshammari@ut.edu.sa (A.N.A.)

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***Abstract*—Massive Open Online Courses (MOOCs) offer rich opportunities for personal and professional development. Despite their importance, these courses face high dropout rates. The body of literature includes several studies that attempted to explore the causes of this issue. However, there is a gap in the literature regarding the impact of learner characteristics on course completion and dropouts, especially in terms of gender differences. In response to this gap, this study aims to examine the gender differences in learning patterns in MOOCs. Data were collected from 324 MOOC learners using learning analytics data. Several statistical methods and tests were employed to explore gender differences in learning patterns in MOOCs. The results showed that the number of attempts required to pass an item significantly affected the overall course grade, with significant gender-based differences. In terms of the timing of the first attempt submission, the results indicated that gender differences were marginally significant (p=0.06), although women took longer than men. While the time of day significantly affected success rates, no significant gender differences were found. Moreover, a cluster analysis revealed three distinct profiles of MOOC learners. The results, including findings, cluster characteristics, and recommendations, were discussed in great detail.**

***Keywords*—Massive Open Online Courses (MOOCs), learning patterns, gender, learning analytics, curriculum design**

I. Introduction

The shift towards competency-based learning has played a key role in enhancing confidence and trust in online learning. Over the past few years, technological advances have triggered a paradigm shift in how people learn and acquire knowledge in this digital world. One significant innovation that has transformed online education is the use of Massive Open Online Courses (MOOCs) [1]. Due to their ability to offer education without borders or limitations, MOOCs attract millions of learners seeking to acquire in-demand skills and competencies, providing them with knowledge and skills through various Web 2.0 tools [2].

The development of Information and Communication Technology (ICT) tools, such as learning management systems (LMSs), has increased the demand for MOOCs over time [3]. These courses are accessible to a broad audience as they are offered for free or at a low cost [4–6]. Therefore, a growing number of universities and higher education schools are offering MOOCs. Today, many instructors use MOOC platforms to design and deliver educational content aligned with their interests and expertise [7]. This trend indicates that MOOCs will continue to play an expanding role in higher education [8]. Despite the significant benefits of MOOCs and their impact on current and future education, these courses face several challenges that can hinder their success, such as high dropout rates.

In Coursera, one of the most popular MOOC platforms, only 2% of learners have completed their courses [9]. Addressing broader issues in MOOCs requires exploring different factors that influence course completion in MOOCs. While the majority of studies in MOOC research focus on motivation and course design factors, the literature highlights a need to expand existing knowledge regarding the impact of learner characteristics on course completion [4, 6], particularly gender. Therefore, it is necessary to analyze gender differences in learning patterns to identify strategies and interventions that support students' needs and enhance course completion and success rates. Since men and women behave differently in MOOCs [10], this study aims to address a gap in the literature on MOOCs and provide course designers and curriculum specialists with research-based recommendations for designing MOOCs that account for gender differences.

MOOCs face a serious issue of a high dropout rate, with 80–90% of students never completing their courses [2, 11]. Since these courses are self-taught, students often struggle to balance their daily responsibilities with course assessments and tasks [7]. Therefore, MOOCs are criticized for several challenges including poor pedagogy, limited interactions between learners and instructors, and inconsistent technology integration [12]. Among these challenges, perhaps the most challenging for MOOC providers is the high dropout rate [11]. This low course completion rate can cause several problems, such as wasting the time, costs, and efforts of learners, instructors, and service providers [13]. Despite efforts in this area, the literature shows that the issue is yet to improve [14]. The literature attributes the high dropout rates to several factors, including learners' motivation, time management skills, prior knowledge and experience, course design, and the level of interaction within the course [15]. However, there remains a need to study the impact of learner characteristics on course completion, especially gender.

Few studies have investigated the role of gender in MOOCs. Most of these studies examine gender-based differences from the perspective of motivation. To fill gaps in the literature, this study provides a comprehensive analysis of gender-based differences in students' learning patterns in MOOCs by analyzing LMS analytics. Such data contain information about learners' interactions, including clicks, submissions, views, and other variables [2, 16]. The literature includes a limited number of studies that have utilized learning analytics to explore the dropout issue in MOOCs [17], with most focusing on the initial participation rather than the continued usage pattern [18].

In response to the gap in the literature, this study aims to analyze data collected from MOOCs analytics to achieve the following objectives:

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- Leveraging learning analytics to explore gender-based differences in learning patterns within MOOCs;
- Investigating the impact of gender on course completion and dropouts from different perspectives;
- Examining the effects of gender on the timing of submissions and number of attempts;
- Conducting cluster analysis to segment MOOC learners based on their learning patterns and behaviors.

The study's findings can guide practical efforts to enhance course design, delivery, and MOOC research. By understanding gender differences in learning patterns, instructional designers and MOOC providers can develop interventions to improve retention, reduce dropouts, and support students' needs in MOOCs.

This study aims to investigate gender-based differences in learning patterns in MOOCs. The primary research question is: how does gender impact the learning patterns in MOOCs? To answer this question, several sub-questions were formulated:

1) Are there any significant gender-based differences (at α = 0.05) in the timing of first attempt submissions in MOOCs?
2) Does the number of attempts required to pass individual items in a MOOC significantly influence overall course grades across genders (at α = 0.05)?
3) Does the time of day when students attempt items in a MOOC significantly influence their success rates across genders (at α = 0.05)?
4) Are there any significant gender-based differences (at α = 0.05) in course completion in MOOCs?
5) What clusters emerge when grouping students in MOOCs based on learning patterns and gender?

II. Literature Review

A. The History of MOOCs

The initial concept of MOOCs was to serve as an Open Educational Resource (OER) platform, defined as "educational resources that are freely available for use, reuse, adaptation, and sharing" [6]. The first MOOC was developed and offered by Stephen Downes and George Siemens in 2008, titled "Connectivism and Connective Knowledge" [19]. The course aimed to explore and test the theory of connectivism [20]. Therefore, MOOCs as OERs aim to make education available and accessible to everyone [7]. The term MOOC is defined as "open access to a global learning environment that provides access to educational content—in the form of digital data in multiple formats and alternative forms of interaction—to a significant number of registered users anywhere and at any time" [3].

Based on connectivism theory, two types of MOOCs have been developed: cMOOCs and xMOOCs. cMOOCs focus on knowledge sharing within an online community of learners. In contrast, xMOOCs are structured courses with well-defined course learning outcomes (CLOs) and clearly designed course materials [21, 22]. These courses share similarities with higher education courses but are offered through commercial platforms, such as Coursera and edX [2, 20]. Over the years, MOOCs have evolved from an OER idea to a powerful educational force that offers different learning options, including earning credits, professional certificates, and educational degrees.

MOOCs have become an important component of online learning. These courses offer learners a variety of benefits to advance their careers and support their lifelong learning [23]. Similar to most LMS technologies, MOOC platforms incorporate essential e-learning elements such as interactive content, assignments and submissions, quizzes, videos, and more [3]. Starting with 2,200 learners in 2008 [24], millions of learners now take MOOCs across various platforms [4]. According to Coursera, one of the most popular MOOC platforms, over 129 million learners are enhancing their skills through MOOCs offered on this platform[25]. In higher education, many institutions today integrate MOOCs into their traditional courses [17, 18, 26].

B. Importance and Benefits

MOOCs have created new learning opportunities for global collaboration and knowledge sharing [6, 21].These courses enable learners to access high-quality educational resources from anywhere [27], and enhance their job opportunities by developing skills that are in high demand within the labor market [28]. MOOCs are often offered asynchronously to attract many learners [6]. The educational content in these courses is delivered through several formats, including videos, lectures, assignments, quizzes, and discussion forums [7, 29]. Most MOOCs do not require enrollment restrictions or prerequisite requirements [30]. Learners who are interested in these courses can enroll regardless of their age, educational background, culture, or personal attributes [4].

MOOCs and traditional higher education online learning share several similarities. However, they differ in terms of the number of learners, ease of access to learning resources, student-to-faculty ratio, course scheduling flexibility, and levels of student-instructor interaction [31]. Moreover, MOOCs offer a convenient and flexible way for learners to pursue their education and take assessments without the fear of penalties if they fail the course [6]. In higher education, MOOCs can support learners in many ways. For example, when college students face challenges in course availability and scheduling constraints, MOOCs allow students to enroll and study at their own convenience [21]. MOOCs provide learners with opportunities to develop job-related skills and competencies to enhance their career performance [32]. The literature indicates that participating in MOOCs can enhance workers' ability to retain their employment [23]. According to the Harvard Business Review [33], 61% of MOOC learners found the courses beneficial and 72% reported that they developed valuable career skills. A recent report highlighted that over 220 million students enrolled in over 19,400 courses, 1,670 micro credentials, and 70 MOOC-based degrees [34]. The report listed the most common MOOC providers, including Coursera (97 million), edX (42 million), FutureLearn (17 million), and Swayam (22 million).

C. Reasons to Enroll in MOOCs

MOOCs have a unique structure for offering learning content. The structure can be described as "WAVWAVWAVAAQ": Watch a Video, Watch a Video, Watch a Video, and Attempt a Quiz [35]. MOOC students are required to be independent and develop self-directed motivation [31]. However, students have different reasons for enrolling in MOOCs [36]. Some students enroll in MOOCs because they are interested in learning new subjects, earning certifications from well-known institutions, or pursuing courses for professional development and personal motivation [6]. Other students take MOOCs because they want to experience the dynamics of massive courses with thousands of learners [37]. Whether their motivation is intrinsic or extrinsic, both types of motivation can significantly influence students' participation levels in MOOCs [20]. Moreover, students' motivation is linked to the perceived value of learning and their personal and career benefits [38].

Students in MOOCs show different levels of motivation compared to students in traditional learning platforms. A few studies have investigated the reasons behind students' completion of their MOOCs [6]. However, how motivation varies based on student backgrounds or characteristics remains unclear [39]. In terms of course completion rates, the literature indicates that completing the course is not a common motivation for all MOOC students [40, 41]. Moreover, students' intentions to adopt MOOCs can predict their intentions to complete their courses [42]. Several individual and contextual factors, including cultural and socioeconomic backgrounds, can predict students' behavior and learning patterns in MOOCs [43]. The question, therefore, becomes: could gender also play a role in shaping these patterns in MOOCs?

D. The Challenges of MOOCs

The literature includes several studies on enhancing learners' experiences from different perspectives, such as acceptance of use, challenges and motivations, and retention and dropouts [44]. Despite the benefits of MOOCs, these courses face several challenges, including fear of using new technology [21]. Several studies have addressed technology acceptance, but few have explored the role of time in this matter [45]. Since MOOC learners come from different backgrounds and characteristics, designing these courses to align with these characteristics is another challenge that educators need to consider [46]. In terms of learning design, MOOCs require effective teaching and evaluation methods to improve the quality of these courses [22]. Among these challenges, perhaps one of the most crucial is the high dropout rate [5, 47, 48].

The high dropout rates in MOOCs are a major concern for educators, higher education institutions, and service providers. The rates are around 80-90% of total enrollments [2]. In Coursera, only 2% of MOOC learners complete their courses [9]. Despite the seriousness of this issue, very little research has explored factors affecting dropouts in MOOCs [6], and the problem still exists [14]. The factors leading to this issue can be categorized into five groups: course attributes, social status, cognitive ability, emotional factors, and learning behavior [13]. Other studies have identified more factors contributing to dropout rates in MOOCs, including learners' motivation, time management skills, prior knowledge and experience, course design, the level of interaction, academic skills and abilities, prior experience, feedback, social presence, and social support [9, 15]. Since video lessons are a core element of MOOCs, failing to watch the whole video can contribute to course dropouts [49].

In terms of motivation, factors such as performance expectancy, effort expectancy, and social influence are assumed to affect students' intention to complete the course [18]. Low course completion rates are also linked to students' personal intentions and goals [17]. The lack of live interactions between students and instructors can lead to dropouts in MOOCs. MOOCs do not offer students the same level of instructor–student interactions as in face-to-face or traditional online courses [6].

The perception of time is crucial for success in MOOC [45]. Most MOOCs are organized as lessons and modules that can be studied weekly [3], which requires effective time management skills. Lack of time management skills can contribute to high dropout rates in MOOCs [2]. Successful time management requires commitment. However, MOOC learners can study without the fear of penalties if they fail the course [6]. Therefore, low commitment can be considered as another factor related to dropouts in MOOCs [9]. Despite the importance of the previously mentioned factors, the high dropout rates in MOOCs are related to individual student choices rather than issues with course design or quality [17].

E. Learning Analytics

MOOCs platforms generate important data and learning analytics, which provide insights into learner engagement and behaviors. The data include information about different types of learner interactions and engagement, such as clicks, videos metrics, discussion posts, assignments, and quizzes [5, 49]. Such data can be leveraged for data-driven teaching strategies to improve student's performance and completion rates [6]. For instance, one study used log data to predict learners' performance in MOOCs, and highlighted several variables, such as number of chapters, total forum posts, and learners' age, that can predict performance [4]. Another study analyzed patterns in student performance using analytics data and found temporal submission patterns in MOOCs [50].

Information collected from learning analytics can provide detailed insight for researchers into different aspects of learning in MOOCs, including learner engagement, peer learning [2], and learner behaviors [46]. Learning analytics can be used to explore the relationships between students' behavior and performance [51]. Moreover, learning analytics can be analyzed using cluster analysis to explore methods for increasing engagement and performance [52].

F. Gender Differences in MOOCs

The analysis of gender differences in learning patterns in MOOCs is important, yet it has not received sufficient attention in MOOC research. However, the limited number of studies shows that women may exhibit different learning patterns in MOOCs. Women tend to prefer rhetorical, closed, and consent questions over discussions and hypothetical questions [53]. In terms of motivation, gender differences exist regarding the reasons why students enroll in MOOCs [39]. In terms of perceived interactivity attributes of MOOCs, perceived synchronicity has a greater impact on engagement for men compared to women, and perceived active control and perceived two-way communication are more predictive of engagement in MOOCs for women than men [54]. A recent study examined the differences in students' motivation levels to enroll in MOOCs and did not find any significant gender differences [10].

Studying gender differences in MOOCs is essential for improving the accuracy of predictive models in students' performance in MOOCs. For example, while machine learning has been used to predict student outcomes in MOOCs, some models produce biased predictions by ignoring key demographic variables like gender [55]. In terms of performance and persistence in MOOCs, the literature shows no gender differences in persistence, performance, and course completion between men and women [56]. However, women show slightly lower performance and higher dropout rates compared to men [57]. Confirming the results of the previous studies, the literature shows that gender does not contribute to students' acceptance of MOOCs [45]. However, there is a dearth in the literature on whether there are gender differences in learning patterns and behaviors in MOOCs, starting from the time of their first submission.

III. Methods

A. Setting and Dataset

The dataset contained 8,905 records collected from 324 MOOC students. The MOOC platform was Coursera, one of the largest MOOC platforms in the world. The platform was selected because it offers a wide range of courses, specializations, and professional certifications aligned with students' majors and coursework. Moreover, the platform includes additional features such as support for multiple languages and a mobile app. The students were college students enrolled in different programs at a public university in Saudi Arabia and came from diverse academic backgrounds. The dataset included 126 men and 198 women pursuing different degrees, such as bachelor's, associate diplomas, and intermediate diplomas. Since gender is an import factor in this study, students were divided into strata by gender. Participants were randomly selected within each stratum. Data were collected from learning analytics, such as logs. Therefore, students were not directly recruited for the study. All data were treated confidentially, with records being anonymized to ensure that no identifiable information could reveal students' identities. Students were required to take a selected list of MOOCs as part of their university coursework. The lists of courses were identified early in the semester by their professors, based on the students' majors and field of study, and aligned with their coursework. Students were automatically registered in the selected courses at the same time. The courses were divided into several subjects, including computer science, data science, information technology, personal development, health, math, and engineering.

B. Variables

The collected data included a list of variables that offer information about students' learning patterns in MOOCs. Table 1 provides a brief of the key variables selected for this study.

Table 1. Variable descriptions

Variable	Description
Gender	The gender of the student enrolled in the course.
Course Name	The name of the MOOC that the student is taking.
Module	A specific section within the course content.
Lesson	A smaller instructional content within a module focused on a particular topic.
Item	An individual content piece or activity, such as a quiz.
Item Order	The numeric position of the assessment item within the course or project outline.
Attempt Grade	A real number value indicating the percentage score the learner received on the assessment attempt.
Is Attempt Passed?	A yes/no value indicating whether the learner received a passing score on the assessment attempt- usually equal to or higher than 80%
Attempt Date	The date on which the student attempted the item.
Attempt Time	The time of day when the student attempted the item.
Item Attempt Number	A numeric value indicating which number attempt the row provides data for.
Is Course Passed?	A yes/no value indicating whether the learner has completed the course or project (i.e., passed all required assignments).
Content Engagement	A real number value indicating the learner's overall progress in the course.
Engagement Frequency	A real number value indicating the number of unique days a student engaged
Learning Hours	The total number of hours the learner has interacted with instructional items (i.e., watching videos, completing reading items, taking assessments).
Completion Date	The date on which the student completed the course.
Completion Time	The time of day when the student completed the course.
Course Grade	The final grade or score the student achieved for the entire course.

C. Research Procedure

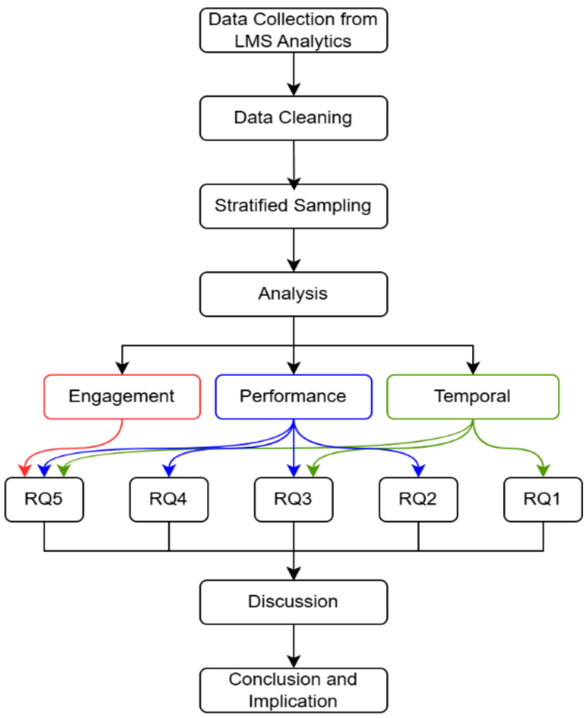


Fig. 1. Research procedure from data collection to conclusion.

The research began by collecting all relevant data needed to address the research questions as seen in Fig. 1. Following this, data were cleaned to detect and treat outliers and missing values. The missing values were removed to ensure that the data used were complete. The Interquartile Range (IQR) method was used as the criteria to identify and treat outliers. Since each learner may be enrolled in multiple courses and each course contains several items, the records were grouped by user, course, module, and item. To address the primary research question, several statistical methods were used, including a Linear Mixed-effects Model (LMM), Generalized Estimating Equation (GEE), and mixed-effects linear regression model. The LMM was selected because it adjusts both fixed effects (i.e., gender) and random effects (i.e., student and course). The GEE was selected over the other statistical models because the outcome is binary (e.g., course completion: 1 = completed, 2 = not completed) and data included repeated measures (e.g., multiple courses per student). Moreover, GEE accounts for within-subject correlation. The mixed-effects modeling was used to examine the fixed effects of total attempts, gender, and their interaction, as well as the random variability across courses. The cluster analysis included descriptive statistics and hierarchical clustering with Ward's linkage to calculate the distance between clusters and to minimize the total variance. To determine the optimal number of clusters, a Silhouette analysis was performed. Moreover, Principal Component Analysis (PCA) was applied to prepare the dataset for clustering, and to ensure the robustness of the clustering results.

D. *Analysis*

To answer the primary question and investigate the impact of gender on learning behaviors and patterns in MOOCs, several sub-questions were analyzed. To address the first research question and examine gender differences in the timing of first-attempt submissions in MOOCs, a new variable called 'time since start' was created to calculate the time elapsed from the earliest recorded submission time to each student's first-attempt submission:

$$TimeSineStart = \frac{AttemptTime - CourseStartTime}{1\ Hour}$$

According to Table 2 and Fig. 2, the results showed that women took longer to submit their first attempt compared to men, by an average of 1.12 h. Since the p-value was 0.06, there were no significant gender-based differences at $\alpha = 0.05$ in the timing of the first attempt submission in MOOCs. However, the p-value can be considered marginally significant. The model also examined the effects of the number of lessons and items per module on submission timing. The number of lessons per module (Estimate = –0.380, p = 0.114) and the number of items per module (Estimate = –0.199, p = 0.250) did not significantly impact the time since the course started for the first submissions.

Table 2. Gender differences in first attempt submission in MOOCs

Variable	Value	Std.Error	DF	*t*-value	Pr(>|t|)
(Intercept)	9.8930	0.7640	377.5679	12.950	<2e–16 ***
Gender.Women	1.1285	0.6018	281.9739	1.875	0.0618
Lessons_Per_Module	–0.3798	0.2400	3468.9816	–1.582	0.1136
Items_Per_Module	–0.1989	0.1728	3571.3950	–1.151	0.2498

Note: *** $p < 0.001$

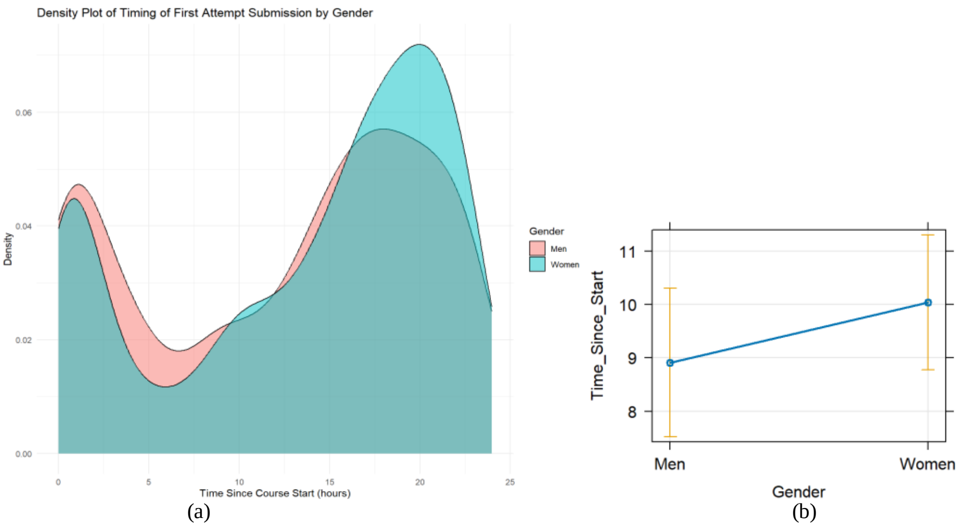


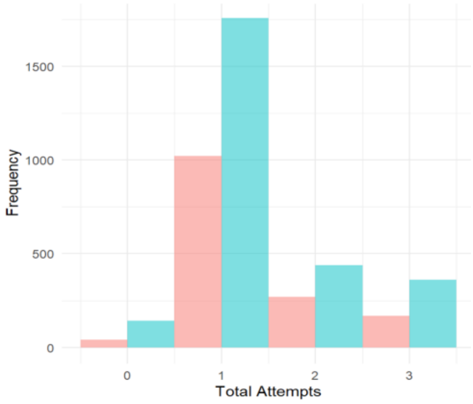
Fig. 2. Plots of gender differences in first attempt submission in MOOCs: (a) density plot by gender showing the distribution of the time of first attempt submission since the course started (in hours); (b) effect plot based on a Linear Mixed-Effects Model visualizing the impact of gender on the timing of first attempts using.

The current study took a step forward to analyze how the number of attempts required to pass individual items in a MOOC impacts course grades across genders. The results showed that the number of attempts required to pass an item in a module significantly affected the overall course grade, with significant gender-based differences at $\alpha = 0.05$. As seen in Table 3, both genders benefited from additional attempts. Each additional attempt increased the course grades by 2.07. While women scored lower than men, the interaction between gender and total attempts (see Fig. 3) was significant (p = 0.028). Therefore, women improved significantly more with each attempt compared to men, with an increase of 1.84 points per additional attempt.

Table 3. Analysis of the number of attempts required to pass MOOC items on grades across genders

Variable	Estimate	Std. Error	df	t-value	Pr(>|t|)
Intercept	73.412	2.044	299.214	35.92	<2e–16***
Total_Attempts	2.072	0.699	4120.324	2.97	0.00304 **
Women	–4.767	1.294	4079.104	–3.68	0.00023 ***
Total_Attempts:Gender. Women	1.837	0.836	4116.814	2.20	0.02801 *

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$



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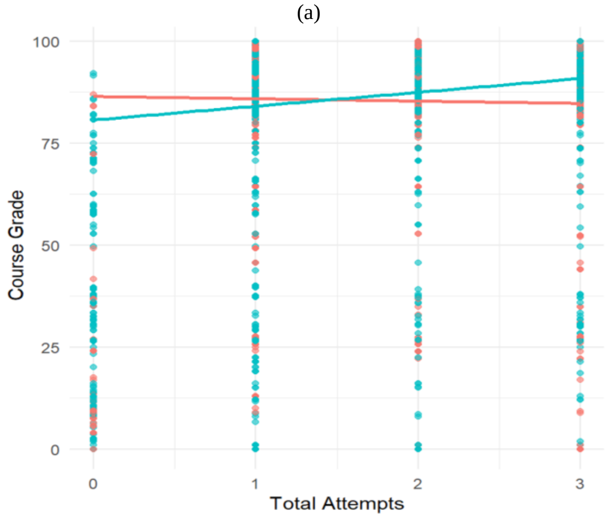


(b)

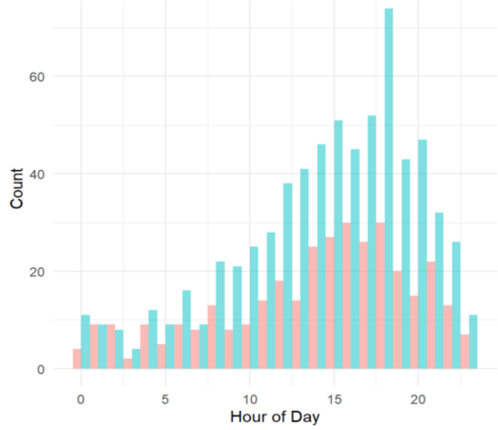
Fig. 3. The effect of the number of attempts required to pass individual items in a MOOC on overall course grades analyzed by gender: (a) histogram by gender showing the distribution of the number of attempts to pass individual items; (b) scatter plot of the relationship between the number of item attempts and overall course grades highlighting trends by gender. Note: red (men), blue (women).

The third research question examined whether the time of day when students attempted items in a MOOC significantly influenced their success rates across different genders at $\alpha = 0.05$. A generalized linear mixed model was used to answer this question, as seen in Table 4. The time of day significantly affected success rates (Estimate = –0.01444, $p = 0.0087$), with the chances of submitting a successful attempt decreasing for every additional hour later in the day. The coefficient for women was –0.26205 and $p = 0.017$, which suggested that women have lower chances of passing an attempt compared to men. The interaction between gender and the time of day was not statistically significant (Estimate = 0.00905, $p = 0.1832$). Therefore, the effect of the time of day on success rates did not differ significantly between men and women. Fig. 4 shows the success rates by time of day and gender.

Table 4. Effect of the time of day in a MOOC on success rates across different genders

Fixed effects:	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.124087	0.110620	1.122	0.26197
Attempt_Hour	–0.014435	0.005505	–2.622	0.00874 **
Women	–0.262053	0.110320	–2.375	0.01753 *
Attempt_Hour: Women	0.009050	0.006800	1.331	0.18323

Note: * $p < 0.05$; ** $p < 0.01$



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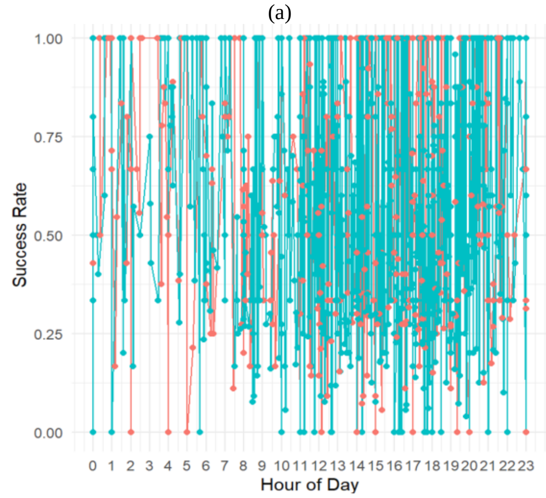


(b)

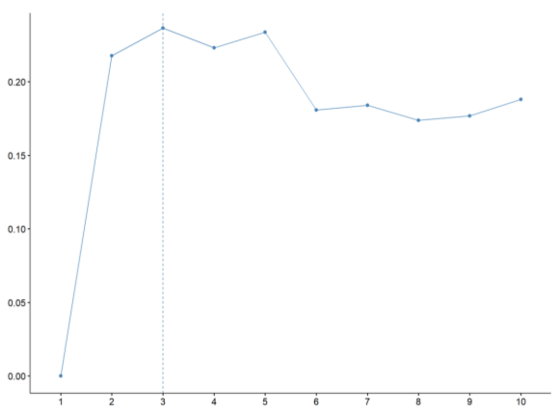
Fig. 4. Plots of the effect of the time of day in a MOOC on success rates across different genders: (a) histogram of average attempt times by gender; (b) line plot showing success rates by time of day and gender. Note: red (men), blue (women).

To answer the fourth research question and identify whether significant gender-based differences exist in course completion rates, the GEE analysis presented in Table 5 showed no significant gender-based differences in the rate of course completion among students in MOOCs, with coefficient of (Estimate= 0.0983 and $p = 0.63$).

Table 5. Effect of gender on course completion

Variable	Estimate	Std.err	Wald	Pr(>|W|)
Intercept	1.6137	0.1588	103.23	<2e–16 ***
Gender.Women	0.0983	0.2031	0.23	0.63

Note: *** $p < 0.001$



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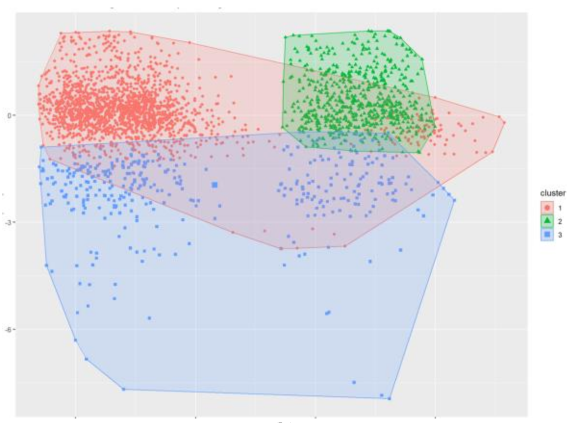

(b)

Fig. 5. Cluster analysis of students learning patterns in MOOCs: a) Silhouette analysis for optimal number of clusters; b) Hierarchical clustering of students based on learning behaviors and patterns.

A cluster analysis was conducted to summarize students' learning patterns and behaviors. To determine the optimal number of clusters, a Silhouette analysis was performed, identifying three distinct clusters ($k = 3$), as shown in Fig. 5. Table 6 provides a summary of the characteristics of each cluster.

Table 6. Summary of cluster characteristics of students' learning patterns in MOOCs

Characteristics	Cluster1	Cluster2	Cluster3
Course Grade (Mean):	89.3	91.74	21.77
Learning Hours (Mean):	158.75	68.62	31.44
Time of Day (Mean):	3.01	2.98	3
Day of Week (Mean):	4.09	4	4.02
Attempts Until Passed (Mean):	2.95	2.51	3.13
Time Spent Per Item	0.4	0.26	0.47
Content Engagement (Mean):	89.79	83.49	59.59
Engagement Frequency (Mean):	6.98	4.9	7.37
Failed Attempts Ratio (Mean):	0.19	0.19	0.33
Speed of Completion (Mean):	27.96	17.86	10.6
Men %	6.77%	100%	44%
Women%	93.23%	0%	56%
%	63%	26%	11%

The first cluster can be named High Engagers. It was represented by women, as the majority of learners 93% were women. In terms of engagement, they were highly engaged, spending an average of 158.75 h on learning the course materials and taking the assessments. They achieved the highest content engagement 89.79% compared to the other clusters. Students in this cluster maintained high-frequency engagement days (6.98 days). In terms of academic performance, the cluster demonstrated high performance, with an average course grade of 89.3. Students in this cluster required 2.95 attempts to pass an item and spent 0.4 h per item. Although the failed attempt ratio was very low (0.19), their speed of learning was the slowest compared to all clusters—they required a high number of days to complete their courses (27.96 days). From a temporal behavior perspective, students in this cluster preferred to learn on Thursdays and in the afternoons. Compared to the other clusters, students in this cluster demonstrated high engagement but slower course completion.

In contrast, the second cluster (High Achievers) consisted entirely of men (100%). Analyzing student engagement in this group revealed less engagement compared to the first cluster. Students spent an average of 68.62 h per course, achieved 83.49% content engagement, and exhibited the lowest engagement frequency (4.9 days) compared to the other clusters. Interestingly, students in this cluster demonstrated the highest performance. They achieved the highest course grade (91.74), required the lowest number of attempts (2.51) to pass an item, and spent the least amount of time per item (0.26h) compared to the other clusters. Although the failed attempt ratio was the same as in the first cluster (0.19), this all-men cluster completed courses significantly faster, with a shorter course completion time of 17.86 days. In terms of temporal patterns, students in this cluster preferred to learn on Thursdays, in the late morning and early afternoon, slightly earlier than students in Cluster 1.

The last cluster is a mix of men and women, with women being slightly higher (56%). This cluster represents the At-Risk Learners. Students in this cluster were poorly engaged, as their learning hours (31.44) and content engagement (59.59%) were the lowest compared to the other clusters. In terms of performance, students in this cluster struggled with their courses, with an average course grade of 21.77, far below the passing score of 80. Moreover, students spent 0.47 h on average per item and required the highest number of attempts (3.13) to pass an item. Although the speed of completion was the shortest (10.6 days) compared to the other clusters, the failed attempt ratio was the highest (0.33). Students in this cluster preferred to learn on Thursday afternoons.

IV. Discussion

Men and women behave differently in MOOCs [10]. However, most MOOCs follow a one-size-fits-all model and do not take into account the differences in learning patterns among students [58]. The literature indicates a need to explore learning characteristics, such as gender-based differences, in students' learning patterns [4, 6]. This study adds to the literature by examining the effect of gender on students' learning patterns from different perspectives. This study began by exploring gender-based differences in students' first attempt patterns. The literature indicates that developing effective time management skills is important in MOOCs [2, 7], especially since these courses are organized into weekly units or modules [3]. Moreover, the literature highlights the importance of time management skills for course completion and dropout rates [15], although its role has not been studied enough [45].

To answer the first research question and examining the gender-based differences in the timing of the first attempt submission in MOOCs, this study did not find statistically significant differences between men and women. One possible explanation for this finding could be the insignificant gender differences in the level of experience with MOOCs [45]. Since the p-value was very close to being significant, the current study showed that women tend to take a longer time to submit their first attempts compared to men. This finding may explain the inconsistency in women's learning times reported by [59]. Moreover, the differences in the timing of the first attempt submission might contradict the results of a previous study, which showed that women have better time management skills [60]. Another possible explanation is that women are achievement-oriented and tend to review their progress reports before submitting their attempts [61].

To control for course complexity, this study examined the effects of the number of lessons and items per module on the timing of first attempts. These variables are related to course design, which plays a significant role in performance and course completion[9, 15, 46]. This study shows that both variables do not have statistically significant effects on the timing of students' first attempt submissions. The findings confirm that performance in MOOCs is related to personal characteristics rather than course design [17].

Zooming out from the time of the first attempt submission to a broader layer, this study examined the effects of the number of attempts required to pass assessments in MOOCs on course grades across genders. To address the second research question, this study contributes an interesting finding to the literature by demonstrating that the number of attempts required to pass assessments has a significant effect on course grades. When it comes to gender differences, both men and women benefit from additional attempts. However, the current study adds an important element to the growing body of knowledge in MOOC research by demonstrating that women benefit more from additional attempts compared to men. The current finding may be attributed to women's achievement-oriented patterns which are associated with their test anxiety [61].

The results suggest that women achieve higher scores with additional attempts, while men show lower progress with more attempts. A possible explanation for this finding could be related to self-regulated learning. Previous research has shown that women perform significantly higher in all three phases of learners' online self-regulated learning: preparatory, performance, and appraisal [62]. From a psychological perspective, one study found that women hold significantly more positive attitudes toward e-learning than men in several countries, including Austria, India, Chile, and Spain [63]. Although men are more likely to be motivated in MOOCs by skill improvement and performance expectancy, another study found no significant gender differences regarding the impact of self-efficacy and perceived ease of use on continuance intention in MOOCs [54]. The study explained this by referring to the research context, as the participants were university students born in the digital age, which is similar to the context of the current study.

To answer the third research question, the study analyzed whether the time of day when students attempted items in a MOOC significantly influenced their success rates across different genders. The literature indicates that the perception of time plays an important role in students' success in MOOCs [45], especially since most MOOCs are organized as lessons and modules that can be studied weekly [3]. Since a lack of time management skills can lead to dropout in MOOCs [2], this study aimed to provide more details on the role of time in success in MOOCs. The results showed that the time of day has a significant effect on success rates, which confirms its importance for course completion and dropout rates in MOOCs [9, 15]. The current study adds to the literature by showing that the chances of submitting a successful attempt decrease with every additional hour later in the day. However, analyzing the interaction between gender and the time of day showed that the effect of time on success rates did not differ between men and women. One possible explanation is that the majority of students submit their attempts at similar times of the day (i.e., afternoons), as observed in the cluster analysis. Therefore, we cannot generalize the findings across all MOOC students, as they differ in their temporal patterns.

Moving from attempt submissions to course completion, this study examined gender-based differences in course completion in MOOCs to respond to the fourth research question. The results showed no statistically significant differences between men and women regarding course completion rates. Previous research indicates that course completion is not a common motivation for all MOOC students [40, 41]. The findings of the current study confirm the findings of previous studies that showed no significant gender differences in online learning [56, 64–66]. Despite gender differences in motivation and reasons for enrolling in MOOCs, the current study confirms that both men and women demonstrate comparable abilities in managing self-discipline effectively in online learning [67], and have similar chances of completing courses [68]. Moreover, this study shows that men perform slightly better than women, which confirms the findings of a previous study [57], and supports the claim that men are more likely to earn certificates in MOOCs [69]. This finding, however, contradicts the results of another study, which showed that women performed better than men in MOOCs [70]. One possible explanation is that men are more likely to persist longer in MOOCs compared to women [71].

The final layer of analysis involved cluster analysis. The study addressed the fifth research question by conducting a cluster analysis to segment MOOC learners based on their learning patterns and behavior. The results make a unique contribution to the literature by identifying three distinct groups: 1) High Engagers, 2) High Achievers, and 3) At-Risk Learners. Based on students' characteristics and variables collected from LMS analytics, the cluster analysis examined the differences from three perspectives: engagement, performance, and temporal patterns.

The current study makes a unique contribution to the literature by examining gender differences in learning patterns. The first cluster, primarily consisting of women, demonstrated high levels of engagement and performance. Students in this group were highly engaged, achieved excellent content engagement, and maintained a high frequency of engagement days. Surprisingly, this cluster showed the slowest course completion speed compared to all clusters, even though their performance was high.

On the other hand, the all-men cluster–previously identified as the High Achievers–demonstrated faster learning and higher achievement. These findings support earlier research suggesting that women spend more time engaging with content and reviewing instructional materials [72]. However, this contradicts the claim that men demonstrate higher levels of engagement with MOOCs compared to women [73]. Moreover, the woman-to-man ratio in the third cluster disagrees with the characteristics of the Whole Engaged cluster identified in [74], which also references several studies contradicting the claim that men demonstrate higher levels of engagement than women.

In MOOCs, women post more frequently in discussion forums compared to men [71, 75], which may explain the higher levels of engagement in the first cluster. From a psychological perspective, one potential explanation for the higher levels of engagement in the first cluster could be associated with the greater intrinsic motivation to study MOOCs observed in women compared to men [39]. While students' motivation has a significant impact on their performance and course completion in MOOCs, the chances of course completion are higher for students motivated by interest (i.e., intrinsic motivation) or by the desire to earn a certificate from the MOOC provider—most of whom are likely men [69]. Supporting this, a recent study examined MOOC learners' behavioral patterns and found that men exhibit higher levels of engagement with the content and achieve more course completions than women [76]. These findings confirm the current results regarding the slightly higher achievement demonstrated by men in the second cluster but contradict the higher levels of engagement in the first cluster. Moreover, the study provides an important explanation: women from different countries may behave differently. Since all participants in this study were from the same country, further research should account for the effects of country and additional demographic variables on learning patterns.

The third cluster makes a contribution to the literature by showing that struggling with MOOCs was not associated with gender, as the cluster included participants of mixed genders. Although it represented a small proportion of learners, the characteristics of this cluster align with the findings of the research questions addressed earlier. For example, while both men and women in the first and second clusters demonstrated high levels of performance, the third cluster consisted of both men and women, with women being slightly more represented. This supports the earlier findings that, although men perform slightly better than women, there are no gender differences in course completion rates in MOOCs.

Another interesting finding is the consistency of temporal characteristics. One study showed that students who study at consistent times tend to perform better [77]. In contrast, another study found that women with low hourly consistency performed better than men [59]. In terms of temporal analysis, the results showed that in both the first and third clusters, where women were the majority, the time of day and day of the week were consistent. Both groups tended to study on Thursday afternoons.

The current study adds to our understanding of gender differences in learning patterns in MOOCs. Based on the cluster analysis, it appears that women may benefit from strategies and interventions aimed at enhancing their course completion speed. On the other hand, men could benefit from interventions that focus on improving their engagement levels and learning experience with the courses and the MOOC platform. The third group, which consists of a small proportion of mixed-gender learners who struggled with MOOCs, would benefit from strategies and interventions designed to provide adaptive feedback, enhance their time management skills, and support their performance and engagement levels.

The cluster analysis supports the earlier findings regarding attempt summations and course completion rates and gives insights into the characteristics of each group and learning patterns in terms of content engagement, learning performance, and temporal trends in learning patterns.

V. Implications

Based on the analysis of the results, this study provides insights and guidelines for MOOC educators, instructional designers, researchers, and providers based on the analysis of the results. Researchers should consider the role of gender in their research experiments and studies to ensure unbiased findings. MOOC providers and educators need to pay enough attention to gender differences in attempt patterns when they design and offer courses. For example, some MOOC providers limit the number of attempts or prevent students from submitting another attempt for a certain number of hours. This strategy may affect women's progress as they benefit from additional attempts and exhibit consistent temporal behavior. Since men's progress declines with additional attempts, MOOC providers should consider making the opportunity to submit additional attempts more meaningful. One possible approach is to integrate adaptive feedback systems, especially AI-powered systems. These systems can provide students with information about their attempts, what went wrong, and how to avoid making the same mistakes again. The gender differences in temporal patterns can guide instructional designers and researchers in developing MOOCs that support personalized learning. Most MOOCs offer flexible deadlines. However, understanding gender differences in temporal patterns can help in designing adaptive reminder systems that account for these differences. Finally, this study identified three groups of MOOC learners based on their learning patterns and behaviors. The findings allow educators and researchers to explore and understand different aspects of MOOC challenges, such as dropout rates. For example, men may benefit from interventions that focus on enhancing their learning experience and content engagement, while women may benefit from interventions aimed at improving their speed of course completion. Creating a short survey based on the learner characteristics identified in this study and using it at the beginning of a MOOC can give educators, researchers, and instructional designers a better understanding of students and their learning patterns.

VI. Conclusion

Ever since their introduction, MOOCs have opened up a world of possibilities for lifelong learning, skill development, and career success. These courses can support students in acquiring skills and competencies that are in demand in the labor market. However, despite their importance, MOOCs often face several challenges related to learning characteristics. Due to the limited literature on gender differences in learning patterns in MOOCs, the current study revealed several important findings that contribute new knowledge to MOOC research. While the literature highlights the importance of developing effective time management skills in MOOCs, the current study demonstrated that women may take longer than men to submit their first attempt. Additionally, the current study confirms previous findings that men and women do not differ in their course completion rates. However, it adds to the literature by showing that women exhibit higher levels of engagement and take more time to complete their courses compared to men. In terms of the number of attempts required to pass an item, the current study contributes to the literature by showing that while both men and women benefit from additional attempts, women benefit more compared to men. Expanding on the importance of time management skills for course completion in MOOCs, the current study also highlights that the chances of submitting a successful attempt decrease with every additional hour later in the day. Furthermore, three distinct groups of MOOC learners were identified based on their learning patterns and gender.

The study aimed to utilize LMS analytics to explore gender differences in learning patterns within MOOCs. The study used several statistical techniques to provide a comprehensive understanding of gender differences in learning patterns. Like any study, there were multiple limitations. The research was limited to Saudi higher education students. Therefore, generalizing the findings to learners from other countries or educational levels should be done with caution. Moreover, students were required to take the courses as part of their university coursework, which might not represent learners who are self-motivated to enroll in these courses. Another limitation is related to the available log data in the LMS analytics. Data were collected from Coursera. Although most MOOC platforms share similar features, generalizing the findings across other platforms requires further investigation, especially platforms that offer different subject areas. The dataset did not provide information about students' interaction with the learning materials, such as time spent on readings. Such information could provide valuable insights. The study was limited to the LMS analytics data and did not allow for qualitative data to be collected nor for students' experiences of taking MOOCs to be described. Further work to better understand the learner's experience in MOOCs was outside this study's scope.

Future research, particularly qualitative studies, is needed to fully understand and explore students' lived experiences in MOOCs across genders. Since the current study focused on gender differences, future research should examine the impact of other demographic variables on learning patterns in MOOCs. Additionally, longitudinal studies are required to track changes in learning patterns over time. Finally, future research should explore cross-cultural variations in gender-based learning patterns.

CONFLICT OF INTEREST

The author declares no conflict of interest.

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