Seductive Details in MOOCs: Distraction or Engagement?

Abstract (119/120 words)
This study examines the role of seductive details (engaging but irrelevant information) in Massive Open Online Courses (MOOCs), where self-directed learning environments pose challenges for learner engagement. While some research suggests that seductive details may hinder learning by diverting attention from content, they may also serve to enhance emotional engagement, support motivation, and reduce attrition. By analyzing 70 MOOCs across diverse disciplines, this study investigates whether seductive details are associated with increased engagement and performance. Findings suggest that seductive details correlate positively with certain engagement metrics, such as module completion and time spent on course items, but do not significantly affect learner performance. These results call for a reassessment of the seductive details effect in online, self-regulated learning environments.

Word count: 1984/2000 words

1. Objective

In instructional design, researchers caution against incorporating seductive details—engaging but irrelevant information—as they negatively impact learning. Studies demonstrate that such details can reduce comprehension and retention by diverting learners' cognitive resources from core instructional content (Harp & Mayer, 1998; Mayer, 2005; Rey, 2012) Consequently, instructors are advised to remove seductive details from teaching materials (Harp & Maslich, 2005)

However, most of this research has been conducted in controlled laboratory settings, with limited investigation into more dynamic learning environments such as flipped classrooms, synchronous online courses or high stakes lecture-based instruction (Fries et al., 2019; Maloy et al., 2019; Zambrano R. et al., 2024). Replication studies have also shown inconsistent results across different instructional contexts (Rey, 2012; Sitzmann & Johnson, 2014). In non-traditional and authentic contexts, seductive details—vivid anecdotes, humor, emotionally engaging examples—may increase interest, engagement, and course completion (Sitzmann & Johnson, 2014). These inconsistencies call for renewed examination of seductive details in real-world settings, particularly in self-directed digital learning environments such as Massive Open Online Courses (MOOCs).

MOOCs differ substantially from traditional classroom environments. Learners in MOOCs are typically self-directed, enroll for varying reasons, and possess diverse levels of prior knowledge and motivation (Kizilcec & Schneider, 2015; Loizzo et al., 2017).

While the unstructured and asynchronous learning in MOOCs offers flexibility for learners, sustaining learner engagement and preventing attrition are ongoing concerns (De

Freitas et al., 2015), making them a valuable context for exploring the effects of seductive details on student engagement and performance

This paper investigates whether seductive details hinder or enhance learner engagement in self-directed, distraction-prone environments, specifically MOOCs. By focusing on diverse learner motivation and autonomy in online education, we reassess the role of seductive details as a valuable design element for engaging learners in digital learning environments.

1.1 Prior Work and Theoretical Framework

Seductive details effect

Seductive details are "highly interesting and entertaining information that is only tangentially related to the topic but irrelevant to the author's intended theme" (Harp & Mayer, 1998). The learning decline associated with these details is known as the *seductive details effect* (Garner et al., 1989; Harp & Mayer, 1998). Grounded in Cognitive Load Theory, seductive details effect suggests that irrelevant elements --such as jokes, anecdotes, or vivid images -- overload working memory, impairing comprehension, retention, and transfer (Rey, 2012). Many studies show learners exposed to seductive details perform worse on comprehension tests (Mayer, 2005; Rey, 2012).

Initially examined in textbooks, seductive details were found to hinder comprehension and recall (Garner et al., 1989; Lehman et al., 2007). Research later expanded to multimedia and e-learning, with many studies reporting similar negative effects (Park et al., 2015). However, findings vary based on how details are integrated and learner characteristics (Mayer et al., 2008; Rey, 2012). For instance, Park et al. (2011) found seductive details helped learners under low cognitive load.

In online courses, evidence are mixed. Maloy et al. (2019) found that seductive details in flipped classrooms did not hinder content understanding and even increased memorability and interest. Zambrano R. et al. (2024) found in an online math course, novice learners performed worse with seductive details, while advanced learners were less affected. Similarly, Sitzmann & Johnson (2014) noted seductive details could benefit or hinder learning depending on prior knowledge, interest, and self-regulation.

These nuances are relevant in MOOCs, where instructors often use humor and personal stories to engage diverse audiences (Deng & Gao, 2023). While seductive details are traditionally linked with impaired learning, in MOOCs they may instead function as motivational "hooks," helping capture attention, reduce attrition, and sustain engagement (Fries et al., 2019).

Challenges to Engagement in MOOCs

MOOCs consistently face high dropout and low completion rates due to factors like prior experience, course design, feedback, social presence, and social networks (Aldowah et al., 2020). Their self-directed structure and varied learner motivations—often personal interest or career relevance rather than certification—further reduce retention (Kizilcec & Schneider, 2015; Loizzo et al., 2017). Unlike students in blended or synchronous courses, MOOC learners operate autonomously in an unstructured and multitasking environment with digital distractions (Zhu et al., 2020). Therefore, strategies are needed to address disengagement tied to independence and fluctuating motivation (Cristina et al., 2024; Joksimović et al., 2018).

In this context, rethinking the role of seductive details is crucial. Rather than distracting, they can foster emotional engagement and humanize learning, helping maintain attention and motivation (Maloy et al., 2019; Rey, 2012). Studying their role in MOOCs could therefore, meaningfully impact course design.

In this study, we inspect if seductive details hurt or are helpful to learner engagement and academic performance in MOOCs? Specifically, we ask the following research question: Is the presence of seductive details in MOOC associated with better or worse course engagement and learner performance?

2. Methods

2.1 Data Source

This study analyzed data from 70 MOOCs offered on the Coursera platform, spanning a range of disciplines including Engineering, Mathematics, Psychology, Law, and Management. Course and learner data were obtained through the MOOC Replication Framework (MORF) platform (Gardner et al., 2018). To ensure consistency across courses the analysis included learner activity from January 1, 2020, to May 30, 2023. Only courses offered in English were included.

Data sources included (1) Log data such as learners' course progress and personal learning goal achievement for assessing learner engagement, and (2) Lecture transcripts from sampled courses to code for the presence of seductive details.

2.2 Engagement and Performance Metrics from Log Data

We measured learners' behavioral engagement and academic performance by extracting variables from Coursera's log data. We extracted a total of 9 engagement metrics, comprising 7 behavioral metrics and two learner performance measures. The behavioral engagement metrics included: 1) Completing at least one module, 2) Time spent on course items, 3) Students with 50% Assignment Progress, 5) Students Passing Any Week 1 Module, 6) Personal Learning Goal Achievement, 7) Students with Early-Stage Assignment Progress, and 8) Time spent on assignments. The learner performance metrics were: 1) Students with grade above 70% and 2) Course pass percentage.

2.3 Qualitative coding for seductive details

To code for the presence of seductive details, we developed a codebook using deductive coding based on definition by Harp & Mayer (1998) ,followed by thematic analysis to identify additional themes (Braun & Clarke, 2006). We hand-coded all Week 1 lecture transcripts for each course using a binary scale (0 = absent, 1 = present), treating each sentence—defined by line breaks, question marks, or exclamation marks—as the unit of analysis. Week 1 was selected for consistency across courses of varying lengths.

Two human coders and author 1 independently annotated a sample of 100 posts to establish inter rater reliability. We calculated inter-rater reliability using Cohen's Kappa (McHugh, 2012).

All codes reached κ≥0.7. We resolved disagreements through social moderation (Eagan et al., 2020). Author 1 coded 50 courses, Author X coded 8 courses (Cohen's Kappa = 0.79 with Author 1), and Author Y coded 12 courses (Cohen's Kappa = 0.77 with Author 1). We present the coding criteria and examples in Table 1.

2.4 Analysis

We first conducted a descriptive analysis to examine how the presence of seductive details varied across course disciplines. We then used Spearman's rank correlation to account for the non-normal distribution of the data and assessed the relationship between the percentage of seductive details (pct_SED) and course-level engagement metrics. While determining statistical significance, we controlled for inflated Type I error from multiple comparisons by adjusting alpha levels using the Benjamini-Hochberg procedure. (Benjamini & Hochberg, 1995).

To further inspect the relationship between the presence of seductive details and learner engagement and course performance, we fitted linear regression models to predict engagement outcomes using pct_SED as the independent variable. The additional analysis through the linear regression models helped predict engagement in MOOCs above and beyond seductive details, by adjusting for course-level features.

The predicted engagement variables were rank transformed to be consistent with assumptions from Spearman's correlation. To control for differences in course design, we included the number of assignments, number of peer assignments, number of programming assignments, number of forums, and average time spent on the entire course as predictors. These variables accounted for course features that could independently influence learner engagement, such as increased interactivity or workload. We checked for multicollinearity using Variance Inflation Factors among variables for the models with a threshold set to 5 (high multicollinearity) (Thompson et al., 2017).

3. Results

3.1 Seductive details across course types

We found that the presence of seductive details varied across different course types. For example, an average of 17.5% of the content in Psychology courses consisted of seductive details, whereas only 0.3% of content in Math courses included them. Psychology courses also showed high variability (SD = 11.5%) compared to other disciplines. Courses in Education (SD = 4.6 %) and Law (SD = 5.1%) displayed medium variability, which may reflect differences in content design. In contrast, Math and ESG courses showed relatively low variability, suggesting more uniformity in how instructors presented course material. Table 2 presents descriptive statistics for the number of seductive details across courses.

3.2 Seductive Details and Engagement metrics

We found that seductive details were significantly associated with some engagement metrics. Specifically, they showed a positive correlation with 'completing at least one module' (Spearman's

Rho = 0.392, $p < .001$, adj $\alpha = 0.003$) and ‘time spent on course items’ (Rho = 0.285, $p = 0.0168$, adj $\alpha = 0.007$). No significant correlations appeared between pct_SED and other engagement measures like ‘completing at least one module,’ ‘progress to later stages in assignments,’ or ‘time spent on assignments,’ nor with learner performance metrics like ‘grade above 70%’. Table 3 summarizes all engagement variable correlations.

In linear regression models accounting for course features, the percentage of seductive details (pct_SED) significantly predicted ‘completing at least one module’ ($\beta = 77.94$, $p = 0.029$). ‘Number of peer assignments’ also showed a significant positive association with the same outcome ($\beta = 0.146$, $p = 0.013$), suggesting more peer assessments in the course may increase completion of one module. Other predictors—‘number of assignments,’ ‘number of forums,’ ‘number of programming assignments,’ and ‘time spent on the entire course’—were not significant.

Similarly, pct_SED showed a significant positive trend with ‘time spent on course items’ ($\beta = 117.90$, $p = 0.001$). ‘Number of programming assignments’ was significantly associated with ‘time spent on course items’ ($\beta = -2.15$, $p = 0.013$). Other predictors— ‘number of assignments,’ ‘number of peer assessments,’ ‘number of forums,’ and ‘time spent on course’—were not significantly associated ($p > 0.05$). No other engagement metrics were significantly related to pct_SED.

Additionally, seductive details showed no significant relationship with learner performance variables such as ‘grades above 70%’ or ‘course pass percentage.’ Estimates and p-values for all linear models are provided in the Appendix.

4. Significance, Limitations and Future Work

While prior research shows seductive details can harm learning by diverting attention from essential material, our findings in MOOCs suggest a more nuanced picture. We found that few engagement metrics—like completing at least one course item and time spent on content—positively correlated with seductive details, whereas other metrics like personal learning goal achievement, and assignment progress are not significantly related. Additionally, no significant association was found between seductive details and learning outcomes.

These results suggest that in self-paced, asynchronous learning environments, seductive details may serve a different function than previously understood. Rather than undermining academic performance, they may enhance learner engagement—key factor in environments where external accountability and instructor presence are limited. Our findings contribute to the discussion on context-sensitive instructional design by re-examining the seductive details effect in MOOCs.

However, these results should be interpreted cautiously. The lack of learning effects may reflect a small dataset or limited measures. We did not control for learner traits like motivation or prior knowledge, which influence outcomes (Rey, 2012). Future research should include broader engagement metrics, dropout patterns, and longitudinal data.

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Tables

Table 1: Coding criteria for seductive details in MOOC transcripts

Codes	Example
Details/anecdotes of the instructor	"Hi, I'm X and I am the director of [Redact], and I use computational thinking to solve problems ; The [Redact] working dog center is a research and training facility, which we raise and train detection dogs to help save lives."
History or background of the field that is tangential to the core topic	"Over the last 30 years, the number of UAVs in the world have grown exponentially"
Personal opinions	"I believe AI is similar, and I've previously argued why AI should be viewed as a general purpose technology that can have impact on a number of different industries"
Humor	"Mr. Professor, I learned a ton of accounting in Montessori school. But shouldn't you explain this stuff more for those who didn't?"
Industry aspect of the field mentioned in number estimates (e.g., market value or projection)[1]	"In 2010, there were predictions of a $10 billion industry"
Mentions name/details/quotes of experts in the field	"General [Redact], the person who actually used drones and actually popularized the use of drones within the military"
Irrelevant phenomenon (e.g. unrelated social trends or scientific findings)	"Every week we hear about studies that show that one thing is associated with another. Some of your friends quickly share this on social media while others remain skeptical"

[1] Not considered seductive details for courses where business is relevant to the course topic

Table 2: Descriptives - Seductive details by course

Course type	Number of courses in each course type	mean	std	min	max
Robotics	6	0.032	0.02994	0.004	0.087
Analytics	6	0.029	0.021	0.001	0.058
AI (Artificial Intelligence)	5	0.040	0.044	0	0.110
Math	5	0.003	0.004	0	0.010
Programming	3	0.023	0.012	0.015	0.037
Education	4	0.063	0.046	0.006	0.117
Psychology	8	0.175	0.115	0.035	0.359
Law	11	0.067	0.051	0.011	0.146
ESG (Environment, Society, Governance)	8	0.032	0.014	0.006	0.054
Health	5	0.037	0.026	0	0.072
Marketing & Business	9	0.021	0.022	0	0.057

Table 3: Correlations between Percentage of Seductive Details and Engagement/ Performance Variables

#	Variable Name	Variables Description	Spearman r	*p*- value	Std Error	CI_lower	CI_upper	Adjusted alpha
1	Completing at least one module	proportion of students who completed at least one item/ module in the course	0.392	0.0007	0.126	0.144	0.641	0.003
2	Time spent on course items	average time spent by students on Week 1 course items	0.284	0.0168	0.124	0.040	0.529	0.007
3	Students with Later Stage Assignment Progress	proportion of students who progressed to a later stage in assignments in Week 1	-0.134	0.2713	0.122	-0.374	0.106	0.030
4	Students Passing Any Week 1 Module	proportion of students who passed any one of Week 1 modules	0.117	0.3306	0.122	-0.122	0.358	0.038
5	Personal Learning Goal Achievement	proportion of students who completed a goal set by the learner	0.109	0.3685	0.122	-0.131	0.349	0.042
6	Students with Early Stage Assignment Progress	proportion of students who progressed to early stage in an assignment in Week 1	0.089	0.4624	0.122	-0.150	0.329	0.046
7	Time spent on assignments	average time spent on assignments in Week 1	-0.080	0.5105	0.122	-0.320	0.159	0.05
8	Students with grade above 70%	proportion of students who score above 70% in course	0.147	0.224	0.122	-0.093	0.387	0.024
9	Course pass percentage	percentage of students who passed course modules	0.122	0.3116	0.122	-0.117	0.363	0.034

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Appendix

Table 4: Estimates and p values for all models

Predictor	Model 1 completing at least one module	Model 2 time spent on course items	Model 3 Students with 50% Assignment Progress	Model 4 Students with Later Stage Assignment Progress	Model 5 Students Passing Any Week 1 Module	Model 6 goal completion	Model 7 Students with Early Stage Assignment Progress	Model 8 Time spent on assignments	Model 9 Students with grade above 70%	Model 10 Course pass percentage
pct_SED	77.268 **(0.029)**	117.906 **(0.001)**	-45.014 (0.228)	-50.064 (0.170)	73.545 (0.067)	74.095 (0.065)	-20.147 (0.588)	-70.069 (0.057)	45.755 (0.182)	34.290 (0.313)
number of assignments	-0.051 (0.076)	0.006 (0.819)	-0.033 (0.269)	0.018 (0.535)	-0.017 (0.589)	-0.019 (0.552)	-0.031 (0.305)	0.038 (0.195)	-0.052 (0.064)	-0.058 (0.040)
number of peer assignments	0.146 **(0.013)**	-0.009 (0.872)	-0.042 (0.498)	-0.060 (0.317)	0.017 (0.794)	0.030 (0.642)	0.044 (0.469)	-0.003 (0.962)	-0.007 (0.899)	-0.008 (0.891)
number of programming assignments	-0.598 (0.483)	-2.158 **(0.013)**	-0.254 (0.780)	-2.178 (0.016)	0.873 (0.370)	1.089 (0.263)	-1.548 (0.092)	-2.002 (0.027)	-0.799 (0.339)	-0.736 (0.377)
number of forums	0.093 (0.901)	-0.249 (0.741)	-1.337 (0.100)	-1.668 (0.037)	-0.410 (0.634)	0.110 (0.898)	-1.086 (0.180)	1.142 (0.149)	-0.411 (0.578)	-0.265 (0.718)