Appendix A. Challenges of Incomplete Consumption in Serialized E-Books

A persistent challenge faced by serialized e-books is the high incidence of incomplete consumption, with many readers abandoning content long before reaching the conclusion. A New York Times article recently reported that 90% of book readers abandon consumption after only five chapters in books with over 30 chapters (Alter et al. 2016). Surprisingly, a mere 5% of books are fully consumed by more than 75% of readers, even when considering best-selling titles. This incomplete consumption poses a significant hurdle, leading to unsatisfactory user experiences and hindering subsequent purchases of other serialized e-books, impacting platform loyalty. Incomplete consumption not only affects user satisfaction, but also directly influences revenues, presenting a new source of challenges for platforms, authors, and publishers, particularly for those dealing with lengthy serialized books. Unlike visually oriented enjoyment of TV programs, reading demands greater concentration and attention, making sustained engagement with lengthy content a challenging task (Lin et al. 2011). Given the declining completion rates of digital content in general (e-books, TV series), and serialized formats in particular (Broe 2019), content partitioning and consumption have become critical factors influencing the financial stability and user base of publishing entities, including platforms, authors, publishers, and retailers. However, there is a notable lack of understanding among platforms and authors regarding the implications of content partitioning on consumption, engagement, and economic behaviors. Motivated by the need to address these gaps, this study endeavors to shed light on the intricate dynamics of content partitioning and consumption patterns. By doing so, the research aims to equip business stakeholders with insights to successfully monetize serialized books and foster enhanced consumer engagement with lengthy content.

Reference:

Alter, A., and Russell, K. 2016. *Moneyball for book publishers: A detailed look at how we read*, The New York Times (March 14th, 2016)

Broe, D. (2019). Birth of the Binge: Serial TV and the End of Leisure. *Wayne State University Press*.

Lin, L., Lee, J., & Robertson, T. (2011). Reading while watching video: The effect of video content on reading comprehension and media multitasking ability. *Journal of Educational Computing Research*, *45*(2), 183-201.

Appendix B. Additional Related Literatures on Consumption and Engagement with Digital Content

Datta et al. (2018) investigated how the adoption of music streaming services affects listening behaviors and showed that streaming adoption encourages consumers to increase consumption quantity and diversity. This listening pattern is more pervasive immediately after adoption and then decays over time. Liebman et al. (2019) demonstrated that individuals' music preferences and consumptions vary according to a temporal context and in sequence. The authors developed personalized playlists that reflect such sequential patterns to enhance music consumption experiences. Recently, Matos and Ferreira (2020) conducted field experiments to understand the effects of binge-watching on subscription to video on demand and found that binge-watchers tend to go through their favorite programs rapidly to diminish their short-term willingness to pay for the subscription.

Reference:

Datta, H., Knox, G., & Bronnenberg, B. J. (2018). Changing their tune: How consumers' adoption of online streaming affects music consumption and discovery. *Marketing Science*, 37(1), 5-21.

Godinho de Matos, M., & Ferreira, P. (2020). The effect of binge-watching on the subscription of video on demand: Results from randomized experiments. *Information Systems Research*, *31*(4), 1337-1360.

Liebman, E., Saar-Tsechansky, M., & Stone, P. (2019). The right music at the right time: Adaptive personalized playlists based on sequence modeling. *MIS quarterly*, *43*(3).

Appendix C. Additional Related Literatures on Effects of Segmentation on Cognitive Performance

Given the cognitive limitations inherent to human comprehension and perception, researchers examined how the division of learning material affects individuals' cognitive capabilities and learning performance. A consensus has emerged among these studies with respect to the positive effects of segmentation on mental competence and cognitive processing. Mayer and Chandler (2001) found that students who learn about scientific problems through a segmented version of narrated animation acquire higher test scores than those derived by students who study the same material in an unsegmented, continuous form. Spanjers et al. (2012) articulated that segmentation increases the salience of boundaries between events in learning instruction and that this temporal cuing facilitates the reduction of cognitive efforts by students, as necessary, and the enhancement of performance.

Subsequent explorations broadened our understanding of the outcomes of segmentation on performance by identifying an array of moderating factors. A learners' level of prior knowledge or expertise on a given task, for example, significantly moderates the beneficial effects of segmentation in educational contexts; that is, a segmentation effect is more pronounced for novice learners than domain experts (e.g., Kalyuga and Renkl 2010; Khacharem et al. 2013). Because experts are equipped with a cognitive processing proficiency that surpasses that of neophyte learners, the benefits of segmentation are less prominent among the former. Occasionally, segmentation can increase, rather than decrease, cognitive load and disrupt effective learning for expert learners (Schnotz and Kürschner 2007). An opportunity to receive repeated educational instruction can also moderate the effectiveness of segmentation in advancing human cognition. Learners who have no such opportunity can benefit more fully from segmentation than those who are exposed to iterative instruction (Singh et al. 2012).

Reference:

Mayer, R. E., and Chandler, P. 2001. "When learning is just a click away: Does simple user interaction foster deeper understanding of multimedia messages?," *Journal of educational psychology*, 93(2), pp. 390.

Spanjers, I. A., Van Gog, T., Wouters, P., and Van Merriënboer, J. J. 2012. "Explaining the segmentation effect in learning from animations: The role of pausing and temporal cueing," *Computers & Education*, 59(2), pp. 274-280.

Kalyuga, S., and Renkl, A. 2010. "Expertise reversal effect and its instructional implications: Introduction to the special issue," *Instructional Science*, 38(3), pp. 209-215.

Khacharem, A., Spanjers, I. A., Zoudji, B., Kalyuga, S., and Ripoll, H. 2013. "Using segmentation to support the learning from animated soccer scenes: An effect of prior knowledge," *Psychology of Sport and Exercise*, 14(2), pp. 154-160.

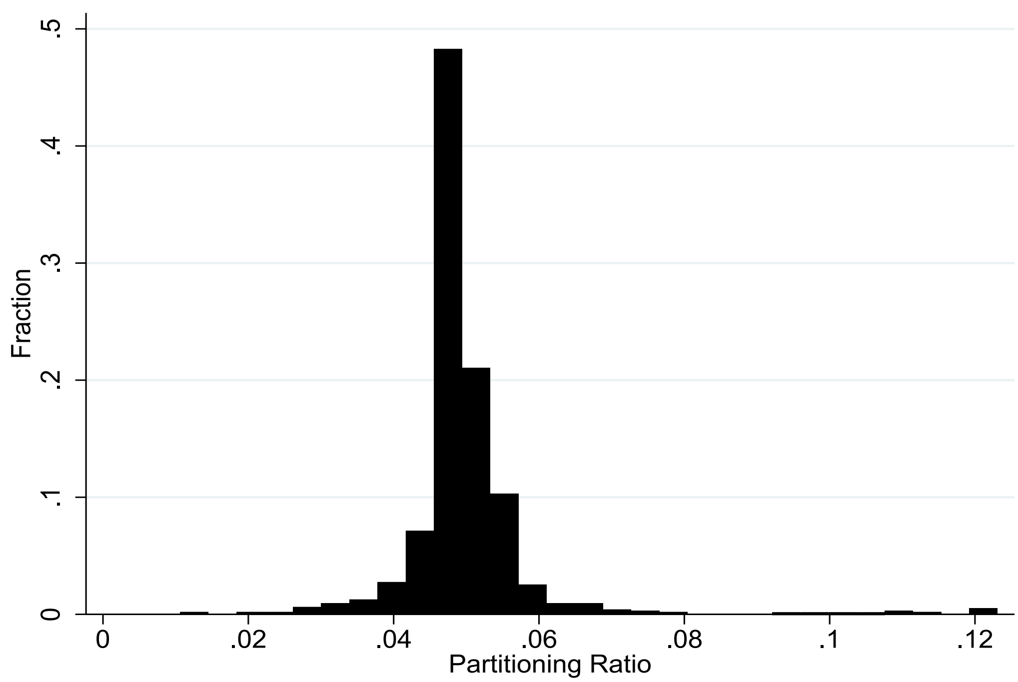
Schnotz, W., and Kürschner, C. 2007. "A reconsideration of cognitive load theory," *Educational psychology review*, 19(4), pp. 469-508.

Singh, A. M., Marcus, N., and Ayres, P. 2012. "The transient information effect: Investigating the impact of segmentation on spoken and written text," *Applied Cognitive Psychology*, 26(6), pp. 848-853.

Appendix D. Institutional Details and Empirical Identification

In consultation with the authors, the company selected serialized contents for authors who consented to the experiment, and this percentage amounts to 64.52% of the total serial book. For these samples, each serialized book composed of the episodes that the artist originally envisioned (SP) was newly redivided to form a largely partitioned content (LP). Regarding the repartitioning characteristics, the segmenting ratio (i.e., the ratio of the number of LP episodes to the number of SP episodes) has schemed with a goal of 0.05 on average (e.g., LP episodes are 20 times thicker than SP episodes) under the agreement of the author and the company. Also, within one format, the length of each episode was segmented equally. Figure D shows the distribution of the partitioning ratio of experiment samples, and it follows a normal distribution. Comprehensively, for every serialized e-book title, the average number of episodes available through an SP scheme was 255, whereas that provisioned by an LP arrangement was only 12. LP-based episodes are therefore approximately 21 times “thicker” than their SP counterparts when all else is equal.

Figure D. The Distribution of Partitioning Ratio



The platform simultaneously released the completed original serialized content (SP) and the widely subdivided series (LP) for the same content but places them in different categories. This means that both formats can be used at the same period, but in different categories within the platform. Specifically, SP was arranged in the 'Genre Books' category, while LP was placed in the 'Novel' section. Since each format can only be searched within each category, it is difficult for consumers to notice that a single content exists in two formats in the platform. Moreover, we leveraged clickstream data to filter out a few observations that accessed both SP and LP prior to content consumption. Thus, these settings reduce potential endogeneity concerns about an individual's format choice. Consequently, these institutional details provide a unique opportunity to conduct counterfactual analyses of the effects of content partitioning.

Appendix E. Measurement of Review Topic and Valence

We extract content features of reviews by employing a topic modeling approach to retrieve main themes ($RevTopic$) in the review content (Puranam et al. 2017; Khern-am-nuai et al. 2018). Specifically, we utilize Latent Allocation (LDA) models, which is unsupervised machine learning method, to retrieve main topics in reviews submitted by consumers. LDA models use each textual document (i.e., reviews) as a mixture of a pre-determined number of latent topics, wherein each of documents is modeled as a distribution over some high-frequency key terms extracted from the whole set of textual documents (Blei 2012). We use topicmodels package in R (Hornik and Grun 2011), which utilizes Gibbs sampling to estimate the distribution of key terms over the topics and the distribution of topics over the textual descriptions. We repeat the models with different numbers starting from 2 to 20 as the number of topics needs to be determined prior to the estimation. In order to evaluate the model performance, we closely follow the prior literature (e.g., Puranam et al. 2017; Khern-am-nuai et al. 2018) and use metrics proposed by Cao et al. (2009) and Devuaud (2014) to determine the optimal number of topics (Figure E-1). We identified two topics (i.e., sentiment and product specifics) are the optimal number of topics in our review dataset. The top 3 terms that most frequently appear in each topic is presented in Table E-1. $RevTopic$ is coded 1 if the topic belongs to product specifics.

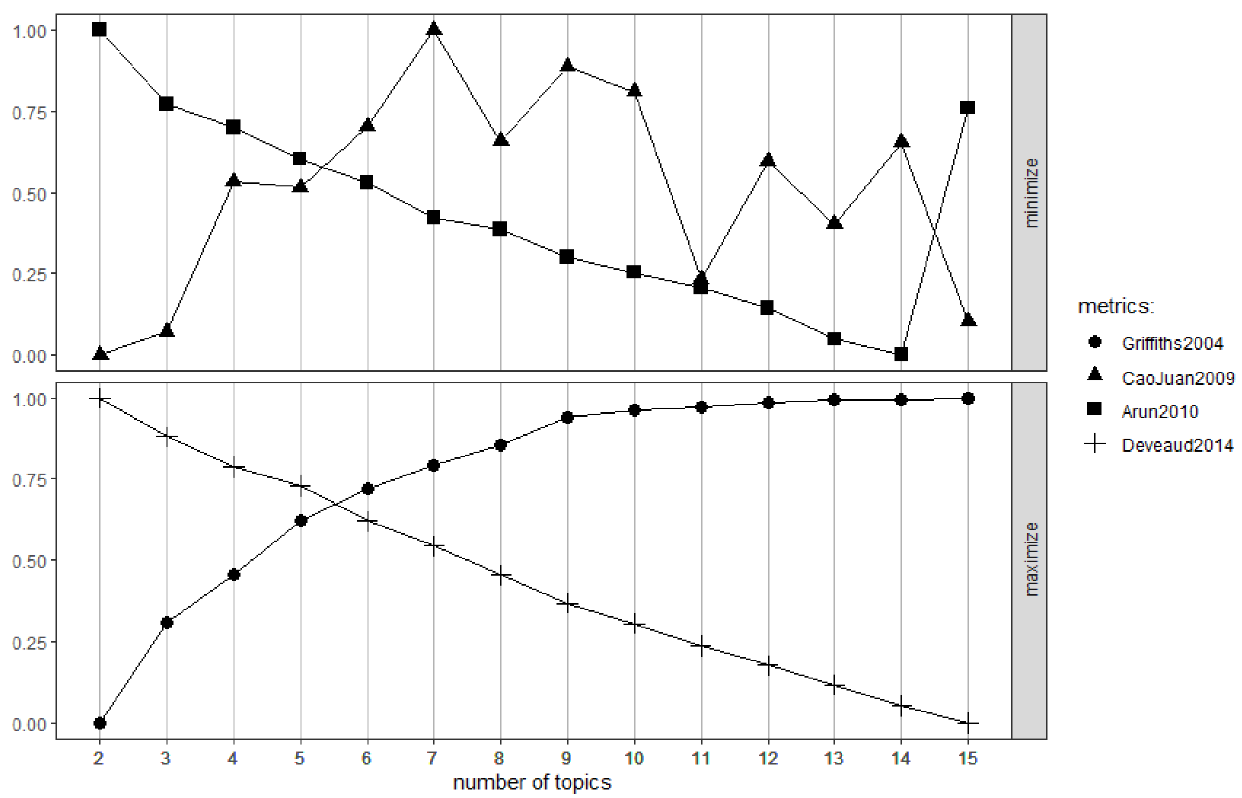


Figure E-1. Testing the Number of Topics

Table E-1. Top 3 Terms in Each Topic	
Topic 1 **Sentimental**	**Topic 2** **Features**
Good	Story
Best	Female-Characters
Perfect	Character

Lastly, we collect valence of each review ($RevValence$) entered by a consumer by using Linguistic Inquiry and Word Count (LIWC) dictionary. LIWC has been widely used in marketing and IS literatures (Sridhard and Srinivasan 2012, Haung et al. 2017), which enables to measure linguistic characteristics, such as positive and negative valence based on the matching percentage between the document (i.e., reviews) and a predefined keyword list (Pennebaker et al. 2015). We closely follow text-mining process used in Haung et al. 2019 to capture valence embedded in online consumer reviews. Specifically, we obtain the linguistic measures for each review by using "posemo" and "negemo" measures in LIWC and compute review valence by subtracting the negative-sentiment measure from the positive-sentiment measure. A higher valence indicates the more positive review was generated by a consumer.

Reference:

Blei, David M. "Probabilistic topic models." *Communications of the ACM* 55.4 (2012): 77-84.

CaoJ, Xia T, Li J, Zhang Y, Tang S (2009) A density-based method for adaptive LDA model selection. *Neurocomputing* 72(7):1775–1781.

Deveaud R, SanJuan E, Bellot P (2014) Accurate and effective latent concept modeling for ad hoc information retrieval. *Document numérique* 17(1):61–84.

Grün, B., & Hornik, K. (2011). topicmodels: An R package for fitting topic models. *Journal of statistical software*, 40, 1-30.

Huang, Ni, Yili Hong, and Gordon Burtch. "Social network integration and user content generation." *MIS quarterly* 41.4 (2017): 1035-1058.

Khern-am-nuai, Warut, Karthik Kannan, and Hossein Ghasemkhani. "Extrinsic versus intrinsic rewards for contributing reviews in an online platform." *Information Systems Research* 29.4 (2018): 871-892.

Pennebaker, James W., et al. "The development and psychometric properties of LIWC2015." (2015).

Puranam, Dinesh, Vishal Narayan, and Vrinda Kadiyali. "The effect of calorie posting regulation on consumer opinion: A flexible latent Dirichlet allocation model with informative priors." *Marketing Science* 36.5 (2017): 726-746.

Sridhar, Shrihari, and Raji Srinivasan. "Social influence effects in online product ratings." *Journal of Marketing* 76.5 (2012): 70-88.

Appendix F. Validity Tests for IV

- *Relevance Condition Test*

To validate our instrumental variables, we utilized the Cragg-Donald F-statistics, yielding a value of 118.135. This value significantly exceeds the critical values recommended by Stock and Yogo's (2005) (a diagnostic rule of thumb is 10), thereby mitigating concerns related to weak instruments (Angrist and Pischke 2008). Regarding the relevance condition, we found a correlation of 0.548 between $HistLargePartitioning$ and $LargePartitioning$ ($p<0.001$), indicating a positive correlation between the historical purchase of LP arrangement and the current choice of content format.

Additionally, we computed correlation statistics between $HistLargePartitioning$ and dependent variables (i.e., consumption quantity, progression rates, consumption intensity, reviewing, review length, review informativeness, review valence, and purchase likelihood). The absolute values obtained were below 0.2, indicating a low correlation (Table F-1). This suggests that the alternative instrument exhibits a high correlation with the endogenous variable ($LargePartitioning$), but a low correlation with the dependent variables, suggesting the inference of possibility exogeneity.

Table F-1. Correlation between Instrument ($HistLP$) and Review Characteristics

Correlation (ρ)	Cons. Quantity	Prog. Rates	Cons. Intensity	Review	Rev. Length	Rev. Inform.	Rev. Valence	Purchase
$HistPurLP$	-0.055	0.059	0.046	0.077	-0.089	-0.034	0.071	0.145

- *Sensitivity and Reliability Tests to Support Exogeneity*

We undertook sensitivity and robustness checks to validate our instrumental variable and ensure the reliability of our results, adhering to the identification approach of IV estimations. Initially, we employed copula-based joint estimation to address potential endogeneity without relying on external instrumental variables. Following the methodology of Park and Gupta (2012), we used Gaussian copulas to assess the correlation between consumers' consumption patterns and the error term in our model, presenting an alternative model specification. While instrumental variables are commonly employed to address endogenous issues (Wooldridge 2010), copulas offer an approach that does not necessitate external instrumental variables (Park and Gupta 2012, Datta et al. 2015). The results of the copula-based joint estimation are presented in Tables F-3, F-4, and F-5, demonstrating qualitative consistency in most coefficients with the results obtained from the IV-probit estimation in the primary analyses. These findings support the validity of our proposed instrumental variables, contingent upon the assumption of the exogeneity of the instruments.

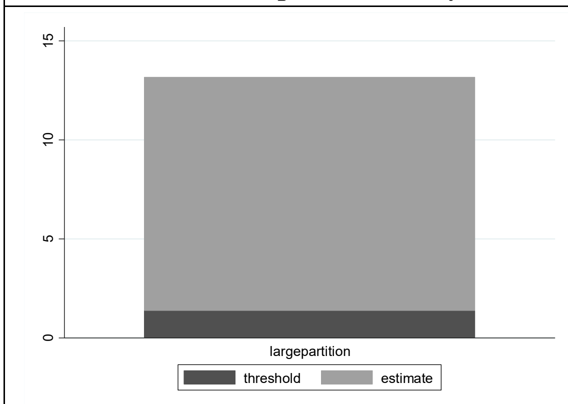
Next, we assessed the reliability of causal inferences derived from our instrumental variable identification by scrutinizing the degree of bias associated with omitted confounding variables, aiming to challenge such inferences (Frank et al. 2013). This method, grounded in Rubin's causal model (Rubin 1974), quantifies the correlation linked to an omitted confounding variable, thereby challenging the inference. The procedure involves replacing observed cases with unobserved cases where there was no treatment effect (Frank et al. 2013). The results of the sensitivity analysis reveal consistently high percentages, particularly for $HistPurLP$, indicating a robust and resilient nature of the findings (Table F-2). Figure F-1 visually illustrates substantial proportions of estimates exceeding specified thresholds. These outcomes from the sensitivity tests suggest that the two instrumental variables (IVs) utilized for identification purposes remain highly robust against potential biases arising from endogeneity.

Table F-2. Results of Rubin's Causal Model

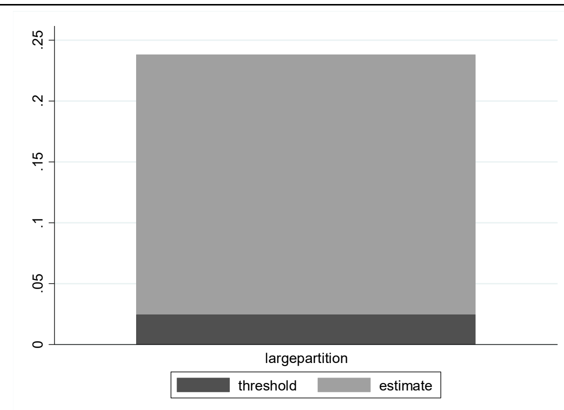
Threshold % Bias	Cons. Quantity	Prog. Rates	Cons. Intensity	Review	Rev. Length	Rev. Inform.	Rev. Valence	Purchase
$HistPurLP$	88.46	87.99	94.56	80.22	94.95	84.95	88.56	72.56

Figure F-1. Proportions of Estimates in Sensitivity Analyses

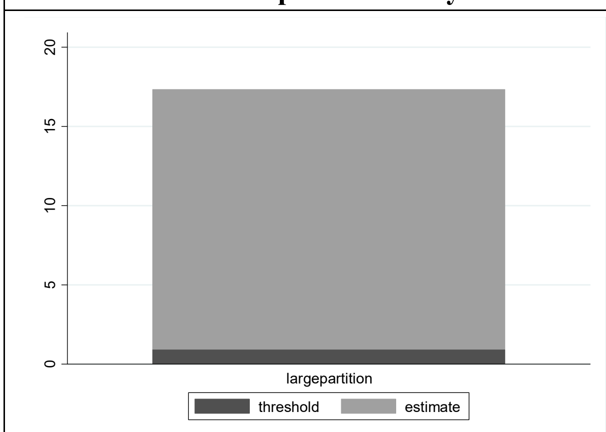
Consumption Quantity



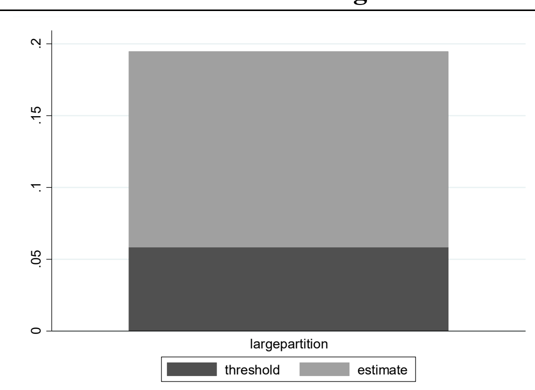
Progression Rates



Consumption Intensity

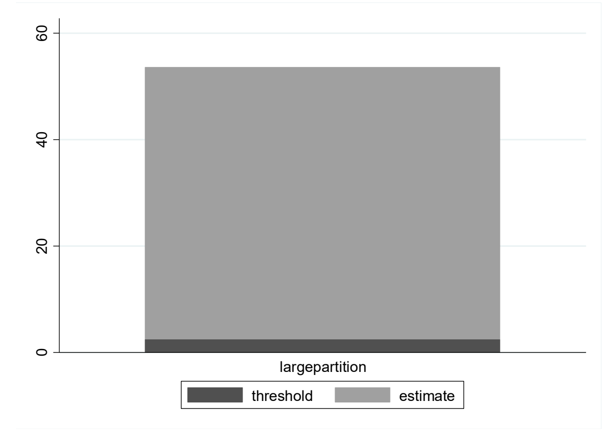


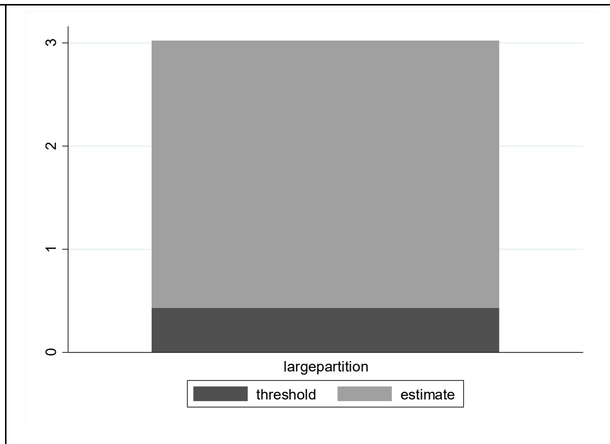
Reviewing



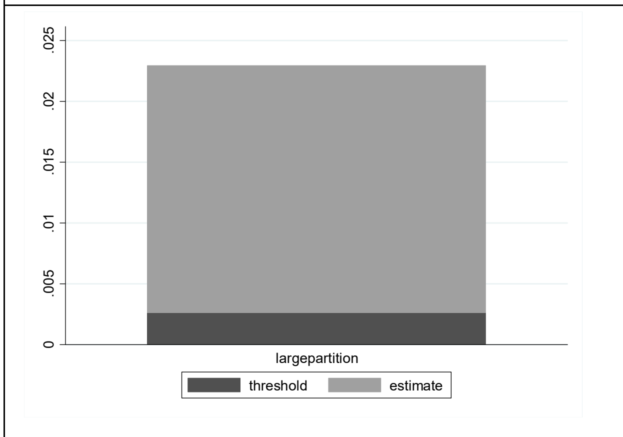
Review Length

Review Informativeness





Review Valence	Purchase



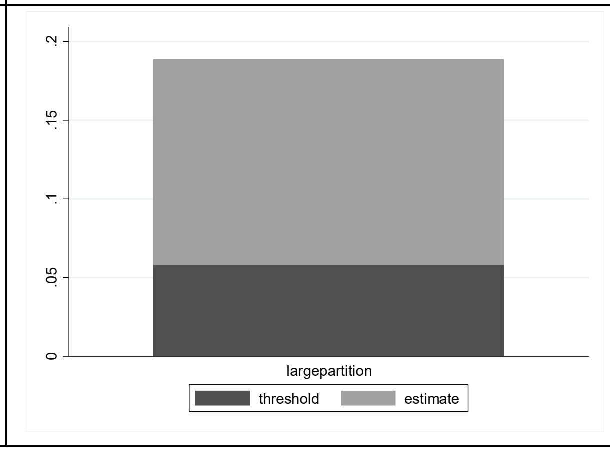


Table F-3. Estimated Results for Copula-based Joint Estimation (Consumption Patterns)

	H1a	**H1b**
Variables	Consumption Quantity	Progression Rates
LP	-0.596***(0.015)	0.526***(0.021)
$ReviewVolume$	5.19e-05***(2.48e-06)	2.98e-05***(5.46e-07)
$ReviewRating$	0.052**(0.021)	0.425***(0.003)
$Length$	-0.001***(0.000)	-0.001***(3.58e-05)
$Price$	2.08e-05***(2.11e-06)	5.69e-07(4.98e-07)
$Discount$	1.72e-06(1.69e-06)	3.59e-06*(1.25e-06)
$PublishDate$	2.46e-06(5.19e-07)	1.59e-05***(2.46e-07)
$SeriesOrder$	-0.001(0.004)	0.012***(0.001)
Constant	0.025***(0.005)	0.534***(0.001)
Individual FE	Yes	Yes
Book FE	Yes	Yes
Observations	127,524	127,524
R-squared	0.116	0.123

*Standard errors are in parenthesis: ***p<0.01,**p<0.05, *p<0.1. We indicate LargePartitioning as LP. The robust standards errors are clustered at both the individual level and the book level*

Table F-4. Estimated Results for Copula-based Joint Estimation (Moderating Effects)		
Variables	Consumption Quantity	Progression Rates
LP	-0.189***(0.012)	0.412***(0.00120)
$ReviewVolume$	5.15e-05***(2.69e-06)	3.94e-05***(1.16e-05)
$ReviewRating$	0.022***(0.003)	0.150***(0.00149)
$Length$	-0.006***(0.000)	-0.000622***(4.72e-05)
$LP * RevVolume$ $(\boldsymbol{H2a}, \boldsymbol{H2b})$	-2.68e-05***(1.02e-06)	1.68e-05***(6.81e-07)
$LP * RevRating$ $(\boldsymbol{H2a}, \boldsymbol{H2b})$	-0.008***(0.002)	0.157***(0.00342)
$LP * Length$ $(\boldsymbol{H2c}, \boldsymbol{H2d})$	0.005***(0.001)	-0.000786***(0.000108)
$Price$	2.98e-05***(1.89e-06)	1.01e-07(5.43e-07)
$Discount$	2.22e-06(3.85e-06)	3.17e-07(5.38e-07)
$PublishDate$	3.98e-06**(1.98e-06)	1.21e-05***(1.93e-07)
$SeriesOrder$	-0.003(0.008)	0.00725***(0.00142)
Constant	0.015***(0.003)	0.963***(0.00133)
Individual FE	Yes	Yes
Observations	127,524	127,524
R-squared	0.125	0.191

*Standard errors are in parenthesis: ***p<0.01,**p<0.05, *p<0.1. We indicate LargePartitioning as LP. The robust standards errors are clustered at both the individual level and the book level*

Table F-5. Estimated Results for Copula-based Joint Estimation (Engagement and Purchase)						
		H3a		**H3b**		
Variables	Consumption Intensity	Reviewing	Review Length	Review Informat	Review Valence	Purchase
LP	0.772***	0.525***	0.124***	0.938***	0.048***	0.320***
	(0.021)	(0.122)	(0.039)	(0.266)	(0.002)	(0.0235)
$ReviewVol$	0.000***	0.004***	0.003***	0.000***	2.57e-05***	0.003***
	(2.26e-05)	(3.98e-05)	(4.18e-05)	(9.19e-05)	(1.42e-06)	(0.000)
$ReviewRat$	0.077*	0.441***	0.029**	0.596*	0.056***	0.003***
	(0.0443)	(0.110)	(0.011)	(0.358)	(0.00178)	(0.001)
$Length$	1.39e-06***	1.38e-06***	-4.63e-07	-5.05e-08	9.57e-08***	-0.438***
	(1.68e-07)	(4.94e-07)	(3.10e-07)	(9.32e-07)	(1.06e-08)	(0.044)
$Price$	0.000***	0.001***	0.000***	8.81e-05	-5.98e-06***	-5.48e-05***
	(5.43e-05)	(6.08e-05)	(3.27e-05)	(0.000132)	(1.12e-06)	(7.57e-06)
$Discount$	0.000***	-0.005***	-0.003***	0.001***	1.77e-05***	0.072***
	(1.76e-05)	(5.31e-05)	(3.26e-05)	(0.000111)	(1.11e-06)	(0.001)
$Publish$	1.36e-05**	-8.10e-05***	-5.83e-05***	-0.000***	-3.53e-05***	-0.000***
	(6.28e-06)	(2.95e-05)	(1.16e-05)	(6.52e-05)	(3.84e-07)	(5.31e-06)
$SeriesOrd$	0.299***	-0.109**	0.202*	0.435*	0.046***	-0.105***
	(0.0603)	(0.047)	(0.112)	(0.193)	(0.004)	(0.020)
IMR			-0.039***	-0.069*	-0.035***	0.078***
			(0.005)	(0.027)	(0.005)	(0.017)
Constant	1.474***	-4.700***	0.0854***	-1.382***	0.021***	
	(0.0118)	(0.0551)	(0.0218)	(0.122)	(0.000743)	
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Book FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	127,524	127,524	11,799	11,799	11,799	127,524
R-squared	0.112		0.103		0.105	
Log-likelihood		-8,822		-1,114		

*Standard errors are in parenthesis: ***p<0.01,**p<0.05, *p<0.1. We indicate LargePartitioning as LP The robust standards errors are clustered at both the individual level and the book level.*

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Stock, J., and Yogo, M. 2005. "Asymptotic distributions of instrumental variables statistics with many instruments," *Identification and inference for econometric models: Essays in honor of Thomas Rothenberg*, *6*, 109-120.

Appendix G. Equation for Moderating Effects Analyses

$$
\begin{aligned}
&ConsumptionPattern_{ij} \\
&= \beta_0 + \beta_1 LargePartitioning_{ij} + \beta_2 ReviewVolume_{ij} + \beta_3 ReviewRating_{ij} + \beta_4 Length_j \\
&+\beta_5 LargePartitioning_{ij} * ReviewVolume_{ij} + \beta_6 LargePartitioning_{ij} * ReviewRating_{ij} \\
&+\beta_7 LargePartitioning_{ij} * Length_j + \beta_8 SeriesOrder_{ij} + \beta_9 Price_j + \beta_{10} Discount_{ij} \\
&+\beta_{11} PublishDate_{ij} + \gamma_i + \varepsilon_{ij}
\end{aligned}
$$

where i denotes an individual, j represents serialized content, and γ_i refers to individual fixed effect. Note that we do not include book fixed effect in this analysis as our variables of interest includes time-invariant e-book characteristic (i.e., length of book). Dependent variables are the total number of words consumed ($ConsumptionQuantity$), the ratio of the number of consumed episodes ($ProgressionRates$). Our model is a function of whether content is largely partitioned (i.e., $LargePartitioning$), and content characteristics, such as existing review volume (i.e., $ReviewVolume$), valence (i.e., $ReviewRating$), and length (i.e., $Length$). We additionally controlled whether a consumer purchased entire series ($SeriesOrder$), sales price ($Price$), discount offered to a consumer ($Discount$), the number of days elapsed since the content was released ($PublishDate$), and consumption initiation time (i.e., $Month$, Day, and $Hour$). Also, in order to examine how the content partitioning effect is moderated by content characteristics, we interact $LargePartitioning$ with content characteristics variables (i.e., $ReviewVolume,\ ReviewRating,\ Length$).

Appendix H. Moderating Effects on Post-Consumption Activities

We turn our attention to moderating effect of content characteristics on consumer engagement. The estimated results of interaction between $LargePartitioning$ and online reviews (i.e., $ReviewVol$ and $ReviewVal$) in Table H-1 are positive and significant, suggesting that the positive effect of $LargePartitioning$ on engagement is accentuated with review volume and review valence. In other words, consumers tend to exhibit higher consumption engagement when they read popular and high-quality content of LP. Lastly, the estimated coefficient of interaction between $LargePartitioning$ and $BookLength$ in third column is negative and significant at 0.01 level, indicating that the positive effect of $LargePartitioning_{ij}$ is attenuated with longer e-book content.

Table H-1. Estimated Results for Moderating Effect of Content Characteristics on Reviewing Behavior

Variables	Consumption Intensity	Reviewing	Review Length	Review Informativeness	Review Valence
LP	0.473***	0.236***	0.353***	1.107***	0.0649***
	(0.0388)	(0.051)	(0.0630)	(0.333)	(0.00205)
$ReviewVolume$	0.000359***	0.002***	0.001*	0.00020***	0.19e05***
	(2.20e-05)	(0.000)	(0.001)	(0.02e-05)	(2.18e-06)
$ReviewRating$	0.371***	0.114*	0.007*	0.163*	0.0781***
	(0.0483)	(0.051)	(0.002)	(0.080)	(0.00581)
$Length$	-2.91e-06***	-6.17e-06***	-0.38e-07***	-0.023	9.83e-08***
	(1.53e-07)	(1.26e-06)	(0.06e-07)	(0.0247)	(1.86e-08)
$LP * ReviewVolume$	0.00110***	0.001***	0.000***	0.000343***	2.46e-05***
	(0.000375)	(4.03e-05)	(4.20e-05)	(9.24e-05)	(1.29e-06)
$LP * ReviewRating$	0.448***	0.473***	0.002*	0.636***	0.0561***
	(0.111)	(0.047)	(0.001)	(0.126)	(0.00161)
$LP * Length$	-3.98e-06***	1.85e-06***	4.75e-08	1.33e-07	6.99e-08***
	(3.50e-07)	(4.92e-07)	(3.19e-07)	(9.40e-07)	(9.82e-09)
$Price$	0.000194***	0.001***	0.000***	1.88e-05	-6.16e-06***
	(1.75e-05)	(6.26e-05)	(3.31e-05)	(0.000141)	(1.02e-06)
$Discount$	-1.36e-05	-0.011***	-0.003***	0.001***	1.43e-05***
	(1.74e-05)	(5.37e-05)	(3.28e-05)	(0.000)	(1.01e-06)
$PublishDate$	9.65e-05***	-8.44e-05***	-1.93e-05*	-0.000***	-3.33e-05***
	(6.25e-06)	(2.96e-05)	(1.17e-05)	(6.64e-05)	(3.48e-07)
$SeriesOrder$	0.234***	-0.242***	0.241**	0.456*	0.0160***
	(0.0460)	(0.048)	(0.112)	(0.196)	(0.00345)
IMR			-0.037***	-0.050***	-0.021***
			(0.002)	(0.002)	(0.005)
Constant	1.262***	-4.698***	0.076***	-1.380***	0.0252***
	(0.0430)	(0.055)	(0.022)	(0.122)	(0.000674)
Individual FE	Yes	Yes	Yes	Yes	Yes
Observations	127,524	127,52	11,799	11,799	11,799
R-squared			0.133		0.268

*Standard errors are in parenthesis: ***p<0.01,**p<0.05, *p<0.1.*

We further examine the moderating effect of content on the effectiveness of content partitioning on reviewing behavior (Table H-1). In respect to review entry decision, both interaction effects of $LargePartitioning$ and online reviews (i.e., $ReviewVol$ and $ReviewVal$) in second column are positive and significant at 0.01, suggesting that the positive effect of $LargePartitioning$ is accentuated with review volume and valence. In addition, the estimated coefficient of interaction between

$LargePartitioning$ and $Length$ is positive and significant at 0.01 level, indicating that the positive effect of $LargePartitioning$ is pronounced with longer content. In respect to informativeness of reviews (i.e., review length and review topic), the estimated coefficients of interaction between $LargePartitioning$ and online reviews (i.e., $ReviewVol$ and $ReviewVal$) in both third and fourth columns are positive and significant, suggesting that positive effect of $LargePartitioning$ on the informativeness of reviews is further enhanced with popularity and quality of e-book content. On the other hand, the estimated coefficients of interaction between $LargePartitioning$ and $Length$ are insignificant in respect to both review length and review topic, suggesting that the moderating effect of content length is insignificant.

In regards to review valence, the interaction terms of $LargePartitioning$ and online reviews (i.e., $ReviewVol$ and $ReviewVal$) in fourth column are positive and significant, indicating that the positive effect of $LargePartitioning$ on individual' satisfaction and assessment are accentuated with e-book popularity or quality. In addition, the positive effect of $LargePartitioning$ on consumers' review rating is further increased with the length of the book. In summary, the positive effect of $LargePartitioning$ on consumers' post-consumption assessment is more likely to be heightened with greater review volume (i.e., book popularity) and review valence (i.e., book quality). On the other hand, the interaction effect of length of the content is limited to review entry and rating behavior.

Lastly, in respect to repurchase (Table H-2), the estimated coefficient of interactions between $LargePartitioning$ and online reviews (i.e., $ReviewVol$ and $ReviewVal$) are both positive and significant at 0.01 level, indicating that the positive effect of $LargePartitioning$ on repurchase is enhanced with popularity and quality of content. In addition, the interaction between $LargePartitioning$ and $Length$ is negative and significant at 0.01 level, suggesting that the positive effect of $LargePartitioning$ diminished with length of content. Comprehensively, our findings reveal that digital content with high popularity, high quality, and low length strengthens the spillover effects of high consumption satisfaction and perceived self-efficacy for experiencing reading, which is driven by LP, thereby accelerating subsequent purchase.

Table H-2. Estimated Results for Moderating Effect of Content Characteristics on Purchase

Variables	Purchase
LP	0.325***(0.0246)
$ReviewVolume$	0.003***(0.000)
$ReviewRating$	0.0038***(0.001)
$Length$	-0.444***(0.044)
$LP * ReviewVolume$	0.004***(0.000)
$LP * ReviewRating$	0.077***(0.017)
$LP * Length$	-0.018***(0.002)
$Price$	-3.12e-05***(7.99e-06)
$Discount$	0.072***(0.010)
$PublishDate$	-0.000***(5.31e-06)
$SeriesOrder$	-0.105***(0.020)
IMR	0.071***(0.005)
Individual FE	Yes
Observations	127,524

*Standard errors are in parenthesis: ***p<0.01,**p<0.05, *p<0.1.*

Appendix I. Specification of the Cox Model.

In order to explore consumers' subsequent purchase, we employed survival analyses and scrutinized such behavior patterns with respect to content partition. Specifically, we utilized the extended Cox model characterized by shared frailty (Kleinbaum 2012) to reflect right censoring in our data and time-varying covariates in our model (Scherer et al. 2015).

We employed the proportional hazard model, which enables researchers to leave underlying survival functions unspecified while we can obtain accurate results. In our dataset, each observation was considered an at-risk event following consumer making subsequent purchase after finishing focal content at some time t_0. If a consumer decides to purchase subsequent series of content, the event is regarded as "failed" at time t. We incorporated time-varying covariates into our model to examine the dynamic effects of variables on survival time. In this regard, we specified our proportional hazard models as follows:

$$h_i(t, X) = h_0(t)\exp(\beta X)$$

where $h_0(t)$ describes the baseline hazard function at time t, and βX shows the effects of covariates X. Covariates X encompasses whether the content is partitioned into LP and content attributes. We used Efron (1977) estimation method to take account for the times at which failures occur. This approach allowed us to direct attention to failures that transpire at the same time—an orientation that yields results that are more accurate than those obtained with the Breslow approximation (Cleves et al. 2008; Sherer et al. 2015) which is most widely used method in estimating proportional hazard model.

We also take account for the unobserved heterogeneity shared by individuals who consume same serialized content. In the survival analysis, frailty is analogous to latent random effects, for which within-group correlation was considered in our model. The modeling conducted in this work allowed individual consumers within each serialized content group to share the same level of frailty, wherein unobserved heterogeneity may be common to all serialized content group. The hazard model that was incorporated with shared frailty (α_j)can be specified as:

$$h_i(t|\alpha_j, X) = h_0(t)\alpha_j exp(\beta X)$$

$$\beta X = \beta_0 + \beta_1 LargePartitioning_{ij} + \beta_2 ReviewVolume_{ij} + \beta_3 ReviewRating_{ij} + \beta_4 Length_j$$

$$+ \beta_5 Price_j + \beta_6 Discount_{ij} + \beta_7 PublishDate_{ij} + \beta_8 SeriesOrder_{ij} + \gamma_i + \eta_j + \varepsilon_{ij}$$

where α_j represents the shared frailty of consumers (i) across serialized content (j), which was assumed to be gamma distributed with a mean value equal to 1 and a variance equal to θ.

Reference:

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Appendix J. Moderating Effects of Genre

First, we recognize that the e-book platform we collaborated with offers serialized digital formats exclusively within three genres— romance, fantasy, and chivalrous fiction—all encompassing content centered around hedonic pleasure. Our analysis focused on examining the interaction between *Genre* and *LP*, investigating how the impact of content partitioning varies across these three genres. However, our findings indicate that there is no discernible differential impact among the different genres.

To delve into the heterogenous effects of partitioning across distinct categories, we extended our analysis by exploring the interaction between the *Adult* variable and *LP*. The *Adult* variable indicates a binary classification reflecting whether a fiction is intended for adults or not. Adult fiction, tailored for individuals over 19, generally features more provocative and sexual narratives, aligning with a more *hedonic-oriented* content classification (Illouz 2014 and Leitenberg et al. 1995) compared to non-adult fiction. The results, presented in Tables M1 and M2, reveal that the effects of LP on strategic and skipping consumptions are heightened within the adult category. Here, the consumption quantity decreases while the progression rate increases under adult fiction. Furthermore, the positive effects of LP on consumption engagements and activities are amplified within the adult category. This manifests as an increased likelihood of engagements, higher rates of review submission, longer review lengths, improved review, and an elevated probability of subsequent purchases, particularly within the realm of adult fiction.

These findings contribute empirical support to the theoretical argument that granular partitioning (SP) could be suboptimal for *hedonic-oriented* digital content. The adverse impacts of SP, as opposed to LP, on strategic consumption, engagement, reviews, and purchases are particularly evident in content categories driven by hedonic pleasure. Segmentation appears to impede an individual's seamless immersion and strategic consumption, hindering the effective pursuit of pleasure and emotional satisfaction.

Table J1. The Interaction Effects of Content Partitioning and Genre on Consumption Patterns

Variables	Consumption Quantity	Progression Rates
LP	-0.459*** (0.036)	0.139***(0.029)
$LP * Adult$	-0.017*** (0.005)	0.016*** (0.003)
$Adult$	0.045*** (0.002)	0.003***(0.000)
$ReviewVolume$	0.268*** (0.011)	0.196***(0.033)
$ReviewRating$	0.069***(0.003)	0.041***(0.003)
$Discount$	4.11e-06 (5.97e-06)	3.48e-06 (3.11e-06)
$PublishDate$	0.000 (0.001)	0.000 ***(2.13e-05)
$SeriesOrder$	0.398*** (0.021)	0.478*** (0.085)
Constant	1.159***(0.029)	2.265***(0.154)
Individual FE	Yes	Yes
Observations	100,616	100,616
R-squared	0.119	0.153

*Standard errors are in parenthesis: ***p<0.01,**p<0.05, *p<0.1. We indicate LargePartitioning as LP. The robust standards errors are clustered at both the individual level and the book level. Note that we do not include book fixed effect in this analysis as our variable of interest includes time-invariant e-book characteristic (i.e., Adult).*

Table J2. The Interaction Effects of Content Partitioning and Genre on Engagement and Purchase						
Variables	Consumpt Intensity	Reviewing	Review Length	Review Informat	Review Valence	Purchase
LP	0.422***	3.163***	0.355***	0.124**	0.159***	0.489***
	(0.102)	(0.541)	(0.046)	(0.052)	(0.021)	(0.051)
$LP * Adult$	0.058***	0.652***	0.455***	1.536**	0.645***	0.185***
	(0.005)	(0.055)	(0.012)	(0.862)	(0.110)	(0.045)
$Adult$	-0.012***	0.021***	-0.001***	0.002***	0.003***	0.005***
	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.001)
$ReviewVol$	0.009***	0.001***	0.008***	3.45e-04***	3.48e-04***	5.44e-04***
	(0.001)	(4.11e-05)	(0.000)	(5.16e-05)	(2.46e-05)	(2.12e-05)
$ReviewRat$	0.845***	0.562***	0.555***	0.666***	0.556***	3.481***
	(0.133)	(0.106)	(0.046)	(0.145)	(0.061)	(0.041)
$Discount$	0.002*	-1.942e-04***	-1.41e-04***	-6.64e-04***	2.19e-04***	4.34e-04***
	(0.002)	(2.946e-05)	(1.23e-05)	(9.12e-05)	(1.51e-05)	(1.14e-05)
$PublishDate$	0.004***	-1.51e-04***	-1.92e-04***	-2.65e-04***	-8.26e-05***	-0.002***
	(0.001)	(3.00e-05)	(9.08e-06)	(5.16e-05)	(2.11e-05)	(4.54e-06)
$SeriesOrder$	0.516***	0.645***	0.311***	0.648***	0.446***	0.487***
	(0.088)	(0.071)	(0.046)	(0.152)	(0.112)	(0.061)
IMR			-0.682***	0.210	-0.145	-0.755***
			(0.016)	(0.200)	(0.222)	(0.051)
Constant	1.035***	-11.462***	0.123**	-3.482***	0.030***	
	(0.021)	(2.123)	(0.017)	(1.044)	(0.002)	
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	127,524	127,524	11,799	11,799	11,799	127,524
R-squared	0.128		0.125		0.121	
Log-likelihood		-6,567		-1,528		

*Standard errors are in parenthesis: ***p<0.01,**p<0.05, *p<0.1. We indicate LargePartitioning as LP. The robust standards errors are clustered at both the individual level and the book level. Note that we do not include book fixed effect in this analysis as our variable of interest includes time-invariant e-book characteristic (i.e., Adult).*

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Appendix K. The Effects of Content Partitioning on Reading Concentration

We conducted additional tests to explore the underlying mechanisms of consumers' consumption behavior under different content partitions, focusing on their reading concentration. The key mechanism we propose regarding consumers' responses to various content installments is that small partitions may more effectively alleviate cognitive load, encouraging consumers to fully engage with the content and thereby enhancing consumption quantity. Conversely, large partitions may induce psychological overwhelm due to the presentation of voluminous text, prompting strategic consumption and higher progression rates compared to small partitions. In line with this argument, we scrutinized consumers' reading concentration under different partitioning structures.

To gauge reading concentration, we utilized the number of interruptions as an operational metric. This measure is captured when a consumer closes an e-book file while the reading program is running in the background, indicating the use of other applications. For instance, if a consumer receives a phone call while reading an e-book, our tracking feature records the moment the individual closes the e-book file to answer the call. To ensure that the number of interruptions is not confounded by book length, we normalized the interruptions by the number of words in each episode. Additionally, given that each title of serialized content comprises multiple episodes, we computed the average value of the normalized interruptions across episodes for each title. The estimated results of these analyses are presented in Table K.

Table K. Estimated Results for the Effect of Content Partitioning on Reading Concentration

Variables	Number of Interruption
LP	0.104**(0.0416)
$ReviewVol$	-0.008**(0.004)
$ReviewRat$	-0.222***(0.0414)
$Discount$	0.056(0.038)
$PublishDate$	0.555**(0.262)
$SeriesOrder$	-0.001***(0.000)
Constant	-1.256*** (0.359)
Individual FE	Yes
Book FE	Yes
Observations	127,524
R-squared	0.056

*Standard errors are in parenthesis: ***p<0.01,**p<0.05, *p<0.1. We indicate LargePartitioning as LP. The robust standards errors are clustered at both the individual level and the book level.*

The results reveal that the number of interruptions increases with LP, indicating that consumers who consume content in a large partition experience more frequent stoppages. In other words, consumers who read small-partitioned content are more likely to exhibit a higher level of reading concentration, allocating more cognitive resources to the consumption of each episode. This finding lends suggestive support to our theoretical arguments, suggesting that the recognition of short length (i.e., SP) through sensory cues encourages consumers to fully dedicate cognitive resources to the consumption of each episode. This observed behavior indicates that consumers, influenced by the cognitive architecture established through partitioning, actively manage their mental resources and adapt their consumption strategies. Such adjustments have a direct impact on the level of attention and enthusiasm directed toward the consumption of the product, providing valuable insights into the intricate relationship between partitioning structures and consumer engagement.

Appendix L. The Effects of Content Partitioning on Review Sentiment and Quality

Employing Natural Language Processing (NLP) techniques, we investigate review quality in terms of valence and informativeness. Specifically, we employed the Stanford CoreNLP sentiment analysis tool to measure the sentiment of online consumer reviews, adhering to advanced methodological standards to ensure robust and accurate sentiment assessment (Oh et al. 2023). The process commenced with the collection of textual content from consumer reviews, followed by a meticulous preprocessing phase, such as HTML tags, special characters, and stop-words.

Subsequently, the cleaned text was segmented into individual sentences, as the Stanford CoreNLP tool operates at the sentence level for sentiment classification. Utilizing the pre-trained Stanford CoreNLP sentiment model, which leverages a recursive neural network (RNN) architecture, we classified each sentence into one of five sentiment categories: -2 (very negative), -1 (negative), 0 (neutral), 1 (positive), and 2 (very positive). The RNN model is adept at capturing compositional semantic nuances within sentences, thus significantly enhancing prediction accuracy compared to traditional classification methods.

To validate the performance of our sentiment classifier, we conducted fivefold cross-validation, following the rigorous methodology outlined by Oh et al. (2023). The cross-validation results indicated a prediction accuracy of 74.9%, surpassing the performance metrics typically reported in previous machine learning literature for similar sentiment classification tasks, such as those by Lin et al. (2020). This robust validation underscores the reliability of the CoreNLP tool in sentiment analysis.

For each consumer review, we aggregated the sentence-level sentiment scores to derive an overall sentiment score. This aggregation involved averaging the sentiment scores across all sentences within a review, resulting in a continuous sentiment score that accurately reflects the overall sentiment expressed in the review. This method ensures that the sentiment measures are both comprehensive and precise. The results, presented in Table L-1, show that the estimated coefficient of LP is positive and significant at 0.01 level. This pattern suggests that consumers who consume LP are more likely to generate positive reviews. These results are consistent with our previous analyses, indicating that consumers reading serialized content in LP structures are more likely to produce reviews with a higher valence.

Table L-1. Estimated Results for the Effect of Content Partitioning on Review Sentiment

Variables	$Sentiment$
LP	0.514***(0.031)
$ReviewVol$	0.189***(0.056)
$ReviewRat$	0.012***(0.001)
$Discount$	5.62e-06(6.48e-05)
$Publish$	0.000***(1.33e-05)
$SeriesOrd$	-0.529***(0.091)
IMR	-0.019*** (0.005)
Constant	5.196***(0.499)
Individual FE	Yes
Book FE	Yes
Observations	11,799
R-squared	0.113

*Standard errors are in parenthesis: ***p<0.01,**p<0.05, *p<0.1. We indicate LargePartitioning as LP. The robust standards errors are clustered at both the individual level and the book level.*

Furthermore, we delved into online consumer reviews using text-mining analysis to assess information richness in review content, referring to the extent of objective information encompassing details about the author, story, and characters. Following a method similar to those implemented by previous studies (e.g., Ross 2000), we constructed a variable denoting the quality of reviews by counting the number of words related to keywords (i.e., character, style, story, genre, author, publisher) in reviews. This approach is consistent with Goh et al. (2013), who measured review informativeness by counting the number of concepts extracted from online review content. Additionally, Healey and Kassarjian (1983) found that the number of concepts, such as price and quality, in advertisements indicates information richness. Therefore, a higher number of concepts embedded in reviews suggests a greater likelihood of the content delivering valuable and specific information about the products. The results, presented in Table L-2, reveal that the estimated coefficient of LP is positive and significant at 0.01 level. This suggests that reviews generated after consumption of LP contain more useful insights, including information about the author, story, and characters, compared to reviews generated after the consumption of SP.

Table L-2. Estimated Results for the Effect of Content Partitioning on Review Quality

Variables	Information Richness
LP	0.435***(0.041)
$ReviewVol$	0.000***(4.39e-05)
$ReviewRat$	0.133***(0.016)
$Discount$	0.003***(0.000)
$Publish$	0.555**(0.262)
$SeriesOrder$	0.298**(0.117)
IMR	0.031*** (0.002)
Constant	-2.958*** (0.718)
Individual FE	Yes
Book FE	Yes
Observations	11,799
R-squared	0.089

*Standard errors are in parenthesis: ***p<0.01,**p<0.05, *p<0.1. We indicate LargePartitioning as LP. The robust standards errors are clustered at both the individual level and the book level.*

In summary, our findings collectively indicate that LP leads to more informative and positive reviews, whereas SP induces less informative and less positively driven evaluations. Importantly, these results provide empirical evidence supporting the mechanism explaining why LP leads to higher-quality reviews compared to SP. We established that LP prompts consumers to adopt a strategic and expedited consumption approach, focusing on main ideas and narratives. Consumers under LP are more likely to concentrate on core storylines and skim through peripheral narratives as they are motivated to digest the entire story. Consequently, LP-driven online reviews, crafted based on a comprehensive understanding of main storylines, are expected to be more informative than those rooted in partial consumption of the initial stage of the story (Lee et al. 2021).

For experienced goods, such as fiction, customers derive entertainment value from non-instrumental information in the form of suspense and surprise (Ely et al. 2015) or fantasy, emotional stimulation, and enjoyment (Hirschman et al. 1982). SP-based incomplete partial consumption hinders consumers from experiencing a full course of emotional stimulation and intensified excitement. Additionally, as consumers only partially engage with a book, they are unable to unfold specific details regarding characters and narratives (Lee et al. 2021). Conversely, consumers who comprehensively understand a serialized story under LP fully experience an array of features, ensuring suspense and surprise from the beginning to the end of the book. Consequently, they are more deeply immersed in the book and more willing to express their feelings and emotions about its characters and narratives (Lee et al. 2021).

The positive sentiment observed in LP-driven reviews further supports our theoretical argument concerning perceived self-efficacy. As outlined earlier, we proposed that consumers engaging with LP perceive the acquisition of a relatively higher extent of knowledge about a book (i.e., high self-efficacy) due to the further progression they achieve compared to consumers of SP. Given that perceived self-efficacy is directly correlated with positive evaluation and happiness (Caprara et al. 2006), individuals with higher self-efficacy are more likely to submit reviews based on positive sentiment, as empirically confirmed by our sentiment analyses. In conclusion, these findings provide evidence about what readers specifically comment on and why LP leads to higher-quality reviews.

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Appendix M. The Effects of Content Partitioning on Sales

We conducted additional analyses to delve deeper into the economic impact of content partitioning, specifically focusing on revenue dynamics. The sales *revenue*, measured in USD, represents the amount consumers paid to acquire serialized content. The results are presented in Table M, illustrating the monthly sales revenue in USD. Our findings indicate that LP outperforms SP in generating higher sales revenue. In this context, higher sales revenue implies that consumers advance further by purchasing subsequent episodes. It is noteworthy that our emphasis was on content that was nearly freely available to minimize potential concerns arising from pricing effects. While all other factors are held constant, the implementation of LP yields a monthly revenue per serialized book that is \$0.705 higher than that of SP installments. Considering that the mean price of a serialized book in our sample was \$0.84, the difference of \$0.705 per title is not inconsequential. This observation is consistent with our earlier findings related to subsequent purchases, consolidating the understanding that LP enhances consumer progression.

Table M. Estimated Results for Sales Effect

Variables	Sales (USD)
LP	0.705*** (0.0972)
$ReviewVolume$	0.024*** (0.009)
$ReviewRating$	1.055* (0.612)
$Discount$	0.167*(0.097)
$PublishDate$	-0.015*** (0.002)
Constant	5.860 (5.215)
Book FE	Yes
Observations	16,170
R-squared	0.086

*Standard errors are in parenthesis: ***p<0.01,**p<0.05, *p<0.1. We indicate LargePartitioning as LP.*

Appendix N. Testing Strategic Consumption Behaviors with Alternative Consumption Variables

As noted earlier, individuals occupied with LP structures (vs. SP) are predisposed to consume less content but achieve higher progression rates. To validate such consumption patterns, we used the average consumption rate per episode ($ConsumptionRateAvg$) and the variation in consumption rate per episode ($ConsumptionRateVar$) as parameters that set conditions for a given behavior. Note that both variables capture skipping behaviors, thereby determining the extent to which consumers consciously and independently control serialized consumption. Table N reports the estimation results. In terms of the average consumption rate per episode ($ConsumptionRateAvg$), the estimated coefficient of LP is negative and significant at the 0.01 level, indicating that consumers indulge a propensity to reduce the consumption of each episode when they engage with LP content. The finding suggests that LP more structurally triggers skipping behaviors than does SP under serialized consumption. As for variations in episode consumption rate ($ConsumptionRateVar$), the estimated coefficient of LP is positive and significant at the 0.01 level, implying that consumers more strongly tend toward selective episode consumption when reading LP arranged episodes. In summary, both results consistently provided strong evidence of consumption skipping among readers when LP content is consumed. These findings suggest that LP induces individuals to exhibit self-imposed selective consumption patterns based on their utility compared to SP.

Table N. Estimated Results for Skipping Behaviors

Variables	Consumption Rate Avg.	Consumption Rate Var.
LP	-0.672***(0.576)	0.244***(0.0124)
$ReviewVolume$	0.00411***(0.000617)	0.000502***(1.33e-05)
$ReviewRating$	0.080***(0.0209)	1.469***(0.0260)
$Length$	1.94e-06(4.57e-06)	8.68e-07***(9.84e-08)
$Price$	0.00105**(0.000482)	6.48e-06(1.04e-05)
$Discount$	-0.000225(0.000481)	-5.52e-05***(1.03e-05)
$PublishDate$	0.00363***(0.000171)	0.000308***(3.69e-06)
$SeriesOrder$	0.307(1.646)	-0.118***(0.0354)
Constant	5.695***(0.322)	2.543***(0.00693)
Individual FE	Yes	Yes
Observations	127,524	127,524
R-squared	0.107	0.122

*Standard errors are in parenthesis: ***p<0.01,**p<0.05, *p<0.1. We indicate LargePartitioning as LP.*

Appendix O. Addressing Confounding Effects of Pricing Strategy

- *Subsample Analyses: Free Content*

Another potential confounding issue in our analyses may arise from the differences in pricing schemes for each episode between LP and SP. To further verify the effect of LP on consumption patterns and subsequent engagement activities, we conducted robustness check by leveraging subsamples of serialized content which were freely available during the data collection period. Specifically, we collected data on 940 serialized e-book titles that were freely available in the platform. ABC Books allows members to freely download serialized content in an effort to attract customers to their sites and retain them. When controlling for price issues, we could resolve the potential selection concern driven by pricing differences between LP and SP episodes. Table O-1 and Table O-2 reports results of the robustness check by using samples of serialized content which were offered free. The estimated coefficients of LP are qualitatively consistent with those in main analyses, corroborating our main findings.

Table O-1. Estimated Results for Free Sample Analyses on Consumption Patterns

Variables	Consumption Quantity	Progression Rates
LP	-0.159***(0.011)	0.959***(0.154)
$ReviewVolume$	0.048*** (0.011)	0.206***(0.049)
$ReviewRating$	0.022**(0.002)	0.041***(0.005)
$Discount$	-1.58e-05(3.58e-05)	-3.87e-05(2.97e-05)
$PublishDate$	0.000 (0.000)	0.000***(2.75e-05)
$SeriesOrder$	0.516*** (0.048)	0.379*** (0.042)
Constant	0.131***(0.002)	1.246***(0.341)
Individual FE	Yes	Yes
Book FE	Yes	Yes
Observations	57,711	57,711
R-squared	0.115	0.125

*Standard errors are in parenthesis: ***p<0.01,**p<0.05, *p<0.1. We indicate LargePartitioning as LP. The robust standards errors are clustered at both the individual level and the book level.*

Table O-2. Estimated Results for Free Sample Analyses on Engagement and Purchase

Variables	Consump. Intensity	Reviewing	Length	Informat	Valence	Purchase
LP	0.485***	0.265**	0.415***	0.546***	0.157***	0.249***
	(0.059)	(0.111)	(0.106)	(0.115)	(0.031)	(0.054)
$ReviewVol$	0.001***	0.004***	0.005***	0.006***	2.46e-05***	0.004***
	(2.85e-05)	(1.26e-05)	(2.11e-05)	(2.45e-05)	(1.05e-06)	(0.000)
$ReviewRat$	0.044***	0.123***	0.274***	0.512**	0.166***	0.003***
	(0.015)	(0.011)	(0.045)	(0.144)	(0.005)	(0.000)
$Discount$	0.000***	-0.001***	-0.005***	0.001***	1.44e-05***	0.041***
	(1.11e-05)	(2.19e-05)	(2.11e-05)	(0.000)	(1.15e-06)	(0.003)
$Publish$	1.59e-05***	-1.64e-05***	-2.41e-05***	-0.000***	-1.69e-05***	-0.000***
	(2.41e-06)	(3.45e-06)	(4.64e-06)	(1.46e-05)	(2.45e-07)	(2.14e-06)
$Series$	0.678***	-0.177**	0.225	0.111	0.132***	-0.645***
	(0.105)	(0.066)	(0.244)	(0.147)	(0.006)	(0.045)
IMR			-0.562***	-0.356***	-0.113***	0.111***
			(0.106)	(0.045)	(0.045)	(0.031)
Constant	1.546***	-1.154***	0.516***	-1.155***	0.071***	
	(0.205)	(0.028)	(0.166)	(0.305)	(0.022)	

Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes
Book FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	57,711	57,711	8,965	8,965	8,965	57,711
R-squared	0.078		0.054		0.103	
Log-likelihood		-8,425		-8,895		

*Standard errors are in parenthesis: ***p<0.01,**p<0.05, *p<0.1. We indicate LargePartitioning as LP. The robust standards errors are clustered at both the individual level and the book level.*

- *Subsample Analyses: Entire Series Purchase Occasions*

One may argue that consumers' consumption decision may be influenced by the pricing structure of individual episodes, with small-partitioning formats yielding a lower cost per episode compared to larger partitioning formats. As noted earlier, the total price to be paid to purchase the entire series is identical between LP and SP, but each episode price differs due to the partitioning. We conducted a robustness check to investigate whether disparate episode prices in different partitioning arrangements impact the observed findings. Specifically, we examined a subsample consisting of cases where consumers ordered entire series at once. When a consumer instantly pays for the entire series, the price per episode is unlikely to influence his/her consumption decisions. Upon re-running the main model with this subsample, the results, detailed in Table O-3 and Table O-4, demonstrate that the estimated coefficients are qualitatively consistent with the main analyses. The findings suggest that variations in the price per episode between different partitioning arrangements are unlikely to sway consumers' consumption decisions.

Table O-3. Estimated Results for Subsample of Total Order Occasions on Consumption Patterns

Variables	Consumption Quantity	Progression Rates
LP	-0.660***(0.158)	0.854***(0.0975)
$ReviewVolume$	0.175*** (0.014)	0.177***(0.089)
$ReviewRating$	0.014**(0.005)	0.043***(0.003)
$Discount$	-2.43e-05(5.38e-05)	-2.45e-05(3.32e-05)
$PublishDate$	0.000116 (7.04e-05)	0.000122***(4.34e-05)
$SeriesOrder$	0.215*** (0.035)	0.388*** (0.067)
Constant	1.653***(0.0926)	3.251***(0.0571)
Individual FE	Yes	Yes
Book FE	Yes	Yes
Observations	100,616	100,616
R-squared	0.108	0.154

*Standard errors are in parenthesis: ***p<0.01,**p<0.05, *p<0.1. We indicate LargePartitioning as LP. The robust standards errors are clustered at both the individual level and the book level.*

Table O-4. Estimated Results for Subsample of Total Order Occasions on Engagement

Variables	Consump. Intensity	Reviewing	Length	Inform	Valence	Purchase
LP	0.596***	0.175***	0.077***	0.567***	0.352***	0.596***
	(0.074)	(0.025)	(0.021)	(0.101)	(0.044)	(0.046)
$ReviewVol$	0.000***	0.008***	0.001***	0.001***	5.16e-05***	0.007***
	(4.05e-05)	(1.59e-05)	(2.61e-05)	(3.48e-05)	(1.44e-06)	(0.000)
$ReviewRat$	0.058**	0.177***	0.211***	0.695**	0.077***	0.005***
	(0.035)	(0.015)	(0.019)	(0.289)	(0.003)	(0.001)
$Discount$	0.000***	-0.001***	-0.009***	0.001***	1.41e-05***	0.028***
	(1.26e-05)	(2.56e-05)	(2.09e-05)	(0.000)	(1.08e-06)	(0.001)

$Publish$	1.12e-05***	-2.15e-05***	-2.69e-05***	-0.000***	-1.25e-05***	-0.000***
	(1.25e-06)	(2.48e-06)	(4.51e-06)	(2.44e-05)	(1. 47e-07)	(2.99e-06)
$Series$	0.211***	-0.285**	0.526*	0.114	0.085***	-0.165***
	(0.051)	(0.045)	(0.358)	(0.263)	(0.005)	(0.021)
IMR			-0.256***	-0.344***	-0.112***	0.516***
			(0.022)	(0.026)	(0.019)	(0.044)
Constant	3.512***	-1.895 ***	0.184***	-1.946***	0.425***	
	(0.551)	(0.246)	(0.041)	(0.345)	(0.120)	
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Book FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	100,616	100,616	7,279	7,279	7,279	100,616
R-squared	0.087		0.099		0.151	
Log-likelihood		-9,485		-1.279		

*Standard errors are in parenthesis: ***p<0.01,**p<0.05, *p<0.1. We indicate LargePartitioning as LP. The robust standards errors are clustered at both the individual level and the book level.*

Appendix P. Addressing Confounding Effects of Online Reviews

To address concerns related to this issue, we implemented a robustness check by comparing the consumption patterns of early-stage adopters of serialized content with those who adopted the content at a later stage after its publication. This approach stems from the understanding that online reviews tend to be less abundant in the early stages of publication compared to later stage. We first identified serialized content with at least one online consumer review generated within the data period. Subsequently, we subsampled consumption observations of consumers who purchased and consumed the serialized content within a 2-week window following publication, a period when online reviews are less likely to be available. In addition, we extracted consumption observations of consumers who purchased and consumed the serialized content after a 2-month interval following publication. The analysis revealed that 98% of consumers in the early adopter group acquired the serialized content when online consumer reviews were unavailable, while 96% of consumers in the later group made their purchases when online consumer reviews were accessible. We specify the model as follows:

$$ConsumptionPatterns_{ij} = \beta_0 + \beta_1 LargePartitioning_{ij} + \beta_2 LargePartitioning_{ij} * EarlyAdopt_i + \beta_3 EarlyAdopt_i + \beta_4 Discount_{ij} + \beta_5 PublishDate_{ij} + \beta_6 SeriesOrder_{ij} + \gamma_i + \theta_j + \varepsilon_{ij}$$

where i denotes an individual, j represents serialized content, and γ_i and θ_j refer to individual and e-book fixed effects, respectively. $EarlyAdopt_i$ equals to 1 if a consumer purchased and consumed the serialized content within 2 weeks after its publication. The coefficient β_2 captures the differential impact of LP contingent on variations in adoption periods, specifically between early adopters and later adopters, where online consumer reviews were inaccessible to the former group but available to the latter. The results are presented in Table P-1 and Table P-2. The estimated coefficient for the interaction between $LargePartitioning_{ij}$ and $EarlyAdopt_i$ is statistically insignificant, suggesting that there is no differential impact of LP depending on whether online reviews are available to consumers. These results mitigate concerns related to potential confounding effects of online reviews.

Table P-1. Results for Robustness Checks for Review Confounding Effects on Consumption Patterns

Variables	Consumption Quantity	Progression Rates
LP	-0.794*** (0.0222)	0.308*** (0.0136)
$LP * EarlyAdopt$	-0.006 (0.036)	0.005 (0.0219)
$EarlyAdopt$	0.883*** (0.164)	0.485*** (0.035)
$Discount$	0.000*** (1.77e-05)	1.92e-05* (1.08e-05)
$PublishDate$	0.000*** (1.76e-05)	0.000*** (3.71e-06)
$SeriesOrder$	0.304*** (0.0604)	0.403*** (0.0369)
Constant	1.454*** (0.0117)	3.353*** (0.00714)
Individual FE	Yes	Yes
Book FE	Yes	Yes
Observations	10,153	10,153
R-squared	0.114	0.163

*Standard errors are in parenthesis: ***p<0.01,**p<0.05, *p<0.1. We indicate LargePartitioning as LP . The robust standards errors can be clustered at both the individual level and the book level.*

Table P-2. Results for Robustness Checks for Review Confounding Effects on Engagement

Variables	Consump.	Reviewing	Length	Inform	Valence	Purchase

	Intensity					
LP	0.158***	0.074***	0.059***	0.195***	0.154***	0.341***
	(0.011)	(0.013)	(0.005)	(0.023)	(0.028)	(0.055)
$LP * EarlyAdopt$	0.000	0.015	0.001	0.004	0.017	0.000
	(0.021)	(0.033)	(0.002)	(0.004)	(0.021)	(0.000)
$EarlyAdopt$	0.045	0.000	0.005	0.003	0.000	0.001
	(0.055)	(0.001)	(0.013)	(0.003)	(0.000)	(0.000)
$Discount$	0.000***	-0.005***	-0.007***	0.005***	2.16e-05***	0.032***
	(2.03e-05)	(2.11e-05)	(1.50e-05)	(0.000)	(1.12e-06)	(0.003)
$Publish$	2.62e-05***	-2.08e-05***	-1.52e-05***	-0.000***	-2.16e-05***	-0.000***
	(1.50e-06)	(2.21e-06)	(2.11e-06)	(5.16e-05)	(1. 99e-07)	(2.74e-06)
$Series$	0.425***	-0.163**	0.455*	0.111	0.074***	-0.425***
	(0.053)	(0.054)	(0.516)	(0.216)	(0.003)	(0.015)
IMR			-0.415***	-0.415***	-0.159***	0.416***
			(0.021)	(0.023)	(0.017)	(0.064)
Constant	2.165***	-1.548 ***	0.144***	-1.846***	0.345***	
	(0.642)	(0.251)	(0.046)	(0.341)	(0.051)	
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Book FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,153	10,153	2,849	2,849	2,849	10,153
R-squared	0.041		0.074		0.077	0.087
Log-likelihood		-8,415		-7,465		

*Standard errors are in parenthesis: ***p<0.01,**p<0.05, *p<0.1. We indicate LargePartitioning as LP. The robust standards errors are clustered at both the individual level and the book level.*

Appendix Q. Incorporation of Author Fixed Effects

Table Q-1. The Effectiveness of Content Partitioning on Consumption Patterns with Author Fixed Effects

Variables	Consumption Quantity	Progression Rates
LP	-0.729***(0.0213)	0.098***(0.013)
$ReviewVolume$	0.636***(0.272)	0.173***(0.064)
$ReviewRating$	0.156***(0.0433)	0.200***(0.026)
$Length$	-0.001***(1.69e-05)	-5.66e-04*** (1.65e-05)
$Price$	1.58e-05*** (2.76e-06)	5.99e-05*** (2.77e-06)
$Discount$	0.010***(0.001)	0.010 (0.008)
$PublishDate$	1.73e-04***(5.03e-05)	1.18e-04*** (3.18e-05)
$SeriesOrder$	0.277*** (0.051)	0.417*** (0.101)
Constant	1.194***(0.0300)	4.163***(0.0182)
Individual FE	Yes	Yes
Author FE	Yes	Yes
Observations	127,524	127,524
R-squared	0.118	0.088

*Standard errors are in parenthesis: ***p<0.01,**p<0.05, *p<0.1. We indicate LargePartitioning as LP.*

Table Q-2. The Effects of Content Partitioning on Engagement and Purchase with Author Fixed Effects

Variables	Consumption Intensity	Reviewing	Review Length	Review Informat	Review Valence	Purchase
LP	0.120***	0.946***	0.527***	0.495**	0.037***	0.263***
	(0.0275)	(0.100)	(0.0433)	(0.190)	(0.002)	(0.030)
$ReviewVol$	0.257***	0.549***	0.177***	0.0876***	0.644***	0.017***
	(0.00335)	(0.0124)	(0.00551)	(0.0272)	(0.079)	(0.004)
$ReviewRat$	0.865***	0.227***	0.0073***	0.978***	0.786***	0.019***
	(0.0810)	(0.019)	(0.001)	(0.349)	(0.092)	(0.006)
$Length$	1.92e-06***	1.02e-06***	-3.79e-07	-5.03e-08	2.75e-08***	-5.59e-05***
	(1.84e-07)	(6.03e-07)	(2.68e-06)	(5.26e-08)	(2.81e-08)	(1.68e-05)
$Price$	0.000***	0.003***	0.000***	4.59e-05	-5.21e-06***	-4.62e-05***
	(4.15e-05)	(1.62e-05)	(2.79e-05)	(0.000)	(1.02e-06)	(5.81e-06)
$Discount$	0.000***	-0.004***	-0.004***	0.001***	2.10e-05***	0.047***
	(2.11e-05)	(1.48e-05)	(2.47e-05)	(0.000)	(1.56e-06)	(0.002)
$Publish$	2.68e-05**	-4.52e-05***	-4.08e-05***	-0.000***	-2.74e-05***	-0.000***
	(4.05e-06)	(2.44e-05)	(1.00e-05)	(5.78e-05)	(4.05e-07)	(4.82e-06)
$SeriesOrd$	0.318***	-0.144**	0.211*	0.512*	0.054***	-0.251***
	(0.041)	(0.059)	(0.100)	(0.298)	(0.003)	(0.041)
Constant	1.502***	-4.416***	7.096***	-0.793***	33.25***	2.243***
	(0.0399)	(0.135)	(0.0608)	(0.295)	(6.385)	(0.0431)
Obs.	127,524	127,524	11,799	11,799	11,799	127,524
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes
Aut. FE	Yes	Yes	Yes	Yes	Yes	Yes
R-sq	0.174		0.101		0.097	
ll		-8,745		-1,526		-1,930

*Standard errors are in parenthesis: ***p<0.01,**p<0.05, *p<0.1. We indicate LargePartitioning as LP.*

Appendix R. Alternative Analysis Based on Matching

One potential concern with our analysis is that consumers' decision to consume LP versus SP may be correlated with unobserved factors. To rule out the potential selection problem and verify the robustness of our estimates, we carried out propensity score matching (PSM) (Rosenbaum and Rubin 1983). Specifically, we obtained additional data prior to experiment where the content was only available in SP in the platform. We conducted PSM to match consumers who purchased and consumed SP content prior to the experiment and those who purchased and consumed content laid out in LP format after the experiment. The following observable variables were involved in matching: (1) $Gender$ (i.e., a binary variable indicating whether a consumer is female or male), (2) Age (i.e., the age of an individual), (3) $RegistrationDate$ (i.e., the duration elapsed between January 1, 2010 and the date at which a consumer registered date, (4) $Experience$ (i.e., the amount of historical purchase of LP serialized book), (5) $ConsumptionRate$ (i.e., the historical average consumption rate for an e-book), and (6) $MobileDevice$ (i.e., the historical propensity to use mobile devices rather than PCs). We expected a consumer's decision to consume LP content as related to the aforementioned factors, which reflect demographic characteristics and individual preferences.

We performed PSM using the one-to-one nearest-neighbor matching algorithm, which is a widely used method in the literature (Figure R). The groups have no significant differences across all the variables, implying that our PSM matching was successful in such a way that the variance between the groups comes primarily from content partitioning structures. As shown in Table R-1 and Table R-2, the estimated effect of LP is qualitatively consistent across different consumption patterns and post-consumption behaviors, corroborating our results in the main findings.

Figure R. Results of Propensity Score Matching

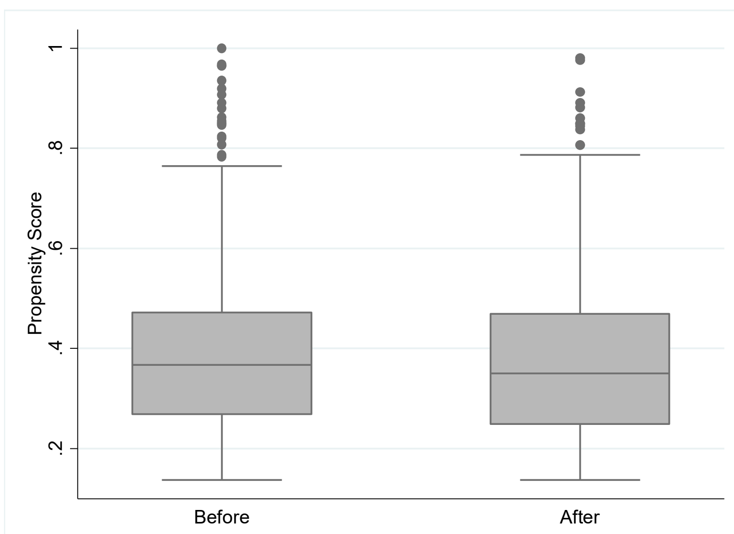

Table R-1. PSM based Robustness Check for the Effects of Partitioning on Consumption		
Variables	Consumption Quantity	Progression Rates
LP	-0.165***(0.026)	0.264***(0.021)
$Controls$	Yes	Yes
Constant	0.132***(0.045)	0.412***(0.106)
Individual FE	Yes	Yes
Book FE	Yes	Yes
Observations	127,524	127,524
R-squared	0.119	0.160

*Standard errors are in parenthesis: ***p<0.01,**p<0.05, *p<0.1. We indicate LargePartitioning as LP. The robust standards errors are clustered at both the individual level and the book level.*

Table R-2. PSM based Robustness Check for the Effects of Partitioning on Engagement and Purchase

Variables	Consumption Intensity	Reviewing	Review Length	Review Informativeness	Review Valence	Purchase
LP	0.264***	0.216***	0.415***	0.415***	0.105***	0.462***
	(0.019)	(0.045)	(0.056)	(0.079)	(0.022)	(0.047)
$Controls$	Yes	Yes	Yes	Yes	Yes	YES
IMR			-0.024***	-0.022**	-0.046***	0.055***
			(0.003)	(0.009)	(0.003)	(0.003)
Constant	1.145***	-2.165***	0.044***	-1.561***	0.046***	
	(0.354)	(0.278)	(0.010)	(0.241)	(0.003)	
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Book FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	127,524	127,524	11,799	11,799	11,799	127,524
R-squared	0.154		0.079		0.145	
Log-likelihood		-8,546		-8,145		

*Standard errors are in parenthesis: ***p<0.01,**p<0.05, *p<0.1. We indicate LargePartitioning as LP. The robust standards errors are clustered at both the individual level and the book level.*

Reference:

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika,* 70(1), 41-55.

Appendix S. Determining the Optimal Partitioning Strategy

Broadly, our findings indicate that the optimal number of episodes for an e-book depends on a careful balance of factors, including the book's length, the nature of the content, and the provider's objectives. By considering these elements, providers can strategically segment their content to enhance both consumption quantity and engagement, ensuring a more satisfying and effective reader experience. For example, a content provider aiming to maximize both engagement and retention for a hedonic-oriented lengthy fantasy novel might opt for fewer, longer episodes to maintain immersion, while another provider focused on a short educational guide might choose shorter episodes to facilitate easy consumption.

More specifically, by understanding the trade-offs between consumption quantity and progression rate, as suggested by our findings, content providers can tailor their partitioning strategies. For example, pay-per-episode models can be more beneficial to vendors of e-books parceled out into large segments, whereas pay-per-word-count schemes would work more effectively for products delivered in small portions.

With the results of main analysis (Table 2), the estimated coefficient of LP for consumption quantity is -0.674, suggesting that opting for LP decreases the consumer's reading word count by 49.1% ($1 - e^{-0.674} = 0.491$) points compared to adopting SP. Considering the average number of episodes available through an SP scheme was 255, whereas that provisioned by an LP arrangement was only 12, one episode reduction from 255 decreases the consumer's reading word count by (49.1% / 255-12) = 0.20% points on average. Similarly, the estimated coefficient of LP for progression rates is 0.260, suggesting that opting for LP increases the consumer's progression rates by 29.7% ($e^{0.260} = 1.297$) points compared to adopting SP. Thus, one episode reduction from 255 increases the consumer's progression rates by (29.7% / 255-12) = 0.12% points on average.

Please understand that the optimal number could be dependent on the conditions of *pay-per-episode* or *pay-per-word-count schemes*. For an example, we assume that the e-book platform follows a \$0.05 pay-per-word-count consumption and a \$0.005 subtraction-per-episode squared. When a 255 episodes-based SP has an average of 10,000 words read, the revenue for SP is (\$0.05*10,000 - \$0.005*255^2) = \$174.875. When we consider the number of episodes as x, the reading word count could be expressed as follows, given that one episode reduction from 255 decreases the consumer's reading word count by 0.20% points on average.

$$(reading\ word\ count) = 10{,}000 * \big(1 - 0.002 * (255 - x)\big) = 4{,}900 + 20x$$

The revenue model incorporating the reading word count term is expressed as follows.

$$Revenue\ (x) = 0.05 * (reading\ word\ count) - 0.005 * x^2$$

$$Revenue\ (x) = 0.05 * (4{,}900 + 20x) - 0.005 * x^2 = 245 + x - 0.005x^2$$

$$\frac{d}{dx}\big(Revenue(x)\big) = 1 - 0.01x$$

Thus, in these payment scenarios, the optimal number of episodes to maximize the revenue is calculated to be 100.

Appendix T. Several Potential Directions for Future Research

We provide several potential directions for future research that explores the partitioning effects of video content. Unlike reading, the visually oriented enjoyment of TV programs may require less concentration, cognitive attention, and time, potentially making sustained engagement with lengthy content less challenging (Lin et al. 2011). Partitioning in video content consumption could be more effective in facilitating frequent reinvigoration of working memory, enabling consumers to reset their attention, mindset, and cognition. Additionally, watching video content could be more unstructured in terms of individual emotional reactions. Consumers can easily stop and re-watch certain scenes or selectively skip some narratives to directly enjoy the most interesting parts. In this case, the effects of partitioning could be influenced by the presence of "*decision points*" between each episode. The seamless transition to the next episode can effectively sustain individual engagement, potentially enhancing the effects of segmenting on consumption quantity. However, excessively convenient transitions, such as "autoplay" feature allowing automatic switching to the next episode, might compromise an individual's self-control ability toward hedonic content consumption, leading to "binge-watching" patterns. Future works can focus on the role and friction of these "*decision points*" to provide theoretical insights into the distinctions of the effects of segmentation.

Reference:

Lin, L., Lee, J., & Robertson, T. (2011). Reading while watching video: The effect of video content on reading comprehension and media multitasking ability. *Journal of Educational Computing Research*, 45(2), 183-201.