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Sustaining New Product Performance in Digital Marketplaces: The Roles of Post-Sales Responsiveness, Customer Engagement, and Store Maturity

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Abstract

Digital marketplaces have changed how new products are commercialized after launch, yet little is known about why post-launch performance declines faster for some products than for others. Drawing on product life cycle theory and viewing demand in digital marketplaces as jointly organized by the platform, customers, and the selling firm, this study examines three factors that may shape post-launch performance trajectories: post-sales responsiveness (firm–platform interaction), customer engagement (firm–customer interaction), and store maturity (store-level characteristics). Using a monthly panel of 73 new products sold through 23 official flagship stores on a leading Chinese business-to-consumer (B2C) marketplace from July 2020 to July 2021, we find that monthly sales revenue of new products declines as products age. This negative relationship remains statistically significant at the 10% level under wild cluster bootstrap inference. The decline is weaker for products sold by stores with faster refund processing and for products that have accumulated more customer reviews, and it is steeper for products sold by stores with longer tenure on the platform. These findings indicate that the post-launch decline of new products is not merely a function of elapsed time but varies systematically with the roles of platforms, customers, and firms in the commercialization process, with implications for firms and platform operators.

Keywords: digital marketplaces; new product performance; product life cycle; post-sales responsiveness; customer engagement; store maturity

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Academic Editor: Adel Ben Youssef

Received: 24 August 2026
Revised: 19 October 2026
Accepted: 23 October 2026
Published: 20 November 2026

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1. Introduction

The rapid development of digital platforms has fundamentally transformed how firms commercialize innovations and compete in contemporary markets [1,2]. Unlike traditional market channels, digital platforms provide firms with access to large customer bases and platform-based resources and services that facilitate product commercialization, customer interaction, and market expansion [3,4]. As an increasingly important business environment, digital platforms have reshaped the commercialization process of new products by altering how firms acquire resources, engage with customers, and respond to market feedback. Therefore, understanding how firms sustain new product performance after market introduction in digital platform environments has become an important issue in management research.

A growing body of research examines how digital platforms influence firm behavior and performance [5–7]. Prior research suggests that participation in digital platforms enables firms to access valuable external resources, improve operational efficiency, and develop new capabilities through digital technologies and data-driven practices [8,9]. By providing technological infrastructures, market intelligence, and coordination and governance mechanisms, digital platforms can enhance firms' ability to develop and commercialize innovative offerings [10–13]. Furthermore, interactions with platform stakeholders allow firms to acquire complementary resources, expand knowledge networks, and strengthen their market responsiveness [14]. More recent work conceptualizes platforms and ecosystems as structures that emerge in response to specific market failures but can, in turn, generate functional and distributional failures of their own [15], and shows that complementors' performance within a platform ecosystem is heterogeneous and shaped by their strategic choices, such as multihoming to other platforms [16]. Closest to our question, Kapoor and Agarwal [17] show that the structural and evolutionary features of an ecosystem shape whether complementors can sustain superior performance: higher ecosystem complexity helps app developers sustain their performance, whereas platform transitions initiated by the platform owner erode it. These studies have substantially advanced our understanding of how digital platforms contribute to firm growth and innovation activities [17,18].

However, existing research provides limited insight into how digital platforms influence the evolution of new product performance after market introduction. Previous studies on new product performance have primarily focused on antecedents at the firm, customer, and institutional levels [19,20]. Firm-level studies emphasize the roles of knowledge integration [21], organizational experience [22], and entrepreneurial orientation [23] in improving new product outcomes. Customer-oriented research highlights the importance of customer innovativeness, brand attachment, and market acceptance [24,25]. Institutional perspectives further demonstrate how external environments, such as government support and intellectual property protection, affect innovation success [26–28]. Although these studies provide valuable explanations for why some new products outperform others, they have largely examined traditional market settings and paid less attention to how digital platform environments reshape the commercialization trajectories of newly launched products.

Digital platforms differ from traditional markets in several important ways that may fundamentally alter new product performance trajectories. First, digital platforms have evolved beyond simple transaction channels and increasingly function as coordination and governance mechanisms that facilitate continuous interactions among firms, platforms, and customers. These interactions allow firms to obtain rapid market feedback and adjust commercialization strategies throughout the product life cycle [29,30]. Platforms also evaluate sellers' service performance, such as refund processing time, through codified rules and use these evaluations to govern sellers' visibility and access to promotional resources [31]. Recent studies of marketplace governance further show that e-commerce sellers' compliance with platform rules depends on whether these rules are linked to public enforcement [32], and analyze how marketplaces can curb sellers' attempts to take transactions off the platform through instruments such as limiting buyer–seller communication or hiding the sellers concerned [33]. Second, product performance in digital marketplaces is shaped by platform-specific mechanisms, including information diffusion, data-driven recommendation, and customer engagement, which influence product visibility and market response over time [14,34]. Customer reviews, in particular, accumulate over time and remain visible to subsequent customers, shaping their purchase decisions [35]. Third, digital platforms connect firms with platform infrastructures, customer communities, and market resources [18], and stores accumulate these connections over time, so that a store with longer tenure on the platform typically sells each new product alongside an estab-

lished product portfolio. While such maturity may provide firms with opportunities to enhance commercialization capabilities, it may also reduce the attention that a store devotes to any single new product [36]. Together, these differences imply that demand for a new product in a digital marketplace is jointly organized by the platform, its customers, and the selling firm. Therefore, understanding how these platform-related conditions shape the dynamic evolution of new product performance represents an important extension of existing innovation and strategy research.

To address this research gap, this study investigates how firms sustain new product performance in digital marketplace environments. Specifically, adopting a multi-actor framework encompassing platforms, customers, and firms, we examine how post-sales responsiveness, customer engagement, and store maturity shape the post-launch performance trajectories of new products. Drawing on longitudinal product-level data from 73 new physical products sold through 23 official flagship stores on Tmall, one of China's largest B2C digital marketplaces, we employ panel regression models with store and year–month fixed effects using monthly sales observations from July 2020 to July 2021. This research setting provides a unique opportunity to examine how new products evolve after market introduction and how firms' relationships with digital platforms influence their commercialization outcomes over time. The results reveal that newly launched products generally experience a persistent decline in sales revenue as they age, although the decline decelerates over time. This baseline negative relationship remains statistically significant at the 10% level under wild cluster bootstrap inference. We further find this decline is weaker for products sold by stores with faster post-sales responsiveness (measured by refund processing speed) and for products with more accumulated customer reviews. In contrast, products sold by more mature stores (i.e., stores with longer tenure on the platform) experience a steeper decline in performance. The findings are further examined through a series of robustness checks involving alternative measures of product performance and customer engagement, as well as a restricted sample excluding stores with only one sampled product. The three moderating effects remain consistent across these specifications, including when sales volume replaces sales revenue as the performance measure, although the baseline negative relationship between product age and performance is not statistically significant under the alternative performance measure.

This study contributes to the literature in four ways. First, it extends research on new product performance [19,20] by adopting a dynamic perspective on how performance evolves after market introduction. Rather than treating post-launch decline as a uniform function of elapsed time, we show that its trajectory varies systematically with the roles of platforms, customers, and firms in the commercialization process. Second, it advances digital platform research by suggesting how platforms' codified service requirements may link firms' routine operational behavior to platform-allocated resources, extending research on platform governance and ecosystem performance [17] to the level of individual products. Specifically, faster post-sales responsiveness is associated with a slower post-launch decline. Third, it extends customer engagement research by showing that customer engagement is consequential not only for customer decision making but also for the evolution of product performance after launch. Fourth, it contributes to the attention-based view of the firm [36] by identifying store maturity as an important boundary condition shaping new product performance trajectories over time. Together, these contributions provide a multi-actor explanation of why new product performance trajectories diverge after market introduction in digital marketplaces.

2. Theoretical Framework

Drawing on the digital platform literature [10], this study examines how firms sustain new product performance in digital marketplaces. Digital platforms provide a distinct market environment in which firms can reach customers, access market information, and leverage platform-based resources and services to commercialize new products [37]. Unlike traditional market channels, digital platforms facilitate continuous interactions among firms, platform operators, and customers, thereby reshaping how products are introduced, promoted, and sustained after market entry [4,38,39]. In digital marketplaces, these distinctive features of product commercialization may give rise to performance trajectories that differ from those observed in conventional markets.

2.1. New Product Performance Trajectories in Digital Marketplaces

Product Life Cycle (PLC) theory suggests that product sales evolve over time following market introduction, typically progressing through introduction, growth, maturity, and decline stages [40,41]. Rather than assuming a constant relationship between product age and performance, PLC theory emphasizes that sales patterns vary across different stages of a product's market life. The duration and shape of these stages, however, may vary considerably across products and market environments.

Although PLC theory provides a useful foundation for understanding changes in product performance over time, digital marketplaces may reshape the pace and pattern of this evolution. Platform-based search and recommendation systems facilitate product discovery and increase products' visibility to potential customers by shaping the alternatives included in customers' consideration sets [42]. Compared with traditional offline markets, these mechanisms allow customers to discover and evaluate new products more efficiently, potentially accelerating the early stages of product commercialization.

At the same time, the visibility gained by new products in digital marketplaces may be difficult to sustain. Digital marketplaces aggregate a large number of competing products, intensifying competition for limited customer attention [43]. Evidence from the Android app store further shows that the entry of additional products makes existing products less visible and directly reduces their downloads, creating congestion externalities [44]. Moreover, observable market signals, such as ratings, reviews, and prior sales, allow customers to continuously evaluate and compare available alternatives [45,46]. As competing alternatives emerge and customer attention shifts, products may therefore lose their initial visibility and sales more rapidly than in traditional markets.

Taken together, these characteristics suggest that new products in digital marketplaces may exhibit a more compressed performance trajectory than that implied by conventional PLCs, with substantial market exposure occurring shortly after introduction and performance declining as products age and customer attention shifts toward competing alternatives. At the same time, digital marketplaces provide firms with resources and mechanisms through which they can influence this post-launch trajectory. Examining how new product performance evolves over time, and how firms can mitigate its decline, therefore extends product life cycle research to the context of digital marketplaces. Accordingly, we propose the following hypothesis:

H1. *Product age is negatively associated with new product performance in digital marketplaces.*

2.2. A Multi-Actor Perspective on New Product Performance Trajectories

The commercialization of new products in digital marketplaces involves multiple actors whose activities jointly shape product performance over time. Platforms influence product visibility and market access, customers contribute to demand through their interactions

and purchasing behaviors, and firms allocate resources and operational attention across their products. From this perspective, sustaining new product performance depends not only on product characteristics but also on the roles of platforms, customers, and firms in shaping post-launch market outcomes.

Building on this multi-actor perspective, we identify three factors that may shape the relationship between product age and performance. On the platform side, post-sales responsiveness captures firms' service performance that may affect platform evaluations and stores' access to platform-organized marketing resources (H2). On the customer side, customer engagement captures ongoing customer interactions that may help sustain demand over time (H3). On the firm side, store maturity reflects differences in firms' allocation of resources and operational attention across products (H4). Together, these factors capture how platforms, customers, and firms may shape the post-launch performance trajectories of new products, as illustrated in Figure 1.

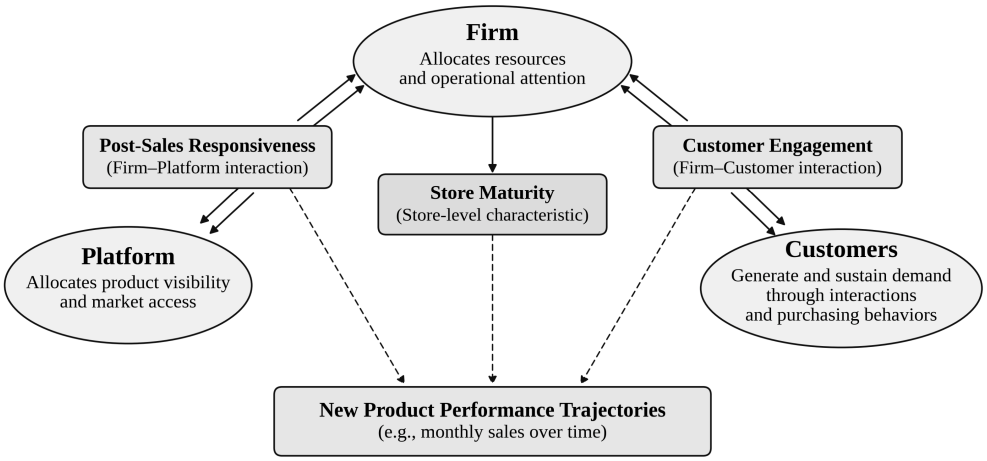


Figure 1. A multi-actor framework of new product performance trajectories in digital marketplaces. Note: Solid arrows indicate actor relationships, and dashed arrows indicate the proposed moderating effects on product performance trajectories.

2.2.1. Post-Sales Responsiveness

In online retailing, returns and refunds constitute an important component of firms' post-sales operations. The effective handling of problems and returns represents an important dimension of electronic recovery service quality [47]. Research based on Tmall data further shows that customers' satisfaction with post-sales services shapes their complaint intentions [48]. Building on this literature, we use the term post-sales responsiveness to refer to the speed with which a firm processes customers' return and refund requests.

Importantly, post-sales responsiveness also forms part of the firm–platform relationship because digital marketplaces not only facilitate transactions but also govern participating sellers through rules and other nonprice mechanisms [13,32,49]. On the focal platform, refund processing time was incorporated into the after-sales experience dimension of its basic service assessment. Under Article 4 of the Tmall Merchant Marketing Access Basic Rules in force during our observation period, a store had to reach the basic service assessment score required for its main category in order to join platform-organized marketing activities [50]. Thus, post-sales service performance was not merely recorded by the platform but incorporated into a formal evaluation system that determined stores' eligibility for platform marketing opportunities. Better post-sales responsiveness could therefore help stores maintain access to platform-organized promotional resources as their products aged.

Such platform evaluation can have important consequences for sellers. Changes in platform governance can induce systematic adjustments in seller behavior and generate

performance consequences [13]. In this setting, the platform's service assessment can have discrete consequences: seller demand has been shown to change discontinuously around rating thresholds on the same platform group [51]. Post-sales responsiveness can therefore influence firms' access to platform marketing opportunities through its role in the platform's service assessment.

Post-sales responsiveness may become particularly consequential as new products age. As the initial attention that new products attract declines, maintaining access to platform-organized marketing opportunities can help sustain product exposure. Such exposure is important in digital marketplaces because visibility affects whether products are discovered and considered by customers and is often difficult to sustain in competitive platform environments [52]. Platform-based recommendation mechanisms can further expand customers' consideration sets and thereby increase purchase propensity [42]. Firms with greater post-sales responsiveness are therefore better positioned to retain platform marketing opportunities and sustain product exposure as products age, thereby slowing the deterioration of new product performance. Accordingly, we propose the following hypothesis:

H2. *A firm's post-sales responsiveness weakens the negative relationship between product age and new product performance.*

2.2.2. Customer Engagement

Beyond firm–platform relationships, digital marketplaces enable continuous interactions between firms and customers throughout the commercialization process. Customer engagement reflects customers' interactive experiences with firms and their offerings and has become an increasingly important feature of digitally mediated markets [53,54]. In digital marketplaces, such engagement can take various forms, including reviews, ratings, inquiries, and other online interactions through which customers contribute their experiences and evaluations.

Customer engagement can help sustain product demand by enriching the information available to other customers. Online reviews, as an important manifestation of customer engagement, supplement other product information and assist customers in making purchase decisions [55,56]. More recent research further shows that online reviews can influence purchase likelihood by helping customers resolve product uncertainty [57], while how customers interpret information across multiple reviews can shape their product evaluations and purchase decisions [58].

The role of customer engagement may become particularly important as new products age. As products become less novel and compete for continued customer attention, stronger customer engagement can provide a continuing basis for customers to evaluate and consider these products. It can therefore help sustain market demand as products age, thereby slowing the deterioration of new product performance over time. Accordingly, we propose the following hypothesis:

H3. *Customer engagement weakens the negative relationship between product age and new product performance.*

2.2.3. Store Maturity

Firms participating in digital marketplaces differ in the maturity of their online operations. As stores mature over time, they accumulate operating experience and develop more established organizational structures and routines [59,60]. Firm age can consequently shape product-related strategic decisions, including firms' expansion into new product

lines and their responses to emerging market opportunities [61]. As stores develop more established operations, a focal new product is more likely to constitute only one of multiple ongoing operational priorities rather than the primary focus of the store.

Store maturity influences how firms allocate attention to individual new products. Organizational attention is limited and must be selectively distributed across competing issues and opportunities [36,62]. Such allocation has behavioral consequences because sustained attention shapes organizational priorities and subsequent action [63,64]. For mature stores with more established operations, a focal new product competes with other ongoing operational priorities for continued attention. In contrast, a new product is likely to remain relatively more salient to less mature stores.

This difference in attention allocation should become more pronounced as the focal product ages. Shortly after introduction, a new product represents a new market opportunity and is likely to attract firm attention across stores. As the product ages and its initial market potential diminishes, however, continued support increasingly competes with other operational priorities. Mature stores are therefore more likely to shift attention away from the focal product, whereas less mature stores have stronger incentives to maintain attention to it. The resulting divergence in continued support should cause new product performance to decline more rapidly in mature stores as products age. Accordingly, we propose the following hypothesis:

H4. *Store maturity strengthens the negative relationship between product age and new product performance.*

The theoretical framework of this study is illustrated in Figure 2.

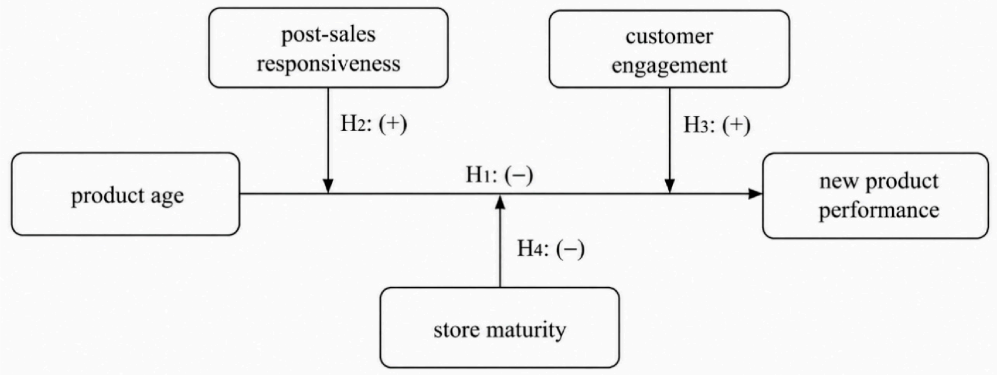


Figure 2. Theoretical model and hypotheses.

3. Materials and Methods

3.1. Sample Selection and Data Sources

This study draws on product-level data from Tmall Heybox (Tianmao Xiaoheihe), a dedicated new product launch channel on Tmall—one of China's largest business-to-consumer (B2C) digital marketplaces. Launched in March 2017 as a designated product-debut tool, Tmall Heybox is specifically designed to support brands in launching new products online for the first time, offering consumer insights and data-driven strategies to improve new product success rates. A defining admission requirement of Heybox is that participating products must be first-time online launches, with their online launch dates no later than their offline market entry dates. Both online launch dates and offline market entry information are provided and verified by the Heybox business team.

Our sample consists of newly launched physical products sold through official flagship stores on Tmall, spanning three product categories: consumer electronics, beauty and

skincare, and personal care and household cleaning. Each official flagship store is operated by a single brand owner; we therefore treat the store as the firm's operating unit on the platform. All sampled products made their first online debut through Tmall Heybox between January and November 2020. We collect our dataset from three sources. Product-level information—including launch dates, category assignments, and official store identifiers—comes directly from the focal platform. Monthly product sales, customer reviews, store tenure, and store operating performance are obtained from a commercial analytics firm specializing in digital marketplace intelligence. Firm-level information on the entity operating each store is collected from the Qichacha business registry database and is used only to check the correspondence between stores and brand owners.

The data cover the 13 calendar months from July 2020 to July 2021. The raw panel contains 924 product–month records for 78 new products sold by 25 Tmall flagship stores. We obtain the estimation sample in five steps. First, we drop the 21 records that precede a product's recorded launch date (negative product age), because these reflect pre-launch listings rather than sales of the new product. Second, we drop the 48 records from the two stores for which the post-sales responsiveness measure is unavailable. Third, we drop the 59 records for which the cumulative review stock used as the customer-engagement moderator cannot be computed. Fourth, we drop the 42 records for which the one-month lagged store favorites cannot be constructed. Fifth, we excluded one record with an anomalous sales value due to a data capture error by the provider, rather than treating it as a genuine zero-sale observation. The estimation sample is an unbalanced panel of 753 product–month observations covering 73 products from 23 official flagship stores over the 11 months from September 2020 to July 2021. The estimation window begins later than the raw panel because the cumulative review stock is measured as of $t - 1$ and one control enters with a one-period lag; the earliest months of the panel therefore serve only to construct these variables, which is why the estimation sample starts in September 2020. The 73 products comprise 35 consumer electronics products, 28 beauty and skincare products, and 10 personal care and household cleaning products. The number of products per store ranges from 1 to 7, with a median of 3, and the average store–month cell contains 3.0 products. Two stores contribute only one product each (19 observations, 2.5% of the sample); for these stores, product-level and store-level variation cannot be separated and no within-store comparison across products is possible. We therefore re-estimate the model excluding these two stores as a robustness check (Section 4.4.4).

3.2. Measures

3.2.1. Dependent Variable

Product performance is measured as the natural logarithm of one plus the product's monthly sales revenue. This log-transformation is standard in empirical studies of online product performance, as it reduces the skewness of sales data and allows coefficient estimates to be interpreted as approximate percentage changes (e.g., [35,65–67]).

3.2.2. Independent and Moderating Variables

Product age is defined as the number of months elapsed since the product was first introduced on the focal digital marketplace. Rooted in the product life cycle (PLC) framework [40,41,68], which posits that products go through predictable stages of growth, maturity, and decline, product age captures the post-launch tenure of each product and serves as the key explanatory variable in the baseline model (H1). In digital marketplaces, where information diffusion is accelerated and competitive visibility is high, product age also proxies for the declining novelty and customer attention that new products experience over time.

Post-sales responsiveness is measured as the inverse of the store's average refund processing time (days). This measure is observed at the store level and is time-invariant within stores over the observation period. It captures the speed with which a store handles return and refund requests, reflecting the firm's operational efficiency in post-sales service [47,69]. A higher value indicates faster refund processing and thus stronger post-sales responsiveness. As a component of platform-generated service ratings [31,70], post-sales performance is directly monitored by the platform and, on Tmall, tied to stores' eligibility for platform-organized marketing activities [50]. The average refund processing time is computed over the same 13-month window as the sales data, from July 2020 to July 2021. The measure takes a single value for each store and does not vary across months, so it captures differences between stores rather than within-store changes over time.

Customer engagement is operationalized as the natural logarithm of one plus the cumulative number of customer reviews received up to the previous month ($t-1$). This stock-based measure is consistent with our theoretical framing, which holds that customer reviews sustain demand by providing subsequent customers with an accumulating body of product information and evaluations rather than through contemporaneous flows [55,57]. Using the cumulative value up to $t-1$ also makes the moderator predetermined with respect to current sales, which mitigates concerns about simultaneity and reverse causality.

Store maturity is measured by the number of months elapsed since the store was established on the focal digital marketplace. This measure captures the maturity of a store's platform-based operations rather than the age of the firm itself. Research on organizational age suggests that age is associated with differences in organizational processes and structures [59]. By analogy, longer store tenure reflects a more established operating presence on the focal marketplace. We therefore use store tenure as a proxy for store maturity.

3.2.3. Control Variables

We include a set of control variables that may influence new product performance, following prior research on seller performance in online marketplaces [71,72]. Store followers, the natural logarithm of the store's monthly average number of followers, are included as a control for the store's scale on the platform. Because store fixed effects absorb all differences between stores, this variable captures within-store variation only. Product favorites, defined as the natural logarithm of one plus the number of product favorites lagged by one month, capture pre-launch and ongoing customer interest in the product, which is likely to be associated with subsequent sales performance. Net store sales, calculated as the natural logarithm of one plus the store's monthly sales revenue net of the focal product's sales revenue, control for the overall scale and performance of the store. Finally, we include store fixed effects and year–month fixed effects; the latter also absorb platform-wide promotional periods and common seasonal shocks.

3.3. Model Specification

The empirical analysis draws on an unbalanced product–month panel. To examine how new product performance evolves after launch, we estimate fixed-effects regressions with product performance (log monthly sales revenue) as the dependent variable and product age as the key regressor, including both store fixed effects and year–month fixed effects. The baseline specification for testing H1 is

$$Product\ performance_{it} = \alpha_0 + \beta_1 \cdot Product\ age_{it} + \gamma' Controls_{it} + \eta_t + \mu_j + \varepsilon_{it} \quad (1)$$

where i indexes products, t indexes months, and j indexes stores. $Controls_{it}$ denotes the vector of control variables; η_t captures year–month fixed effects, which absorb common temporal shocks such as seasonality and platform-wide promotions; μ_j captures store fixed

effects, which absorb time-invariant differences across stores; and ε_{it} is the idiosyncratic error term.

To test whether each of the three factors moderates the age–performance relationship, we estimate separate interaction models for H2 through H4. Each model takes the form

$$\begin{aligned} Product\ performance_{it} = \alpha_0 + \beta_2 \cdot Product\ age_{it} + \beta_3 \cdot Product\ age_{it} \times Moderator_{it} + \\ \beta_4 \cdot Moderator_{it} + \gamma' Controls_{it} + \eta_t + \mu_j + \varepsilon_{it} \end{aligned} \quad (2)$$

The baseline specification contains the time-varying controls only and no moderator, so that the coefficient on product age describes the average post-launch trajectory before conditioning on platform, customer and store conditions. In the interaction models, the main effect of customer engagement—the only moderator that varies within stores over time—is included in the control vector. The main effects of post-sales responsiveness, which is time-invariant within stores, and of store maturity, which equals calendar time minus a store-specific constant, are jointly absorbed by the store and year–month fixed effects and are therefore not separately identified; we do not report them in the tables.

All models are estimated by ordinary least squares using the same estimation sample of 753 product–month observations. Store and year–month fixed effects are included in all models, with store fixed effects absorbed through Stata's areg command. Standard errors are clustered at the store level (23 clusters). All analyses are conducted in Stata 18 (StataCorp LLC, College Station, TX, USA).

4. Results

4.1. Descriptive Statistics

Table 1 presents the descriptive statistics for the main variables used in the regression analyses. The estimation sample consists of 753 product–month observations. The dependent variable, product performance (log sales revenue), has a mean of 13.815 and a standard deviation of 2.324. Product age averages 7.702 months, with a standard deviation of 4.009 months and a range from 0 to 18 months.

Table 1. Descriptive statistics for main variables.

Variable	N	Mean	SD	Max	Min
Product performance	753	13.815	2.324	19.856	5.984
Product age	753	7.702	4.009	18	0
Post-sales responsiveness	753	1.238	0.670	2.632	0.322
Customer engagement	753	8.351	2.697	14.932	0
Store maturity	753	93.826	36.670	160	26
Store followers	753	15.099	1.329	16.822	11.964
Product favorites	753	8.243	2.145	14.681	0
Net store sales	753	18.164	1.562	21.713	13.376

Table 2 reports the correlation matrix for the main variables. Product performance is negatively correlated with product age ($r = -0.164$, $p < 0.01$), providing preliminary support for the baseline hypothesis. The largest correlation among independent variables is 0.736 (between store followers and net store sales), which is below the 0.8 level at which multicollinearity usually becomes a concern.

Table 2. Correlation matrix of main variables.

Variable	1	2	3	4	5	6	7	8
1. Product performance	1							
2. Product age	−0.164 ***	1						
3. Post-sales responsiveness	0.131 ***	0.109 ***	1					
4. Customer engagement	0.509 ***	0.293 ***	0.381 ***	1				
5. Store maturity	−0.215 ***	0.002	−0.374 ***	−0.436 ***	1			
6. Store followers	0.248 ***	0.133 ***	0.499 ***	0.265 ***	0.072 **	1		
7. Product favorites	0.700 ***	−0.114 ***	0.232 ***	0.721 ***	−0.466 ***	0.147 ***	1	
8. Net store sales	0.338 ***	−0.024	0.282 ***	−0.049	0.262 ***	0.736 ***	−0.004	1

Notes: *** $p < 0.01$, ** $p < 0.05$.

4.2. Baseline Hypothesis Test

Table 3 reports the baseline model for H1, which predicts that new product performance declines with product age. The coefficient on product age is negative ($\beta = -0.097$), implying that each additional month of product age is associated with approximately 9.2% lower monthly sales revenue ($100 \times [\exp(-0.097) - 1]$). Under clustered standard errors the coefficient is significant at the 5% level ($t = -2.10$, 22 degrees of freedom, $p = 0.048$). Under the wild cluster bootstrap, which is the appropriate benchmark with 23 clusters, it remains significant at the 10% level ($p = 0.058$; Table 3 note). We therefore regard H1 as supported, with the qualification that the coefficient is significant only at the 10% level under the wild cluster bootstrap. Figure 3 provides a descriptive view of this pattern for products launched within the observation window.

Table 3. Baseline hypothesis results: effect of product age on product performance.

Variable	Product Performance
Product age	−0.097 **
	(0.047)
Store followers	−3.070 **
	(1.138)
Product favorites	0.731 ***
	(0.064)
Net store sales	0.271
	(0.171)
Constant	47.948 ***
	(16.863)
Year–month fixed effects	Yes
Store fixed effects	Yes
Observations	753
R-squared	0.792

Notes: Standard errors in parentheses are clustered by store (23 clusters); *** $p < 0.01$, ** $p < 0.05$. Wild cluster bootstrap p-value for product age (9999 replications, null imposed, clustering by store): 0.058. The coefficient is therefore significant at the 5% level under clustered inference and at the 10% level under the bootstrap.

Because store fixed effects absorb all differences between stores, the coefficient on store followers is identified from within-store changes over the estimation window, during which a store's follower base moves by only a few percent. It therefore reflects store-specific month-to-month variation, such as shifts in a store's promotional focus and traffic allocation across its products, rather than the cross-store differences in store scale described in Section 3.2.3, and we do not interpret it as an effect of follower size on product sales.

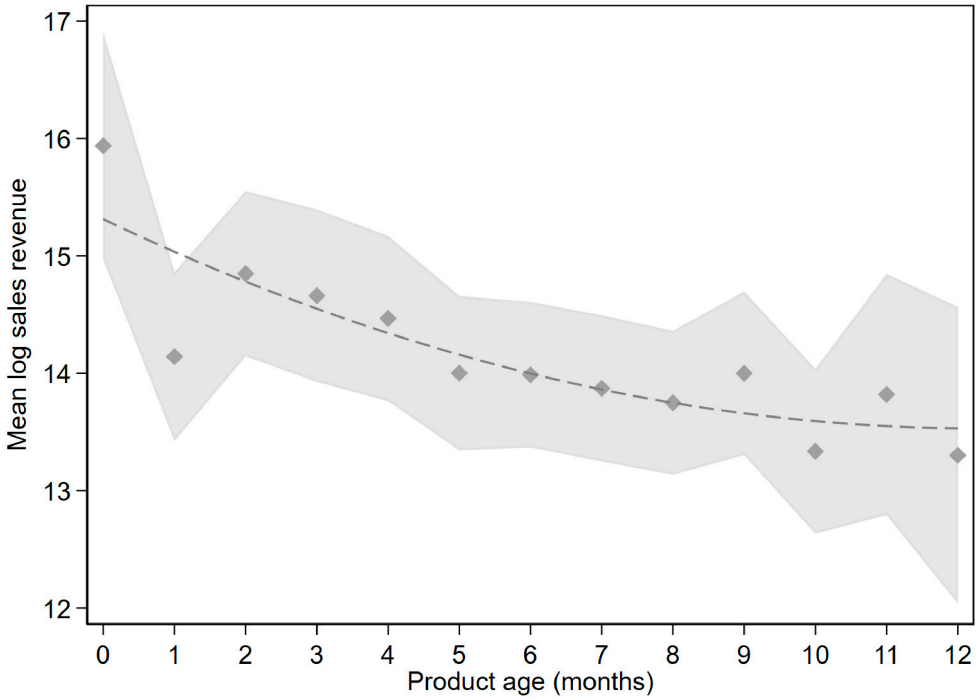


Figure 3. Mean log sales revenue by product age. Note: Diamonds represent observed mean log sales revenue, the dashed line indicates the quadratic fitted trend, and the shaded area represents the 95% confidence interval.

The figure uses the estimation sample and is restricted to products launched within the data window (36 products, 360 product–month observations). Diamonds mark means, the shaded band is the 95% confidence interval, and the dashed line is a quadratic fit. Numbers of observations vary across product ages and are smallest at the launch month, because the lagged measures used in the analysis cannot be constructed for a product's first observed month and for two months of the observation window. Products that debuted before the start of the data window are necessarily excluded, because their launch month is not observed.

To assess potential multicollinearity, we compute variance inflation factors (VIFs) for the baseline specification, including all year–month dummy variables. The largest VIF is 3.22, and the mean VIF is 2.55, both well below the conventional threshold of 10. These results indicate that multicollinearity does not pose a serious concern in the regression analyses.

4.3. Main Hypothesis Tests

Table 4 presents the results for the three main moderating hypotheses (H2–H4). Each column corresponds to a separate model that includes one interaction term between product age and a focal moderator.

H2 posits that post-sales responsiveness attenuates the negative effect of product age on new product performance. Column (1) of Table 4 shows that the interaction term between product age and post-sales responsiveness is positive and statistically significant ($\beta = 0.066$, $p < 0.01$). This result supports H2: products sold by stores with faster refund processing (i.e., higher post-sales responsiveness) experience a slower decline in performance over time. This finding is consistent with a firm–platform governance mechanism: the platform's service assessment incorporates post-sales service performance into merchants' eligibility for platform-organized marketing activities, suggesting that stores with stronger post-sales responsiveness may be better positioned to maintain access to platform-based promotional

opportunities as product novelty diminishes (Tmall Merchant Marketing Access Basic Rules [50]).

Table 4. Main hypothesis results.

Variable	(1) Product Performance	(2) Product Performance	(3) Product Performance
Product age × Post-sales responsiveness	0.066 ***		
	(0.020)		
Product age × Customer engagement		0.042 ***	
		(0.005)	
Product age × Store maturity			−0.0016 ***
			(0.0005)
Product age	−0.206 ***	−0.479 ***	0.031
	(0.056)	(0.047)	(0.053)
Customer engagement	0.218 *	−0.050	0.179
	(0.111)	(0.095)	(0.104)
Store followers	−2.311 **	−3.043 ***	−3.687 ***
	(1.024)	(0.992)	(1.038)
Product favorites	0.555 ***	0.547 ***	0.564 ***
	(0.113)	(0.096)	(0.107)
Net store sales	0.393 **	0.524 ***	0.491 ***
	(0.142)	(0.130)	(0.162)
Constant	22.382 *	30.367 **	36.455 ***
	(12.092)	(11.360)	(11.822)
Year–month fixed effects	Yes	Yes	Yes
Store fixed effects	Yes	Yes	Yes
Observations	753	753	753
R-squared	0.806	0.842	0.808

Notes: Standard errors clustered by store in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Wild cluster bootstrap p-values: age × post-sales responsiveness = 0.020; age × customer engagement < 0.001; age × store maturity = 0.021. All three interaction coefficients are significant at the 5% level under bootstrap inference. Post-sales responsiveness is time-invariant within stores, and store maturity equals calendar time minus a store-specific constant; both main effects are absorbed by the store and year–month fixed effects and are therefore not reported.

H3 predicts that customer engagement attenuates the negative relationship between product age and performance. Column (2) of Table 4 reveals a positive and significant interaction between product age and customer engagement ($\beta = 0.042$, $p < 0.01$), lending support to H3. Products with stronger customer engagement experience a slower decline in performance after launch. This finding is consistent with the view that customer engagement generates accumulated product-related information and evaluations that continue to shape customer decision making over time. In our setting, cumulative customer reviews capture this accumulated engagement because reviews remain publicly available and provide information to subsequent customers. Because cumulative reviews mechanically increase with product age, the interaction should be interpreted as comparing products of the same age that differ in their accumulated level of customer engagement.

H4 proposes that store maturity exacerbates the negative effect of product age on new product performance. Column (3) of Table 4 shows that the interaction between product age and store maturity is negative and significant ($\beta = -0.0016$, SE = 0.0005, $p < 0.01$), providing support for H4. Products from more mature stores experience steeper performance declines after launch. This finding is consistent with the attention-based explanation that as products age, mature stores may allocate relatively less operational attention and service resources to individual products because focal products compete with other organizational priorities.

In contrast, less mature stores may have stronger incentives to maintain attention toward individual new products because these products occupy a more important position in their ongoing operations.

Because the moderators are not centered, the coefficient on product age in Table 4 is the age slope evaluated at a moderator value of zero, which lies outside the observed range for post-sales responsiveness (0.32–2.63) and store maturity (26–160 months). Evaluated at the sample means of the three moderators (1.24, 8.35, and 93.8, respectively), the age slope is −0.124 (SE = 0.043), −0.127 (SE = 0.025), and −0.117 (SE = 0.039), and is negative and significant at the 1% level in all three cases ($p = 0.009$, <0.001, and 0.007). The negative age–performance association is therefore common to all three columns; the interactions capture how its strength varies with each moderator. Taken together, these interaction results show that the post-launch decline of new product performance is not solely a function of product age. Instead, the decline trajectory varies systematically with platform-related operational conditions, customer engagement, and store maturity.

4.4. Robustness Checks

To ensure the reliability of our main findings, we conduct a series of robustness checks. The results are reported in Tables 5–8.

4.4.1. Alternative Dependent Variable

First, we re-estimate all models using an alternative measure of product performance: the natural logarithm of one plus product sales volume (in units) instead of sales revenue. As shown in Table 5, the moderating effects remain consistent with our main analysis. The interaction between product age and post-sales responsiveness remains positive and significant ($\beta = 0.080$, $p < 0.01$), the interaction with customer engagement is positive and significant ($\beta = 0.042$, $p < 0.01$), and the interaction with store maturity is negative and significant ($\beta = -0.0013$, $p < 0.05$). The baseline coefficient on product age remains negative but is not statistically significant ($\beta = -0.067$, $p > 0.10$; column (1)), which suggests that part of the revenue decline may reflect lower prices rather than fewer units sold. These results indicate that the moderating effects are not sensitive to the choice of revenue as the performance measure, whereas the evidence for H1 is weaker when performance is measured in units.

Table 5. Robustness check: alternative dependent variable (product sales volume).

Variable	(1) Sales Volume	(2) Sales Volume	(3) Sales Volume	(4) Sales Volume
Product age	−0.067	−0.201 ***	−0.454 ***	0.030
	(0.052)	(0.048)	(0.045)	(0.071)
Product age × Post-sales responsiveness		0.080 ***		
		(0.021)		
Product age × Customer engagement			0.042 ***	
			(0.005)	
Product age × Store maturity				−0.0013 **
				(0.0005)
Customer engagement		0.292 **	0.026	0.263 **
		(0.125)	(0.118)	(0.124)

Table 5. *Cont.*

Variable	(1) Sales Volume	(2) Sales Volume	(3) Sales Volume	(4) Sales Volume
Store followers	−3.156 ***	−2.227 **	−3.103 ***	−3.614 ***
	(1.014)	(0.949)	(0.988)	(1.036)
Product favorites	0.761 ***	0.524 ***	0.511 ***	0.523 ***
	(0.083)	(0.137)	(0.119)	(0.131)
Net store sales (volume)	0.131	0.287	0.420 ***	0.379 *
	(0.244)	(0.193)	(0.140)	(0.198)
Constant	45.841 ***	21.996 **	32.819 **	37.558 ***
	(14.620)	(10.307)	(12.264)	(12.135)
Year–month fixed effects	Yes	Yes	Yes	Yes
Store fixed effects	Yes	Yes	Yes	Yes
Observations	753	753	753	753
R-squared	0.819	0.836	0.862	0.835

Notes: Standard errors clustered by store in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Post-sales responsiveness is time-invariant within stores, and store maturity equals calendar time minus a store-specific constant; both main effects are absorbed by the store and year–month fixed effects and are therefore not reported. Column (1) is the baseline specification and does not include customer engagement.

4.4.2. Nonlinear Product Age Effect

Second, we address the possibility of a nonlinear age–performance relationship by adding a quadratic term of product age to the interaction models. Table 6 reports the results. The coefficient on product age squared is positive and significant across all specifications ($\beta = 0.015$, 0.008, and 0.015, respectively; all $p < 0.05$ or better), indicating that the rate of decline slows as products age—i.e., the trajectory is convex rather than linear. This pattern is consistent with a decelerating decline rather than an inverted-U shape. Importantly, all three interaction terms remain statistically significant with the same sign as in the main analysis, indicating that our moderating effects are robust to accounting for nonlinearity in the baseline age–performance relationship.

Table 6. Robustness check: nonlinear product age effect (quadratic specification).

Variable	(1) Product Performance	(2) Product Performance	(3) Product Performance
Product age	−0.439 ***	−0.575 ***	−0.254 **
	(0.096)	(0.081)	(0.106)
Product age^2	0.015 ***	0.008 **	0.015 ***
	(0.004)	(0.003)	(0.004)
Product age × Post-sales responsiveness	0.045 **		
	(0.020)		
Product age × Customer engagement		0.038 ***	
		(0.005)	
Product age × Store maturity			−0.0014 **
			(0.0005)
Customer engagement	0.260 **	−0.003	0.226 *
	(0.116)	(0.104)	(0.114)
Store followers	−2.452 **	−3.005 ***	−3.527 ***
	(0.870)	(0.974)	(0.962)
Product favorites	0.531 ***	0.537 ***	0.542 ***
	(0.105)	(0.093)	(0.101)

Table 6. *Cont.*

Variable	(1) Product Performance	(2) Product Performance	(3) Product Performance
Net store sales	0.407 ***	0.519 ***	0.496 ***
	(0.127)	(0.131)	(0.153)
Constant	24.628 **	30.143 **	35.079 ***
	(11.024)	(11.100)	(10.412)
Year–month fixed effects	Yes	Yes	Yes
Store fixed effects	Yes	Yes	Yes
Observations	753	753	753
R-squared	0.818	0.845	0.821

Notes: Standard errors clustered by store in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Post-sales responsiveness is time-invariant within stores, and store maturity equals calendar time minus a store-specific constant; both main effects are absorbed by the store and year–month fixed effects and are therefore not reported.

4.4.3. Alternative Customer Engagement Measure

Third, we examine whether the moderating effect of customer engagement is robust to an alternative operationalization. Because reviews arrive after purchases, the cumulative stock of reviews partly reflects a product's past sales and rises mechanically with product age. We therefore replace the cumulative stock of reviews with a lagged flow measure (the number of reviews received in the previous month) as the moderator, while retaining the cumulative stock as a control. As shown in Table 7, the interaction between product age and monthly reviews remains positive and significant ($\beta = 0.028$, $p < 0.01$), indicating that the moderating role of customer engagement holds under both stock and flow specifications.

Table 7. Robustness check: alternative customer engagement measure (monthly reviews).

Variable	Product Performance
Product age × Monthly reviews	0.028 ***
	(0.006)
Product age	−0.234 ***
	(0.045)
Customer engagement (cumulative)	0.134
	(0.083)
Store followers	−1.635
	(1.034)
Product favorites	0.518 ***
	(0.111)
Net store sales	0.375 **
	(0.140)
Monthly reviews	−0.006
	(0.106)
Constant	42.487 ***
	(14.650)
Year–month fixed effects	Yes
Store fixed effects	Yes
Observations	645
R-squared	0.876

Notes: Standard errors clustered by store in parentheses. *** $p < 0.01$, ** $p < 0.05$. Post-sales responsiveness is time-invariant within stores, and store maturity equals calendar time minus a store-specific constant; both main effects are absorbed by the store and year–month fixed effects and are therefore not reported.

4.4.4. Excluding Single-Product Stores

Finally, we examine whether our results are sensitive to the inclusion of single-product stores, for which the distinction between store-level and product-level characteristics may be less meaningful. We exclude observations from the two single-product stores and re-estimate all models on the reduced sample of 734 product–month observations. As reported in Table 8, the results remain substantively unchanged: the interaction coefficients for post-sales responsiveness ($\beta = 0.064$, $p < 0.01$), customer engagement ($\beta = 0.042$, $p < 0.01$), and store maturity ($\beta = -0.0017$, $p < 0.01$) remain significant and of similar magnitude to the main results. The baseline coefficient on product age is also unchanged ($\beta = -0.097$, $p < 0.05$; column (1)). This indicates that our findings are not driven by the inclusion of single-product stores.

Table 8. Robustness check: excluding single-product stores (N = 734).

Variable	(1) Product Performance	(2) Product Performance	(3) Product Performance	(4) Product Performance
Product age	−0.097 **	−0.203 ***	−0.476 ***	0.041
	(0.046)	(0.057)	(0.048)	(0.052)
Product age × Post-sales responsiveness		0.064 ***		
		(0.020)		
Product age × Customer engagement			0.042 ***	
			(0.005)	
Product age × Store maturity				−0.0017 ***
				(0.0005)
Customer engagement		0.220 *	−0.045	0.177
		(0.112)	(0.096)	(0.106)
Store followers	−3.013 **	−2.204 *	−2.966 ***	−3.625 ***
	(1.172)	(1.067)	(1.024)	(1.081)
Product favorites	0.733 ***	0.554 ***	0.545 ***	0.568 ***
	(0.064)	(0.114)	(0.097)	(0.108)
Net store sales	0.239	0.368 **	0.513 ***	0.469 **
	(0.176)	(0.147)	(0.135)	(0.167)
Constant	47.660 **	21.349	29.459 **	35.612 ***
	(17.419)	(12.725)	(11.698)	(12.428)
Year–month fixed effects	Yes	Yes	Yes	Yes
Store fixed effects	Yes	Yes	Yes	Yes
Observations	734	734	734	734
R-squared	0.792	0.806	0.841	0.809

Notes: Sample excludes products from single-product stores (reduced from 753 to 734 observations). Standard errors clustered by store in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Post-sales responsiveness is time-invariant within stores, and store maturity equals calendar time minus a store-specific constant; both main effects are absorbed by the store and year–month fixed effects and are therefore not reported.

5. Discussion

This study examined how the performance of new products evolves after launch in a digital marketplace and how platforms, customers, and firms shape this evolution. We find that monthly sales revenue declines as products age (in revenue terms; see Section 4.4.1) and that the decline decelerates over time. Importantly, the rate of decline varies systematically across products. The decline is slower when stores exhibit greater post-sales responsiveness and when products receive stronger customer engagement, but faster when products

are sold by more mature stores. These findings reveal substantial heterogeneity in post-launch performance trajectories and highlight the roles of multiple actors in shaping the commercialization of new products in digital marketplaces.

5.1. Theoretical Implications

First, our findings extend research on new product performance by shifting attention from performance outcomes to their evolution after market introduction. Prior research has identified numerous determinants of new product performance [19,20], while product life cycle research emphasizes that product performance changes systematically over time [40]. Our results show that, after accounting for time-invariant store differences and common monthly shocks, products of the same age decline at different rates depending on the conditions under which they are commercialized. The theoretical implication is that post-launch performance should be studied as a trajectory whose shape is structured by firm–platform, firm–customer, and within-firm conditions, rather than as an outcome determined by elapsed time alone. Thus, understanding new product performance requires attention not only to how performance changes over time, but also to why the rate of change differs across products.

Second, our findings advance digital platform research by showing how firms' routine operational behavior can become consequential for individual product performance through platform governance. Digital platforms govern participating firms through rules and other nonprice mechanisms that shape seller behavior and performance [13,32,49]. On the focal platform, refund processing time forms part of the platform's service assessment, which is linked to merchants' eligibility for platform-organized marketing activities. Consistent with this mechanism, we find that greater post-sales responsiveness mitigates the decline in new product performance as products age. This finding extends Kapoor and Agarwal [17] by shifting the unit of analysis from complementor-level sustained performance to individual product trajectories and by showing how a routine firm behavior can become consequential for product performance through platform governance. Because we do not directly observe traffic allocation or campaign participation, the access mechanism remains an inference from the platform's written rules and warrants direct testing in future research.

Third, our findings extend customer engagement research by showing that customer engagement is consequential for the evolution of product performance after launch. Customer engagement arises from interactive and co-creative customer experiences that unfold iteratively over time [53,54]. Online reviews provide product information that can inform subsequent purchase decisions [55,57]. We find that stronger customer engagement is associated with a flatter post-launch decline in new product performance as products age. This finding extends the role of customer engagement beyond its immediate implications for customer decision making by showing that it is also associated with differences in longer-term product performance trajectories.

Fourth, our findings reveal store maturity as an important store-side condition shaping post-launch product performance. The attention-based view suggests that organizational attention is selectively allocated across competing issues and opportunities and that this allocation shapes organizational behavior [36,64]. Building on this logic, our findings suggest that as products age, mature stores are more likely to shift attention toward other operational priorities, whereas new products remain relatively more salient to less mature stores. This finding shows that the consequences of store maturity extend beyond firms' product-related decisions to the trajectories of individual products after market introduction. Because store maturity is operationalized using store tenure, we do not directly observe attention allocation itself. Future research could examine this mechanism using more direct measures of firms' product-level attention and resource allocation.

5.2. Practical Implications

The findings also offer practical implications. For firms, launching a product on a digital marketplace marks the beginning rather than the end of its commercialization. Because the decline is flatter when post-sales service is responsive, firms should treat refund processing and other codified service metrics as platform-facing assets and maintain them throughout a product's life, particularly ahead of major promotional campaigns. Because accumulated customer evaluations are associated with more durable demand, firms should encourage and manage reviews soon after launch so that new products build an evaluation stock before novelty fades. Mature stores should recognize that new products risk being treated as marginal additions to an established portfolio and may require dedicated post-launch resources and attention to avoid premature decline. For platform operators, the results suggest that codified service standards not only protect customers but may also influence which new products sustain their sales, a consideration that deserves attention in the design of seller assessment and campaign eligibility rules.

6. Conclusions

This study asked why the post-launch performance of new products in digital marketplaces declines faster for some products than for others. Using 753 product–month observations on 73 new products sold through 23 official flagship stores on Tmall between July 2020 and July 2021, we estimated models with store and year–month fixed effects and standard errors clustered by store. Our results indicate that monthly sales revenue declines as products aged, although the evidence for this baseline relationship is less robust than that for the moderating effects. The negative age–performance relationship is statistically significant under conventional clustered standard errors but only marginally significant under wild cluster bootstrap inference, and is not statistically significant when performance is measured by sales volume. The moderating effects, however, are more consistent across specifications. The decline is weaker for products sold by stores with faster post-sales responsiveness and for products with a larger stock of accumulated customer reviews, whereas it is steeper for products sold by stores with longer tenure on the platform. These findings speak to post-sales responsiveness, measured by refund processing speed, and to store maturity, measured by store tenure on the platform; they should not be read as evidence on broader constructs such as overall service quality or firm-level organizational capabilities.

This study has several limitations. First, our measures remain at some distance from the constructs they represent. Refund processing time in our data covers all refunds, whereas the platform's own assessment metric may be computed on a narrower scope, such as refunds completed by sellers without platform intervention; store tenure is an indirect indicator of store maturity that may also reflect brand strength. Second, the evidence comes from 73 products sold on a single platform, and the sampled products entered the market through Tmall's Heybox new-product launch channel, which may involve selective admission; the findings should therefore be extended to other platforms, product categories, and launch routes with caution. Third, although our research design mitigates some concerns about reverse causality, the observational nature of the data does not allow us to fully rule out potential endogeneity arising from unobserved factors. In addition, we do not directly observe how the platform allocates traffic or campaign slots, so the proposed mechanism linking service assessments to continued access to platform resources is inferred from the platform's written rules rather than observed directly. The estimates should therefore be interpreted as associations rather than causal effects. Future research could draw on multiple platforms, employ more direct measures of platform-related operations and channel structures, and exploit exogenous changes in platform governance rules or other

quasi-experimental settings to examine these mechanisms more directly and strengthen causal identification.

Author Contributions: Conceptualization, H.D. and R.X.; methodology, software, validation and formal analysis, H.D.; writing—original draft preparation, R.X.; writing—review and editing, X.S.; funding acquisition, H.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Philosophy and Social Sciences Work Office of Zhejiang Province, under the Zhejiang Provincial Philosophy and Social Sciences Planning Project (General Project), Grant No. 26NDJC017YB.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets generated during the current study are available from the corresponding author on reasonable request due to confidentiality and data-sharing restrictions imposed by the third-party data provider.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

B2C	Business-to-consumer
PLC	Product life cycle
VIF	Variance inflation factor

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