These Deals Won't Last! Longevity, Uniformity, and Bias in Product Badge Assignment in eCommerce Platforms

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Abstract

Product badges are ubiquitous in e-commerce platforms, acting as effective psychological triggers to nudge customers to buy specific products, consequently boosting revenues. However, to the best of our knowledge, there has been no attempt to systematically study these badges and their several idiosyncrasies – we intend to close this gap in our current work. Specifically, we try to answer questions such as: How do the products that receive badges differ from those which do not, in terms of price, customer rating, etc.? How long does a product retain a badge on a given platform? If a product is sold on different platforms, then does it receive similar badges? We collect longitudinal data from several e-commerce platforms over 45 days, and find that although most of the badges are short-lived, there are several permanent badge assignments, and that too for badges meant to denote urgency or scarcity. Furthermore, it is unclear how the badge assignments are done, and we find evidence that highly-rated products are missing out on badges compared to lower quality ones. Our work calls for greater transparency in the badge assignment process to inform customers, as well as to reduce dissatisfaction among the sellers dependent on the platforms for their revenues.

Keywords

eCommerce platform, digital nudging, badge assignment

1. Introduction

Today, e-commerce marketplaces like Amazon, eBay, Rakuten, and Alibaba have emerged as indispensable online platforms helping millions of customers with their purchase needs. At the same time, they provide livelihood to thousands of sellers and producers worldwide [1]. Especially, during the pandemic-induced restrictions on physical sales, these e-commerce marketplaces have become the lifeline for numerous small sellers [2]. Given the sheer scale of the product space in these platforms, algorithmic systems, such as search and recommendation systems, mediate the interactions between customers and sellers, decide the customer experience and determine the fate of the sellers [3].

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When a customer visits an e-commerce website and searches for something to buy, products matching the search query are returned. Interestingly, the returned product lists often contain products highlighted with certain badges, such as, 'Best Seller', 'Deal of the Day', 'New Arrival', 'Discount', etc. These badges evoke specific psychological reactions in a customer and nudge her to buy the corresponding products. For example, a 'Best Seller' badge means that many other customers have already bought this popular product and hence, one can go forward and buy it. Whereas the badge 'Deal of the Day' creates a sense of urgency that the customer may miss out on a wonderful opportunity if that product is not bought immediately. In fact, product badges have been found to increase purchase conversion rates by as high as 55% [4, 5]. A specific use case of the cosmetics brand Ulta has been reported by Davies [6], where product badges have played a key role in boosting the company's overall revenue by 23%.

Recognizing the importance, several Software-as-a-Service (SaaS) providers for smaller e-commerce businesses (including WooCommerce [7], BigCommerce [8], Crobox [9], and PrefixBox [10]) put major emphasis on product badge assignment. For example, Crobox mentions that effective badge assignments may give an edge to smaller retailers to maintain competition with bigger players like Amazon [11]. These commercial tools allow creation of a number of badges, and may include the option of automatically assigning badges to products [5]. The time duration for which a badge can be displayed on a platform can also be controlled by these tools.

However, since the badges can be assigned to only a handful of products without risking the dilution of customer attention, it may deprive some products of getting the attention they truly deserve. Specially in some platforms, getting a badge can bring huge revenue opportunities for certain products. For example, the products with 'Amazon's Choice' badges can be bought on Amazon with zero clicks! If a customer uses a voice-activated device, such as Echo or Alexa, and says "Alexa, order a pillow", then the 'Amazon's Choice' product would be the default choice for that keyword [12]. Interestingly, although some patterns have been recorded for which products have received the 'Amazon's Choice' label, it is unclear to sellers that how Amazon's algorithm chooses which products should receive this badge [13]. It has been reported by Dash et al. [14] that Amazon may provide preferential treatment to its own private label products over third-party sellers' products during recommendation; a lack of transparency in badge assignment may further fuel the dissatisfaction among the sellers.

Despite its ubiquitous presence and associated implications, only a few research studies have focused on product badges. Adaji et al. [15, 16] discussed different persuasive strategies employed in e-commerce platforms to boost sales, such as star ratings, votes, or reviews, but disregarded the role product badges play. A blogpost [17] provided the first comprehensive categorization of different badges displayed on e-commerce websites, and our categorization scheme for badges borrows from this line of work. However, there is no cross-platform study looking at different aspects of product badges – how long a product retains a particular badge, whether the platforms utilize badges for mis-selling, for example, a product always getting a badge *'10% off only for today'*, whether a product receives a badge uniformly across platforms, and so on.

In this work, we bridge this gap by extensively collecting data from 12 e-commerce platforms over 45 days. Out of these 12 platforms, 10 cater to only niche domains, and the rest 2 are generic which sell a wide variety of products across multiple domains. All of our data is made publicly available[1] which, to the best of our knowledge, is the first comprehensive dataset that focuses on product badges, and includes details such as name of the e-commerce platform, query executed, returned results ranked in order with brand names, badges assigned, prices, discounts, ratings, links, and other useful relevant features. Using this data, we attempt to answer the following three research questions:

RQ1. Assignment bias: How do the products that receive badges differ from those which do not? What is so special about these products with badges?

RQ2. Longevity: How long does a product retain a badge on a given platform? Does it vary depending on the platform, domain, or type of badges?

RQ3. Uniformity: If a product is sold on different platforms, does it receive similar badges?

Our investigation reveals that though most of the badges are short-lived, there are several products that retained a badge over the full data collection period. Most surprising are the badges denoting scarcity or urgency; one might expect them to be short-lived, yet we find these assignments to be permanent. The same products seem to get different types of badges on different platforms; so there is no cross-platform consensus in badge assignments. We did not find any clear pattern in the product choices for badge assignment; in fact, products without badges seem to be higher rated than the products with badges. Overall, we take the first step towards exploring the badge landscape in this work, and we hope it can spawn future works looking at product badges in a holistic manner.

2. Related Work

In this section, we briefly survey the prior works on e-commerce platforms and digital nudging.

2.1. eCommerce platform designs

eCommerce websites deploy multiple techniques to attract and retain customers to increase their revenue, which include persuasive strategies targeting human psychology [18] or attractive interface design [19]. Furthermore, customers' social networks are also utilized for boosting sales, in a form of e-commerce named 'Social Commerce' [20, 21]. Having realized the potency of these strategies, many SaaS companies [8, 9] incorporate these in their services to small e-retailers that include search engine optimization, hosting, marketing, etc.

Even within a platform, there are various means to steer a customer's attention to a specific product, which may include explicit identifiers, such as stars, votes, reviews, and badges, along with some implicit ones, such as the rank of the product in the recommendation list [22]. However, unlike the rest of the explicit identifiers, badges are conferred to a chosen few products. Zhang [23] looked into how the 'SuperHost' badge in Airbnb helps improve sales at a higher charge. There are external companies that provide specialized badges to e-commerce websites, such as Shopify [24] which provides payment related trust and security badges, and Yotpo [25]

[1] https://github.com/architbansal28/Product-Badges

which provides product reviews related badges. Adaji and Vassileva [26] reported how Amazon persuades its customers to write more reviews by giving the 'Hall of Fame' badge. They further looked into various persuasive strategies that are employed in e-commerce [15, 16]; however, they surprisingly did not cover product badges which are a common sight across all e-commerce platforms and can be an effective tool to steer customers towards particular products.

2.2. Digital nudging

Thaler and Sunstein [27] introduced nudging as a tool to achieve societal goals by exploiting some mental shortcuts people take. Following this work, there have been many applications of nudge theory in several domains, including in digital platforms. For example, Mota et al. [28] designed interface nudges to steer more donations to poorer schools in an educational charity platform. Bhuiyan et al. [29] designed nudges to increase consumption of credible news on Twitter, which can help to curb misinformation. A comprehensive survey on digital nudging can be found by Jesse and Jannach [30]. According to their taxonomy, product badges should fall under the category 'Attracting Attention', which, in turn, falls under the super-category 'Increase salience of information'. However, the authors did not talk about product badges other than in a footnote, where they describe product badges as 'visual highlighting tools'.

Saari et al. [31] tried to categorize different persuasive techniques in e-commerce. Unfortunately, product badges have been skipped in this work as well – in fact, product badge does not belong to any of the categories mentioned by the authors, although the 'visual layout' category comes close. Another way to nudge customers to buy products borrows ideas from gamification [32], such as, through loyalty points, coaxing customers to enter contests, etc. Some researchers have also criticized the interface design choices of e-commerce platforms to push users into making unintended purchases as *dark patterns* [33].

Overall, we see that psychologically targeting customers and subtly persuading them towards purchasing specific products is prevalent in e-commerce; however, product badges seem to be a comparatively new phenomenon and not well explored in the literature. In this work, we attempt to bridge this gap.

3. Dataset Gathered

As mentioned in the introduction, in this work, we attempt to explore the badge assignments across different e-commerce platforms. For this purpose, we looked into platforms that serve a niche domain vis-a-vis generic platforms that sell a variety of products across domains, including the niche ones. We are also interested to know whether the same products sold on different platforms get similar badges. Therefore, we restricted ourselves to websites that target a specific country; otherwise the products (brands) being sold might be quite different. In this study, we have chosen websites that are operational in India.

We concentrate our study on four niche domains: (i) baby products, (ii) cosmetics, (iii) fashion, and (iv) home decor. These domains were chosen based on two factors. Firstly, we tried to make the niche domains as diverse as possible. Though there may be small overlaps, e.g., websites related to baby products and fashion may both include garments for babies; we carefully selected

Table 1
Data collection: e-commerce websites from different domains and the queries we used to collect the corresponding product listing.

Domain	Niche Websites	No. of unique products	Search Queries
Baby Products	FirstCry (firstcry.com) Hopscotch (hopscotch.in) My Baby Babbles (mybabybabbles.com)	4145 1196 972	Baby diaper, Baby toys, Baby boy clothes, Stroller, Baby towel, Baby shampoo, Baby girl dresses, Onesies, Baby footwear, Baby food
Cosmetics	e.l.f. Cosmetics (elfcosmetics.com) Nykaa (nykaa.com)	226 1413	Eyeliner, Lipstick, Blush, Cleanser, Moisturizer, Face primer, Makeup removers, Face brush, Lip balm, Mascara
Fashion	Bewakoof (bewakoof.com) LimeRoad (limeroad.com) Max Fashion (maxfashion.in)	1275 6536 1024	Women dresses, Women kurtis, Women jackets, Women jeans, Women shirts, Men casual shirts, Men trousers, Men polo t-shirts, Men socks, Men track pants
Home Decor	Pepperfry (pepperfry.com) Urban Ladder (urbanladder.com)	2319 3498	Bed, Dining set, Mattress, Bedsheet, Table lamp, Sofa set, Study table, Wall mirror, Chair, Artificial plants
Domain	**Generic Websites**	**No. of unique products**	**Search Queries**
All four	Amazon (amazon.in) Snapdeal (snapdeal.com)	23784 16501	All queries mentioned above

the queries to collect data from different websites so that the returned product lists are different across domains. Secondly, the selected domains should have websites that are popular in India.

For each domain, we picked two or three niche websites, totaling ten websites across four domains, as listed in Table 1. As generic websites, we chose *Amazon* and *Snapdeal*, which sell products across all these domains.[2] Next, we selected ten different queries for each of these four domains so that the corresponding e-commerce websites (niche and generic) returned a considerable number of products as results. These queries are also reported in Table 1.

To automatically collect the product listing against each query, we used the Selenium Web-Driver (selenium.dev) to automate the process of firing the search query to these websites and retrieve the results returned. Further to ensure that the site does not realize that the same user is firing the queries and therefore somehow get influenced while assigning badges, we cleared the cookies and launched a fresh search every time we fired a query. We considered the results up to a maximum of 100 products, and also stored other metadata associated with the products, such as product name, price, discount, average customer rating, number of ratings, and most importantly, the badge assigned to a product (if available). We call one instance of the data collected across all websites as a *snapshot*. Our dataset contains data collected over 45 days during June–August 2021, with 2 snapshots per day at a gap of 12 hours, i.e., altogether there are total 90 snapshots. Overall, the data consists of $62,889$ unique products across platforms, out of which $27,016$ (42.9%) products got some badge in at least one of the snapshots.

4. Categorization of Badges

As discussed in the last section, we explore a total of 12 e-commerce websites, and all of these assign multiple types of badges to different products, where these badge names are often unique to the site. To perform a cross-platform study, we group different badges into coherent categories. Badges are designed to trigger specific psychological reactions from customers, so that they take

[2]It is worth noting that for platforms with a global presence, we have considered their India specific website, e.g., Amazon.in.

Table 2
Badges assigned at different e-commerce websites and their respective categories. Here 'X' and 'Y' represent different numbers used in the actual badges – for example, 'Only 5 Left in Stock', 'Buy 3 Get 2', etc.

Website	Badge	Category
Amazon	Best Seller, Kids Gift Ideas	Social Proof
	Only X Left in Stock	Scarcity
	Deal of the Day, Limited Time Deal, Deal is X% Claimed, Prime Day Deal	Urgency
	Amazon's Choice	Endorsement
	Prime Day Launch	Exclusivity
Bewakoof	Few Left, Last Sizes Left - Special Price	Scarcity
	Flash Sale	Urgency
	Buy X Get Y, Buy X for Y, Color of the Month	Promotional
e.l.f. Cosmetics	Best Sellers, Trending, Glam Award	Social Proof
	New	Recency
	Holy Grail	Endorsement
FirstCry	Bestseller, #1 Mom's Pick	Social Proof
	X Left	Scarcity
	New!	Recency
	Super Saver	Promotional
Hopscotch	X Left	Scarcity
LimeRoad	Flash Sale, Freshness Unplugged Season Sale, Brand Day Sale	Urgency
	New	Recency
	Offer: Buy X Get Y Free, Offer: Freebie, Best Price	Promotional
	Exclusive	Exclusivity
Max Fashion	New	Recency
	Buy X Get Y, Buy X at Y, Buy X at Y% Off, Flat X% Off	Promotional
My Baby Babbles	Sale	Urgency
Nykaa	Bestseller	Social Proof
	Sale	Urgency
	New	Recency
	Offer	Promotional
	Featured	Endorsement
Pepperfry	Best Seller	Social Proof
	Clearance Sale!	Urgency
	New	Recency
	30/100 Nights Trial	Promotional
Snapdeal	Trending, Top Seller, X Orders in Last Y Days, X People Just Ordered, X% Positive Feedback	Social Proof
	X Left!	Scarcity
	Featured	Endorsement
Urban Ladder	Best Seller	Social Proof
	Only X Left	Scarcity
	New Arrival	Recency

a mental note of the products with the badges and get swayed towards buying them. Following the lines of Cialdini [18] and Davies [17], we categorize the badges into the following categories, based on the psychological triggers they fire.

Social Proof: These badges indicate that the product is popular among customers, e.g., 'Best Seller', 'Trending'.

Scarcity: This type of badges communicate that the product is only available in a small quantity, e.g., 'Few Left', 'Only 5 Left in Stock'.

Urgency: These badges convey that one needs to buy the product quickly, else she will miss a great opportunity, e.g., 'Deal of the Day', 'Limited Time Deal'.

Recency: This type of badges indicate that the product has been introduced recently, e.g., 'New Arrival', 'New'.

Promotional: This type of badges indicate that by buying the product now, a customer will receive a special offer or discounted price, e.g., 'Buy 1 Get 1', 'Super Saver'.

Endorsement: These badges carry the endorsement from the platform or some expert, e.g., 'Amazon's Choice', 'Featured'.

Exclusivity: This type of badges indicate that the product is available exclusively on a platform or for a chosen set of customers, e.g., 'Exclusive', 'Prime Day Launch'.

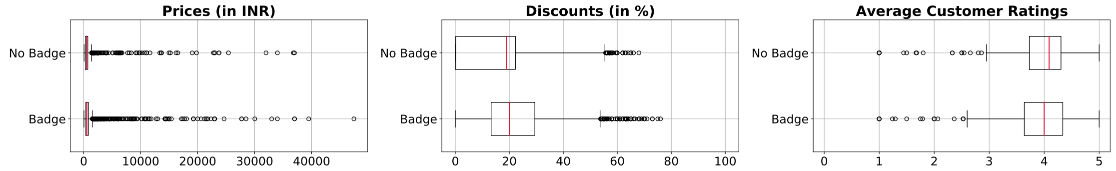
It is worth noting that a type of badge may invoke a mix of emotions. For example, a *Scarcity* badge also indicates that the product should be bought urgently and hence can also be put in *Urgency* category. Furthermore, a *Scarcity* badge also tacitly implies that the product has been selling fast, and thus serves as a *Social Proof.* Similarly, a badge like '10 People Just Ordered' can belong to both *Social Proof* and *Recency* categories. To reduce the chance of misinterpretation, three annotators were asked to independently assign categories to the badges we encountered in our dataset, by examining their nomenclature, and we choose the category of a badge based on the majority opinion. Table 2 lists all badges present on different websites and their respective category information. Note that we did not include the 'Sponsored' badge in our study because it is assigned in exchange for a fee, and thus does not shed any insight on the badge assignment policies. For similar reasons, we also did not consider 'Out of Stock' and 'Sold Out' badges in our study.

5. Customer Survey

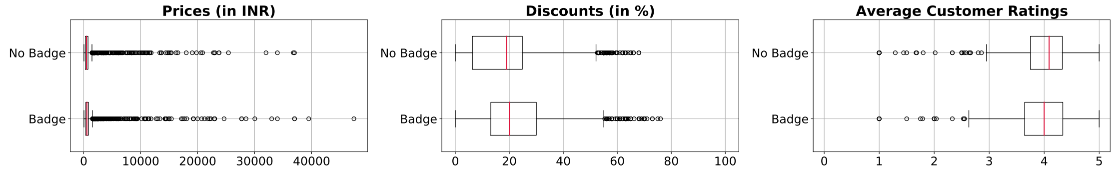
To understand the role that badges play while buying products online, we conducted a survey that 203 people participated in. Out of 203 participants, 81% reported that they buy from e-commerce sites on a mid to high frequent basis. We asked each participant 10 questions where we showed her a pair of items – exactly one of these items had a product badge, and asked "Suppose you are looking for <query string>. Which of the following would you prefer to buy?" It is important to note that the pair of items had similar images, ratings, and prices, so that the badge becomes the primary difference between the two while not being explicitly so. We had a couple of questions to test the participants' perception of the availability of items with *Scarcity* badges, and another couple of questions to test the preference for one type of badge over another. We shall get to the details of these in the subsequent sections, where we motivate the research questions posed by us on the basis of the survey responses.

6. RQ1. Assignment bias: What is so special about the product?

Our survey showed that badges indeed have a positive influence on customers; we noticed that the number of participants who chose products with badges varied from 65% to 88% across products. Since having a badge helps a product get the desired traction with the customers, it is



(a) Scheme 1



(b) Scheme 2

Figure 1: Comparing products with and without badges on FirstCry website, following two different schemes (details in text).

pertinent to ask whether the products with badges are any different from those which did not get badges. This can also help predict the underlying badge assignment policies employed by different websites. We look into the following four attributes: price, discount, average customer rating (CR), and number of customer ratings to compare the products. To clarify the attribute 'discount', if the original price of a product is X but currently it is available at a lower price Y, then the discount is $\frac{X-Y}{X}$. It is important to note that e-commerce websites can give discounts without any explicit *Promotional* badges. Moreover, in such cases, we consider the 'price' of the product to be its current selling price, i.e., Y in our example.

Since the badge assignment to a product can vary across snapshots, we followed two schemes while creating the list of products with 'Badge' and with 'No Badge': 1. we include a product in the 'Badge' list if it has received a badge in at least one snapshot; 2. we include a product in the 'Badge' list only for those snapshots where it has received a badge, and do not include for snapshots where it did not get a badge. Figure 1 shows the comparison between these two types of products in both schemes for the FirstCry website. Interestingly, there is no significant difference in the comparison results between these two schemes. For both, products with badges offer higher discounts; a few of them are higher priced, although the median price is similar for both types. Surprisingly, we found that the average rating is higher for products without badges, raising concerns about whether lower quality products are being promoted using the badges. We found a similar trend for other platforms as well.

6.1. Products with multiple badges

In addition to the earlier experiments, we dived into the recommendation lists to see which products received multiple badges in a platform. We found that 9 out of 12 websites assigned 2, 3, or 4 badges to a single product (in different snapshots or, in some rare cases, even in the same snapshot). For example, in Amazon, Harpa Women's A-Line Dress received 4 badges: Amazon's Choice (*Endorsement*), Best Seller (*Social Proof*), Only X Left in Stock (*Scarcity*), and Deal of the Day (*Urgency*). Similarly, in Nykaa, Lakme Eyeconic Liquid Eyeliner received 4 badges:

Table 3
Number of instances where multiple badges were assigned to the same product in a platform.

Platform	#Instances
Amazon	2-679, 3-74, 4-8
Bewakoof	2-192, 3-16
FirstCry	2-154, 3-3
LimeRoad	2-752, 3-53
Max Fashion	2-207, 3-45
Nykaa	2-773, 3-190, 4-23
Pepperfry	2-42
Snapdeal	2-685, 3-65
Urban Ladder	2-214

Table 4
Number of instances where a badge category pair was assigned to the same product.

Category-Pair	#Instances	Category-Pair	#Instances
Urgency–Promotional	1074	Social Proof–Scarcity	748
Recency–Promotional	485	Scarcity–Urgency	480
Urgency–Recency	353	Social Proof–Urgency	276
Scarcity–Recency	261	Urgency–Endorsement	253
Scarcity–Endorsement	214	Social Proof–Endorsement	178
Promotional–Endorsement	173	Scarcity–Promotional	121
Social Proof–Promotional	56	Promotional–Exclusivity	54
Urgency–Exclusivity	26	Social Proof–Recency	10
Scarcity–Exclusivity	10	Recency–Endorsement	5
Social Proof–Exclusivity	2	Recency–Exclusivity	2

Featured (*Endorsement*), Bestseller (*Social Proof*), Sale (*Urgency*), and Offer (*Promotional*). These results are captured in Table 3.

In Table 4, we provide the number of instances, accumulated over all platforms, where two badge categories were assigned to the same product. Thus, if a product receives badges of three different categories, then we will add it to the count of all the three possible category-pairs. Note that no product was assigned both *Endorsement* and *Exclusivity* badges, and hence only this pair is missing in Table 4. From this table, it seems that websites take a two-pronged approach – *Urgency* and *Promotional* – to quickly sell specific products. Furthermore, we conjecture that popular products having *Social Proof* badges may often sell fast, and when the resources are depleted, *Scarcity* badges are assigned to these. We think *Recency* and *Promotional* badges probably go hand-in-hand to mitigate the cold start problem in recommendations. Similar opinions may be formed for other category-pairs with high counts.

7. RQ2. Longevity: How long do the deals last?

After categorizing the badges, we turn our attention to the *stability of badge assignments* at different e-commerce platforms. Knowing how long a product holds a particular badge (termed

as 'Longevity') is important for multiple reasons: (i) if a *Scarcity* or *Urgency* category badge is given to a product for long, it can indicate potentially unfair practice by the platform; retaining the same badge to particular products (ii) may lose its value for the repeat customers, and (iii) may deny opportunities to other products.
In fact, on being asked about when they expect a product with *Scarcity* badge to be sold out, 15% of our survey participants answered "in a few hours", and 44% answered "in a few days".

7.1. Measuring longevity

Longevity of a badge i for a product j ($\mathscr{L}_{i,j}$) is defined as

$$\mathscr{L}_{i,j} = \frac{\text{\# snapshots with } j \text{ having badge } i}{\text{total number of snapshots}}.$$

For example, if Product A has badge X for 60 snapshots out of 90, then $\mathscr{L}_{X,A}$ is $\frac{60}{90} = 0.67$. Average longevity of a badge i ($\hat{\mathscr{L}_i}$) is calculated over all products having this badge:

$$\hat{\mathscr{L}_i} = \frac{\sum_j \mathscr{L}_{i,j}}{\sum_j \mathscr{I}(\mathscr{L}_{i,j} > 0)},$$

where $\mathscr{I}$ is the indicator function.

7.2. Longevity of product badges across platforms

Box plots in Figure 2 present the range of $\mathscr{L}_{i,j}$ values across products and badges in different platforms for the query 'men casual shirt', with $\hat{\mathscr{L}_i}$ values shown in the parentheses. While Figure 2(a) shows the $\mathscr{L}_{i,j}$ values across all badges in a platform for the query (values in parentheses denoting average $\hat{\mathscr{L}_i}$), all other sub-figures show $\mathscr{L}_{i,j}$ values for individual badges in respective platforms. We see that Max Fashion, on average, has badges with the highest longevity; in some cases, the longevity is 1 for Max Fashion and Bewakoof. Diving in, for Max Fashion, *New (Recency)* badges, and for Bewakoof, *Buy X Get Y (Promotional)* badges are the longest lasting. Amazon, on the other end, gave away badges with the least average longevity. However, the *Best Seller (Social Proof)* badges in Amazon have high longevity, including 1 in some cases; in contrast, *Deal of the Day (Urgency)* and *Only X Left in Stock (Scarcity)* badges have low longevity, thereby bringing down the average longevity for this platform.

After exploring the longevity of product badges at a query level, we aggregate the observations across all queries for a platform to identify macro trends. Specifically, we first consider all products with low ($0 < \mathscr{L}_{i,j} \leq 0.2$), medium ($0.2 < \mathscr{L}_{i,j} \leq 0.5$), and high ($\mathscr{L}_{i,j} > 0.5$) longevity. Figure 3 show these products across different websites under different domains. Our data indicates that the longevity of badges for the majority of products is rather small and there is a large churn in the assigned badges. When we look into the individual domains, it is hardest to retain a badge in *Fashion*, while in *Cosmetics*, the badges are retained fairly long.

We also look into the longevity of the product badges based on the categories that these belong to. Figure 4 shows an overview of the same.

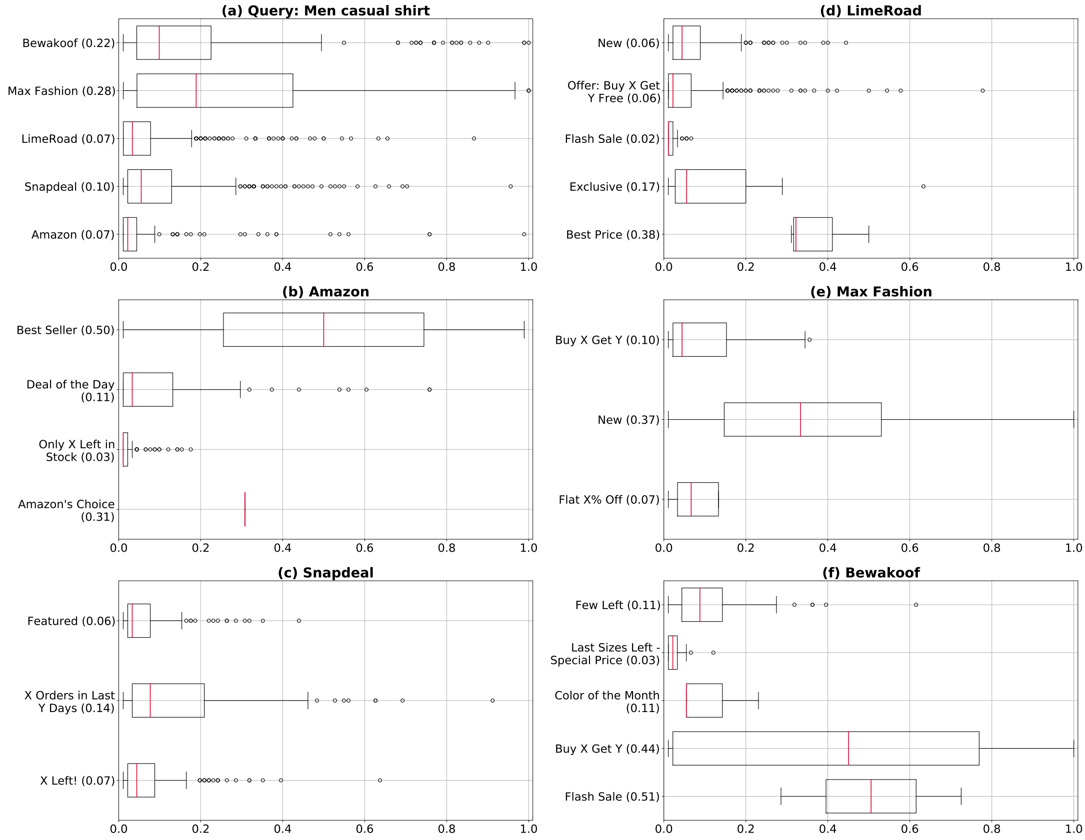


Figure 2: Box plots of Longevity ($\mathscr{L}$) values for the query 'men casual shirt' under *Fashion*. For this query, both generic and niche platforms provided similar number of badges over a similar spectrum of badge categories.

7.3. Measuring Consistency

Additionally, we use another metric *Consistency* ($\mathscr{C}_{i,j}$) as a measure of how long a product j retains badge i continuously. This is related to *Longevity*, but here the focus is on the contiguous time stretch. We measure $\mathscr{C}_{i,j}$ as

$$\mathscr{C}_{i,j} = \frac{max(\#\text{ contiguous snapshots with } j \text{ having badge } i)}{\text{total number of snapshots}}.$$

For example, if a platform assigns badge X to product A in snapshots 1, 2, and 3 but not in 4, $\mathscr{C}_{X,A}$ would be $\frac{3}{4} = 0.75$.

7.4. High consistency for *Scarcity* and *Urgency* badges!

Along with Longevity, we also computed Consistency, and we were particularly interested in badges belonging to the *Scarcity* and *Urgency* categories. Ideally, for these two categories,

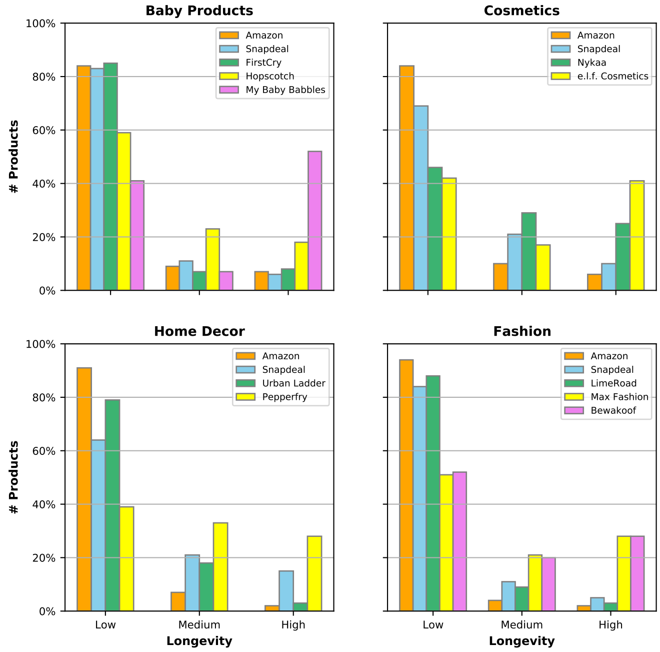


Figure 3: Longevity of badge assignments across different websites and domains.

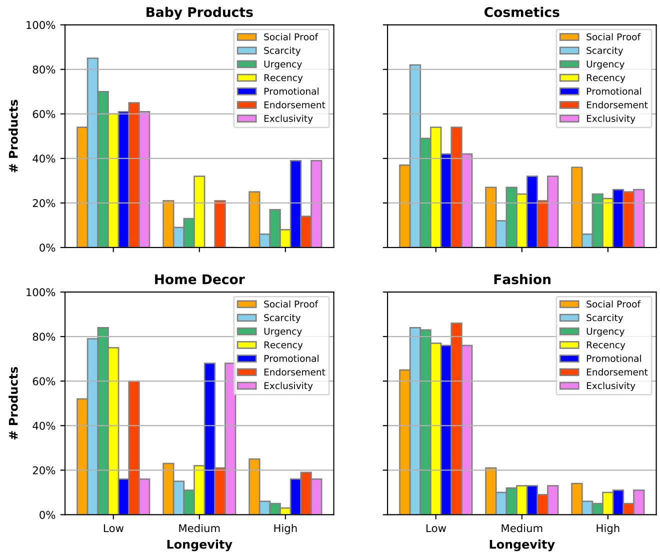


Figure 4: Longevity of badge assignments across different badge categories.

consistency values should be low. In fact, we captured multiple daily snapshots to track the outflux of these 'rare' products. However, the actual scenario is quite different.

For Bewakoof, we found that 9 products (all under 'women kurti' or 'women jackets') had a *Scarcity* badge for all the snapshots. There were 26 products that had a consistency value of more than 0.6 – all of these products are for 'women'; among products for 'men', the highest

Table 5
Examples of products with high consistency values.

Website	Product	Badge
Bewakoof	Women's Sleeveless Button Down Mandarin Collar Side Slit Kurta	Few Left
Bewakoof	Jet Black Plain Sleeveless Puffer Jacket with Detachable Hood	Few Left
Bewakoof	Women's Rib Raglan Dress	Buy X Get Y
FirstCry	Baby Peony Dress Set	X Left
FirstCry	TINY BABY Sleeveless Checked Dress	X Left
Hopscotch	Pink Flower Lace Onesies with Headband	X Left
Hopscotch	Navy Blue LED Shoes	X Left
My Baby Babbles	3 Sprouts Stroller Organiser	Sale
My Baby Babbles	My Milestones Baby Hooded Towel - Modern Stripped	Sale
Snapdeal	Mars 2in1 Makeup Fixer Spray & Face Primer Gel	X Left!
Snapdeal	Mee Mee Pram Cum Stroller With Rocking Function	X Left!
e.l.f. Cosmetics	No Budge Precision Eyeliner	New
e.l.f. Cosmetics	Jelly Poppin' Skincare Set	New
Max Fashion	MAX Printed Straight Kurta	New
Max Fashion	MAX Solid Slim Fit Casual Shirt	New

consistency value was 0.52. Following a similar pattern, in FirstCry, there were 11 products that had a *Scarcity* badge for all the snapshots, and all of these products appeared under 'baby girl dresses'. For gender-agnostic searches in 'Baby Products', products under 'stroller' typically had the highest consistency values, which were around 0.4, barring one (Tiffy & Toffee Portable Stroller with Canopy) that had a consistency value of 0.69 in FirstCry. In Hopscotch, the number of products that had a *Scarcity* badge all throughout was 26 – however, most of these belonged to 'onesies' and 'baby footwear'. Moreover, the consistency values for the products under 'baby boy clothes' and 'baby girl dresses' were comparable for this website. Contrarily, the generic websites typically had lower consistency values, especially Amazon, which had a 'sofa set' with the highest consistency value of 0.71. Snapdeal, however, had a handful of products (8) with consistency values above 0.9; two of these were 'face primer' and the rest belonged to 'sofa set' or 'dining set'. Although we found that the highest consistency values in the generic websites mostly belonged to the 'Home Decor' domain, surprisingly, the niche website Urban Ladder had lower consistency values, with the highest one being 0.61 belonging to a 'table lamp'.

In contrast to *Scarcity* badges, *Urgency* badges had relatively lower consistency values. For the websites Nykaa, LimeRoad, and Pepperfry, the average consistency values were 0.2, 0.3, and 0.32, respectively. For Bewakoof, one product under 'men polo t-shirt' had a consistency value of 0.92. My Baby Babbles, however, had high consistency values (>0.88) for almost all products under 'baby shampoo', 'baby towels', and 'baby diaper'. Three products in Amazon – all moisturizers from Mamaearth – had *Urgency* badge in all 90 snapshots. See Table 5 for more examples.

8. RQ3. Uniformity: Did you get the same deal?

Our survey had specific questions where we showed multiple similar products, each with a different badge category. Almost 47% of the participants chose the products with *Social Proof* badge (e.g., 'Best Seller'). *Endorsement* badge (e.g., 'Amazon's Choice') came second with 24%;

Table 6
Uniformity of badges across platform-pairs.

Platform-Pair	**#Queries**	**#Badge Categories**	**Score$_P$**	**Score$_L$**
Amazon–FirstCry	5	2	0.0399	0.0884
Amazon–Hopscotch	2	1	0.0371	0.0518
Amazon–My Baby Babbles	1	1	0.0233	0.0798
Amazon–Nykaa	9	3	**0.0932**	**0.2509**
Snapdeal–FirstCry	3	1	0.0110	0.0227
Snapdeal–Hopscotch	5	1	0.0157	0.0213
Amazon–Snapdeal	20	3	0.0162	0.0402
FirstCry–Hopscotch	2	1	0.0032	0.0078
Nykaa–e.l.f. Cosmetics	1	1	0.0333	0.1313
LimeRoad–Bewakoof	1	1	0.0082	0.0066

none of the other categories seem to have a significant preference over others. Thus, getting different badges may have a direct impact on the sales of the sellers. Hence, we investigate whether products sold on multiple platforms are assigned similar badges. We found that if a product is present on multiple platforms, the product names are similar (if not exactly the same) across websites, and contain the brand name and product specifications like color, fiber (for apparel), etc. For example, 'Lakme Insta Eye Liner, Black, Water Resistant, Long-Lasting, 9 ml' on Amazon and 'Lakme Insta Eye Liner - Black' on Nykaa. To account for the possibility of not finding an exact name match, we match the products on different platforms based on parameters like brand, color, etc. Moreover, even the names of the badges are often unique across the platforms; thus, we look for matches in the badge category.

Surprisingly, out of the 29 possible platform-pairs, we found that only 10 of these had at least one product that was assigned a badge on both, as mentioned in Table 6. In this table, we mention for each platform-pair, the number of queries (out of 40 for Amazon–Snapdeal pair, and out of 10 for every other pair) for which there is at least one common product that has received the same badge category, the number of different badge categories that these products belong to, and two scores: $Score_P$ and $Score_L$, which we explain with the following example.

Let us consider that there are two platforms, X and Y. For simplicity, let there be a single badge category $\mathscr{B}$. Now let the products having a $\mathscr{B}$-type badge and their corresponding *Longevity* in the two platforms be as follows: $X :: \{A : 0.3, B : 1.0, C : 0.4, D : 0.2\}$, and $Y :: \{A : 0.2, C : 0.6, E : 1.0, F : 0.1\}$. We compute $Score_P$ as the ratio of the number of common products to the number of all products in the two platforms belonging to the same badge category. In this example,

$Score_P = \frac{|\{x : x \in X \wedge x \in Y\}|}{|\{x : x \in X \vee x \in Y\}|} = \frac{|\{A,C\}|}{|\{A,B,C,D,E,F\}|} = \frac{2}{6} = 0.33.$

On the other hand, we define $Score_L$ as the ratio of the *Longevity* of common products to the *Longevity* of all products in the two platforms. Here $Score_L = \frac{\Sigma_{\{x : x \in X \wedge x \in Y\}} \mathscr{L}_{\mathscr{B},x}}{\Sigma_{\{x : x \in X \vee x \in Y\}} \mathscr{L}_{\mathscr{B},x}} = \frac{0.3+0.2+0.4+0.6}{0.3+1.0+0.4+0.2+0.2+0.6+1.0+0.1} = \frac{1.5}{3.8} = 0.3947$. Note that a higher $Score_P$ does not necessarily imply a higher $Score_L$, or vice versa.

Predictably, the maximum number of queries for which there is some common product with an identical badge category occurs for the generic platform-pair: Amazon–Snapdeal. In terms

Table 7
Uniformity of badges from different categories.

Category	#Platform-Pairs	#Queries	Score$_P$	Score$_L$
Social Proof	3	13	**0.1113**	**0.2147**
Scarcity	**6**	**22**	0.0173	0.0341
Urgency	2	10	0.0592	0.2044
Promotional	1	1	0.0082	0.0066
Endorsement	3	7	0.0505	0.2255

of $Score_P$ and $Score_L$, we see that the pair Amazon–Nykaa has the maximum uniformity. If we consider only those platform-pairs where both websites are niche, then we find Nykaa–e.l.f. Cosmetics to have the maximum uniformity in terms of both scores. These observations suggest that there is highest uniformity in the *Cosmetics* domain compared to other domains considered here.

Table 7 shows the summary of product badges based on badge categories. For *Recency* and *Exclusivity* badges, there was no overlap between any platform-pairs, and hence these categories do not appear in Table 7. Based on $Score_P$ and $Score_L$, *Social Proof* badges are the most common – this result may seem intuitive because popular brands should be in demand irrespective of platforms, and the longevity of *Social Proof* badges is normally higher. On the other hand, *Scarcity* badges seem to be assigned most uniformly across platform-pairs and queries.

9. Concluding Discussion

This work has several takeaways for the different stakeholders in an e-commerce business, namely, the customers, the sellers, and the marketplace platform provider. For the customers, firstly, they should be aware of the different emotional reactions that the badges try to trigger – being aware should save them from falling an easy prey; for example, some items may not be as scarce as the *Scarcity* badges would like one to believe. Secondly, products with badges are not necessarily better in quality than those without them, and hence, they should ideally buy after careful comparison.

For the sellers, although they may vie for product badges to get that extra boost in sales, they should bear in mind that badge assignment, especially when it comes to the *Endorsement* category, does not necessarily reflect that the products with badges are superior to those without. Moreover, securing a badge in a platform is also unlikely to guarantee similar success in another platform.

For the e-commerce platforms, first and foremost, they should make the badge assignment process transparent to achieve a level playing field for all the sellers, and thus prevent dissatisfaction among smaller sellers. Furthermore, they should closely regulate badge assignments to restrain some products from retaining a badge for a prolonged period, especially for *Scarcity*, *Urgency*, and *Recency* badges. If standardization of product badge assignment policies can be achieved, it would allow more uniformity across platforms as well, which would provide extra impetus to the sellers to ensure that their products are of high quality, and this, in turn, would benefit the customers.

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