Dark Patterns in Shopping, Education & Health Apps

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***Abstract*—Dark patterns are deceptive or manipulative design techniques in technology. They pose challenges for policymakers because they impact user autonomy and financial well-being. However, the lack of quantifiability complicates regulation efforts, and much of the existing research remains theoretical, lacking practical application. This study aims to address these gaps by identifying and quantifying various types of dark patterns in day-to-day software applications across different domains, namely shopping, health and fitness, and education. Drawing from the conceptual framework outlined in ”What Makes a Dark Pattern...Dark?”, the top three apps in Canada within each application domain were selected for analysis. By identifying dark patterns and assessing the attributes of the identified dark patterns, each app was assigned a darkness score. The findings revealed that Temu, Yuka-Food & Cosmetic Scanner, and Duolingo reported the highest darkness scores within their respective categories, with scores of 7.5, 5, and 6.5, respectively. Furthermore, the shopping category exhibited the highest mean darkness scores, indicating a greater prevalence of dark patterns in this domain. Across all categories, the modification of decision space emerged as the most commonly influenced choice architecture. This study contributes to a deeper understanding of where regulatory efforts should be focused in addressing dark patterns in applications. It also sheds light on the nature of different types of dark patterns, their utilization across various domains, and the similarities and differences in their implementation. Moreover, by quantifying darkness in applications, this research underscores the importance of quantifiability in the evaluation of dark patterns, providing valuable insights for policymakers, researchers, and practitioners.**

***Index Terms*—user interface design, dark patterns, technology policy, ethics**

I. Introduction

In the vast digital landscape, where user experiences shape our interactions with technology, the prevalence of dark patterns in interface design has raised significant concerns. Dark patterns, often referred to as manipulative and deceptive designs, inhabit user interfaces with malicious intent, coercing users into actions they did not intend to take [1]. These design elements are crafted to confuse users or manipulate them into specific actions [2]. One example of a dark pattern is when users can easily sign up for a service or subscription online, but when they try to cancel or unsubscribe, they encounter various obstacles [3]. Previous research has identified objectionable interfaces in many contexts and applications such as online shopping [4] or online games [5]. As a result, the increased usage of dark patterns has resulted in frustration among users due to the harm incurred. These patterns often result in financial loss, impaired decision-making, loss of autonomy, and wastage of time for the user [4]. Consequently, user technology adoption and trust in the system are reduced among users [6]. Additionally, policymakers and regulators are considering taking action to prohibit the use of dark patterns associated with privacy, consent, and enforcement actions in California and the European Union [7].

Despite the importance and implications of dark pattern research, in previous literature there is a lack of understanding of the foundational principles of dark patterns including definitions, characteristics, and design evaluation guidelines. The paper “What Makes a Dark Pattern... Dark” by Mathur et al. [8] identifies multi-dimensional definitions of dark patterns, and characteristics as well as provides a normative lens through which dark patterns can be evaluated. In comparison to other papers, this study stands out for its rigorous approach, employing a comprehensive systematic literature review to establish definitions and theoretical foundations for each taxonomy. This rigorous methodology ensured that the nuances inherent within various types of dark patterns in the latest and most recent research were thoroughly captured. While the theoretical findings contribute to a deeper understanding of dark patterns, the ability to quantify the level of darkness and assess its variation across different application domains in real-world software applications remains a research gap. However, practical application is crucial for informing policy changes and understanding the degree of harm incurred to the user.

In real-world settings, applications in the domains of shopping, healthcare, and education represent critical sectors where significant harm to users has been observed, as evidenced by previous literature findings. Shopping applications are the most popular category of smartphone applications [9]. A study [4] reports the presence of dark patterns such as sneakily adding items to a shopping cart in these applications may cause financial loss for users. Another popular domain of smartphone applications is health and fitness which are often interconnected with various wearable technologies [10].

Recent applications aim to promote healthy behavioral change through these systems. Since these systems directly impact users' health choices and lifestyles, it is important to ensure that the presence of dark patterns does not cause unintended outcomes as it might result in physical and psychological harm to users [11]. Dark patterns in fitness applications can create dependency where a user may still be compelled to use the app even after he/she no longer needs to use the app [12]. Additionally, according to the bioethics involved with the health of individuals [13], users' health choices must not be manipulated. Therefore, investigating interfaces and user experiences to evaluate darkness can ensure these guidelines are followed. In recent years, educational applications have seen widespread adoption as learning aids. However, the utilization of dark patterns within these apps can detrimentally affect the effective learning development of users, especially children. For instance, gamification techniques such as restoring streaks for missed lessons by payment, may impede rather than enhance learning outcomes [14].

Therefore, using the conceptual foundations of dark patterns from Mathur et al. [8], this work aimed to identify different types of dark patterns and quantify dark patterns in day to day software applications across different application domains namely shopping, health and fitness, and education. The research also aimed to answer the question of which application domain reported the highest presence of dark patterns. Furthermore, the paper will undertake a comparative analysis of dark pattern characteristics across the mentioned domains, alongside an exploration of the appropriate normative lens, as delineated in [8], for evaluating applications within specific domains. This research is academically significant as it informs policy decisions and guides resource allocation for regulating dark patterns, identifying where intervention is most needed across different application domains.

II. Relevant Literature

A. Conceptual foundations from Mathur et al. [8]

The goal of the paper was to offer clarity and normative grounding to dark patterns research in Human-Computer Interaction (HCI) and related domains. By reviewing a broad array of research, the authors identified different types of dark patterns and key characteristics of dark patterns by establishing connections with other fields of study. They also proposed normative viewpoints for design evaluation.

1) Choice architecture and attributes: The authors identified two-choice architectures for identifying dark patterns; *modifying decision space*, and *manipulation of information flow*, and assigned various attributes of dark patterns to each architecture. The *modify decision space* choice architecture influences user decisions by modifying the set of available choices whereas the *manipulation of information flow* choice architecture influences user decisions by manipulating the information that is available to to users. Each *choice architecture* had some attributes. The attributes and their definitions are summarised in Table I. One example that can illustrate the *disparate treatment* attribute is the Pay to Skip interface in video games, which unfairly favors users with greater means and hence creates inequality amongst players. Another example of the *deceptiveness* attribute which is under the *manipulate information flow* choice architecture is the countdown timer dark pattern that fabricates a fake deadline to deceive users into thinking a deal is urgent. Moreover, the results from the systematic literature review of the paper summarised various types of dark patterns present in the literature. The presence of these attributes is either to be present required or optional for each type of dark pattern in the relevant choice architecture. A required attribute indicates whether in the definitions of a type of dark pattern, the authors defined a certain characteristic's presence to be mandatory and an optional attribute indicates that the characteristic may or may not be present. For example, in the hidden costs dark pattern defined by Brignull [15], there are two attributes information hiding and deceptiveness. For the dark pattern to be present the information-hiding characteristic has to be present making it a required attribute but the deception may or may not be present.

2) Types of dark patterns: The results from the systematic literature review identified different types of dark patterns. The definitions for each type are discussed in Table II.

B. Other related work

Dark pattern literature identified many prevalent patterns across various domains. A study [16] provided a general overview of harmful interfaces and compiled a substantial list of maliciously designed interfaces through three surveys and reviewing thousands of websites, emphasizing the need to address dark patterns as a widespread issue. Another study [1] explored ethical concerns with dark patterns and then identified user pain points from the analysis of dark pattern subreddits. These studies emphasized the widespread presence of dark patterns and motivated research to explore specific applications. A study [5] primarily focused on game applications and dark patterns present in gamification elements, highlighting financial implications for users. Another study [4] crawled shopping websites to identify dark patterns, and defined attributes, and utilized psychological theories like scarcity bias that are employed in these dark patterns. While these studies identified dark patterns, the dark patterns were not quantifiable. One recent study [18], introduces the System Darkness Scale (SDS). However, this scale does not consider different types of dark pattern and their attributes into consideration. Moreover, these studies do not compare similarities or differences in types of dark patterns across application domains.

III. Methodology

For the selection of apps, Apple App Store's predefined categories of *Shopping*, *Health and Fitness*, and *Education* were chosen. These predefined categories organize apps based on their functionality, purpose, and target audience [19]. Afterward, three top apps in Canada from each category from the

TABLE I: Attributes under each choice architecture and their description

Choice Architecture	**Key Attributes**	**Description**
Modify the decision space	Asymmetric	Obscures user-beneficial options leading to unequal choices
	Covertness	Influences user decisions by hiding the mechanism of influence
	Disparate Treatment	Disadvantages and treats one group of users differently from another
	Restrictiveness	Reduces the users' choice by forcing a certain action or limiting options
Manipulate the info. flow	Deceptiveness	Induce false beliefs through misstatements.
	Information hiding attribute	Obscures or delays important information from reaching users

TABLE II: Different types of dark patterns outlined in literature

Types of Dark Patterns	**Description**
Scarcity [4]	Create a sense of urgency leading users to make hasty decisions Example: Countdown timers, Limited quantity
Trick Questions [15] / Tricks [16]	Used to confuse or mislead users Example: Hidden Agendas, Misleading Choice
Coercion	Social pressure to coerce users into behaviors that benefit the designer or the platform
Manipulating Navigation [16] /Misdirection [4]	Confusing or redirecting users within an application to influence their behavior
Obstruction [4]	Deliberately obstructs or complicates users' attempts to perform certain actions
Nagging [1]	Persistently and intrusively prompt users to take certain actions
Sneaking [1] [4]/Hidden Costs [15]	Intentionally hiding certain elements, misrepresenting information
Forced action [16]/ work [1]	Unnecessary or time-consuming tasks, often to the benefit of the platform
Confirmshaming [15]	Shaming or guilt-tripping users if they choose an alternative option
Monetized Rivalries [5]	Exploits users' competitive instincts and emotions to encourage them to spend more time and money
Social Proof [4]	People tend to follow the actions Example: Reviews with unclear origin
Cuteness of Robots [17]	Deliberately designed to be adorable in a way to evoke positive emotions

App Store were selected from the top free apps chart provided by the App Store. It has been shown that the main traits of an app that affect its ranking are the number of downloads, the reviews, and the ratings [20]. Canada was selected because Canadian users spend more than 4.5 hours on apps per day and it has increased by 1.4 hours since 2019 [21]. Additionally, a study [22] uses the top apps from Apple's App Store from the predefined "Medical" category. It is to be noted that the list of these applications is based on the top charts in the App Store on 24th January 2024. For the shopping category Temu, Shein, and Amazon were selected. For the health and fitness category ShutEye: Sleep Tracker, Sound, Yuka-Food & Cosmetic Scanner, and Me+ Daily Routine Planner were selected. For education applications, Duolingo, PhotoMath, and PlantIn: Plant identifier was selected. In the education category, Google Classroom was the third app in the top charts, however since it is a learning management system with unique features [23] in comparison to other applications in the category, it was excluded and the app in the fourth position of the top chart was selected. Different types of dark patterns outlined by Mathur et al. (2021) were then identified in each of the apps. If the type of dark had an attribute that was required a score of 1 was assigned and for all the optional attributes for each type a half point was assigned. The total scores of all the types of dark patterns in each app were identified. For instance, if the obstruction dark pattern has the required attribute *restrictive* and the optional attribute of *information hiding* the total computed score would be 1 for the required attribute summed with 0.5 points for the optional attribute, resulting in a total darkness score of 1.5. Moreover, the suggestions on the appropriate normative lens to evaluate each category were discussed.

IV. Results

A. Dark patterns in shopping applications

The dark patterns identified in shopping applications are discussed in this section. All definitions of various types of dark patterns, choice architectures, and attributes are discussed in Section II. All the apps, Temu, Shein, and Amazon reported the *hidden costs* dark pattern. The *Hidden Costs* dark pattern, falling under the "Sneaking" category, conceals or delays information that users would likely object to, or misrepresents their activities [1]. It involves introducing additional charges right before completing a purchase, typically in the form of service or shipping fees [4]. Despite being visible, the delay in informing users is partially deceptive [15]. This pattern also exploits the sunk cost fallacy, wherein users continue with a decision due to previous investments, rather than logical assessment [24]. Breckenridge et al. conducted a study that illustrates the prevalence of this cognitive bias, particularly evident when users are prompted to add insurance at checkouts for various applications [25]. This dark pattern influences the *manipulate information flow* choice architecture and has a required attribute of *deception* and an optional attribute of *information hiding*.

All three apps also utilized a dark pattern category known as *scarcity*, where the perception of high demand or limited availability is suggested to enhance the product's perceived worth and desirability [26]. This was primarily achieved through deceptive low-stock messages and high-demand messages. For instance, Amazon displayed "limited time offer" banners without specifying further details, while Temu utilized messaging such as "Almost sold out," which lacks numeric specificity and could be misleading [4]. Shein, on the other hand, transparently showcased the number of products left in stock. According to Mathur et al. [8], *scarcity* dark pattern exhibits required *covert* attribute influencing the *modify decision space* choice architecture and an optional *information-hiding* attribute under the *manipulate information flow choice* architecture. Amazon and Shein demonstrated *covert* attribute, whereas Temu exhibited both *covert* and *information-hiding* attributes. Additionally, all three apps employed countdown timers and limited-time messages to increase urgency, exploiting the scarcity bias [27].*Confirm-shaming* [15] was prevalent in all three applications, particularly during checkout exits and when users opted not to subscribe to a premium model. This dark pattern, under the *modify decision space* choice architecture, exhibited *asymmetric* and *covert* attributes.

Some dark patterns were only present in specific apps. In Temu *nagging* dark pattern is heavily employed by the use of multiple pop-ups to redirect the user. This pattern has a required *asymmetric* attribute influencing the *modify decision space* choice architecture. Additionally in Temu, *tricks* dark pattern is used to steer the choices of the user. Temu employs deceptive language such as "You have won a reward upgrade" to manipulate user actions, utilizing confusing language and misleading interface elements. Giuliani et al.'s study [28] underscores the impact of the framing effect on choice behavior, indicating that users' decisions between risky and risk-averse choices are influenced by how options are presented. This dark pattern required *covert* and *asymmetric* attributes. Temu also uses the *coercion* dark pattern [16] where threatening messages and notifications are sent to the user to perform a certain action. This dark pattern has a required *restrictive* attribute under the *modify decision space* choice architecture. Figure 1 shows an example of the *hidden costs* pattern in the Temu and Shein app and Figure 2 shows a *trick* in Temu where the user is promised $200 but ends up being deceived with multiple criteria needed to avail the money. Figure 3 illustrates the use of the *coercion* dark pattern.

The total dark pattern score for each app is in Table III. Amazon and Shein reported a total score of 3.5 and Temu reported a total score of 7.5. Using Amazon as an example,

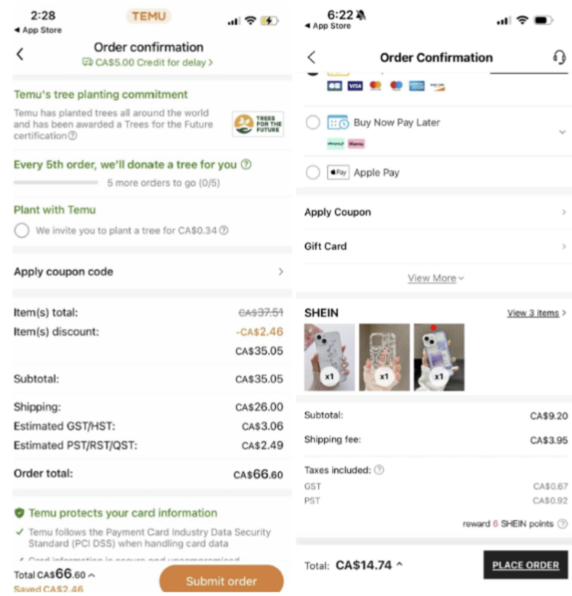


Fig. 1: Additional charges introduced before checkout in Temu and Shein app[1]

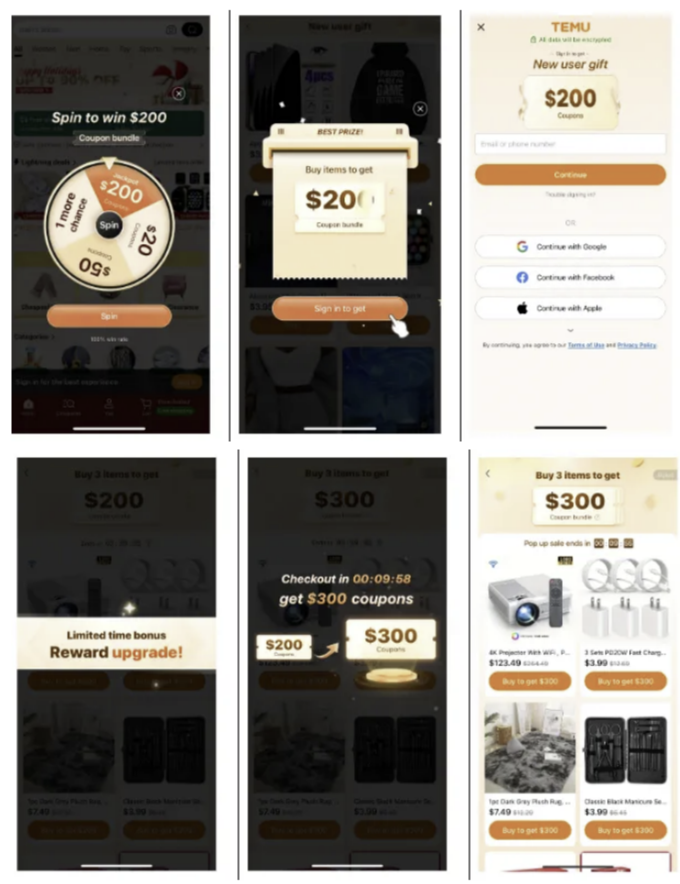


Fig. 2: "Tricks" used by Temu[2]

the computation of the score is described.

1) *Hidden Costs:* For this dark pattern, *deception* is a

[1]Image Source: Collected from the Shein App
[2]Image Source: Collected from the Temu App
[3]Image Source: Collected from emails sent by Temu

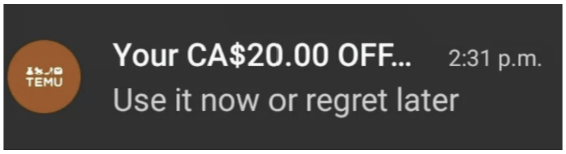


Fig. 3: Threatening messages sent to the user by Temu[3]

required attribute under the *manipulate information flow choice* architecture. So, the *deception* attribute is assigned a score of 1. Additionally, the optional attribute of *information hiding* is assigned a score of 0.5. Therefore, the total *manipulate information flow score* is 1 (deception) + 0.5 (information hiding) = 1.5.

2) *Scarcity: Scarcity* dark pattern has an optional *covert* attribute under the *modify decision space* architecture, which is assigned a score of 0.5.
3) *Confirmshaming:* This dark pattern has a required *asymmetric* attribute (assigned 1) and an optional attribute of *covert* (assigned 0.5) under the *modify decision space choice* architecture. Therefore, the total *modify choice architecture score* is 1 (asymmetric) + 0.5 (covert) = 1.5.

The total score is computed by summing the *modify decision space* score and the *manipulate information flow score*, which is 1.5 (modify decision space) + 1.5 (manipulate information flow) = 3.5. The scores for all the apps discussed in this paper are computed following the same method.

Among the 4 normative lenses stated by Mathur et al. [8], for shopping applications, the most appropriate lens was the *individual welfare* lens. One of the subcategories of the lens was the financial loss that is needed to evaluate shopping applications. From the evaluation of the three apps, it was evident that these applications steer users to spend more money than anticipated. Therefore evaluating financial loss is a good measure of dark patterns.

B. Dark patterns in health and fitness applications

For all three health and fitness apps, canceling subscriptions proved challenging due to the *obstruction* dark pattern. Subscriptions couldn't be canceled within the apps, making the process deliberately cumbersome. The *obstruction* dark pattern had a required *restrictive* attribute and an optional *information hiding* attribute. Figure 4 shows the example of the *obstruction* pattern where subscription cancellation is only possible from the Apple App Store instead of within the application itself. The ShutEye: Sleep Tracker, Sound app, and the Me+ Daily Routine Planner had the presence of the *scarcity* dark pattern where a limited-time deal was shown to the user with a countdown timer. Figure 5 illustrates the offer presented to the user. The optional *covert* attribute of the *scarcity* pattern was identified in these apps. The Yuka-Food & Cosmetic and the ShutEye: Sleep Tracker used the *manipulating navigation/ misdirection* dark pattern. In the ShutEye: Sleep Tracker, the longest and the most expensive

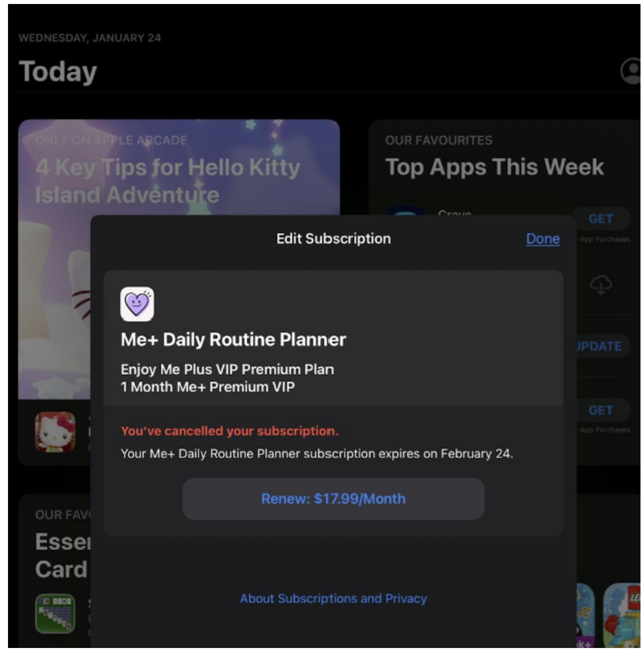


Fig. 4: Process of Subscription Cancellation[4]

subscription plan was selected by default with a visually appealing color. In the Yuka-Food & Cosmetic Scanner app, confusing language and visual elements were used to trick the user. The phrase "pay what you want" is used with a slider to indicate the user can choose how much they want to pay, however, the payment amount is fixed and cannot be changed. For *manipulating navigation/ misdirection* dark pattern, the required *asymmetric* attribute, and the optional *covert* attribute were identified.

Moreover, in the Yuka-Food and Cosmetic Scanner app, the *social proof* dark pattern was used with unclear origins of testimonials [4]. This exploits the bandwagon effect where the user chooses by conforming to the opinion of other people [29]. However, the unclear source of testimonials showed the presence of the required *asymmetric* attribute and the optional *covert* attribute. Overall, ShutEye: Sleep Tracker, Sound, and Me+ Daily Routine Planner reported a total darkness score of 3.5, and Yuka-Food & Cosmetic Scanner reported a total score of 5. The total dark pattern score for each app is in Table III.

The results suggest that the evaluation of these apps is best approached through the lenses of *individual autonomy* and *individual welfare*. By imposing cognitive burdens on users to steer them towards predetermined choices, these apps infringe upon users' ability to make autonomous decisions. Given their influence on users' health decisions and daily routines, it's essential to assess the extent of autonomy violation. This perspective resonates with Sax et al. [11], who underscores how unfair practices can undermine users'

[4]Image Source: Apple App Store
[5]Image Source: Collected from the ShutEye app

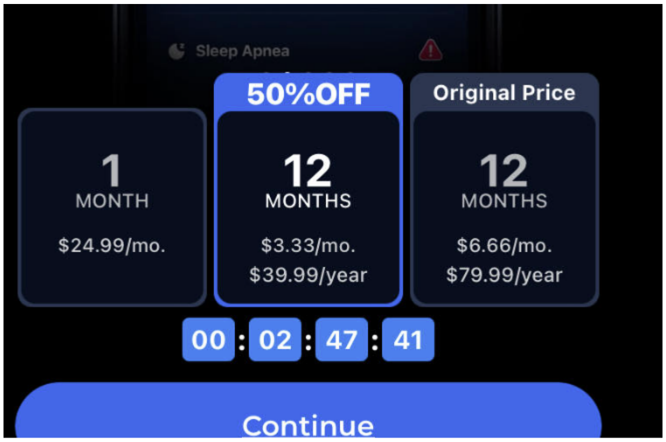


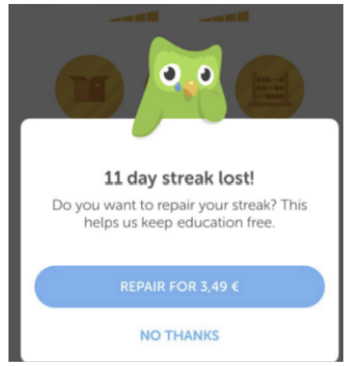
Fig. 5: Limited time deal presented to the user by ShutEye app[5]

autonomy.

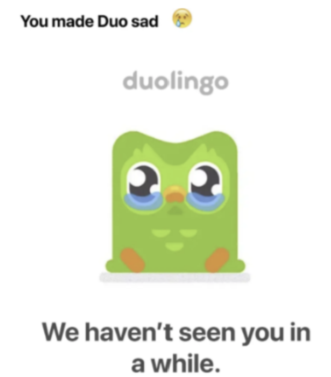
C. Dark patterns in education

Among the three education apps, PhotoMath and the Plantin: Plant Identifier were identified to have *obstruction to cancel* dark patterns as it was not possible to cancel the subscription from within the app. These two apps did not have any other noticeable dark patterns. However, the Duolingo app had multiple dark patterns. The *monetized rivalries'* dark pattern was present and had the required attribute of *disparate treatment*. Duolingo cleverly motivates users to sustain their learning streaks by providing the option to restore streaks through payment, thereby encouraging users to maintain their positions on leaderboards. This strategy taps into users' competitive instincts, prompting them to invest money for in-game recognition, like securing a prominent rank on leaderboards [5]. However, while effective in the short term, such tactics may have adverse effects on learning apps, potentially impeding long-term user retention [30]. This phenomenon is illustrated in Figure 6a.

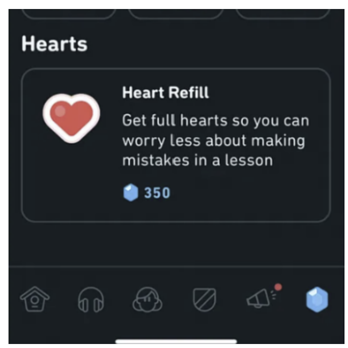
Furthermore, Duolingo employs the *coercion* dark pattern, using threatening and emotionally provoking language within the app. This pattern has the required *restrictive* attribute. Moreover, the *scarcity* dark pattern is evident in Duolingo's promotion of its discounted monthly subscription, artificially creating scarcity by limiting the offer to 48 hours. This scarcity effect may push users towards longer subscription plans due to the presence of the optional *covert* attribute. Additionally, Duolingo utilizes *misdirection* or *manipulating navigation* dark pattern by introducing in-app currency called "Gems" for purchase, obscuring the true value of items through the intermediate currency dark pattern which has been illustrated in Figure 6c. This pattern has the required *asymmetric* attribute and the optional *covert* attribute. This may lead users to buy more gems than intended. Another dark pattern found in the app is the *forced action/ forced work* pattern. The app presents users with the option to



(a) Pay to restore streaks



(b) Use of cute Duo bird with emotions



(c) Use of gems

Fig. 6: Overall figure caption

watch an advertisement in exchange for a "Free Chest" containing gems. This effectively forces users into viewing ads to access app features, particularly when they lack gems for in-app purchases. The gamification present in Duolingo sets it apart from other applications. The Duolingo bird, with its adorable aesthetic and range of animated emotions, plays a significant role in influencing user decision-making. Leveraging its cuteness, the app invokes positive feelings in users [31]. Studies suggest that cute objects stimulate dopamine release in the brain, and the rewards associated with cuteness have been linked to increased consumption [32], [33]. This utilization of the *cuteness of the robot's* dark pattern underscores the app's design to engage and retain users [17]. The pattern has a required *covert* attribute and it

TABLE III: Darkness score for each app

Category	Apps	Modify Decision Space Score	Manipulate Information Flow Score	Total Score
Shopping	Amazon	2	1.5	3.5
	Shein	2	1.5	3.5
	Temu	6	1.5	7.5
Health & Fitness	ShutEye: Sleep Tracker, Sound	3	0.5	3.5
	Yuka-Food & Cosmetic Scanner	3.5	1.5	5
	Me+ Daily Routine Planner	3	0.5	3.5
Education	Duolingo	6	0.5	6.5
	PhotoMath	1	0.5	1.5
	PlantIn	1	0.5	1.5

is shown in Figure 6b. In the education application domain, PhotoMath and PlantIn scored only 1.5, while Duolingo had a higher darkness score of 6.5 as shown in Table III.

From the analysis, it could be concluded that the normative lens that is most applicable to the evaluation of educational apps is *individual welfare*. This is because the gamification present in some educational apps can lead to additional cognitive burden and financial loss while impacting the quality of learning for the user.

D. Summary of dark pattern score and comparison of dark patterns in each category

Across all apps, the computed scores of total darkness and the score for each choice architecture are summarised in Table III. Temu in the shopping category, Yuka -Food & Cosmetic Scanner in health and fitness, and Duolingo in the education application domain reported the highest darkness score. From the analysis of three different categories, it was evident that dark patterns were most commonly present in shopping applications. The average dark pattern score is listed in Table IV to show the prevalence of dark patterns in each category. The average dark pattern score in each choice architecture of *modify decision space* and *manipulate information flow* has also been computed. The table shows that applications in all categories focus on manipulating the choice architecture by modifying the user's decision space.

TABLE IV: Mean darkness score for each category

	Mean modify decision space score	Mean manipulate information flow score	Mean total score
Shopping	3.3	1.5	4.8
Health & Fitness	3.2	0.8	4
Education	2.7	0.5	4.5

V. Discussion

This study employs various categories of dark patterns to assess nine applications across three domains, drawing insights from the comparative analysis of their scores. Notably, in the shopping category, a high prevalence of dark patterns was observed, with many falling under categories such as sneaking as defined by Mathur et al. [4]. This finding aligns with previous literature, indicating that a category-specific approach to investigating dark patterns may yield deeper insights. For instance, apps like Duolingo, incorporating elements of gamification, exhibit dark patterns identified by Zagal et al. [5], reflecting the authors' study of dark patterns in game applications.

In addition to the comprehensive evaluation of dark patterns across different categories, it's important to note that certain patterns transcend specific domains and are found across multiple categories. For instance, the dark patterns of *scarcity* and *misdirection/manipulating navigation* were consistently present across all categories examined in this study. However, it's noteworthy that certain unique patterns, like the *cuteness of robots*, were specifically identified in gamified education apps like Duolingo. This underscores the tailored implementation of dark patterns to suit the particular functionalities within each application category.

While Mathur et al. [8] provide a comprehensive framework for evaluating dark patterns, but the determination of specific attributes within these patterns remains somewhat ambiguous. Future research should aim to devise clearer questions or baseline measures to accurately assess attribute presence. Moreover, this study proposes a scoring system to quantify the extent of dark patterns in each app and compare different categories. However, this scoring method may lack precision, as it may overlook implicit obstructions, such as misdirection tactics employed by apps like Amazon, which redirect users visually to hinder cancellation opportunities. Additionally, inconsistencies in categorizing and terming similar themes of dark patterns have been noted in previous literature, such as the manipulating navigation pattern by Conti et al. [16] and the misdirection pattern by Mathur et al. [4], both of which exhibit similar themes with slight variations.

VI. Conclusion

In conclusion, dark patterns pervade all three categories of applications (Shopping, Health & Fitness, and Education), with a higher prevalence observed in shopping applications. While research on the evaluation of dark patterns has primarily focused on theoretical frameworks and specific application domains, our analysis demonstrates the widespread use of these deceptive techniques even in popular day-to-day applications. As more users rely on technology for routine activities such as shopping and language learning, there is a pressing need for the development of robust frameworks to evaluate dark patterns. Moreover, establishing regulatory policies to address the presence of dark patterns is essential to prevent unethical technology usage and protect user rights. Moving forward, researchers should prioritize the development of methods to quantify dark patterns in user interfaces effectively, allowing for comprehensive evaluations and informed decision-making in the design of applications.

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