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Addictive Platform Features and Digital Addiction: Evidence from Germany

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Abstract

In order to capture users' attention and increase the amount of time they spend using digital devices and services, companies integrate features such as personalised recommendations, autoplay, infinite scrolling and push notifications. These features exploit psychological biases to foster frequent and prolonged usage, which can lead to problematic behaviours. This study uses an online survey to examine how consumers rate attention-grabbing, addiction-promoting designs on three types of platforms, and the relationship between these designs and the addictive use of services. The study also examines users' self-regulation tactics and their perceptions of the impact of these designs on related addictions - in this case, shopping addiction.

Most respondents report no noticeable effects of addictive designs on their usage time or purchasing behaviour. The average perceived impact is nearly neutral. However, when considering only the non-neutral responses, the perceived effects of the individual designs vary considerably. Usage time is more often perceived as prolonged, while shopping activity is perceived as decreased rather than increased. The strength of these effects also varies between different types of platforms. Notably, a stronger perception of the effects of the designs correlates positively with higher values on the addiction scale in both domains. This suggests that these features may contribute to addiction development.

JEL classification: D03, C83

Keywords: dark patterns, manipulation, addiction, consumer survey

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Introduction

Digital devices, platforms and services have long become an integral part of people's everyday lives. These technologies boast a multifaceted application, encompassing a range of functions including the retrieval of information, the execution of specific tasks, and the maintenance of social connections. Nonetheless, in recent years, concerns have been raised that their wide prevalence and people's strong dependency on digital technologies may have led to addictive usage patterns. As posited by Meng et al. (2022), a significant proportion of the general population, estimated to be approximately one quarter, may already be susceptible to some variant of digital addiction. Individuals afflicted by this behavioural disorder have been observed to prioritise the immediate gratification derived from the utilisation of digital technologies over the significant, albeit delayed, negative consequences that may ensue (Bortolato & Madden, 2022). The consequences for the affected individual are numerous and far-reaching, including social isolation, the neglect of social activities, diminished performance in educational or occupational settings, depression, anxiety, and numerous others (Almourad et al., 2020).

Tech companies themselves have a vested interest in encouraging frequent and prolonged use of their devices, services and platforms. In the digital economy, attention is regarded as a scarce and valuable resource (Terranova, 2012; Marković, Popović & Andjelković, 2024). This factor is monetised by companies, who compete with one another to maximise its exploitation. The underlying theory is straightforward: the greater the time spent by a user on a given device, platform or service, the greater the revenue that can be generated (Wu, 2018; Mujica et al., 2022, Monge Roffarello & De Russis, 2022; Wallsten et al., 2023). The integration of persuasive, attention-capturing and addictive design features constitutes a pivotal strategy in this context. Moreover, these design features have been strategically crafted to exploit psychological vulnerabilities and biases, reinforce behaviour and influence users to develop a habit of continuous usage of said technologies (Monge Roffarello & Russis, 2022; Monge Roffarello, Lukoff & Russis, 2023; Esposito & Ferreira, 2024). These features typically fall into the category of 'dark patterns' due to their manipulative nature, which stems from their ability to circumvent conscious awareness and rational decision-making processes (Esposito & Ferreira, 2024; Ye, 2025, Nie et al., 2024). Research indicates that consumers are often unaware of or unable to escape the influence of dark patterns, including addictive design features. In their 2020 study, Di Geronimo et al. (2020) conducted an online experiment in which participants watched videos depicting app usage and were asked to indicate the presence of malicious design features. Many participants failed to recognize any manipulative design features within these videos. Furthermore, respondents asserted that these features had become so prevalent that they are often overlooked, seamlessly integrating into the normal flow of interaction when using applications. Along similar lines, Bongard-Blanchy et al. (2021) and Keleher et al. (2022) conducted surveys in which participants were presented with images of interface designs. Keleher et al. (2022) asked their participants to indicate whether or not each one displayed a manipulative pattern. In contrast, Bongard-Blanchy et al. (2021) instructed their participants to describe the manipulative features and provide a confidence rating for how likely they were to be influenced by the designs exhibited. In their study, Keleher et al. (2022) reported that end users had difficulty identifying manipulative patterns. Despite the finding in the study by Bongard-Blanchy et al. (2021) that participants could detect and recognize the influence of manipulative designs on online behaviour and its potential harm, the authors also highlighted that awareness of such influences does not necessarily enable users to resist them.

A possible explanation for these results could be that users occasionally interpret these manipulative design features as advantageous or favourable. This assertion is corroborated by Lu et al. (2024). The authors concluded that users often perceive persuasive patterns as helpful when they align with their own goals. Utilising an adapted version of the User Experience Questionnaire, Rhomberg and Sandhaus

(2024) demonstrate that patterns described in the literature as addictive or attention-capturing can also have positive aspects. The evaluation of gamification and the 'pull to refresh'-feature by Rhomberg and Sandhaus's participants demonstrates that, despite their perception as addictive, these elements are also considered highly intuitive. Keleher et al. (2022) also found that users do not perceive certain addictive design features as blatantly deceitful or unethical. In fact, they are also regarded as helpful, such as autoplay and push notifications. Mildner et al. (2020) also showed that users are, in principle, able to identify manipulative patterns. Nevertheless, when the participants evaluated these patterns based on characteristics specific to dark patterns, such as asymmetry, covertness, deception etc. the evaluation is rather lenient (Mildner et al., 2020; Rhomberg & Sandhaus, 2024). Dekker & Tverdina (2025) demonstrated that perceived usefulness, ease of use, and perceived manipulation can influence the overall attitude toward addictive features. According to their study, the perceived usefulness of recommendation, auto preview, and autoplay positively influences attitude, while the perceived manipulation of these features negatively influences attitude. Individual's attitudes, in turn, positively influences streaming intention.

Although some manipulative design features are functional and helpful, users of technology featuring these elements often feel that they have lost sight of their goals. They experience regret and a sense of wasted time and loss of control (Esposito & Ferreira, 2024; Monge Roffarello, Lukoff & Russis, 2023 Flayelle et al., 2023). For example, Chaundhary et al. (2022) show the shift in perception of certain addictive design features over time. The authors conducted a diary study with viewers across 228 viewing sessions to understand users' mental states and identify their emotions while interacting with four streaming platforms. As users progressed through the viewing sessions, they transitioned from actively liking video suggestions on autoplay to passively letting them play. After finishing a video selection using autoplay, participants either felt dissatisfied with the content and regretful about how much they had watched or at least satisfied with the content but still regretful about their prolonged usage. Similar feelings were expressed regarding the recommendation feature. In a complementary study, Cho et al. (2021) analysed usage logs to investigate the circumstances in which individuals experience regret when using various social media application features. The study revealed that features designed around "following," such as news feeds, lead to habitual checking behaviours. This is accompanied by regret when repeatedly checking for new content proves unsuccessful. Recommendation-based features, on the other hand, have been shown to encourage habitual use, divert attention from the app's primary purpose, and prompt individuals to extend their usage. Lukoff et al. (2021) took a more direct approach by asking participants if they felt certain addictive design features impacted their sense of control. Using YouTube as a case study, Lukoff et al. (2021) found that autoplay and recommendations primarily undermine the sense of agency, whereas playlists and search functionality tend to support it.

In consideration of the ramifications of these design features, there has been a marked increase in the level of interest from regulators. Within the European Union's Digital Services Act (DSA)[1], the stipulations set forth by the European Commission delineate the obligations of online platforms in ensuring that their digital interfaces are not designed, organised, or operated in a manner that may deceive, manipulate, or significantly impair or hinder the users' capacity to make free and informed decisions. This principle is enshrined in Article 25 (1) of the DSA. Moreover, digital addiction and the associated negative psychological and physical consequences are among the systemic risks that can arise from very large online platforms and should be minimised by them (Section 5 & Recital 83, DSA). Moreover, the European Commission has announced its intention to adopt a Digital Fairness Act (DFA), which is currently under consideration as a legislative proposal. The objective of the initiative is to enhance the protection

1 Verordnung (EU) 2022/2065 des Europäischen Parlaments und des Rates vom 19. Oktober 2022 über einen Binnenmarkt für digitale Dienste und zur Änderung der Richtlinie 2000/31/EG (Gesetz über digitale Dienste), Amtsblatt der Europäischen Union, L277/1.

and digital fairness of consumers. The act will address specific challenges faced by consumers online, including among others deceptive or manipulative interface designs as well as addictive designs of digital products (European Commission, 2025).

The present study aims to make a valuable contribution to the ongoing discourse on addictive and attention-capturing design patterns used by digital platforms. To this end, the study investigates how consumers themselves perceive these design patterns and how they believe they may impact their behaviour and whether they are linked to addictive tendencies. Subsequently, an examination will be conducted into the utilisation of behavioural regulation measures, if any, by consumers.

The design's impact on consumer behaviour and its association with addictive tendencies will be analysed through two distinct lenses. Firstly, the perception and impact of addictive designs will be examined in a service-specific manner linked to the time spent using respective digital platforms. Secondly, from a cross-service perspective, particularly in relation to purchasing behaviour. Many digital services and platforms are essentially free for consumers and primary financed by advertising, and some even incorporate e-commerce features, such as social media and sharing platforms, thereby engendering commercial incentives. Instagram and TikTok are prime examples of services that incorporate such features. Others are entirely based on e-commerce, such as online marketplaces. Accordingly, excessive use of digital platforms can lead not only to addictive behaviour in relation to the platform itself, but also to other forms of addiction, such as compulsive shopping (Jameel et al.,2024; Nyrhinen et al., 2024; Floriano, Silva & Corso, 2024; Zheng et al., 2020).

The remainder of the studies is structured as follows: In the next chapter, we present our research questions and the methodology employed. For this study, we conducted an exploratory survey with consumers in Germany. We also present the survey instruments and measures used to answer the research questions. This is followed by a presentation of the results. The report concludes with a discussion and an overview of the limitations. [2]

2 AI-based applications (ChatGPT 5.1 and DeepL) were used to support the preparation of this paper. They were used solely for literature research and linguistic revision, as well as summarising the author's own work. In one instance, they were also used to refine an argumentative idea. The human authors are solely responsible for the content, selection of sources, verification of facts, collection of primary data and its evaluation, and conclusions. No AI-generated content was included in the text without human review and verification. All cited sources were researched independently. AI was used exclusively to increase the efficiency of the writing and editing process, not to generate primary research data or original ideas.

Research questions and methodology

The study addresses the following three explorative research questions:

Research question 1: How do users of digital platforms perceive addictive design features, and how does this perception link to addictive behaviour in terms of time spent on the platform and propensity to make purchases?

Research question 2: What mechanisms do users of online platforms utilise to regulate their behaviour?

Research question 3: How do the perceived effects of addictive design features and the utilisation of behavioural regulation measures differ depending on the type of platform?

Date collection and sample

To investigate the research questions presented in the previous section, an exploratory online consumer survey was designed and administered in Germany through the provider Bilendi & respondi. The online consumer survey for this study was conducted in November / December 2025 using Computer Aided Web Interviewing (CAWI). The sample size consisted of 3,252 participants. Quota sampling was used to ensure that the sample was adequately representative of the German population aged 16 and above. Age, gender, and region were the main characteristics used to draw the sample for this study. The sample is composed of 48.0 % respondents who identify as male, 51.6 % who identify as female, and 0.5 % who identify as otherwise. The participants' age ranges from 16 to 90 years (mean 49.3, SD 16.5). The distribution of the sample across the Nielsen areas is as follows: area 1 = 15.7 %, area 2 = 21.5 %, area 3a = 13.6 %, area 3b = 13.5 %, area 4 = 16.1 %, area 5 = 4.5 %, area 6 = 7.9 %, and area 7 = 7.3 %.

Survey instruments and measures

The respondents were divided into three groups. Each group was presented with a series of questions pertaining to one of three distinct categories of digital platforms: social networks, online shopping services and video sharing platforms. The approach is modelled in accordance with a between-subject design. The decision to focus on these platforms and services is based on the observation that they incorporate addictive features from similar categories. These types of platforms and services have addictive potential, and some of them are currently classified as 'very large online platforms' under the Digital Services Act (DSA). They are also among the most widely used. This assertion is further substantiated by the empirical evidence provided by the survey data. The proportion of the German population who have access to and utilise social networks, video sharing platforms and online shopping services ranges between 69% and 87%. The only internet activities that surpass the use of the aforementioned platforms and services are those involving sending and receiving emails and messages, conventional internet browsing and visiting news sites.

The allocation to the three groups was carried out on a randomized basis, whereby the prerequisite for allocation to the respective group was that the service was specified as being used by the respondent.

The sample characteristics are summarized in the following table.

Table 1: Sample characteristics

		Sample	Sub-samples: Groups Social networks	 Video sharing platforms	 Online shopping services
Gender	Female	51.6 %	54.8 %	47.4 %	52.9 %
	Male	48.0 %	44.4 %	52.3 %	46.7 %
	Others	0.5 %	0.8 %	0.3 %	0.4 %
Age	Mean	49.3	49.1	46.6	50.8
Living area	West	80.4 %	80.0 %	81.4 %	80.1 %
	East	19.7 %	20.2 %	18.9 %	19.8 %
Highest level of education	Primary education or no education	0.2 %	0.4 %	0.1 %	0.1 %
	Lower secondary education	23.5 %	24.3 %	24.0 %	22.6 %
	Upper secondary education	43.6 %	43.9 %	42.2 %	43.9 %
	Tertiary education	32.3 %	30.7 %	33.4 %	33.0 %
	na	0.5 %	0.8 %	0.4 %	0.3 %
Monthly (net) household income	Median	EUR 3,000 - 3,500	EUR 3,000 - 3,500	EUR 3,000 - 3,500	EUR 3,000 - 3,500
Sample size		3,252	1,049	1,042	1,043

Awareness and perceived impact. The initial question assessed the respondents' subjective perception of addictive design features in services. To this end, they were asked to indicate, from a list of predefined addictive design features, whether the services they use in each respective category employ these features.

We examined a total of six design features that have been classified as addictive in the wider literature. These included features designed to enable the automated, continuous provision of content, thereby facilitating longer engagement with the platform. Within this category, we focused particularly on infinite scrolling and autoplay due to their profound role in ensuring the constant flow of content (Monge Roffarello, Lukoff & De Russis, 2023; Montag et al., 2019). Montag et al. (2019) posit that these two design features encourage users to become increasingly absorbed in the platform, without reaching a natural point where they might easily consider ending their use. In addition, Baughan et al. (2023) reported that these design feature can result in users entering a passive-like state of dissociation, potentially leading to a failure to absorb any content at all and a subsequent perception of wasted time. Furthermore, with regard to autoplay at least, the empirical study conducted by Schaffner et al. (2025) revealed that disabling autoplay can significantly reduce content consumption, including average viewing time and session length. The study focused on Netflix.

Personalisation was another area of interest, particularly in the form of personalised recommendations that platforms display based on users' interests. Showing consumer content based on their previous behaviour and data can lead to prolonged usage of the services, especially if it is paired with an infinite supply of personalised content (Monge Roffarello, Lukoff & De Russis, 2023). This has been confirmed by some empirical studies. For instance, Dekker, Baumgartner & Sumter (2025) conducted a TikTok experiment in which participants switched from a personalised feed to a less personalised one. They found that the daily frequency and duration of TikTok use decreased, whilst self-regulation increased. However, participants derived less enjoyment from using the app. Holtz et al. (2020) demonstrated that personalised podcast recommendations on Spotify resulted in increased streaming time compared to a scenario in which less personalised recommendations were displayed.

In the context of online shopping, personalised content, particularly advertising, can have both positive and negative impacts on purchase intentions. Boerman, Kruikemeier, & Zuiderveen Borgesius (2017) conducted a literature review and found that personalised advertising can be effective in influencing purchasing decisions or intention. However, if the personalisation is perceived as manipulative or otherwise intrusive, it can lead reactance and a reduced purchase intention.

Design features that fall under social investment or social proof also count as addictive design elements. Such mechanisms like likes, reposts, etc. influence users by instilling the idea that they should continue to use the platform to avoid losing the progress they have made. They also create a sense of reward and a positive user experience. Both feelings can lead users to return to the platform (Beltrán, 2025; Monge Roffarello & Russis, 2022) In the context of e-commerce, social proof in the form of customer testimonials can also have an effect on the buying impulse (Sin et al., 2025).

In addition, we focused on two factors that often fall into the 'urgency' category of addiction design features: notifications and time-limited or ephemeral content. These elements create a sense of urgency by setting deadlines or triggering the 'fear of missing out' effect, which creates the need to interact with them quickly (Beltrán, 2025; Mathur et al, 2019). While being a functional and helpful feature, notifications particularly draw attention back to the platform and initiate a new session (Lukoff et al., 2021; Monge Roffarello, Lukoff & Russis, 2023; Yang et al., 2021; Beltrán, 2025) However, experimental studies have produced some nuanced results. Fitz et al. (2019) conducted a randomised field experiment to test whether batching notifications could improve people's mental well-being. Participants whose notifications were batched felt more attentive, productive and in control of their phones, and reported being in a better mood. In contrast, participants who did not receive any notifications experienced fewer of these benefits yet higher levels of anxiety regarding missing out. Meanwhile, Dekker et al.'s (2025) intervention involving disabling notifications did not alter smartphone behaviour. The urgency aspect also plays a special role in e-commerce, particularly with regard to expenditure and purchase intentions, as depicted in the studies by Bies, Bronnenberg and Gijsbrechts (2021) and Sin et al. (2025).

Lastly, we considered gamification. Beltrán (2025) describes gamification as the incorporation of game-like elements and mechanics into non-game contexts to motivate user engagement and influence their behaviour, which is also shown by Barari (2024) and Liao (2024) However, Koivisto & Hamari (2019) conducted a literature review, did not only report positive effects.

Respondents previously saw a brief description of the feature and a simplified illustration of the feature for the respective service category.[3]

Table 2: Addictive design analysed in the survey

Groups		
Social networks	Video sharing platforms	Online shopping services
Infinite scrolling	Autoplay	Infinite scrolling
Personalised content	Personalised content	Personalised content
Gamification	Gamification	Gamification
Likes, Reposts, Followers etc.	Likes, Reposts, Followers etc.	Past purchases, ratings etc.
Notification	Notification	Notification
Time-limited / ephemeral content	Time-limited / ephemeral content	Time-limited / ephemeral products / sales

Subsequently, the respondents were prompted to indicate whether these features have an impact on their usage time and shopping behaviour. Both were evaluated using a 5-point scale. In terms of usage time, the scale ranged from respondents indicating that the design feature resulted in the services being

3 The illustrations were created using ChatGPT 5.1.

used significantly 'less frequently and/or for shorter periods of time' to 'more frequently and/or for longer periods of time'. For purchasing behaviour, the scale ranged from 'making significantly fewer purchases' to 'making significantly more purchases'.

Addictive behaviour. To measure context-specific addictive behaviour, the Bergen Social Media Addiction Scale was utilised and adapted for the other two service categories (Andreassen et al., 2012; Kim et al., 2021). The six-item scale is employed to ascertain the prevalence of specific occurrences and experiences over the preceding year, utilising a five-point scale ranging from 1 (very rarely) to 5 (very often).

To measure cross context addiction in term of online shopping addiction we employed an adopted version of the Bergen Shopping Addiction Scale (Andreassen et al., 2015). The participants were tasked with indicating their level of agreement with seven items designed to elicit their thoughts, feelings and actions in relation to online shopping. A five-point scale ranging from 1 (completely disagree) to 5 (completely agree) was utilised for this purpose.

Table 3: Addictive behaviour - Items

Measure	Items
Service-specific addictive behaviour[1]	How often during the last year have you spent time thinking about […] or the usage of […]?
	How often during the last year have you felt an urge to use […] more and more?
	How often during the last year have you used […]to forget about personal problems?
	How often during the last year have you tried to cut down on the use of […] without success?
	How often during the last year have you used […] so much that it has had a negative impact on your job/studies?
	How often during the last year have you become restless or troubled if you have been prohibited from using […]?
Cross-service addictive behaviour (in relation to shopping)	I think about shopping/buying things all the time.
	I shop/buy things in order to improve my mood.[2]
	I shop/buy so much that it negatively affects my daily obligations (e.g., school and work).
	I feel I have to shop/buy more and more to obtain the same satisfaction as before.
	I have decided to shop/buy less, but have not been able to do so.
	I feel bad if I for some reason are prevented from shopping/buying things.
	I shop/buy so much that it has impaired my well-being.

Note: For the survey, the items were translated into German. 1The corresponding service category was entered into the "[…]"-field for the respective group. 2This item deviates slightly from the original scale.

Mitigation measures. The respondents were requested to provide information regarding the measures that they are currently implementing to regulate their usage times or shopping behaviour.

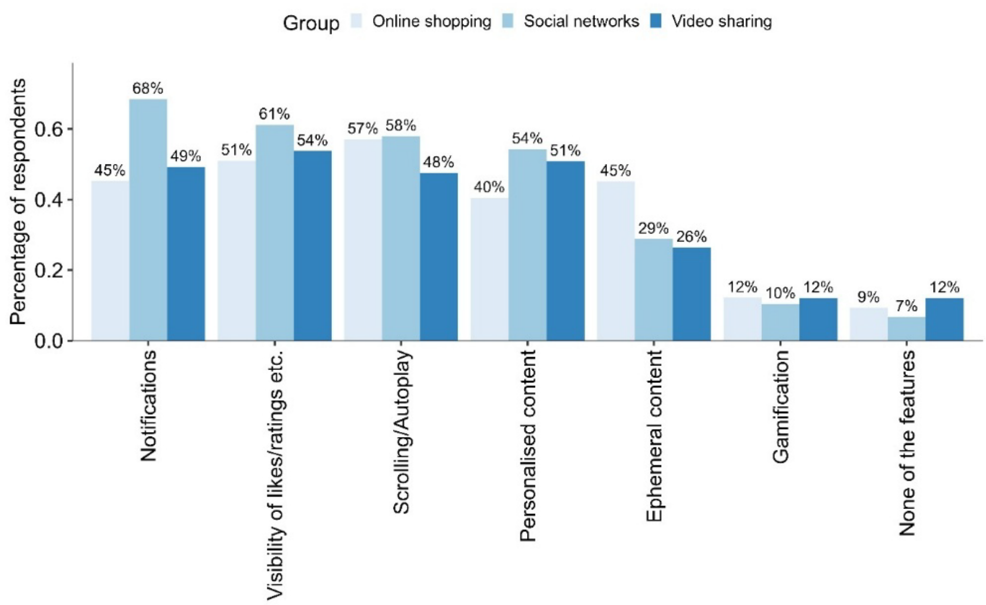
The participants were invited to indicate whether they had made any modifications to the configuration of the services. These modifications included disabling notifications, configuring the way content is recommended or utilising pause functions, if available. Furthermore, respondents were asked whether they had deleted or deactivated the applications in question during a specified period, or whether they had employed third-party services to control or regulate their behaviour.

Results

User-reported exposure to addictive design features

The initial step in the analysis of the perception of addictive design features is the identification of the proportion of respondents who report being exposed to the features in the respective service group. The respondents were asked to indicate whether at least one of the services they use in the respective service category has the addictive design feature in question. In order to indicate this, respondents must be aware of the feature. As illustrated in Figure 1, a medium to low exposure to the addictive design features is reported in all three groups, with gamification having an especially low share. However, with regard to the combination of features, only a relatively small proportion reports being exposed to none of the features. When comparing features, it should be noted that some of them may be more difficult to perceive than others. For instance, receipt of a notification might be a salient event that users directly experience, whereas personalisation is often implicit or invisible, and users may have limited awareness or hold inaccurate beliefs about how content is curated (Eslami et al., 2015; Swart, 2021). Furthermore, during the course of the questionnaire, respondents were asked whether they had deactivated some of these features. With regard to the relevant combinations of feature exposure and feature deactivation, between 9 and 23% of respondents who stated that none of their services uses the respective feature have deactivated it in the past. Therefore, under the assumption that a proportion of respondents are still utilising the service for which they have deactivated the respective function, results indicate that, for a subset of respondents, utilisation is a prerequisite for reporting exposure, which should be considered during the interpretation of results.

Figure 1: Reported exposure to addictive design features



Number of respondents by group: online shopping (N = 1043), social networks (N = 1049), video sharing (N = 1042).

In light of observed variations in service utilisation across age demographics (Ofcom, 2024; Pew Research Center, 2025), an analysis has been conducted on the reported exposure of the youngest decile, comprising individuals aged 26 and below. Their reported exposures are slightly elevated relative to the overall averages in the majority of cases, with an average increase of 4.2%. Only with regard to online shopping services, lower exposures have been reported. When the data is grouped over services, the highest increases in exposure are reported for personalised content, with an increase of 9.4% compared to the overall average, and a 7.4% increase for gamification. The only negative difference observed concerns notifications, with a 2.2% decrease, attributable to a reduced reported exposure to notifications on online shopping services and no discernible difference in exposure between age groups for the other two service categories. The observed variations in reported exposure may be attributable to the utilisation of disparate services, divergent competencies in discerning feature presence, and distinct patterns of deactivation. For instance, the proportion of respondents who reported deactivating notifications is approximately 45% higher in the younger than in the older cohort, thereby potentially explaining the reduced reported exposure.

In addition to the discrepancies observed between the features, notable variations are also present between the service types. Exposure to notifications and the visibility of likes, ratings, etc. is reported more often on social networks than on online shopping and video sharing services. Furthermore, the findings indicate that the prevalence of autoplay on video sharing services is lower than that of scrolling on online shopping services or social networks. Moreover, exposure to personalised content is less often reported on online shopping services than on the other two service types, while the opposite is true for ephemeral content on online shopping services, in the form of time-restricted products and offers, compared to ephemeral content on social networks and video sharing services. Overall, these differences may be attributed to slight variations in feature definitions and service structures, such as a stronger emphasis on social networking for social networks, or a greater reliance on personalised home feeds for social networks and video-sharing platforms, whereas for online shopping services goal-directed product searches with prominent filtering and sorting tools, such as price, may play a more important role.

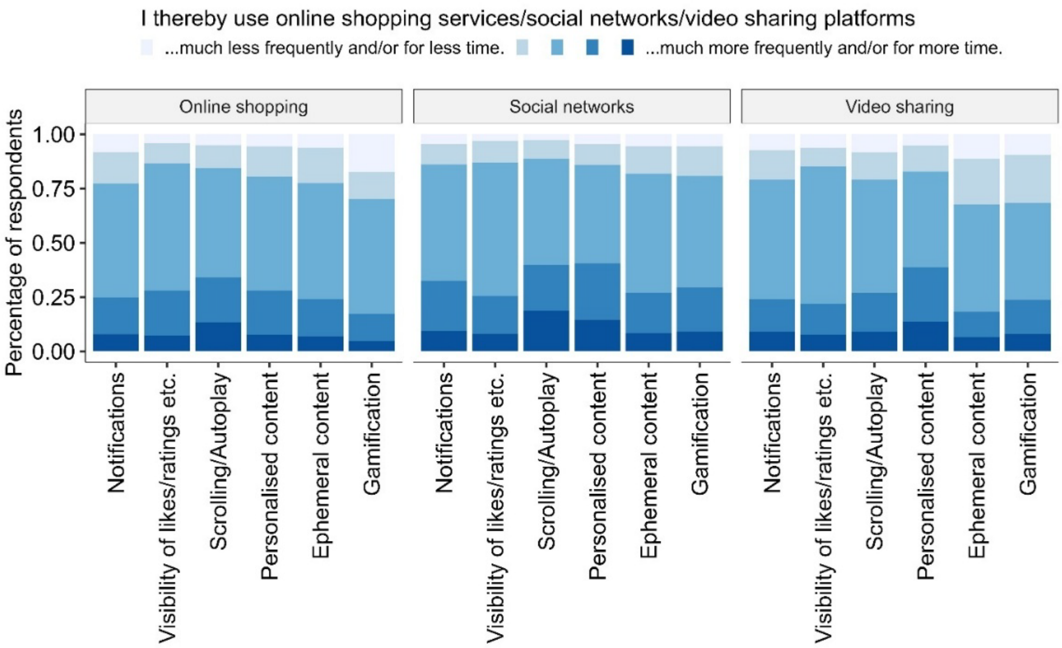
Usage time dimension

Perceived feature effect

The respondents who indicated that they are exposed to the respective feature were asked to indicate how they perceive its effect on their usage time on a 5-point scale. These respondents utilise services equipped with the respective feature and are actively aware of its presence, thereby potentially being able to estimate its effect. Figure 2 depicts the respondents' answers. In most cases, the majority of respondents do not perceive any effect of the respective feature on their usage time of the respective service group, as represented by the middle answer option. Among the remaining respondents, heterogeneity in effects is evident, with a noticeable proportion perceiving time-prolonging effects as well as a significant proportion perceiving time-shortening effects. With regard to the effects differentiated by feature, aggregated over all service groups, in the majority of cases the proportion of respondents perceiving time-prolonging effects exceeds the proportion perceiving time-shortening effects. Only in relation to gamification and ephemeral content does a greater proportion of respondents perceive time-shortening compared to time-prolonging effects. Splitting this up in the different service groups, the three cases of gamification on online shopping services and gamification and ephemeral content on video sharing services are the ones for this is the case.

The feature-service combinations with the highest proportions of respondents perceiving the maximal time-prolonging effect are scrolling on social networks (19%) and personalised content on social networks (15%) and on video sharing service (14%). These three combinations also represent the feature-service combinations for which the highest proportion of respondents indicated a time-prolonging effect in general, with percentages of 40%, 41% and 39% respectively. The feature-service combinations with the highest proportions of respondents perceiving time-shortening (maximal time shortening effects) are ephemeral content on video sharing services and gamification on video sharing and online shopping services with 32% (11%), 32% (10%) and 30% (17%) respectively. Overall, heterogeneity is observable between respondents, as well as between services, features and service-feature combinations.

Figure 2: Perceived effect on usage time



Number of respondents by group, from left to right feature: online shopping (N = 472, 532, 595, 422, 471, 127), social networks (N = 718, 642, 608, 569, 302, 109), video sharing (N = 513, 560, 495, 530, 275, 126).

In order to analyse the effects further, the original categorical scale has been transformed into a numeric one, with 1 representing a much less frequent and/or shorter use and 5 a much more frequent and/or longer use. With regard to all service groups collectively, the largest perceived increase in usage time is observed to be due to scrolling respectively autoplay and personalised content, as illustrated in Table 4. Equality of means between the effects of scrolling/autoplay and personalised content is not rejected, but equality of these two to the others is rejected, thereby indicating that their effects are significantly stronger.[4] Moreover, equality of means cannot be rejected for notifications and the visibility of likes, ratings, etc., and for ephemeral content and gamification. However, the former two have significantly larger effects than the latter two. In addition to an analysis of average effects, the variance of the effects is regarded. The highest variance is observed for gamification, with the lowest variance relating to the visibility of likes, ratings, etc., the former being approximately 44% larger than the latter.[5] This is primarily attributable to the notably lower variance of the visibility relative to other variances, and only to a lesser extent to a comparatively high variance of gamification. This underlines the existence of a different variability in effects between the features.

4 The equality of means has been tested using a Welch's ANOVA test, followed by a pairwise Welch's test with Holm's method being used to adjust for multiple testing. All significant p-values are <0.01. In order to increase the robustness regarding the assumption of normality, the same analysis has been conducted using a Kruskal-Wallis test followed by pairwise Mann–Whitney U tests, leading to the same results.

5 A Levene’s test rejects equal variances across groups at the 1% level.

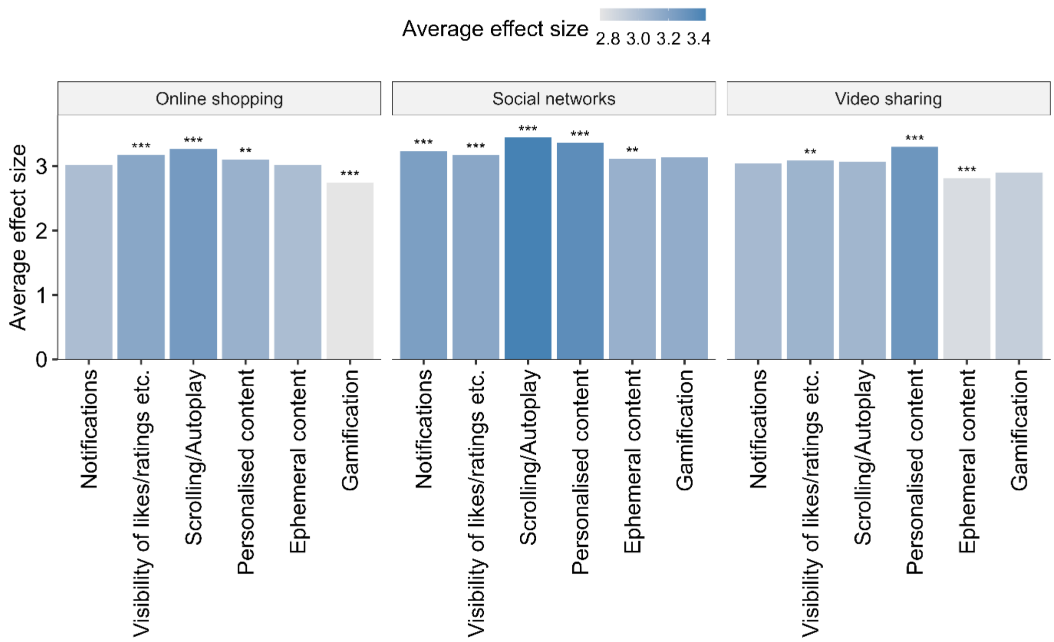
Table 4: Average effect sizes on usage time over all service groups

Feature	Notifications	Visibility of likes/ratings etc.	Scrolling/ Autoplay	Personalised content	Ephemeral content	Gamification
Average effect size	3.12***	3.15***	3.27***	3.27***	2.99	2.92

Statistically significant differences from a neutral effect of 3 using t-tests: ***: 1% level, **: 5% level, *: 10% level. The same results are obtained using a non-parametric Bootstrap approach, which is not dependent on the assumption of a normal distribution.

Figure 3 depicts the division of the aggregated effects by service group. The aggregated effects are reflected in the service-specific effects in most cases, with the largest effects generally occurring for the social networks group. However, not in every case can a significant increase of the features with an aggregated time-prolonging be observed for all service groups. Furthermore, heterogeneity in the effect direction can be observed for the features exhibiting a neutral aggregated effect, with ephemeral content leading to a reduction in the usage time on video sharing services, but to an increase in usage time on social networks.

Figure 3: Average effect size on usage time



Statistically significant differences from a neutral effect of 3 using t-tests: ***: 1% level, **: 5% level, *: 10% level. The same results are obtained using a non-parametric Bootstrap approach, which is not dependent on the assumption of a normal distribution. Number of respondents by group, from left to right feature: online shopping (N = 472, 532, 595, 422, 471, 127), social networks (N = 718, 642, 608, 569, 302, 109), video sharing (N = 513, 560, 495, 530, 275, 126).

In order to ascertain whether there are any significant differences in average perceived effect between the features within the three service groups, equality of means has been tested within each group.[6] The findings imply that the features associated with the most time-prolonging effects in the context of online shopping services are scrolling, personalised content and the visibility of ratings, etc. Conversely, the most time-reducing effect is attributed to gamification. In the context of social networks, scrolling and

6 Testing was conducted using Welch's ANOVA tests followed by pairwise Welch's test, with Holm's method employed to adjust for multiple testing. All significant p-values are <0.05. Non-parametric methods yield the same conclusion.

personalised content exhibit the most pronounced time-prolonging effects. In the context of video sharing services, personalised content exhibits the greatest time-prolongation, while ephemeral content exhibits the greatest time-reduction. With regard to differences in feature effects across the service groups, equal effects are rejected for all features with the exception of visibility of likes, ratings, etc.[7] Social networks are always among the services with the most time-prolonging effects, with the effect of notifications and scrolling/autoplay being significantly higher than the equivalent effects in both and not only one of the two other groups. Furthermore, the effects of autoplay and of ephemeral content on video sharing services are significantly lower than that of scrolling, respectively ephemeral content on the other two groups. The effect of personalised content, respectively gamification, is lowest respectively among the lowest on online shopping services. With regard to the variances for the feature-service combinations and the mean of this across services, the same ranking of variability as in the aggregated analysis is observed. Consequently, the aggregated differences in variances appear to be attributable to the general variance of the feature, rather than to differences in effect across service types.

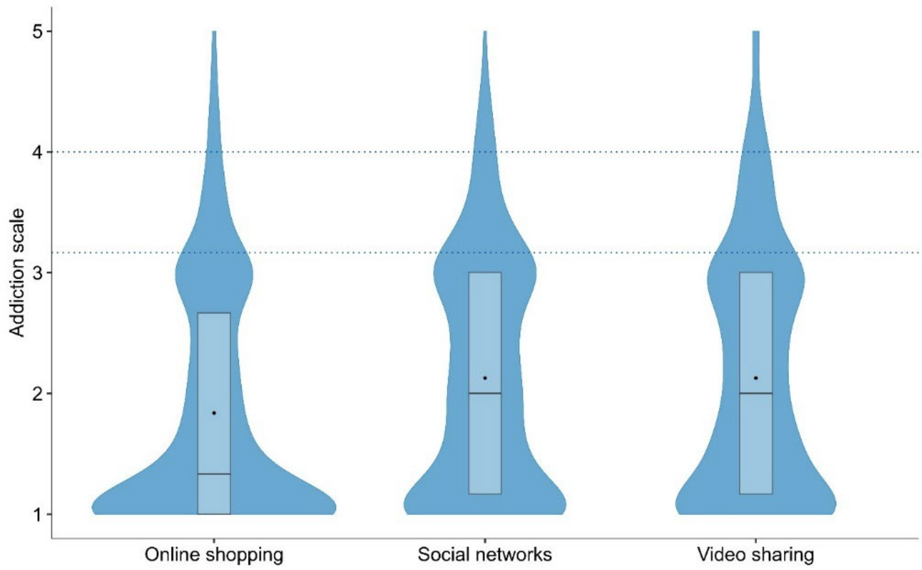
Consequently, overall, it is evident that the general feature effects are consistent across service groups in the majority of cases, though some variations in effect size and even effect direction are also observed. However, the underlying mechanisms causing these variations in effect direction remain to be elucidated.

Addictive behaviour

In order to analyse the relationship between these feature effects and service-addictive behaviour, the distribution of addiction is regarded in aggregate first. As illustrated in Figure 4, which displays the kernel density estimate of the mean of the responses to the three service-specific addiction scales, a significant proportion of respondents do not exhibit any indications of addiction, as evidenced by the wide areas close to a value of one, particularly for online shopping services. However, a proportion of respondents also exhibit medium and high values. In an effort of trying to identify a reliable threshold on the underlying Bergen Social Media Addiction Scale for the classification of respondents at risk of addiction, Bányai et al. (2017) have identified a total score of 19, i.e. an average value of 3.167, as such threshold. However, a more recent study proposed a higher threshold for classification of 24, i.e. an average of 4, based on their research findings as this is reported to yield superior results (Lou et al, 2021). However, this threshold is utilised for the classification of respondents with a disorder. Accordingly, throughout the following analysis, the less rigorous threshold is employed for the classification of being at risk, and the more stringent one for the classification of disorder across all three service types, including for the slightly modified questions concerning online shopping and video sharing services. Consequently, the precision of classification in these two groups may be diminished, as the thresholds have not been evaluated for such an alteration. Employing the delineated methodology, 11.9% (online shopping), 17.6% (social networks) and 17.2% (video sharing) of respondents are categorised as being at risk of the respective service addiction. Furthermore, 3.3%, 4.7%, and 5.0% of subjects in these groups are classified as having a disorder.

7 The same testing approach as before has been utilised.

Figure 4: Service addiction scale averages



Number of respondents by group: online shopping (N = 1043), social networks (N = 1049), video sharing (N = 1042).

In order to ascertain which respondents are particularly susceptible to addictive behaviour, the demographics of the groups with and without a risk of addiction to the respective type of service, based on the previously mentioned threshold, are compared and several differences emerge. With regard to the gender of respondents, the proportion of male respondents is higher in the groups with a risk of service addiction than in the groups without risk for all three service categories. The fractions are 53% vs. 46% (online shopping), 54% vs. 42% (social networks) and 61% vs. 51% (video sharing). Independence between the gender and the addiction risk is rejected in the social network and video-sharing groups (p-values: social networks: >0.01, video sharing: 0.017, online shopping: 0.137).[8] Furthermore, statistically significant differences in the mean age of the groups with and without risk are observable for all three service categories, with the former group exhibiting a significantly lower mean age.[9] The differences are 53 vs. 36 (online shopping), 52 vs. 36 (social networks) and 49 vs. 34 (video sharing) years old. No significant disparities were observed between the East and West regions, nor between the education levels or median incomes of the respective populations. Consequently, there appears to be a slightly elevated probability of developing service addiction in males and younger demographics compared to females and older individuals.

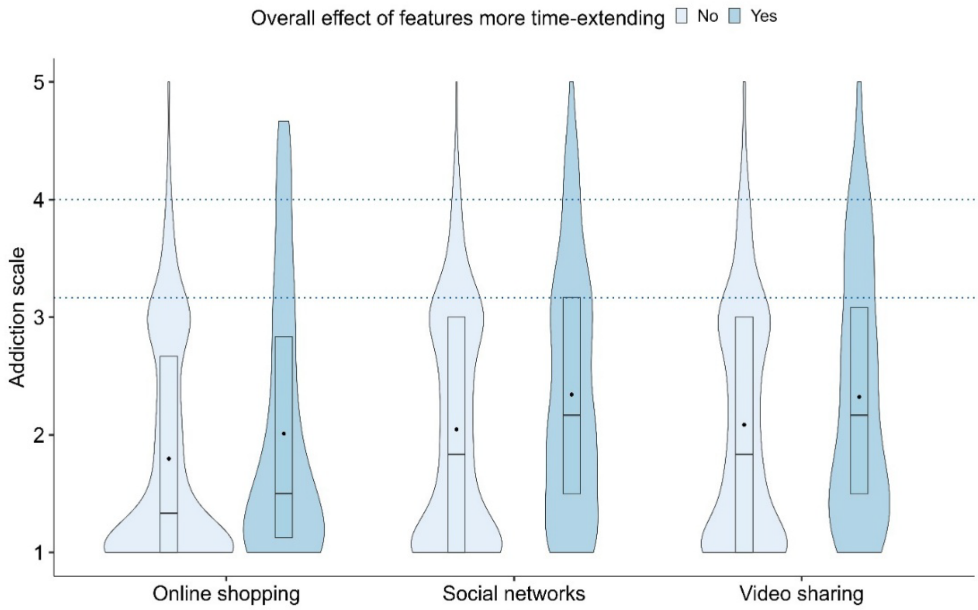
In order to analyse the relationship between addictive behaviour, measured by these addiction scales, and the effect of the addictive design features, an overall time-effect index that aggregates respondents' feature-specific effect ratings has been constructed. Specifically, for each respondent, the deviations from the neutral effect (3) across all features reported as being exposed to has been summed. It is reasonable to assume that the combination of effects of the features influences the overall behaviour, which is reflected in this index. prolonging and time-shortening to offset each other. The respondents were then classified as showing a stronger time-extending overall feature effect if their index exceeded 1 (which corresponds to at least one medium positive deviation from neutral, and lies at the 75th percentile of the index in the full sample). Under this rule, 18.8%, 27.5% and 18.0% of respondents are classified as having stronger time-extending feature effects in the online shopping, social networks and

8 This has been tested using Fisher's exact test with a simulated p-value due to the limited number of observations of respondents with a diverse gender.

9 The differences were tested using Welch's tests. All p-values are <0.01.

video sharing groups, respectively. The resulting densities of the addiction scales separated by feature effect are illustrated in Figure 5. It is evident that a marked upward shift in the addiction scale distribution occurs in all groups when considering only respondents with a stronger overall effect. In all three groups, equality of means between the average addiction scale values of the two groups is rejected.[10] Consistent with this shift, there is a notable decrease in respondents with nearly no symptoms and an increase in respondents with a strong manifestation of symptoms in the groups with stronger feature effects. Utilising the aforementioned thresholds, the proportion of respondents classified as at risk is 18.9% vs. 10.3% (online shopping), 25.3% vs. 14.7% (social networks), and 25.1% vs. 15.4% (video sharing) for stronger vs. less-strong effects; the corresponding disorder shares are 8.7% vs. 2.0%, 8.7% vs. 3.2%, and 9.6% vs. 4.0%. Consequently, a marked positive association between a stronger perceived time-extending feature effect and more pronounced addictive behaviour can be observed.

Figure 5: Service addiction scale averages by overall feature effect on usage time



Number of respondents by group, from left to right: online shopping (N = 847, 196), social networks (N = 761, 288), video sharing (N = 855, 187).

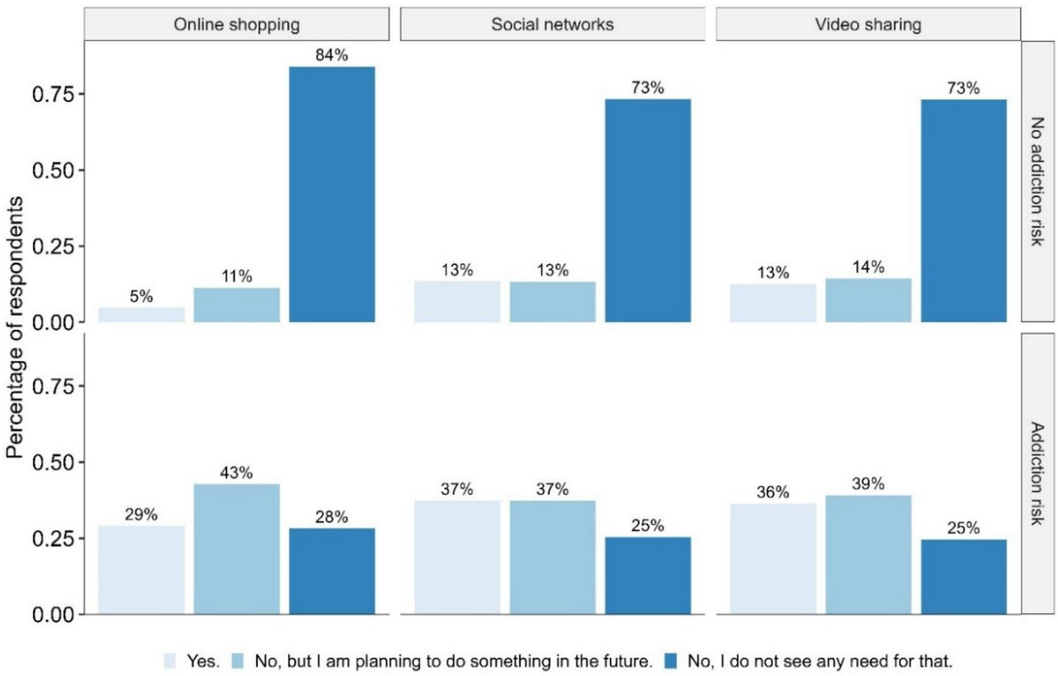
Self-regulation of behaviour

Turning to the regulation of behaviour, the majority of respondents across all three groups indicate that they have not implemented any mechanisms in the past to control the time spent on the respective service category nor do they perceive a need to do so in the future (online shopping: 77%, social networks: 65%, video sharing: 65%). The remaining respondents are relatively equally split between having engaged in this practice in the past and not having done so yet, but planning to do so in the future, except for the online shopping group, in which the latter percentage is approximately twice as large as the former. However, as previously identified, respondents in the online shopping group exhibit lower addiction scores, such that a lower willingness to regulate their behaviour might be adequate. In general, the percentage of respondents having taken action or planning to do so is higher than the percentage of respondents considered to be at risk of addiction.

10 This has been tested using t-tests due to no rejection of equal variance between groups. All p-values are <0.01.

In order to examine whether there are any differences in regulation behaviour according to addiction risk, Figure 6 separates responses according to the risk classification. Across all three service categories, respondents classified as at risk are more likely to report having taken measures or planning to do so, and differences between service types become smaller in the at-risk subsamples. However, it is evident that in all three groups approximately one-quarter of respondents who exceed the risk threshold do not perceive a necessity for self-regulation, and only around 30-40% of respondents with a risk of addiction have attempted to regulate their behaviour. Among respondents meeting the stricter "disorder" threshold, the proportion reporting no perceived need remains substantial in the domains of online shopping and video sharing (approximately 20%); however, this proportion is lower in the domain of social networks (8%). The proportion of respondents reporting past regulation is approximately 35% in the domain of online shopping and video sharing, and around 60% in the domain of social networks. However, the findings must be interpreted taking into account the reduced sample size classified as having a disorder. In general, an increase in the propensity to regulate is observed as the addiction scale increases, although the implementation of actual regulation remains moderate.

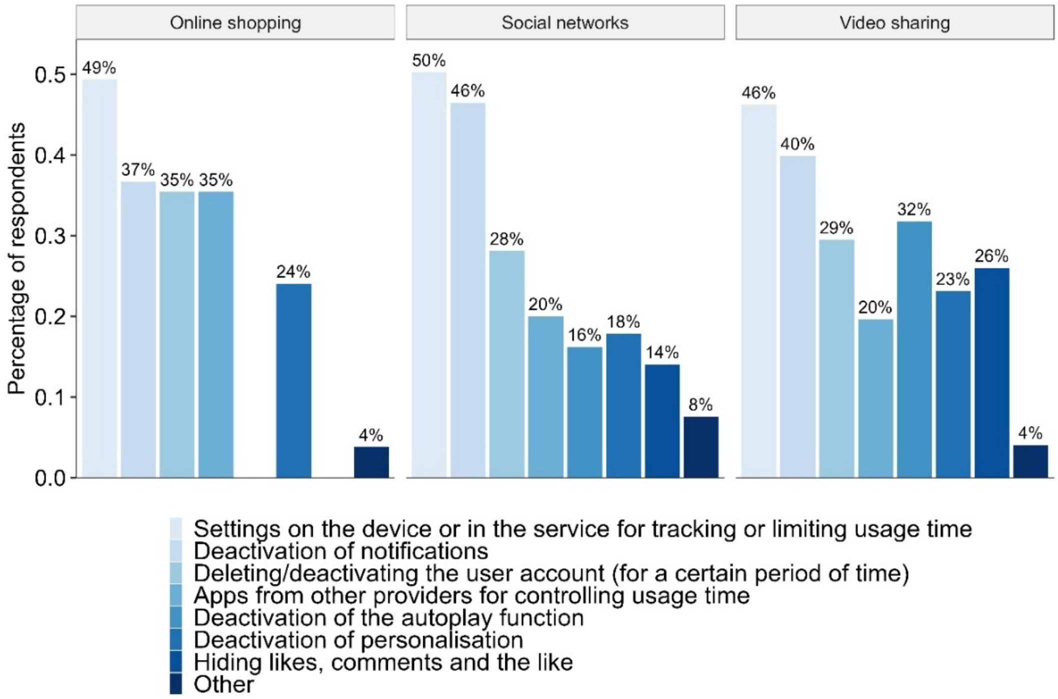
Figure 6: Position on self-regulation of usage time by classification regarding addiction risk



Number of respondents by group, from top to bottom: online shopping (N = 919, 124), social networks (N = 864, 185), video sharing (N = 863, 179).

The specific measures reported by respondents are summarised in Figure 7 as a percentage of respondents indicating that they have taken action in the past. In particular, usage time tracking or limiting, the deactivation of notifications, and even the (temporary) deactivation or deletion of user accounts have been utilised. With regard to differences in behaviour regulation between service groups, the hiding of likes, comments, etc. and the deactivation of the autoplay function are of greater importance on video sharing services than on social networks. These measures have not been presented in the context of online shopping services, as the corresponding features are typically not available or cannot be deactivated in that context. Furthermore, apps from other providers for controlling usage time are to a greater extent utilised with online shopping services than with the other groups. Overall, it appears that measures which do not alter the concrete service design, such as the deactivation of personalisation or the hiding of likes or comments would do, are used more often.

Figure 7: Self-regulation measures for usage time used by respondents having regulated themselves



Number of respondents by group: online shopping (N = 79), social networks (N = 185), video sharing (N = 173).

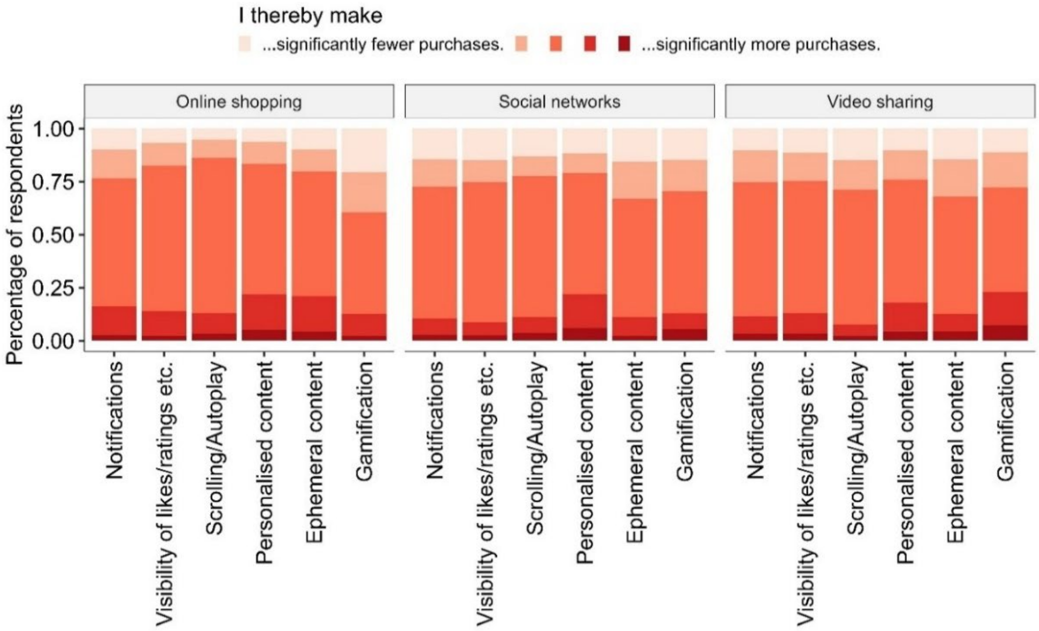
Shopping dimension

Perceived feature effect

In a parallel manner to the question of feature effects on usage time, respondents were asked how they perceive the effects of the features on their general online shopping behaviour. Figure 8 depicts the respondents' answers. An even higher proportion of respondents do not perceive any effects on their general online shopping behaviour compared to findings regarding usage time. However, heterogeneity in responses is evident in terms of shopping behaviour as well, with noticeable fractions indicating purchase-promoting but also purchase-reducing effects. Concerning the effects of the features grouped over all service types, a higher fraction indicate purchase-reducing than purchase-promoting effects for all features. With regard to the effects differentiated by service groups, this statement is generally valid, with the exception of personalised content in the online shopping and social networks groups, and ephemeral content in the online shopping group.

The highest shares perceiving purchase-promoting effects in general (the strongest purchase-promoting effects) are realised by gamification on video sharing services and personalised content on online shopping services and social networks, with 23% (7%), 22% (5%) and 22% (6%) of respondents in each case indicating this. The highest proportions of respondents perceiving a reduction in purchases in general (respectively with the strongest effect) are 39% (21%), 33% (16%) and 32% (15%), achieved by gamification on online shopping services and ephemeral content on social networks and video sharing services. As was the case in the time dimension, heterogeneity is observable between respondents, as well as between services, features and service-feature combinations.

Figure 8: Perceived effect on shopping behaviour



Number of respondents by group, from left to right feature: online shopping (N = 472, 532, 595, 422, 471, 127), social networks (N = 718, 642, 608, 569, 302, 109), video sharing (N = 513, 560, 495, 530, 275, 126).

The original effect scale has been converted into a numeric scale, with 1 representing a significantly lower number of purchases and 5 representing a significantly higher number of purchases. Table 5 shows the mean effect sizes grouped across all service categories. Gamification is associated with the strongest decrease in purchases and personalised content with the smallest one, which is not distinguishable from a neutral effect at the 5% significance level. Equality of means is rejected between the effect of personalised content and all other effects, but no further equalities are rejected.[11] Consequently, personalised content exerts a considerably more neutral effect than the other features, which all demonstrate similar effects at the aggregate level. With regard to the variances of the feature effects, the highest value is observed for gamification, with the lowest being exhibited by scrolling/autoplay, the former being approximately 45% larger.[12] In contrast to the variances regarding time effects, this is primarily due to the variance of gamification being larger than the values of the other features and not scrolling/autoplay having an especially low variance.

Table 5: Average effect sizes on shopping behaviour across all service groups

Feature	Notifications	Visibility of likes/ ratings etc.	Scrolling/ Autoplay	Personalised content	Ephemeral content	Gamification
Average effect size	2.78***	2.8***	2.82***	2.95*	2.8***	2.73***

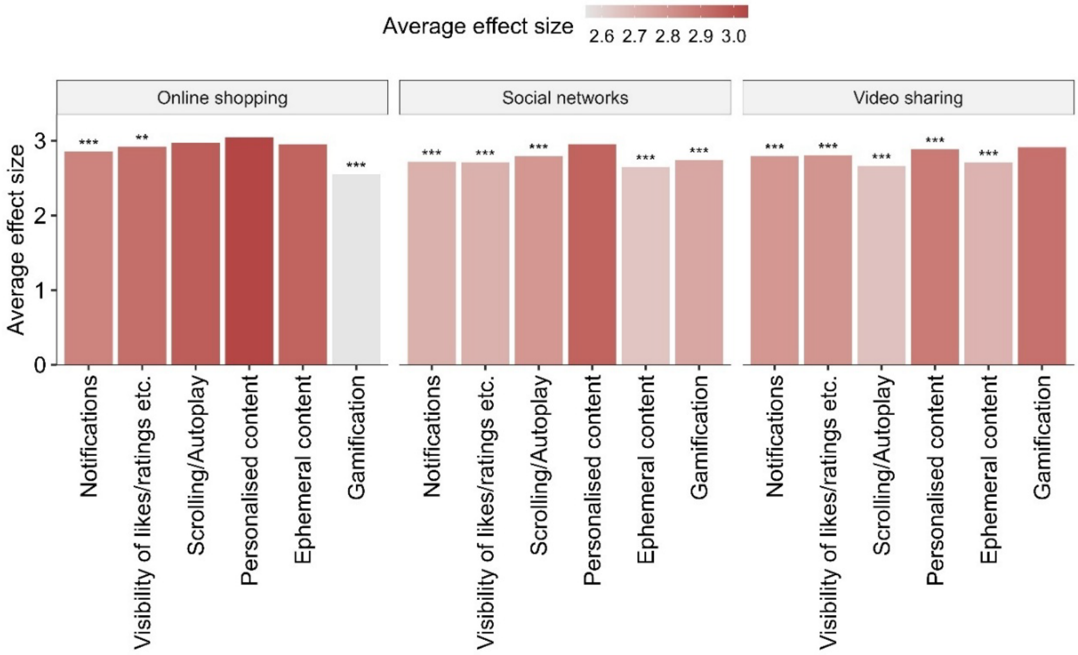
Statistically significant differences from a neutral effect of 3 using t-tests: ***: 1% level, **: 5% level, *: 10% level. The same results are obtained using a non-parametric Bootstrap approach, which is not dependent on the assumption of a normal distribution.

11 The equality of means has been tested using a Welch's ANOVA test, followed by a pairwise Welch's test with Holm's method being used to adjust for multiple testing. All significant p-values are <0.01. In order to increase the robustness regarding the assumption of normality, the same analysis has been conducted using a Kruskal-Wallis test followed by pairwise Mann–Whitney U tests, leading to the same results.

12 A Levene's test rejects equal variances across groups at the 1% level.

Figure 9 illustrates the different effects by service group. In most cases, the aggregated picture fits the service-specific pictures. Except for video-sharing services, personalised content does not have a significantly different effect to a neutral one. However, the purchase-reducing effects are generally less strongly perceived for online shopping services.

Figure 9: Average effect size on general online shopping behaviour



Statistically significant differences from a neutral effect of 3 using t-tests: ***: 1% level, **: 5% level, *: 10% level. The same results are obtained using a non-parametric Bootstrap approach, which is not dependent on the assumption of a normal distribution. Number of respondents by group, from left to right feature: online shopping (N = 472, 532, 595, 422, 471, 127), social networks (N = 718, 642, 608, 569, 302, 109), video sharing (N = 513, 560, 495, 530, 275, 126).

To analyse which features lead to the greatest reduction in purchases, equality of means has been tested within each service group.[13] Regarding online shopping services, gamification is perceived as reducing purchases the most, and notifications are more purchase-reducing than personalised content. This is similar to the effects on usage time, where gamification was found to significantly reduce usage time. For social networks, the effect of personalised content is significantly less purchase-reducing than all other effects except gamification. This is somewhat similar to the effect on usage time. Regarding video-sharing services, the only significant difference arises for personalised content and autoplay. Therefore, fewer differences in effects can be identified in this group. When comparing the feature-service effects on shopping behaviour with the previously analysed effects on usage time, significant differences can be observed in all cases, except for personalised content, gamification, and ephemeral content on online shopping services, and for gamification and ephemeral content on video-sharing services.[14]

13 Testing was conducted using Welch's ANOVA tests followed by pairwise Welch's test, with Holm's method employed to adjust for multiple testing. All significant p-values are <0.05. Non-parametric methods yield the same conclusion.

14 Testing was conducted using Welch's ANOVA tests followed by pairwise Welch's test, with Holm's method employed to adjust for multiple testing. All significant p-values are <0.01. Non-parametric methods yield the same conclusion.

Concerning differences in feature effects between the service groups, equal effects are rejected for all features. [15] Online shopping services are always among those on which the least purchase-reducing effects are reported, except regarding gamification; the effects of scrolling/autoplay, visibility of likes, ratings, etc., and ephemeral content are significantly less purchase-reducing than the equivalent effects in both of the other two groups. Concerning gamification, however, the effect on online shopping services is significantly more purchase-reducing than on video-sharing services. Moreover, autoplay has a significantly greater purchase-reducing effect on video-sharing services than scrolling has on the other two service types. Regarding the variances for the feature-service combinations and the mean across services, the same variability ranking as in the aggregated analysis emerges. Therefore, the differences in variance appear to be caused by general variance of the feature rather than by differences in effect across service types. Furthermore, the online shopping group generally exhibits slightly lower variances, indicating slightly lower heterogeneity in effects for this service type.

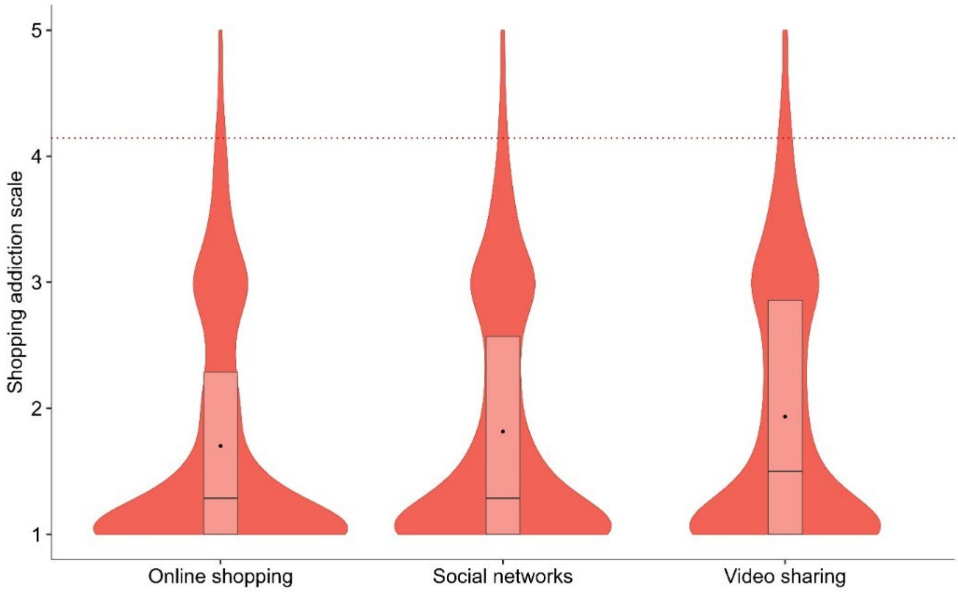
Overall, this highlights that the effect sizes on online shopping services generally reduce purchases the least, except for gamification, and that the effects on video-sharing services and social networks are more consistent with each other than with online shopping services.

Addictive behaviour

To analyse the relationship between the effect of features and addictive behaviour, the responses to the online shopping addiction scale are examined. Figure 10 shows the densities of the average response values. As with service-related addiction, many respondents do not exhibit signs of general online shopping addiction, though some show stronger manifestations. In line with all three groups being asked about their general shopping behaviour, not just their service-specific behaviour, no significant differences between the groups are apparent. Using a proposed threshold of the sum of answers totalling 29 or above (i.e. an average score of 4.14 or above) to classify respondents as being at high risk of shopping addiction, 2–3.2% of respondents in each of the three groups would fall into this category (Zarate et al, 2022).

15 Testing was conducted using Welch's ANOVA tests followed by pairwise Welch's test, with Holm's method employed to adjust for multiple testing. All significant p-values are <0.05. Non-parametric methods yield the same conclusion.

Figure 10: Shopping addiction scale averages



Number of respondents by group: online shopping (N = 1043), social networks (N = 1049), video sharing (N = 1042).

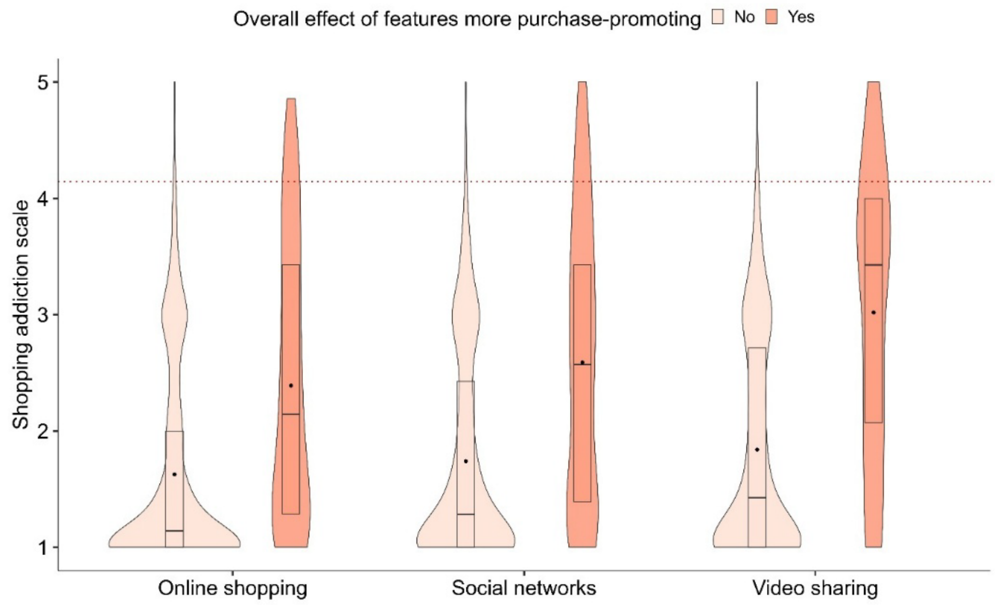
Demographic differences between respondents with and without a high risk of shopping addiction, based on the aforementioned threshold, were analysed to identify those at especially high risk. As the administered shopping addiction scale was not specific to the service group, this analysis is conducted in an aggregated way across all groups. Similarly to before, a higher proportion of males is present in the group at high risk of shopping addiction (61% vs. 48%). However, in this case, the independence of gender and high shopping addiction risk can only be rejected at the 10% significance level (p-value from Fisher's exact test: 0.081). This could be due to the smaller size of the group at high risk of shopping addiction (N = 92). The difference in mean age is again highly significant, with an average age of 37 years compared to 49 years, and younger people being more likely to be in the high-risk group.[16] The median net household income per month is between 2,500 and 3,000 € for respondents without a high risk of shopping addiction, while it is between 3,500 and 4,000 € for those with such a risk. Again, no significant difference can be found in terms of region or education level, although the latter nearly reaches significance at the 10% level, with respondents in the risk group having a slightly higher level of education.

In the same way as for the effects on usage time, an index of the overall shopping effect has been constructed using the perceived effects on shopping behaviour. The same threshold as before of 1 is applied. 8.8%, 9.5% and 8.0% of respondents respectively fall into the groups with stronger overall feature effects in the online shopping, social networks and video sharing categories. Figure 11 shows the resulting densities of the shopping addiction scale. As in the previous case, a noticeable shift in distribution occurs when the effects of features are considered. Equality of means between the two groups' mean addiction scale values is rejected in all three service groups.[17] It is apparent that groups with stronger feature effects comprise a smaller proportion of respondents with hardly any symptoms, as well as a larger proportion of respondents with a strong manifestation of symptoms. With regard to the previously mentioned threshold, 12.0% vs. 1.0% (online shopping), 13.0% vs. 1.2% (social

16 The differences were tested using Welch's tests. All p-values are <0.01.
17 This has been tested using t-tests due to no rejection of equal variance between groups. All p-values are <0.01.

networks), and 21.7% vs. 1.6% (video sharing), of respondents in the groups with stronger versus weaker overall feature effects would be classified as being at high risk of shopping addiction. Therefore, a positive association between feature effect and addictive behaviour is apparent in this case as well.

Figure 11: Shopping addiction scale averages by overall feature effect on shopping behaviour

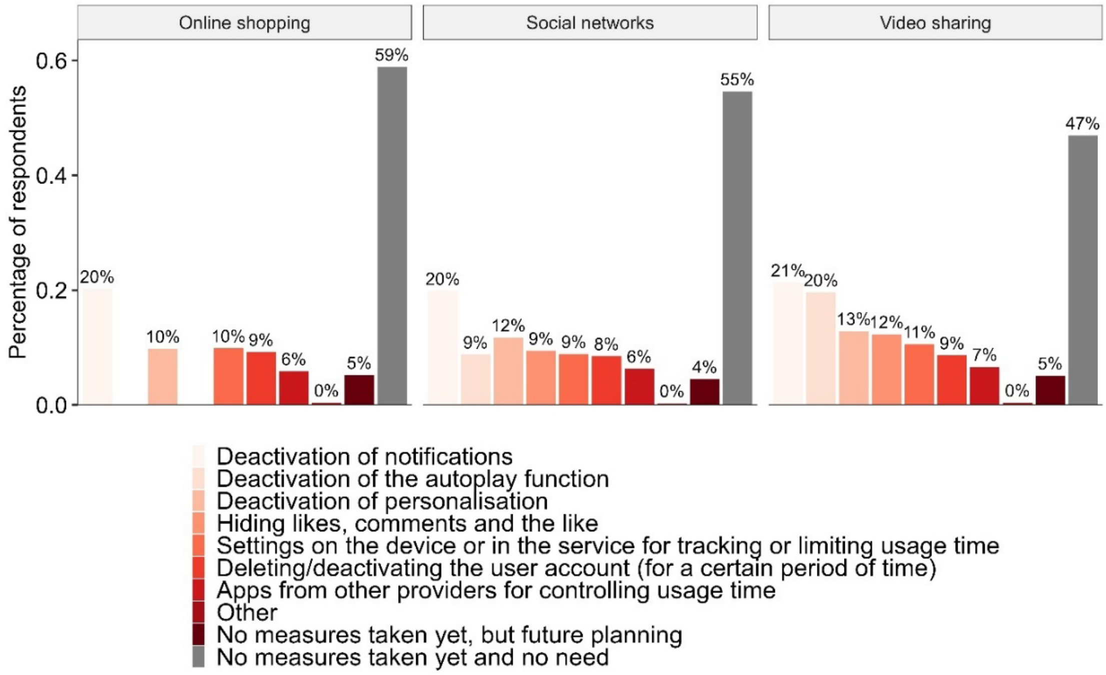


Number of respondents by group, from left to right: online shopping (N = 943, 100), social networks (N = 957, 92), video sharing (N = 959, 83).

Self-regulation of behaviour

As with usage time, the majority of respondents report that they have not taken any steps with regard to the respective service group to regulate their online shopping behaviour, nor do they perceive a need to do so, as illustrated in Figure 12. As before, those with higher addiction scores demonstrate a greater willingness to self-regulate. However, as only the high-risk threshold is considered, and the number of respondents who exceed this threshold is relatively small, no concrete numerical comparisons are made using this classification.

Figure 12: Utilised behaviour regulation regarding shopping



Number of respondents by group: online shopping (N = 1043), social networks (N = 1049), video sharing (N = 1042).

In terms of the specific measures employed to control online shopping behaviour, the deactivation of notifications is widely used, as was the case for regulating usage time. However, compared to measures aimed at limiting time spent, time-tracking or time-limiting settings appear to play a less prominent role in regulating shopping behaviour. With regard to the different behaviours used for the various service groups, deactivating autoplay is more important on video-sharing services than on social networks.

Discussion

Perceived feature effects and their association with addictive behaviour

The study has identified a number of findings regarding the interplay between addictive design features and users. With regard to the first research question, it is evident that in the majority of cases, most respondents do not perceive any effect of the addictive design features on their usage time or shopping behaviour, resulting in average effect sizes that are relatively close to a neutral outcome. However, it is unclear whether this accurately reflects the true impact, or whether their perception is skewed. While experimental literature often shows that these design features have a usage-promoting effect, particularly when compared with scenarios in which the design feature is absent or has been replaced by alternatives, they are often assessed more nuanced in survey-based studies. Furthermore, surveys have demonstrated a lack of awareness regarding addictive design features. These findings suggest the presence of a bias in the perception of the effects of addictive design features, tending towards a neutral outcome. This potential mismatch between perception and actual effect may present an issue, as a lack of awareness of potentially addictive effects could impede appropriate behavioural adjustment, for instance, through the disabling of the feature where such an option is available.

However, with regard to the proportion of respondents perceiving non-neutral effects on their behaviour, a noticeable heterogeneity in perceived effects between respondents is evident, which appears to vary somewhat depending on the specific addictive feature under consideration. In both dimensions of addiction, and especially with regard to the usage time dimension, contrasting effect sizes with relevant shares at both extremes can be observed. The analysed literature has shown that perceptions of addictive or manipulative designs vary among individuals. This is particularly evident in the degree of manipulative and helpful characteristics they attribute to the designs and the sense of agency they perceive through them (Keleher et al., 2022; Lukoff et al., 2021; Mildner et al., 2020). Consequently, observed heterogeneity is largely consistent with the broader results. However, it remains unclear whether the extent of the observed heterogeneity does so, and whether any of this heterogeneity is attributable to different perceptions rather than different actual effects. If heterogeneous effects are present to a noticeable degree, this may necessitate a weighting of different effects when determining the overall utility.

Concerning the average perceived effect with regard to usage time, a prolongation of usage time is reported for the majority of features. In particular, the automated and continuous supply of content in the form of scrolling and autoplay and algorithmic personalisation is associated with increased usage time, although the absolute differences between features remain moderate. However, no significantly increasing effect for gamification and even one significantly decreasing effect was found, although the smaller sample size reporting exposure to this feature should be taken into account. It may be hypothesised that gamification is perceived as bothersome by a significant proportion of respondents, potentially leading to a decline in usage time. Research in this field has identified a variety of mixed effects of gamification in different application scenarios (Koivisto & Hamari, 2019). However, it is not possible to make any definitive statement. Overall, the effects regarding the average effect on usage time are consistent with the nature of addictive design features, which are designed to increase usage time.

It is evident that a divergent perception of effects is present in relation to a different addictive behaviour, namely shopping addiction. The effects of the features are perceived as having a rather purchase-reducing than purchase-promoting effect in this domain. However, the manifestation of this effect is less pronounced and more neutral in the context of algorithmic personalisation. The examined addictive design features are designed to increase usage time, rather than purchases made, which may explain this discrepancy. Nonetheless, it has been demonstrated that design features, such as time-limited offers, can induce a promoting effect on purchasing behaviour. However, it should be noted that there are differences in the effect between the service categories, which will be explained in the next section.

With regard to the second component of the first research question, a positive association was observed between the overall feature effect on the respective behaviour dimension and the respective addiction scale, across both addiction dimensions, usage time and purchases made. Consequently, the addictive design features may contribute to the development of addiction. However, it is not possible to derive the causality of effects. For instance, there may be a third factor influencing addictive behaviour, as well as the vulnerability to the effects of addictive design features.

Self-regulation

Turning to the second research question, which pertains to the mechanisms employed by respondents for self-regulating their behaviour on online platforms, it is evident that the majority of respondents do not perceive a necessity for such measures and, consequently, do not implement any. However, a higher propensity for self-regulation of behaviour is observed in instances where there is a heightened risk of addiction. Nevertheless, even in such cases, a considerable proportion of individuals have not taken any measures and some even do not perceive a future need to do so. In terms of the concrete measures employed, the deactivation of notifications has been found to be relevant for both dimensions of addiction, while time tracking and limiting, and the deactivation of user accounts have been found to be more prevalent in terms of controlling usage time. This is consistent with the fact that the primary behavioural factor in the shopping dimension is purchasing activity rather than time spent, and the two factors are only imperfectly correlated.

Service-specific effects

With regard to the third research question concerning the differences between service groups, many consistent patterns in effects can be observed across services, but some differences in effect size and, in some cases, even effect direction do also emerge. When analysing the differences between the service groups, it should be noted that a between-subject design has been employed, rather than a within-subject design, such that different respondents constitute the different groups.

Concerning the usage time dimension, the effect strength is found to be slightly stronger on social networks than on online shopping or video sharing services, although absolute differences remain modest. One of the in aggregate most influential features, algorithmic personalisation, is related to perceived time-increasing effects across services. The other one, the automated and continuous supply of content, shows slightly more varied effects, with the effect of autoplay on video sharing services appearing to be slightly less time-increasing compared to scrolling on the other service. For ephemeral content, a discrepancy in the effect direction is observable, with its impact on video sharing services being perceived as time reducing and on social networks as time prolonging. It could be hypothesised that ephemeral content on video sharing services reduces the amount of content being consumed due to its availability for shorter periods of time, thereby reducing the likelihood of it being viewed, while on social networks an effect of increased usage time due to the more frequent checking of the service, or the feeling of pressure to consume the content due to a fear of missing out might be present. Nevertheless, it is not possible to make any definitive statements.

With regard to the shopping dimension, the least purchase-reducing effects can generally be observed in the context of online shopping services, with the exception of gamification. Evidently, purchasing on the service itself is more important for online shopping services than for other services, even though TikTok, for instance, also offers an integrated shop. Furthermore, some of the feature variations on online shopping services, such as the visibility of ratings or limited offers, are more directly related to purchasing. Respondents were asked about the effect of the feature on their general online shopping behaviour, for instance taking into account the effect of sponsored content on their purchasing behaviour on other services. However, it is unclear whether the transfer between services was too complex for respondents to consider. For instance, some respondents may have regarded the perceived increase in time spent on social networks due to the feature as a reason for shopping less, as their limited online time becomes crowded out by social network use, without taking into account other potential cross-service purchase-increasing effects. Should the perception of users accurately incorporate cross-service effects on purchases, the associated costs of purchase reductions remain uncertain, for instance in terms of excessive usage time on other services. Concerning the purchase-reducing effects of features on online shopping services, it may, for instance, be the case that many respondents perceive gamification features as manipulative or annoying, reacting with opposition as a result, a similar potential argument as regarding the reducing effect on usage time. However, it is also possible to hypothesise positive reasons for reduced purchases, such as the visibility of ratings potentially helping to avoid unsatisfactory purchases. Nevertheless, definitive statements about the causes of these effects cannot be made.

With regard to the utilisation of self-regulation behaviours across service groups, comparable patterns emerge, although a slightly elevated tendency to deactivate autoplay on video-sharing platforms is observed.

Limitations

Naturally, our paper is not without its limitations. This study focuses on analysing the self-reported effects of addictive design features, a significant and interesting dimension given that user perception may influence behaviour, such as self-regulation or attitudes regarding legal regulation. However, it is important to note that these perceptions may not always perfectly align with the actual, underlying effects. Furthermore, as with any user survey, common biases and measurement errors, such as stemming from social desirability or divergent interpretations of questions, may affect the results. Furthermore, as previously mentioned, when considering the calculated shares of respondents who fall into the different service-addiction classifications for online shopping and video sharing services, it should be noted that the thresholds of the addiction scale have not been validated for this context. Consequently, the shares should be interpreted with caution and only as indicative and not definitive. Moreover, it should be noted that an adjustment for multiple testing concerning the control of false positives has been conducted within but not between tests. Therefore, certain statistically significant results may be attributable to chance findings, although many p-values are notably below 1%, emphasising the robustness of the findings. Future research could further explore through which avenue heterogeneity in perceived effects between users as well as between service groups arises, whether different effects even within a service group can be observed, and it could combine survey perceptions with experimental variations in feature exposure to analyse the relationship between perceived and actual effects.

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