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Mapping Social Media Dependency: Functional and Psychological Platform Reliance as Mechanisms of Digital Vulnerability

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Abstract

Social media dependency is a central mechanism through which digital vulnerability takes shape, making it critical to understand for research, design, and policy. This study distinguishes between functional dependency (needs-based reliance) and psychological dependency (compulsive engagement) and investigates how these dimensions intersect. We surveyed 873 adult users across Europe,

measuring both dependency forms alongside demographics, well-being, motivations, platform choice, and exposure to manipulative design features. Latent profile analysis and multinomial logistic regression revealed five distinct dependency profiles: functional use, low-dependency pragmatic use, high-dependency social use, moderate-dependency hedonic use, and very high-dependency multi-motivated use. These findings show dependency is not uniform but layered and dynamic, shifting with users' circumstances and socio-technical contexts. By situating dependency within both individual and design-related factors, the study advances theoretical debates on digital vulnerability and offers a profiles-based lens that helps inform the design of more autonomy-supportive social media platforms.

CCS Concepts

- **Human-centered computing** → Collaborative and social computing; Empirical studies in collaborative and social computing.

Keywords

social media design, dependency, vulnerability, psychological needs, deceptive design, dark patterns

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1 Introduction

Scrolling through Instagram to stay updated on a friend's life or searching TikTok for information that seems unavailable elsewhere has become routine for millions. What once were optional channels of leisure are now infrastructures that shape not only how individuals connect and communicate but also how they access information and experience the world [e.g., [44, 58, 130]]. Although social media platforms can foster connection, visibility, and information exchange (e.g., [5]), their extensive use has been consistently linked to various harms, including depression and anxiety [104], and social comparison processes [122].

These harms are not merely byproducts of user behavior but also closely tied to the design of the platforms. Researchers in HCI and design [66, 70, 87, 101], as well as law [29, 44], have recognized features such as recommender systems, manipulative design patterns¹, and data-driven business models as powerful drivers of individual manipulation to the detriment of user autonomy and agency. In this sense, social media platforms function as environments that facilitate engagement and cultivate their users' vulnerabilities [101, 106, 129].

¹The research community is studying this phenomenon using a variety of labels, including deceptive design, nudges, anti-patterns, and most commonly "dark patterns" (see [99]). Following the ACM recommendations on diversity and inclusion (ACM), we hereby use the term "manipulative designs" to describe this phenomenon which we believe better represents it.

Vulnerability is both an academic concept and a term employed within European Union (EU) legislation, e.g., Digital Services Act (DSA), the Unfair Commercial Practices Directive (UCPD) [25, 27, 42–44] and the General Data Protection Regulation (GDPR) [26, 75, 101]. In policy as well as in some HCI studies, a particularistic interpretation of the term has been favored whereby additional safeguards are granted to certain groups identified as vulnerable on the basis of socio-demographic characteristics, e.g., minors [129], older adults [14, 52] and minorities [11]. This view is contrasted by scholars who argue for the universal interpretation of the concept [10, 30, 72], especially in digital environments [42–44, 75], and that view vulnerability as the dynamic process of exposure to harm resulting from experienced and innate dependency on others [36] and the limited available personal or structural avenues for resistance [71].

Acknowledging this tension especially in the digital domain [101], we adhere to the notion of vulnerability as layered [68, 69]. This means that we view vulnerability as contextual, relational, and situated. Vulnerability, while universal, can be uniquely experienced by users due to the overlapping and cumulative effect of structural and personal factors [39, 69, 75, 101]. Humans are inherently fragile given the socio-spatial and temporal dependence on 'others' [72], including those institutions that can amplify or mitigate users' well-being or resilience (e.g., [10, 30, 72]). In this regard, both resilience, as a way of recovering from harm, and dependency, as a potential driver of exposure to harm, compound the idea of social media platforms as mediators of vulnerability [10, 30, 72, 96, 101]. Understanding how dependency operates on social media platforms is, therefore, a necessary step in analyzing the role of social media and the design of these platforms in producing and structuring user vulnerability by design.

To this end, we investigate how social media dependency manifests, how it is shaped by the interplay of individual factors (i.e., socio-demographic characteristics, well-being), use-related factors (i.e., use motivations, platform choice) and platform design (i.e., exposure to manipulative features). Together, these dimensions allow us to situate dependency not only in relation to who users are and how they engage with social media, but also in terms of the technological environments that structure those engagements. To explore these relationships, we conducted a survey study ($n = 873$) among adult social media users. In our analysis, we distinguish between two forms of dependency: functional dependency, which refers to reliance on social media to accomplish goals and needs, and psychological dependency, which refers to habitual or compulsive forms of engagement characterized by diminished control. Methodologically, we combine latent profile analysis with multinomial logistic regression to capture patterns of dependency across users. Our analysis reveals five distinct profiles of social media dependency: (1) functional use, (2) low-dependency pragmatic use, (3) high-dependency social use, (4) moderate-dependency hedonic use, and (5) very high-dependency multi-motivated use.

Our study makes a three-fold contribution. First, it advances theory by empirically demonstrating how social media dependency functions as a dynamic element of digital vulnerability. By integrating functional (needs-based reliance) and psychological (compulsive engagement) dimensions, the study shows that dependency is best understood as a layered and dynamic phenomenon. In line

with this, findings revealed that dependency reflects layered vulnerabilities shaped by the interplay of individual, use-related, and design-related factors. These findings also contribute to a more fundamental perspective for socio-legal and HCI debates: dependency is not a unitary state but a layered experience. Second, it offers practical insights for HCI and design. The five dependency profiles provide a concrete frame for understanding patterned heterogeneity in user reliance on platforms. This perspective shifts design debates from treating dependency solely as the absence of agency toward recognizing when dependency coexists with resilience and when it signals heightened vulnerability. By linking user profiles to the use of different social media platforms, the study underscores the structural role of design in shaping dependency and highlights the need for interventions tailored to different dependency configurations. Third, these insights are also relevant for advancing and interpreting policy by advocating for a more dynamic (legal) understanding of vulnerability by enforcement authorities and policymakers.

2 RELATED WORK

2.1 Vulnerability in the Digital Domain

The notion of vulnerability has been approached in different ways across scholarship and regulation. Whereas EU legal instruments applicable to the digital domain, such as the GDPR [75], DSA [42] and UCPD [25, 99], tend to lean on personalistic perspectives [44, 75] that target pre-defined socio-demographic groups, a growing body of academic work calls for a more nuanced understanding [45, 96, 101, 129].

Sociolegal and feminist theorists emphasize that vulnerability highlights the universal fragility and dependence of individuals on social and institutional structures [10, 30, 31]. This understanding places a political and ethical obligation on institutions to provide safeguards [30, 72]. Vulnerability is not uniform, it is shaped by the non-hierarchical interplay of, among others, personal resources and structural affordances, or what Luna coined as ‘layers’ of vulnerability [68, 69].

Scholars from the fields of law, HCI, and design build on this frame and highlight how platform architectures produce and amplify vulnerability. In HCI and design, Rossi et. al. [101] illustrate this in the case of manipulative design, showing how macro-, meso-, and micro-level factors, combined with platform affordances, drive vulnerability. In legal scholarship, Helberger et. al. [42] advance the notion of digital vulnerability, pointing to systemic power imbalances created by automation, datafication, and platform choice architectures. Similarly, Figà-Talamanca [29] argues that recommender systems generate ‘digitally scaffolded vulnerabilities’ by structuring user choices in ways that restrict autonomy. These perspectives demonstrate the importance of the vulnerability framework for understanding individual experiences on digital platforms and reinforce the argument that social media platforms do not merely host vulnerability but actively generate it through their business models and design structures. At the same time, these perspectives remain open to be complemented through empirical investigation. We, therefore, focus on understanding how dependency contributes to experiences of vulnerability in practice.

2.2 Social Media Dependency

Dependency is a central mechanism through which vulnerability materializes. When individuals rely on external actors to meet essential needs – social, emotional, informational, economic, etc. – especially where alternatives are limited or costly, they enter asymmetric relations that can be leveraged to others’ advantage [24, 28]. On social media, this dynamic may be amplified as platforms can displace other avenues for meeting these needs, becoming the default – or, at times, the only – channel through which individuals sustain connections and access information. Social media platforms have therefore been described by Khan [58] as “gatekeepers” of essential resources, and by Helberger et. al., [44] as creators of situational monopolies that undermine user autonomy through the accumulation of knowledge of users’ persuasion profiles and the exploitation thereof. For example, a recent research report indicates that 75% of UK youth (aged 16 to 25) use social media as their primary gateway to news, reducing reliance on traditional, offline outlets [130].

Crucially, dependency in this context is not merely a matter of excessive use, but of being structurally tethered to systems that mediate access to key resources. In this sense, dependency manifests as a constraint on choice: users may wish to disengage, yet often face prohibitively high social, educational, or professional costs when doing so (e.g., [88, 117]).

We conceptualize social media dependency along two interrelated dimensions: functional dependency and psychological dependency. The first, functional dependency, refers to reliance that arises because platforms have become the default – or sometimes the only – means of meeting needs. This includes maintaining social connections, coordinating professional activities, sustaining community visibility, or accessing news and services. According to media dependency theory, the more individuals depend on a medium to satisfy salient goals, the greater its influence in their lives [3]. Contemporary accounts highlight this dynamic: for many, disconnecting and disengagement from social media platforms is rarely a realistic option when elements such as social life, schoolwork, or business are organized on these platforms [8, 117].

The second dimension, psychological dependency, refers to reliance rooted in compulsive engagement, habit formation, and perceived loss of control. We deliberately use this term in place of “social media addiction”, reflecting on ongoing debates about how best to conceptualize behavioral dependencies in digital contexts. The notion of social media addiction has been criticized for pathologizing high engagement without clear evidence of clinical impairment, for neglecting contextual and functional aspects of use, and for importing neurobiological analogies from substance dependence that may not be warranted in the digital domain [6, 56]. By contrast, psychological dependency reflects the nuanced ways in which platform design, individual motivations, and social context jointly shape reliance on social media.

Psychological dependency may be fueled by a fear of missing out (FOMO) on social events, trends, or conversations [32], by the pull of reinforcement where variable rewards such as likes, comments, or new content keep users returning [22], or by the pursuit of social validation, as metrics such as follower counts or likes become tied to self-worth [12, 104]. Psychological dependency may also emerge

when platforms are used as a default response to boredom [13] or as a means of regulating anxiety through reassurance or distraction [128]. These processes are further intensified by design features, such as algorithmic content curation and other design patterns (e.g., infinite scrolling), that capture and prolong user attention (e.g., [15, 16, 63, 84, 87]).

Arguably, functional and psychological dependence may co-occur and reinforce one another. From the perspective of media dependency theory, high functional reliance increases frequency and depth of social media use, creating fertile conditions for the habit formation and emotional attachment central to psychological dependency [62]. Conversely, compulsive engagement can expand the range of functions platforms serve, weaving them into more aspects of their daily life. This dynamic aligns with the displacement hypothesis [60, 95], which suggests that heavy use of one medium can crowd out alternatives. When compulsive use narrows the repertoire of channels through which needs are met, social media platforms increasingly become the default means of satisfying both functional and psychological demands. Over time, this feedback loop can entrench dependency to the point where both needs-based reliance and compulsive engagement operate in tandem, making disengagement increasingly difficult – even when desired.

2.3 Individual, structural and intersectional factors in social media dependency

Social media dependency, whether functional or psychological, does not manifest uniformly across individuals, nor is it evenly distributed. Patterns of reliance are shaped by intersecting personal, social, economic, and cultural factors that can create structural vulnerabilities, a point well established in digital inequality scholarship [46, 98, 120].

For instance, *functional* dependency is often most pronounced among younger users, whose education, friendships, and leisure activities are increasingly embedded in social media [8]. Sexual orientation and gender identity also intersect with patterns of reliance: for LGBTQ+ users, platforms provide vital spaces for identity expression and community (e.g., [20, 41]). Well-being offers another important dimension. Rather than focusing on single indicators such as loneliness or mental health [e.g., [105]], the concept of life position [102] offers an integrated measure that reflects individuals' overall satisfaction with their social connections, health, and happiness. This approach provides a richer basis for understanding dependency because it indicates how well people are resourced in their lives overall. Importantly, the facets that make up life position are deeply interdependent, such that strains in one domain often ripple into others, creating broader conditions under which users may become more dependent on digital environments to meet everyday needs. For example, individuals with weaker life position – who may face a combination of fewer social interactions, limited opportunities for participation, and reduced emotional or physical resources [102] – may be especially likely to develop functional dependency. For them, social media can become a primary channel for maintaining relationships, accessing information, or staying engaged with society, thereby filling gaps left by offline contexts [113]. Motivations for use further deepen this reliance: when platforms are central to meeting salient goals such as sustaining ties

or obtaining information, disengagement becomes increasingly costly (e.g., [117]). Examples include migrants maintaining transnational family ties [4], influencers whose livelihoods depend on algorithmic visibility [19], individuals with disabilities who benefit from online opportunities for connection (e.g., [92]), and activists from oppressed groups that aim to strengthen their identity (e.g., [49, 109]). These examples collectively underscore how functional dependency is not uniform but shaped by diverse (social) positions, motivations, and structural circumstances.

Psychological dependency likewise intersects with personal and structural elements. From an intersectional perspective [21], factors such as age, gender, ethnicity, disability, and socioeconomic status shape not only the intensity of dependency but also its experiential texture – whether reliance is felt as a lifeline, a compulsion, or a combination of both. Research on social media use confirms these notions: younger users [114], women [115], and individuals from more collectivist cultures [17] appear particularly prone to compulsive engagement. Psychological dependency is also amplified by life position. When people experience dissatisfaction, isolation, or other limitations in their life, they may turn to social media for distraction, validation, or mood regulation. Over time, such compensatory use can evolve into psychological dependency [110, 125], where engagement persists even when it no longer supports well-being. Specific use motivations further reinforce this pattern: those who use social media to seek social connection, entertainment, or escapism when stressed or bored are especially prone to habitual checking and compulsive engagement (e.g., [50, 85]).

These disparities highlight that social media dependency cannot be reduced to platform design or individual behavior alone; it is also shaped by structural conditions that influence both access and exposure to digital environments. At the same time, dependency is not a sufficient explanation for vulnerability in itself. Rather, in line with layered conceptualizations of vulnerability [68, 69], it operates in entanglement with resilience and contextual factors, which together determine how vulnerability is produced and experienced.

2.4 Social Media Dependency and Platform Design

A growing body of HCI and design scholarship examines how design practices affect smartphone and social media use patterns that can shape functional and psychological dependency. While these works do not explicitly consider dependency, they frame platforms as actors that maximize users' engagement and limit their agency. This vision aligns with the perspective of design features that can foster dependency and limit users' autonomy. Prior studies [47, 61, 81, 94] explore interventions, such as goal prompts, reminders, and newsfeed alterations [70], and alternative social media designs which helped to reduce users' consumption.

In particular, studies of smartphone and social media use show that many behaviors emerge from habitual patterns rather than deliberate choice, suggesting that users may develop a form of dependency on these technologies. Smartphones are often picked up out of habit [18, 67, 91, 116] or used as pacifiers in moments of negative states [48, 67, 82]. Hornbæk et al. [48] further note that users consider social media platforms “special” because they help them remember and relive experiences, communicate with others,

and establish and sustain a sense of identity. This ambivalence is reflected in the love-hate relationship many users describe with social media, often labeling the applications as “addictive” [48, 67, 108]. Schoenebeck [111], for instance, found that more than one-third of users who pledged to quit Twitter (now ‘X’) before Lent² failed to do so, with many returning even after temporarily leaving. Similarly, Hiniker et al. [47] found that participants in their study most often sought to change the time they spent on specific activities – particularly social media.

Part of users’ ambivalence relates to how platforms condition user expectations and behaviors. Users often engage with the anticipation of rewards [33, 47, 67], but when these are not obtained, they frequently regret the time spent in habitual, meaningless activities [18, 67]. The literature on manipulative design documents how interface features can subvert user autonomy by steering, coercing, or deceiving users toward actions they might not otherwise choose [37, 38]. These designs are known to exploit psychological mechanisms such as the aforementioned habit formation, reward-seeking, and reinforcement [64, 67, 91, 116]. Major platforms – such as Facebook [61, 63, 83, 84], X (Twitter) [63], YouTube [15, 66, 86], LinkedIn [63] or TikTok [57, 81] – implement these features that capture attention and prolong engagement. These configurations (e.g., algorithmic curation, endless feeds, and personalized notifications) can funnel users into “rabbit holes” of content [18, 97] or prompt them to return in moments of boredom or for escapism [63].

In social media, manipulative designs are particularly salient. Infinite scroll removes natural stopping cues, notifications manufacture urgency, and “time fog” features obscure awareness of time spent (e.g., [15, 87]). Monge Roffarello et al. [87] have systematized common attention-capture design features, while Chen et al. [16] extend this work by developing a taxonomy of ‘extended-use designs’ (EUDs) that explicitly incentivize prolonged engagement. Complementing this, Kender and Frauenberger [57] highlight the role of ‘aesthetic design power’ across platforms such as Twitter, Instagram, Facebook, and TikTok, which use similar visual language and prominently feature ephemeral content to anchor interactions and draw users back. In a related effort, [33] propose a taxonomy of design features that systematically reduce user control by reinforcing schedules, personalizing triggers, interfering with deliberation, partially fulfilling users’ goals, and exploiting cognitive biases.

Notably, social media platforms differ in their use of such patterns and in the risks of dependency they generate. For example, TikTok’s endless scroll and algorithmically curated short videos are designed to maximize continuous engagement, whereas Snapchat emphasizes streaks and ephemeral messaging to encourage frequent daily check-ins. These distinct design strategies highlight why the risks of dependency cannot be understood in general terms. This is further established by van Der Wal et al. [119], who found that the mental health impact of social media on adolescents varies by platform, suggesting that platform-specific user experiences and features play a role in shaping outcomes. In line with this, scholars argue for the importance of developing platform-specific measures (e.g., [103]), noting that differences across platforms may shape

²Lent refers to a period of penitence before Easter that is adopted by some religions. Typically, around this time people give up certain (unhealthy) habits such as specific drinks or food.

their habit-forming potential. This evidence underscores that both the intensity of dependency and its consequences can be partly determined by the (design) practices of specific social media environments. Thus, users’ preferred platforms, and the manipulative design patterns they deploy, should be considered when examining patterns of dependency.

2.5 Present Study

Although prior scholarship has documented compulsive patterns of social media engagement, less is known about how different forms of social media dependency manifest together in everyday life and across users and platforms. Moreover, existing research often focuses either on individual behaviors or on mechanisms of persuasive and manipulative design, with limited attention to how these perspectives intersect. Studies that adopt an addiction³ framing, in particular, tend to frame social media dependency at the level of individual pathology and coping strategies, with little consideration for how engagement-driven design features shape these dynamics [45]. Conversely, HCI research highlights the role of manipulative patterns but often without situating them in relation to users’ lived experiences and contexts. What is missing is an integrative approach that examines the interplay between individual dispositions, social circumstances, and design architectures – while avoiding technological determinism or fatalism [45].

To bridge this gap, our overarching research question is: How do users experience functional and psychological dependency on social media platforms, and what role do individual, use-related, and platform design-related factors play in shaping these patterns?

To address this overarching question, we pursue four research questions:

RQ1: To what extent do users experience functional and psychological dependency on social media platforms?

RQ2: How are these forms of dependency associated with individual factors (i.e., demographics, life position), use-related factors (i.e., motivations, platform choice), and design-related factors (i.e., exposure to manipulative features)?

RQ3: What profiles of social media dependency emerge when functional and psychological dependency are considered together?

RQ4: How do individual, use-related, and design-related factors shape these profiles of dependency?

Through these questions, the study develops empirically grounded profiles of social media dependency that capture how functional and psychological reliance intersect in diverse ways across users.

3 METHODOLOGY

3.1 Study Design and Sample

This study used a cross-sectional survey design and was part of a larger research project RESOCIAL that seeks to identify, measure, and mitigate human vulnerabilities on social media platforms. The survey was administered online and hosted on Qualtrics. Recruitment was conducted through the online research platform Prolific. After reading the study information sheet, participants provided informed consent before proceeding. The average completion time

³Here, we retain the term “addiction” to directly reflect the language used by other authors or research participants, to accurately represent their original framing.

was approximately 31 minutes, and participants were compensated at a rate consistent with Prolific's fair pay policy. All responses were anonymous, and participants could withdraw at any time before submitting the survey. Ethical approval for this study was obtained through the Institutional Review Board of Leiden University.

Participants were eligible to take part if they met the following criteria: (a) aged 18 years or older, (b) a current social media user, and (c) a resident of an EU member state. In Prolific, we used prescreening filters to ensure eligibility. The final sample consisted of 873 participants, ranging in age from 18 to 77 years ($M = 34.41$ years, $SD = 10.75$). The majority identified as cisgender male (60.1%) or cisgender female (37.1%), with a small proportion identifying outside the binary (2.8%). Most participants identified as heterosexual (84.1%), while 15.9% identified with an LGBTQIA+ orientation. Participants resided across 21 out of the 27 EU member states, with the largest groups residing in Spain (12.8%), Poland (12.7%), Germany (11.9%), Portugal (10.3%), and Italy (10.0%). A thorough overview of the demographic composition of the study sample is provided in Appendix I.

3.2 Measures

For all administered scales, the items can be found in Appendix II.⁴

Social media dependency. Two scales were used to measure social media dependency, one for functional dependency and one for psychological. These scales reflect our conceptual distinction between functional and psychological dependency. The functional dependency items relate to needs-based reliance (e.g., autonomy, relatedness, identity continuity, safety), consistent with theory (see Sections 2.2 and 2.3). The psychological dependency items capture compulsive engagement, diminished control, preoccupation, and FOMO, aligning with prior perspectives on digital dependency (see Sections 2.2 and 2.3).

Functional dependency. For the purpose of this study, we developed a 13-item scale informed by Karahanna et al.'s [55] needs-affordances-features framework, expanded with two needs from Maslow's hierarchy (safety, self-esteem) [79] and additional needs identified in recent work on functional dependency (support, political participation, business; [76]). The final scale covered autonomy, relatedness, competence, having a place, self-exploration, self-expression, identity continuity, safety, esteem, support, political participation, and business needs. An example item is: "I rely on social media to stay connected with others." Responses were given on a 5-point scale (1 = only on social media; 2 = mostly on social media; 3 = equally on both; 4 = mostly on other resources; 5 = only on other resources). The items were reverse coded such that high scores reflect high dependency. Factor analysis (principal axis factoring with promax rotation) indicated a clear one-factor solution ($KMO = .887$; Bartlett's test $p < .001$), with all items loading $> .40$. Internal consistency was high (Cronbach's $\alpha = .854$).

Psychological dependency. This was measured with nine items: six from the Social Media Disorder Scale [118], one adapted loss-of-control item from the Facebook Intrusion Questionnaire [23], one from the Bergen Social Media Addiction Scale [2], and one

item capturing fear of missing out (FOMO) that was created specifically for this study. Responses were given on a 5-point frequency scale (1 = never; 5 = very often). Factor analysis (principal axis factoring with promax rotation) supported a one-factor solution ($KMO = .910$; Bartlett's test $p < .001$), with all items loading $\geq .40$. Reliability was excellent ($\alpha = .909$).

Sociodemographic Variables: Age, Gender and Sexual Orientation.

Age. Participants reported their age as a continuous variable ("What is your age?").

Gender identity. Gender identity was assessed with the question, "How do you identify your gender? 'Cis' (short for cisgender) means that a person's gender matches the sex they were assigned at birth." Response options included: male (cis), female (cis), transgender man, transgender woman, bigender, agender, genderfluid, genderqueer, non-binary, "I don't know," "I prefer not to say," and "Other, please specify." Due to the very small number of participants identifying outside the cisgender male and female categories ($n = 24$; 2.7% of the sample) and the dispersion of these cases across multiple categories, the gender variable was recoded into a dichotomous measure distinguishing cisgender men (1) and cisgender women (2). This decision was made to enable group comparisons and avoid statistical noise introduced by extremely small subgroup sizes.

Sexual orientation. We assessed sexual orientation with the item, "What is your sexual orientation?". Response options included: heterosexual/straight, gay, lesbian, bisexual, pansexual, queer, asexual, questioning/unsure, "I prefer not to say," and "I prefer to self-describe." Given that group sizes for non-heterosexual orientations were too small to analyze separately, responses were recoded into a dichotomous variable differentiating heterosexual participants (= 1) from LGBTQIA+ participants (= 2).

Life position indicators. Life position was measured using seven items from Rubin & Rubin's [102] life position scale, which assesses perceived life satisfaction, social activity, and physical health. To extend the measure, we added two items capturing mental health ("In general, my mental health – including my mood and my ability to think clearly – is in good shape") and societal participation ("I feel like an active participant in society, able to engage in work, education, and social or civic activities as I would like to"). Responses were given on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Factor analysis (principal axis factoring, promax rotation) supported a one-factor solution ($KMO = .868$; Bartlett's test $p < .001$), with all items loading $\geq .40$. Reliability was good ($\alpha = .856$).

Motivations for social media use. After indicating their primary social media platform, participants rated the importance of six motivations for using that platform: information, social connection, entertainment, escapism, business, and romantic/sexual interest. The first five were adapted from validated scales [9, 67], and the sixth was added to capture romantic/sexual motives. Responses were provided on a 5-point scale (1 = not important, 5 = important), then dichotomized for analysis (0 = not important/neutral [1–3], 1 = important [4–5]). As analyses were conducted at the item level, no factor or reliability analyses were performed.

Most used platform. Use of eight platforms – Instagram, TikTok, Facebook, X (Twitter), LinkedIn, Snapchat, Pinterest, and YouTube – was assessed. These platforms were selected based

⁴The full survey instrument is available on OSF at: [https://osf.io/ky4gu/overview?view_only=\\$fa9c4c1a68e6405e8e1fa04ca7d7d9cb](https://osf.io/ky4gu/overview?view_only=$fa9c4c1a68e6405e8e1fa04ca7d7d9cb)

on their designation as Very Large Online Platforms (VLOPs) under the DSA. Given that the definition of social media remains unsettled in prior literature [124], we relied on the Nationaal Social Media Onderzoek [51] – the largest annual survey on social media use in the Netherlands – to determine which VLOPs under the DSA qualify as social media platforms. Participants ranked these eight platforms by frequency of use (e.g., Instagram = 1, TikTok = 2). Non-use was indicated with “I do not use this platform.” For analysis, a categorical variable was created for each participant’s most frequently used platform. Due to the small number of participants reporting LinkedIn ($n = 16$), Snapchat ($n = 3$), or Pinterest ($n = 1$) as their primary platform, these were combined into a single “other” category.

EUD exposure. We examined how design features intended to prolong engagement influence users’ dependency. Thirteen patterns were selected by combining the catalogue of Attention-Capture Deceptive Designs [87] with additional strategies from Extended-Use Design [16] that cover elements related to the platform architecture that were not included in the former. Full descriptions are provided in Appendix III.

For each pattern, respondents were shown a screenshot or short video that illustrated how the pattern appears in practice. To ensure variation and ecological validity, examples were drawn from different social media platforms across the 13 patterns rather than a single platform, and participants were explicitly informed that such patterns can appear across different platforms. To reduce fatigue, each participant was randomly shown only two of the 13 patterns and answered follow-up questions for both. To assess exposure, participants indicated how often they encountered each presented pattern when using social media, on a scale from 1 (= never) to 5 (= very often). An overall EUD exposure score was calculated by averaging responses, providing a general measure of exposure to manipulative design features rather than to any single pattern.

3.3 Analytical Plan

In line with established analytical procedures for latent profile analysis (LPA), the data were analyzed in sequential stages that collectively facilitate the identification, evaluation, and interpretation of latent subgroups. All analyses were conducted in SPSS (version 30.0; IBM) except the LPA, which was conducted in R using Rstudio.

Step 1. Descriptive analyses. First, we computed descriptive statistics for all study variables, including the prevalence of functional and psychological dependency. These summaries provide a foundational understanding of the data structure and the distributions of key constructs prior to modelling.

Step 2. Preliminary bivariate associations. Second, to characterize the relations among study variables before estimating latent profiles, we examined bivariate associations. Pearson correlation analyses were conducted across continuous and dichotomous variables (step 2a), while associations involving the categorical variable ‘most used platform’ were assessed through Kruskal-Wallis H (KWH) tests with Bonferroni-adjusted post-hoc comparisons (for continuous variables) and Chi-square tests (for dichotomous variables) (step 2b). KWH tests were selected due to unequal group sizes across platform categories. Such preliminary analyses support

subsequent profile interpretation by highlighting basic patterns of association within the data.

Step 3. Latent profile estimation. Third, the core stage of the analysis involved estimating latent profiles based on participants’ indicators of social media dependency. We performed an LPA using the tidyLPA package [100] with mclust [112] as the estimation engine. Unlike heuristic clustering approaches (e.g., k-means), LPA is model-based, provides likelihood-based fit indices (e.g., AIC, BIC), and accounts for measurement error, making it well-suited to identifying theoretically meaningful subgroups in psychological and behavioral data [90, 123]. Models specifying one to six latent profiles were estimated under two parameterizations (model 1 and model 3), with fit assessed using AIC, BIC, SABIC, CAIC, entropy, the Lo-Mendell-Rubin bootstrap likelihood ratio test (BLRT), and considerations of parsimony and interpretability. The best-fitting solution was retained, and participants were assigned to their most likely profile.

Step 4. Predictors of profile membership. Fourth, to examine factors associated with latent profile membership, we estimated multinomial logistic regression models. Predictors included age, gender, sexual orientation, social media use motivations, life position, EUD exposure, and primary platform as covariates. To obtain all pairwise comparisons between profiles, each regression was re-estimated with a different reference category. This step provides insight into the individual, motivational, and contextual factors that distinguish the profiles.

Step 5. Construction of descriptive profiles. Lastly, descriptive profiles were constructed by integrating results from the multinomial regressions with descriptive information on all individual factors (demographics, life position), use-related factors (motivations, platform choice), and design-related factors (exposure to manipulative features) within each profile.

4 FINDINGS

4.1 Step 1. Prevalence of Functional and Psychological Social Media Dependency (RQ1)

On average, respondents reported low to moderate levels of functional ($M = 2.63$, $SD = 0.61$) and psychological ($M = 2.26$, $SD = 0.83$) social media dependency, with slightly higher occurrence of functional dependency. Pearson correlation analysis revealed a moderate positive association between both forms of dependency ($r = .388$, $p < .001$), meaning that respondents who reported more functional dependency were also more likely to report psychological dependency of social media.

4.2 Step 2a. Correlates of Social Media Dependency (RQ2)

4.2.1 Bivariate Associations between Social Media Dependency and Study Variables. Pearson correlations were computed to examine associations between functional and psychological dependency and other study variables (see Table 1). Both forms of dependency were positively associated with sexual orientation (LGBTQIA+), social media use for information, connection, escapism, and romantic/sexual purposes, as well as exposure to EUDs. Psychological

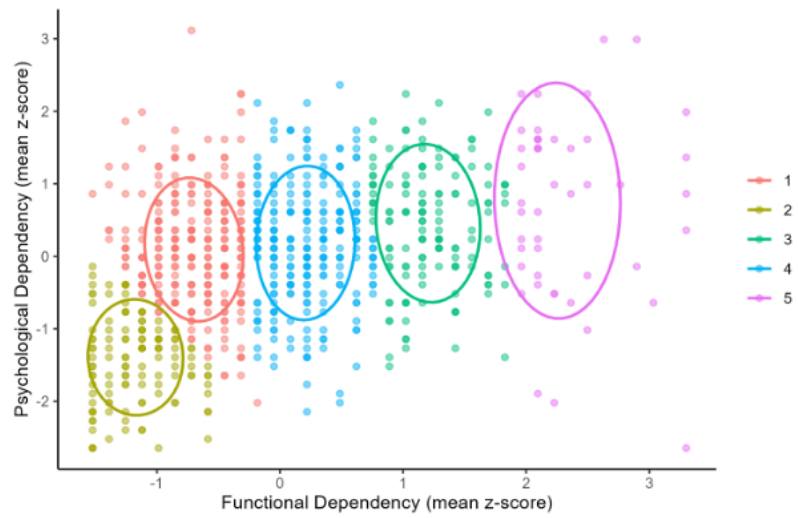


Figure 1: Distribution of Respondents by Profile⁶

dependency was also significantly higher among women. Conversely, both forms of dependency were negatively associated with age and life position, indicating that younger participants and those with lower overall well-being reported stronger dependency.

Additionally, correlation analyses revealed several significant patterns across the other continuous and dichotomous study variables. Age was significantly positively associated with life position, but negatively with entertainment, escapism, romantic/sexual motives, and exposure to EUDs. This suggests that older individuals were more well-positioned and that younger respondents endorsed more use motivations and reported greater exposure to EUDs. Gender was also significantly linked to use motivations: female respondents more strongly endorsed connection, entertainment, and escapism than men. With regard to sexual orientation, LGBTQIA+ respondents reported significantly lower life position and greater exposure to manipulative design compared to heterosexual participants. Life position itself further showed significant positive associations with connection and escapism, indicating that those who use social media for these purposes also reported somewhat higher well-being. Finally, several motivational orientations tended to significantly cluster: information seeking correlated positively with both connection and business, while connection was also tied to business and romantic/sexual interest. In contrast, entertainment and escapism were strongly interrelated but negatively linked to business motives.

4.3 Step 2b. Dependency Differences across Platforms

Kruskal-Wallis H tests were conducted to examine associations between ‘most used platform’ and functional and psychological dependency. *Functional dependency* significantly differed across platforms (KWH = 21.55, $p < .001$), with the highest scores among TikTok users⁵ ($M = 2.83$, $SD = .61$) and the lowest among Facebook

($M = 2.49$, $SD = .69$) and YouTube users ($M = 2.55$, $SD = .60$). Post-hoc tests confirmed that TikTok users reported significantly higher functional dependency than Facebook or YouTube users.

Psychological dependency also differed significantly across platforms (KWH = 54.79, $p < .001$). Again, dependency was highest among TikTok users ($M = 2.68$, $SD = .96$) and lowest among Facebook ($M = 2.05$, $SD = .75$) and YouTube users ($M = 2.08$, $SD = .76$). Post-hoc comparisons showed that individuals who indicated they most used TikTok or Instagram ($M = 2.43$, $SD = .81$) reported significantly higher psychological dependency than those reporting Facebook or YouTube as their most used platform.

Beyond dependency, platform choice was also associated with demographic and motivational factors, as well as EUD exposure. The following provides a concise overview of these associations, detailed statistics are presented in Appendix IV. Significant age differences emerged across platforms (KWH = 98.78, $p < .001$), where Facebook users were significantly the oldest ($M = 44.61$, $SD = 12.12$) and TikTok users the youngest ($M = 30.81$, $SD = 11.04$) compared to the other platforms. Gendered patterns were also evident ($\chi^2(5) = 112.82$, $p < .001$). Women were more likely than men to report Instagram, TikTok, and Facebook as their most-used platforms, whereas men more often selected YouTube and X. Sexual orientation was also significantly associated with platform choice, ($\chi^2(5) = 21.61$, $p < .001$). LGBTQIA+ participants were more likely than heterosexual participants to report TikTok and less likely to report Facebook as their most used platform. Instagram and YouTube were popular across both groups. Life position differed modestly across platforms (KWH = 15.997, $p = .007$). Pairwise tests indicated that those who use YouTube most reported somewhat higher life position than individuals who use Instagram or Facebook most, though these differences did not remain significant after Bonferroni correction.

⁵In this section, ‘[platform] users’ refer to participants who identified the platform in question as their most frequently used.

Table 1: Pearson Correlation Coefficients for Study Variables

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1. Functional dependency	-											
2. Psychological dependency	.388**											
3. Age	-.179**	-.210**										
4. Gender (2 = female)	.045	.158**	.028									
5. Sexual orientation (2 = LGBTQIA+)	.068*	.134**	-.100*	.184**								
6. Life position	-.155**	-.188**	.092**	-.046	-.208**							
7. Information	.085*	.071*	-.028	.054	-.082*	-.009						
8. Connecting	.081*	.147**	.042	.171**	-.010	.139**	.123**					
9. Entertainment	.019	.021	-.117**	.073*	-.001	-.021	.061	-.092*				
10. Escapism	.102*	.161**	-.142**	.089*	.062	-.106**	.012	-.097*	.427**			
11. Business	-.006	.041	.048	-.026	.037	.068	.141**	.069*	-.134**	-.073*		
12. Romantic/sexual	.104*	.163**	-.118**	-.040	.036	.065	.012	.290**	.009	.002	.107*	
13. EUD exposure	.085*	.110**	-.245**	-.011	.116**	-.031	.049	-.041	.058	.026	.006	.032

Note. ** $p \leq .001$; * $p < .05$

Motivational orientations further distinguished participants' platform choice. Information-seeking varied significantly ($\chi^2(5) = 58.52, p < .001$): those who primarily used Instagram were less likely to report information-seeking, whereas information seekers were more likely to report YouTube or X as their main platform. Connection motives showed the strongest association ($\chi^2(5) = 363.63, p < .001$): participants who primarily used Instagram or Facebook were more likely to endorse connection, while those who primarily used YouTube were less likely to do so. Entertainment motives also varied ($\chi^2(5) = 175.30, p < .001$): participants naming TikTok or YouTube as their main platform more often endorsed entertainment, whereas those primarily using Facebook were less likely. Escapism motives followed a similar pattern ($\chi^2(5) = 84.14, p < .001$), with escapism most common among those whose main platform was Instagram, TikTok, or YouTube, and least common among those reporting Facebook or "other" platforms. Business-related motives differed as well ($\chi^2(5) = 45.90, p < .001$): participants naming "other" platforms (i.e., LinkedIn, Pinterest, or Snapchat) as their main platform were more likely to endorse business motives, while individuals who most often used Instagram or TikTok were less likely. Finally, romantic/sexual motives also differed significantly ($\chi^2(5) = 54.19, p < .001$): they were more common among those primarily using Instagram and less common among those primarily using YouTube.

4.4 Step 3. Latent Profile Analysis (RQ3)

Latent profile analysis (LPA) was conducted on functional and psychological dependency. Across solutions, the five-profile solution under Model 1 (equal variances, zero covariances) showed the best fit, with lower AIC (4689.35), BIC (4765.70), and SABIC (4714.89)

values, and entropy of .69 (moderate classification accuracy). The Bootstrap Likelihood Ratio Test (BLRT) - which compares k vs $k-1$ profiles - was significant ($p = .010$), supporting the 5-profile model over a 4-profile model.

Profile sizes were well distributed, with the smallest still exceeding 5% of the sample. Table 2 presents profile sizes and mean scores on both dependency dimensions, and Figure 1 visualizes their distribution. Overall, the five-profile solution provided a parsimonious and interpretable representation of heterogeneity in social media dependency.

4.5 Step 4. Predictors of Profile Membership (RQ4)

Multinomial logistic regression was conducted to examine predictors of membership in the five dependency profiles. The model fit statistics and odds ratios are presented in Appendix V. Age, life position, several social media use motivations (information, connection, escapism, romantic/sexual), and platform choice significantly improved model fit, while gender effects were limited, and sexual orientation and EUD exposure were not significant predictors. Below, all significant parameter effects are discussed. An overview of all parameter effects is presented in Appendix V.

Age. Age significantly distinguished between several profiles. Older participants had greater odds of belonging to profile 2 compared to profile 1. Conversely, age reduced the odds of being in profile 3 relative to profile 1, in profile 3 relative to profile 2, in profile 4 relative to profile 2, and in profile 5 relative to profile 2.

⁶This graph was created using the 'ggplot2' R package (<https://ggplot2.tidyverse.org>).

Table 2: Profile Size and Mean Dependency Scores

Profile	<i>n</i> (%)	Functional dependencyM (SD)	Psychological dependencyM (SD)
1	280 (32.1%)	2.70 (0.47)	1.68 (0.24)
2	125 (14.3%)	1.75 (0.36)	1.29 (0.23)
3	143 (16.4%)	2.90 (0.50)	3.27 (0.26)
4	278 (31.8%)	2.73 (0.50)	2.44 (0.24)
5	47 (5.4%)	3.05 (0.78)	4.21 (0.36)

Table 3: Descriptive Statistics of Study Variables per Profile

	Profile				
	1(<i>n</i> = 280)	2(<i>n</i> = 125)	3(<i>n</i> = 143)	4(<i>n</i> = 278)	5(<i>n</i> = 47)
Age	35.54 (11.56)	39.67 (10.04)	31.44 (8.78)	33.17 (10.44)	30.17 (8.82)
Gender	68.8% male	69.1% male	51.1% male	60.3% male	42.2% male
Sexual orientation	87.3% het.	90.4% het.	82.4% het.	85.2% het.	68.1% het.
Life position	3.40 (0.82)	3.50 (0.80)	3.11 (0.70)	3.21 (0.74)	3.04 (0.91)
Motivation 1. information	74.2% yes	58.5% yes	70.4% yes	72.9% yes	78.3% yes
Motivation 2. connecting	37.6% yes	34.1% yes	54.2% yes	49.1% yes	54.3% yes
Motivation 3. entertainment	92.1% yes	86.2% yes	91.5% yes	91.3% yes	89.1% yes
Motivation 4. escapism	80.3% yes	64.2% yes	85.9% yes	80.9% yes	95.7% yes
Motivation 5. business	19.4% yes	22.0% yes	15.5% yes	20.6% yes	39.1% yes
Motivation 6. romantic/sexual	10.8% yes	4.9% yes	16.9% yes	12.3% yes	26.1% yes
Platform top 1					
Instagram	21.4%	21.6%	37.1%	37.8%	34.0%
TikTok	8.6%	4.0%	16.8%	10.4%	27.7%
Facebook	12.1%	20.8%	10.5%	8.6%	4.3%
X	10.0%	6.4%	5.6%	8.6%	10.6%
YouTube	45.7%	45.6%	26.6%	32.4%	21.3%
Other	2.1%	1.6%	3.5%	2.2%	2.1%
EUD exposure	3.2 (1.04)	3.10 (0.99)	3.42 (1.07)	3.26 (1.00)	3.60 (0.90)
Functional dependency	2.70 (0.47)	1.75 (0.36)	2.90 (0.50)	2.73 (0.50)	3.05 (0.78)
Psychological dependency	1.68 (0.24)	1.29 (0.23)	3.27 (0.26)	2.44 (0.24)	4.21 (0.36)

Note. het. = heterosexual.

Gender. Men had lower odds of being in profile 3 compared to profile 1 and profile 5 compared to 1.

Life position. Higher life position scores consistently predicted lower odds of membership outside the lower-dependency profiles. Compared to profile 1, higher life position reduced the odds of being in profile 3, profile 4, and profile 5. Compared to profile 2, higher life position was again associated with lower odds of being in profile 3, profile 4, and profile 5.

Social Media Use Motivation 1. Information. Endorsing this motive increased the odds of being in profile 2 relative to profile 1, but reduced the odds of being in profile 4 compared to profile 2 and in profile 4 compared to profile 3.

Social Media Use Motivation 2. Connection Endorsing this motive increased the odds of being in profile 2 versus profile 1, but reduced odds of being in profile 3, profile 4, and profile 5 compared to profile 2.

Social Media Use Motivation 3. Entertainment. Endorsing this motive increased the odds of profile 3 compared to profile 2.

This result should be interpreted with caution, however, given the sparse data and wide CIs.

Social Media Use Motivation 4. Escapism Endorsing this motive increased the odds of being in profile 2 versus profile 1, but reduced odds of profile 3 and profile 4 compared to profile 2.

Social Media Use Motivation 5. Business. Endorsing this motive reduced the odds of being in profile 5 compared to profile 1, profile 3, and profile 4.

Social Media Use Motivation 6. Romantic/sexual interest. Endorsing this motive reduced the odds of being in profile 3 and profile 5 compared to profile 1. Also, lower odds of profile 3 and profile 5 compared to profile 2, and of profile 5 compared to profile 4. However, endorsement increased odds of being in profile 4 relative to profile 3.

Most used platform. Platform differences also emerged. Participants who reported YouTube as their primary platform had lower odds of being in profile 3 compared to profile 1.

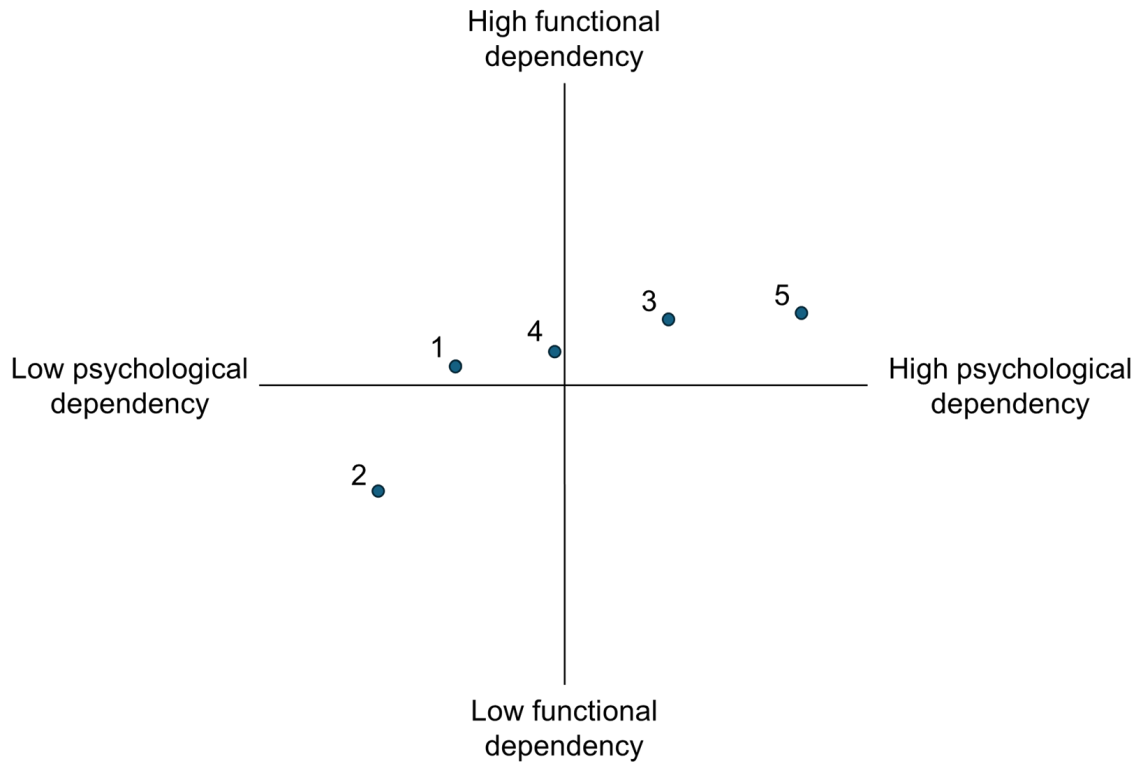


Figure 2: Distribution of Functional and Psychological Dependency Scores Across the Five Profiles

4.6 Step 5. Profiles of Social Media Dependency (RQ3)

To characterize the five profiles, we combined results from the multinomial logistic regression with descriptive statistics on individual, use-related, and design-related variables (Table 3).

In characterizing the five profiles, our approach was hierarchical: regression findings were used to identify the defining features that significantly distinguished profile membership, while descriptive statistics provided additional context on age, gender composition, platform preferences, and motivational patterns, even where differences were not statistically significant. Each profile is thus named and described by highlighting its key differentiating factors and situating these within the broader descriptive picture. The five profiles are presented in Table 4.

The five profiles differed meaningfully in functional and psychological dependency experiences. Some profiles showed primarily functional dependency with little psychological pull (e.g., profile 1), whereas others exhibited strong dependency across both dimensions (e.g., profile 3 and 5). Although Profiles 1 and 2 reflect low to moderate dependency, we retain them within the dependency framework because the LPA identifies patterns along a continuous dependency spectrum. The term “dependency” here refers to relative positioning on this continuum rather than implying problematic reliance. To illustrate these patterns more intuitively, we additionally created a scatterplot that maps profiles’ functional and psychological dependency scores along two axes, see Figure 2.

5 DISCUSSION

5.1 Dependency as a Factor of Layered Vulnerability

This study examined how functional and psychological dependency on social media manifest, what factors shape them, and how they cluster into distinct profiles. In doing so, we aimed to provide an empirical basis for understanding social media dependency as a factor which enables experiences of vulnerability online and to draw insights for platform design.

Across RQ1 to RQ4, our findings show that users report moderate functional and psychological dependency. The positive correlation between functional and psychological dependency suggests a mutually reinforcing relationship, where needs-based reliance could facilitate habit formation and compulsive use, while compulsive engagement could, in turn, expand the range of functions a platform fulfills. Our findings further show that functional and psychological social media dependency cluster into five distinct profiles shaped by age, life position, gender, motivations, and platform preference. The profiles capture meaningful differences in how users relate to social media: older and more socially secure individuals tended to fall into profiles marked by low or primarily functional dependency, while younger users with weaker life position were more likely to belong to profiles combining high functional and psychological dependency. Motivations for entertainment, escapism, and romantic or sexual interest were especially characteristic of the more

Table 4: Five Profiles of Social Media Dependency

Profile	Label	Description
1	Functional Use	<p>Profile 1 was marked by moderate functional dependency and low psychological dependency, reflecting a form of reliance that is more instrumental than compulsive. Members of this profile tended to be somewhat older and reported relatively high life position scores compared to most other profiles. No specific motivations uniquely defined this profile in the regression analyses. Descriptively, Functional Users were predominantly male, largely heterosexual, and most often used YouTube as their primary platform. Many endorsed information seeking, entertainment, and escapism, though these motives were not distinctive relative to other groups. Thus, Functional Users represent relatively stable individuals who engage with social media to meet practical needs, with little evidence of psychological dependency.</p> <p>Dependency level: Moderate functional, low psychological</p>
2	Low-Dependency Pragmatic Use	<p>Profile 2 exhibited the lowest levels of both functional and psychological dependency, indicating minimal reliance on social media overall. Members were on average the oldest of all profiles and reported the strongest life position scores. Motivationally, they were characterized by information seeking as well as social connection, but these motives were endorsed at lower rates than in more dependent groups. Descriptively, this profile was heavily YouTube-oriented and, compared to the other profiles, Facebook-oriented, predominantly heterosexual, least motivated to engage in social media for entertainment or escapism out of all profiles, and socially well-positioned.</p> <p>Thus, Low-Dependency Pragmatic Users are older, socially stable individuals who engage with social media primarily for pragmatic reasons, and whose overall dependency is very limited.</p> <p>Dependency level: Low functional, low psychological.</p>
3	High-Dependency Social Use	<p>Profile 3 combined high functional dependency with high psychological dependency, making it one of the most dependent groups. Members were younger than the two low-dependency profiles and had weaker life position scores. Motivationally, they were especially defined by entertainment and social connection, which distinguished them from less dependent groups. Descriptively, they were gender-balanced, slightly more diverse in sexual orientation, driven to use social media for entertainment, escapism, and out of interest for romantic and sexual connections, and more likely to use Instagram and, to a lesser extent, TikTok.</p> <p>Thus, High-Dependency Social Users are younger, socially and hedonically motivated individuals who rely on social media both for functional purposes and in compulsive ways.</p> <p>Dependency level: High functional, high psychological.</p>
4	Moderate-Dependency Hedonic Use	<p>Profile 4 showed moderate levels of both functional and psychological dependency, situating them between the (pragmatic) low-dependency groups and the highly dependent groups. They were younger than the low-dependency profiles. Motivationally, they were less oriented toward information or connection and more consistently driven by entertainment and escapism. Descriptively, they were somewhat more male, predominantly heterosexual, and active on Instagram and YouTube.</p> <p>Thus, Moderate-Dependency Hedonic Users rely on social media mainly for leisure and distraction, reflecting moderate but not extreme levels of dependency.</p> <p>Dependency: Moderate functional, moderate psychological.</p>
5	Very High-Dependency Multi-Motivated Use	<p>Profile 5 stood out for the highest scores on both functional and psychological dependency, making it the most dependent group. Members were the youngest overall, had the weakest life position scores, and were more often female compared to the other profiles. Motivationally, they were particularly defined by escapism and romantic/sexual motives, and they also endorsed business-related motives more than most other groups. Descriptively, they were the most likely to name TikTok or Instagram as their primary platforms and showed the broadest spread of social media motives.</p> <p>Thus, Very High-Dependency Multi-Motivated Users are young, multi-motivated, marked by weaker social ties and lower well-being, and showing strong reliance across both functional and psychological dimensions.</p> <p>Dependency: Highest functional, highest psychological.</p>

dependent profiles. Profiles with higher dependency favored platforms such as TikTok and Instagram, whereas lower-dependency profiles comparatively centered more on YouTube and Facebook. Importantly, low-dependency profiles occupy the lower end of a functional-psychological dependency continuum, offering a contrast that helps clarify how stronger forms of dependency emerge.

Together, these findings extend scholarship on social media and vulnerability in several important ways. First, they empirically distinguish functional and psychological dependency as (interconnected) elements of vulnerability, moving beyond addiction framings toward a more nuanced conceptualization of dependency. Second, they highlight how structural and intersectional factors - such as age and life position - interact with motivations and the platform to shape dependency. Together, the five profiles demonstrate that dependency is heterogeneous: ranging from pragmatic reliance among older, well-positioned users to multi-motivated, compulsive engagement among younger, less well-positioned users. This stratification underscores that social media dependency - and the vulnerability it produces - is layered and shaped by the interplay of individual, motivational, and platform factors. Finally, and in line with this, our results lend tentative support to the idea that vulnerability is dynamic in digital environments [39, 44]. Dependency is not a fixed state but shifts with users' circumstances, motivations, life position, and platform practices. For example, younger users in Profile 5 showed the highest dependency, whereas older users in Profile 1 were the least dependent, resonating with Jungselius and Weilenmann [53]'s observations of shifting social media trajectories and Haimson [40]'s notion of social media as "social transition machinery". Taken together, these insights advance a more layered, dynamic, and context-sensitive understanding of digital vulnerability, with direct implications for theory, platform design, and policy interpretation.

5.2 Designing for agency is not designing for (in)dependency

Our findings support calls for layered and relational approaches to vulnerability in HCI and platform design research (e.g., [101]). The identification of five dependency profiles contributes a typology of user experiences that moves the field beyond average effects or predefined "at-risk" groups, recognizing instead the patterned heterogeneity in dependency. By mapping distinct configurations of dependency, our work provides empirical grounding for theorizing dependency as a spectrum of user-platform relations. Our paper thus provides a conceptual and methodological framework that HCI research can use to understand users' dependency in a nuanced way. Additionally, the identified profiles may serve as an analytic tool that can help identify relevant mechanisms, can be mapped onto platform affordances, and that can inform tailored interventions.

To illustrate this, the results also allow us to show preliminary design implications, but this list is not meant to be exhaustive since it requires further investigation (see Section 5.4.). The profiles also reveal that different design approaches may be needed to address different forms of dependency, highlighting multiple angles through which design theory and practice can engage with dependency. In the following, we suggest and draw four distinct lessons.

First, not everyone may need a design intervention, but learning from other contexts is beneficial. Profiles 1 and 2 may experience lower forms of functional and psychological dependency, being reliant on social media for pragmatic use (profile 1) and information-seeking purposes (profile 2), meaning their use of social media is instrumental and task-oriented. Together, these profiles teach us that some users may not always need a design intervention to regulate their dependency towards social media platforms. Nevertheless, a beneficial design direction derived from the distinction between these profiles is the inclusion of clearer alternatives for accessing information that can benefit users in profile 2. Learning from other contexts (e.g. online misinformation), could help to rethink alternatives [e.g., [1]]. For instance, 'warning-based' and explanatory approaches could be applied to other harms beyond misinformation, i.e., the integration of visual cues that caution the users of the existence of harm and that explain why that is the case [59]. In addition to Kirchner and Reuter [59], 2020], Martel and Rand [78] have also confirmed the effectiveness of such labelling.

Second, tackling engagement may require context-aware interventions. Profiles 3 and 5 (highly dependent), lead us to look at platform engagement as the opposite of independence to platforms, and value the recent works on manipulative design and user-engagement designs [16, 66, 87]. Highly dependent profiles (3 and 5) may require interventions focused on promoting non-use and agency [47, 61, 66, 70, 81]. However, these profiles are special for two reasons. First, they are driven by motivations such as escapism and social connection, unlike other profiles with more pragmatic motivations (e.g., profiles 1 and 2). Second, they are characterized by lower life position scores, which may indicate less social offline support and a limited ability to seek alternatives to social media platforms [106], echoing findings from prior research which suggests that feelings of loneliness can be antecedent for more intense social media use [105]. This means that, for the users in these profiles, agency may be more illusory and that, consequently, agency-enhancing features risk being ineffective unless, for instance, they are enabled by default or embedded in ways that reduce reliance on constant self-regulation.

These findings align further with previous studies [47, 67], which argue that interventions to reduce smartphone and social media consumption must account for the types of experiences users themselves find meaningful or meaningless (see also Section 2.4.). These works have raised doubts about the effectiveness of external strategies to promote user agency. For instance, Zhang et. al., [127] demonstrated that interventions, such as time limits, were insufficient in fostering and stimulating agency. Similarly, strategies which are commonly deployed to promote agency, such as goal-setting features, reminders and timers, or removing elements such as the newsfeed [47, 70], may be suboptimal when applied to highly dependent user profiles which require more contextual and nuanced interventions that are attuned to the associated escapist and social connection motivations, and the experiences that are represented within lower life position scores. Our results, therefore, align with prior work that explores and argues for making context-aware interventions on social media [81, 93].

Third, design interventions need to look at social aspects of interactions to tackle dependency. In addition to the patterns observed above, profile 3 shows differences with profile 5 in the

emphasis of social connections as motivators for social media use that relate to functional and psychological dependency – seeking connection, intimacy, or romantic partners. This indicates that social dimensions of dependency deserve more design attention. Social media platforms are “social”, so naturally users may be looking for meaningful connections within their use [105]. For platform design, this insight is particularly relevant because the need for social connections may be exploited through design strategies that target this profile. Indeed, scholars that study manipulative design have already highlighted this relationship [106, 108]. When users rely (excessively) on social media to seek meaningful connections, other manipulative designs such as play-by-appointment, grinding, or autopopulated fields that suggest new content to search, may prey on users’ social rather than utilitarian needs and feed that dependency.

In addition, these social aspects that characterize forms of dependency present in profile 3 go beyond questions of exploitation through manipulative design and highlight different contexts in which dependency may be more problematic: work on dating apps (e.g., [54]) and partner-seeking on social media platforms (e.g., [121]) provide useful reference points for analyzing how platforms support or exploit these needs.

Fourth, design affordances may be related to dependency because of users’ motivations on social media. Users in profile 5 show high dependency with a multipurpose approach. This profile may converge with polymedia theories [7, 73, 74]. These theories explain that users do not engage with social media platforms in isolation but as an ecosystem from which they can select and switch among platforms based on the combined effect of their motivations and the available affordances [7] – i.e. opportunities for behavior afforded by design [89]. For instance, although a user can post a picture on Instagram, Facebook, Snapchat, or Twitter they may prefer Snapchat because it affords ephemerality (p. 255) and better aligns with their motivations for sharing. Therefore, Boczkowski et al. [7] highlight the need of assessing the role and effect of affordances on a case-by-case basis.

This is in line with our argument: design affordances may be related to users’ motivations, and therefore, to dependency. In this regard, platform choice also appears relevant: profiles 1 and 2 represent the least dependent use patterns and most YouTube as preferred platform, while more dependent users clustered around TikTok and Instagram. While Instagram and Tiktok have similar features and affordances, and, together with YouTube, are video-platform social media, the way YouTube presents videos is different. Although our study did not disentangle the specific role of content formats, prior work indicates that short-form formats foster greater engagement than long-form [126]. Other studies similarly highlight how features like algorithmic curation, ephemeral content – e.g. grinding or play by appointment techniques –, and interaction metrics can amplify compulsive use [33, 87] (See also Section 2.4.). Together, these findings underscore the need for future research that systematically compares platforms, their affordances, and how these shape the users’ experience of dependency (see Section 5.4).

In sum, our findings show that designing social media platforms to account for diverse experiences of dependency cannot rely on one-size-fits-all solutions. Instead, effective design responses grounded in the specific variables that shape the different forms

of dependency, as evidenced by the identified user profiles, may be more effective. Together with the insights previously retrieved from existing HCI literature (see e.g., current Section and Section 2.4.), our findings strengthen the conceptualization of dependency as dynamic and call for tailored, nuanced and contextual mitigation strategies. Furthermore, our analysis also echoes perspectives from literature on vulnerability which argue that effective response strategies should be reflective of the layered, and context-specific nature of vulnerability experiences [68, 69, 101]. Consequently, the following section returns to the conceptual link between dependency and vulnerability (see Section 2.1.), and briefly considers the broader, emerging implications of our findings for research, policy and practice.

5.3 Vulnerability is Dynamic: Emerging Implications for Research, Policy and Practice

The idea of dependency as dynamic [39, 44] holds several significant research, policy and practitioner-oriented implications. Regarding research, our findings respond to calls that emphasize the need for innovative methods to capture vulnerability and how it evolves in the digital domain [e.g., [39, 129] and that advocate for further collaboration among the HCI and legal disciplines [see e.g., Gairola and Gray [34]] For HCI and social computing, our method and findings provide a working ground from which it is possible to incorporate dynamic perspectives in existing design methods, for example through the creation and use of personas [77, 80] that reflect shifts in user profiles and dependency patterns. In other words, our findings and methods provide the foundational vocabulary and methodology to support future empirical work that aims to uncover the manifestation of dependency as an element of vulnerability. In relation to socio-legal literature that debates the significance of the term ‘vulnerability’ and also supports its interpretation in policy [see e.g., [75], our findings are closest aligned with Luna’s [68, 69] work. Consistent with our findings that underline the dynamic and multifaceted nature of dependency, Luna [61] conceptualizes vulnerability as composed of multiple layers that produce cascading effects, i.e., cumulative consequences, in individuals’ lives. Similarly, we interpret dependency as one such layer of vulnerability that is, in turn, shaped and cumulatively intensified by various factors, such as life position, and motivations for use. Similarly, for legal researchers, our findings may respond to existing theoretical debates regarding the interpretation of the term (human) ‘vulnerability’ that is employed within EU regulations [e.g., [42, 44, 75] by providing an empirically-informed understanding of dependency as a component of vulnerability.

In particular, despite the significant academic support for the dynamic interpretation of ‘vulnerability’ within EU legal instruments from both academia (e.g., [44]) and an earlier report of the European Commission [65], current regulatory approaches, including the GDPR [75], DSA [42] and UCPD [25, 99], largely rely on static, personalistic categories (e.g., credulity, disability, children, older adults). Our results contain relevant implications for policy by suggesting that vulnerability, through the dynamic experience of dependency, may emerge situationally from combinations of motivations, life position, and platform choice. More specifically,

our findings highlight that static definitions of “vulnerable groups” and one-size-fits-all policy solutions may not fully capture and address users’ experiences of vulnerability on social media platforms. The employment of a dynamic understanding of vulnerability by enforcement authorities or its embedding in future policy efforts could contribute to better protection of users experiencing vulnerability on social media platforms. Building on the preceding point regarding the potential of our findings to stimulate further (interdisciplinary) research, it can be possible to imagine that such research may, in turn, contribute to and support efforts towards future evidence-based policymaking initiatives.

Lastly, for educators and practitioners (e.g., mental health counselors), the dependency profiles provide a useful framework for digital literacy and support services. They offer a practical vocabulary for recognizing different forms of dependency – whether primarily functional, psychological, or both – and for reducing stigma around social media use by acknowledging that dependency is not inherently harmful. Instead, by fostering awareness of how motivations and platform choices and design shape dependency, educational and counseling initiatives can equip individuals with strategies to sustain more autonomy-supportive relationships with social media.

5.4 Study Limitations and Future Work

Several limitations of this study should be acknowledged. First, the cross-sectional design precludes causal inference. While we observed significant associations between individual characteristics, motivations, platform choice, and dependency, it remains unclear whether these factors drive dependency or whether dependency itself shapes them. For example, motivations for social media use may change or strengthen as dependency deepens. Future longitudinal or experimental studies are needed to examine temporal dynamics and causal mechanisms, such as whether functional dependency evolves into psychological dependency or how changes in life position affect dependency on platforms.

Second, reliance on self-report measures raises concerns about biases, such as social desirability or recall inaccuracies. Future work could combine self-reports with behavioral trace data (e.g., digital logs of time spent, scrolling patterns, or interaction types) and ecological momentary assessment methods to provide more objective and richer insights into user experiences and dependency.

Third, although our sample covered multiple EU member states, the distribution of participants across countries was highly uneven with very small subsamples for several countries, making meaningful cross-national comparisons infeasible. Moreover, as the present study focused on identifying overarching dependency profiles rather than mapping regional variation, we did not pursue such analyses here. Nevertheless, it is important to acknowledge that even within the EU, differences in platform cultures, digital infrastructures, and socio-cultural norms may shape how dependency takes form. Dependency may manifest differently in non-Western settings (e.g., [17, 35]) or among groups whose everyday activities are less bound to digital infrastructures. Comparative cross-cultural research would provide valuable insights into the universality versus specificity of the dependency profiles identified in this study.

Fourth, our measure of exposure to EUDs was aggregated across only two randomly assigned examples. While this reduced participant burden, it limited the granularity with which we could analyze exposure to specific design patterns. Moreover, manipulative features are highly contextual [107], and aggregation into a single score may obscure their specific effects. Future research should examine how specific design patterns interact with different forms of platform use (e.g., passive vs. active, job seeking vs. social connection), across platforms (e.g., Instagram, TikTok, LinkedIn, YouTube), and across design types (e.g., infinite scroll, time fog), to better understand how they drive or mitigate different forms of dependency.

Fifth, although the latent profile analysis identified five theoretically meaningful profiles, entropy was moderate, and profile sizes varied. Replication with larger samples is needed to confirm their stability and to refine their characterization.

Finally, while conceptualized as layered and dynamic, this study approached dependency primarily at the individual level. The profiles capture differences in functional and psychological dependency across users, but they do not account for the relational and structural contexts in which such dependency is embedded. Yet, dependency is contextual [30, 69]: for example, reliance on social media may be reinforced by peer norms that make constant availability a prerequisite for belonging, by family expectations that platforms be used for coordination and care, or by workplace and educational settings that institutionalize social media as channels for visibility and communication. Future research should therefore move beyond individual profiles to examine how such contexts amplify, buffer, or transform dependency over time.

6 Conclusion

This study conceptualized and empirically examined functional and psychological dependency, showing how reliance on social media is shaped by individual, use-related, and design-related factors, and how these dependencies cluster into five distinctive profiles. The findings demonstrate that dependency is not uniform but patterned, sometimes coexisting with resilience and at other times signaling heightened vulnerability. By embedding dependency within broader socio-technical and individual contexts, this study advances theoretical accounts of digital vulnerability, refines media dependency theory, and extends HCI discussions of vulnerability. Moreover, the identified profiles offer a practical framework for policymakers, designers, and educators to better recognize and address the layered ways users depend on platforms.

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A APPENDICES

Appendix I. Demographic Characteristics Study Sample

	Total (<i>n</i> = 873)
Age	<i>M</i> = 34.41 (<i>SD</i> = 10.75)
18 - 30 years	395 (45.2%)
31 - 77 years	478 (54.8%)
Gender	
Cisgender male	525 (60.1%)
Cisgender female	324 (37.1%)
Transgender male	2 (0.2%)
Transgender female	4 (0.5%)
Agender	2 (0.2%)
Genderfluid	2 (0.2%)
Genderqueer	1 (0.1%)
Non-binary	7 (0.8%)
I don't know	3 (0.3%)
I prefer not to say	3 (0.3%)
Sexual orientation	
Heterosexual	734 (84.1%)
Gay	22 (2.5%)
Lesbian	12 (1.4%)
Bisexual	67 (7.7%)
Pansexual	5 (0.6%)
Queer	9 (1.0%)
Asexual	10 (1.1%)
Questioning / unsure	6 (0.7%)
I prefer not to say	6 (0.7%)
I prefer to self-describe	2 (0.2%)
Country of Residence[†]	
Austria	10 (1.1%)
Belgium	16 (1.8%)
Croatia	7 (0.8%)
Czech Republic	15 (1.7%)
Denmark	9 (1.0%)
Estonia	15 (1.7%)
Finland	10 (1.1%)
France	57 (6.5%)
Germany	104 (11.9%)
Greece	71 (8.1%)
Hungary	38 (4.4%)
Ireland	27 (3.1%)
Italy	87 (10.0%)
Latvia	8 (0.9%)
The Netherlands	42 (4.8%)
Poland	111 (12.7%)
Portugal	90 (10.3%)
Slovakia	4 (0.5%)
Slovenia	18 (2.1%)
Spain	112 (12.8%)
Sweden	22 (2.5%)

Note. [†]None of the respondents resided in the following member states: Bulgaria, Cyprus, Lithuania, Luxembourg, Malta, Romania.

Appendix II. Scale Items

Construct	Items	Mean (SD)	Cronbach's alpha
Functional social media dependency	<p>Please indicate to what extent you rely on social media or other resources or places, to...</p> <ol style="list-style-type: none"> 1. Learn how to manage different aspects of my life 2. Stay connected with others 3. Engage in activities that help me feel capable and competent 4. Create a personal space where I feel at home 5. Explore my thoughts, feelings, and preferences 6. Express my personality and share who I am with others 7. Keep a connection to my past through memories and shared experiences 8. Keep up with changes and make sense of the world around me 9. Feel recognized and appreciated 10. Connect with communities where I feel supported 11. To stay informed about political issues and stay connected to movements that matter to me 12. Participate in political campaigns and other forms of online activism 13. Promote my professional activities, my business or connect with customers 	2.63 (0.61)	.854
Psychological social media dependency	<p>In general, how often do you...</p> <ol style="list-style-type: none"> 1. Feel the need to use social media more and more? 2. Spend more time on social media than initially intended? 3. Feel tense or restless if you aren't able to look at social media? 4. Feel bad when you cannot use social media? 5. Try to reduce your social media use, but failed? 6. Not have enough sleep because you are using social media? 7. Have problems at work or in your social life because you are spending too much time on social media? 8. Lose track of how much you use social media? 9. Feel like you are missing out when you are not on social media? 	2.26 (0.83)	.909
Life position	<ol style="list-style-type: none"> 1. I get to see my friends as often as I would like 2. I have ample opportunity for conversation with other people 3. I often visit friends, relatives, or neighbors in their homes 4. I often participate in games, sports, or activities with others 5. I find a great deal of happiness in my life 6. I am very content and satisfied with my life 7. I usually feel in great physical condition 8. In general, my mental health - including my mood and my ability to think clearly - is in good shape 9. I feel like an active participant in society, able to engage in work, education, and social or civic activities as I would like to 	3.28 (0.79)	.856

Appendix III. EUD descriptions

EUD	Definition
Infinite scroll	The user is provided with never-ending content.
Casino pull-to-refresh	When users refresh the page they might get new content, or not.
Autoplay	Once a video is finished, a new one immediately starts.
Guilty pleasure	Personalized suggestions tailored to users' highly personal interests.
Disguised ads	Advertisements and recommendations are mixed with normal content into the social networks' feed.
Recapture notifications	Notifications are sent after a period of inactivity.
Play-by-appointment	"Rewards" to users (e.g., a streak and "snap score" on Snapchat) for continuing to use the platform.
Grinding	Social media feature that encourages users to use the platform at specific times to interact with the content.
Roach motel	Platform that requires the user to take several steps and confirm several times to delete their account.
Time fog	The clock disappears.
Fake social notifications	Notifications from a social media platform about content the user has never interacted with.
Autopopulated field	Platform that, by default, completes the search and suggests you search for something new with one click.
Overwhelming content	Prominent, brightly colored images or visuals that cover the entire screen or main content area.

Note. These definitions were derived from Chen et al. [16] and Monge Roffarello [78]

Appendix IV. Additional Pearson Correlation Analyses and Chi-square tests

Most Used Platform vs Individual, Motivational, and Design-Related Factors

To explore how user characteristics and motivations relate to platform choice, we examined differences across participants' most-used platform. Beyond dependency, these analyses provide insight into how individual, motivational, and design-related factors are associated with platform choice.

Age. Significant age differences emerged across platforms (Kruskal-Wallis $H = 98.78$, $p < .001$). Facebook users were consistently the oldest, significantly older than TikTok (Test Statistic = -322.35 , $p < .001$, Adj. $p = .000$), Instagram (-259.05 , $p < .001$, Adj. $p = .000$), YouTube (-212.43 , $p < .001$, Adj. $p = .000$), X (-210.48 , $p < .001$, Adj. $p = .000$), and Other (-209.99 , $p < .001$, Adj. $p = .010$). TikTok users were the youngest, significantly younger than YouTube users (-109.92 , $p < .001$, Adj. $p = .003$). Instagram users were younger than Facebook users ($p < .001$, Adj. $p = .000$). Overall, results indicate a clear age gradient: Those who use Facebook most often skew older, TikTok younger, with Instagram, YouTube, and X in between.

Gender. Gender was strongly associated with most-used platform ($\chi^2(5) = 112.82$, $p < .001$). Cisgender men most often reported YouTube (47.4%), followed by Instagram (23.6%) and X (10.7%). Cisgender women favored Instagram (41.0%) and TikTok (19.1%), with fewer selecting YouTube (18.5%). Residuals indicated women were overrepresented on Instagram (+5.4), TikTok (+6.1), and Facebook (+2.2), while men were overrepresented on YouTube (+8.5) and X (+3.1). These results highlight gendered usage.

Sexual Orientation. Platform use also varied by sexual orientation ($\chi^2(5) = 21.61$, $p < .001$). Heterosexual participants most often used YouTube (37.9%) and Instagram (29.2%), whereas LGBTQIA+ participants leaned more on Instagram (35.4%) and TikTok (18.9%). Residuals showed LGBTQIA+ users more often reported using TikTok most (+3.2), and least often reported using Facebook most (-3.2).

Life Position. Life position scores varied modestly across platforms (KWH = 15.997 , $p = .007$). YouTube users reported higher scores than Instagram (Test Statistic = 60.13 , $p = .004$, Adj. $p = .062$) and Facebook (82.24 , $p = .004$, Adj. $p = .063$), though these differences did not hold after Bonferroni correction. Descriptively, Other-platform users had the highest life position ($M = 3.56$), followed by Facebook ($M = 3.45$), while TikTok ($M = 3.22$) and X ($M = 3.23$) were lowest. Overall, these results suggest that life position varies modestly across platforms, with those who use YouTube most tending toward slightly higher life position compared to some other groups, though corrected significance levels limit firm conclusions.

Social Media Motivations. All six motivations varied by most used platform.

Information: A chi-square test indicated a significant association between information-seeking motivation and most-used platform, $\chi^2(5) = 58.52$, $p < .001$. Non-seekers most often used Instagram (44.4%; residual = 5.8). Information seekers most often used YouTube (42.5%; residual = 5.2) and X (10.4%; residual = 3.7).

Connection: A chi-square test indicated a significant association between connection motivation and most-used platform, $\chi^2(5) = 363.63$, $p < .001$. Connection seekers mainly used Instagram (51.9%; residual = 12.5) and Facebook (22.6%; residual = 9.2). Non-seekers most often used YouTube (61.0%; residual = 16.4).

Entertainment: A chi-square test indicated a significant association between entertainment motivation and most-used platform, $\chi^2(5) = 175.30$, $p < .001$. Entertainment seekers most often used YouTube (39.8%; residual = 5.3) and TikTok (11.9%; residual = 2.9). Non-seekers most often used Facebook (30.0%; residual = 5.5) and Other platforms (20.0%; residual = 11.1).

Escapism: A chi-square test revealed a significant association between escapism motivation and most-used platform, $\chi^2(5) = 84.14$, $p < .001$. Escapism-motivated users most often used YouTube (39.5%; residual = 3.1) and TikTok (12.6%; residual = 3.0). Non-seekers most often used Facebook (21.3%; residual = 4.6) and Other platforms (9.2%; residual = 6.8).

Business: A chi-square test revealed a significant association between business-related motivation and most-used platform, $\chi^2(5) = 45.90$, $p < .001$. Business-motivated users most often used YouTube (37.1%) and Other platforms (9.0%; residual = 6.7). Non-seekers more often used Instagram (31.3%) and TikTok (11.5%).

Romantic/Sexual Interest: A chi-square test showed a significant association between romantic/sexual motives and most-used platform, $\chi^2(5) = 54.19$, $p < .001$. Those with romantic/sexual motives most often used Instagram (57.5%; residual = 6.6). Those without these motives most often used YouTube (40.5%; residual = -5.6).

EUD Exposure. Manipulative design exposure differed by platform (KWH = 13.91, $p = .016$). Facebook users reported significantly less exposure than Instagram (87.68, $p = .003$, Adj. $p = .041$), YouTube (-101.30, $p < .001$, Adj. $p = .006$), and TikTok (106.00, $p = .003$, Adj. $p = .044$). No other comparisons remained significant after correction. Overall, these findings suggest that Facebook users encounter manipulative design features less often than users of Instagram, YouTube, or TikTok, while exposure is otherwise relatively consistent across platforms.

Taken together, these findings show that platform choice aligns systematically with individual, motivational, and design-related factors. Those who used Facebook most tend to be older, heterosexual, and less exposed to manipulative designs, whereas those who used TikTok and Instagram most were younger and more LGBTQIA+ users with strong social and hedonic motives. YouTube, by contrast, is most often used by older individuals, men, and those using social media to seek information.

Appendix V. Multinomial Logistic Regression Analyses (Continued)

	Ref = Model 2						Ref = Model 3				Ref = Model 4	
	Class 3		Class 4		Class 5		Class 4		Class 5		Class 5	
	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI	OR	95% CI
Age	0.943**	[0.916, 0.970]	0.961**	[0.939, 0.983]	0.952*	[0.911, 0.995]	1.019	[0.993, 1.046]	1.010	[0.965, 1.057]	0.991	[0.950, 1.034]
Gender (ref = female)	0.564	[0.308, 1.032]	0.882	[0.516, 1.507]	0.443*	[0.190, 1.034]	1.565	[0.979, 2.503]	0.786	[0.357, 1.730]	0.502	[0.237, 1.065]
Sexual orientation (ref = LGBTQIA+)	1.424	[0.588, 3.444]	1.024	[0.464, 2.260]	0.745	[0.265, 2.095]	0.720	[0.377, 1.373]	0.523	[0.214, 1.278]	0.727	[0.316, 1.673]
Life position	0.442**	[0.305, 0.640]	0.567**	[0.409, 0.785]	0.419**	[0.252, 0.698]	1.283	[0.965, 1.706]	0.949	[0.594, 1.515]	0.740	[0.473, 1.156]
Motivation 1: information (ref = no)	0.614	[0.273, 1.378]	0.22**	[0.099, 0.491]	0.693	[0.198, 2.424]	0.359*	[0.157, 0.818]	1.130	[0.334, 3.822]	3.150	[0.900, 11.027]
Motivation 2: connection (ref = no)	0.324**	[0.162, 0.648]	0.274**	[0.153, 0.492]	0.256*	[0.083, 0.789]	0.846	[0.455, 1.575]	0.792	[0.259, 2.425]	0.936	[0.320, 2.741]
Motivation 3: entertainment (ref = no)	6.317*	[1.326, 30.107]	2.899	[0.689, 12.191]	9.990	[0.730, 136.757]	0.459	[0.106, 1.989]	1.581	[0.128, 19.480]	3.446	[0.278, 42.752]
Motivation 4: escapism (ref = no)	0.217*	[0.079, 0.600]	0.264**	[0.128, 0.544]	0.106	[0.011, 1.053]	1.214	[0.441, 3.341]	0.490	[0.046, 5.157]	0.403	[0.041, 3.955]
Motivation 5: business (ref = no)	1.135	[0.642, 2.009]	1.089	[0.663, 1.788]	0.493	[0.226, 1.075]	0.959	[0.613, 1.499]	0.434*	[0.210, 0.897]	0.452*	[0.227, 0.902]
Motivation 6: romantic/sexual interest (ref = no)	0.502	[0.253, 0.996]	0.980	[0.521, 1.846]	0.307*	[0.127, 0.740]	1.954*	[1.199, 3.184]	0.612	[0.286, 1.310]	0.313*	[0.150, 0.652]
EUD exposure	1.043	[0.795, 1.369]	0.950	[0.748, 1.205]	1.175	[0.797, 1.732]	0.911	[0.734, 1.130]	1.127	[0.783, 1.621]	1.237	[0.874, 1.752]
Most used platform												
Instagram	0.439	[0.070, 2.734]	0.919	[0.162, 5.223]	0.841	[0.063, 11.262]	2.094	[0.574, 7.636]	1.916	[0.197, 18.635]	0.915	[0.097, 8.640]
TikTok	1.068	[0.138, 8.293]	1.401	[0.197, 9.978]	2.732	[0.171, 43.720]	1.312	[0.330, 5.218]	2.558	[0.246, 26.640]	1.950	[0.192, 19.794]
Facebook	0.217	[0.032, 1.489]	0.350	[0.058, 2.112]	0.199	[0.010, 3.841]	1.610	[0.378, 6.845]	0.915	[0.061, 13.800]	0.568	[0.039, 8.226]
X	0.323	[0.041, 2.533]	0.952	[0.143, 6.341]	1.147	[0.069, 19.111]	2.951	[0.656, 13.284]	3.555	[0.290, 43.647]	1.205	[0.106, 13.651]
YouTube	0.196	[0.032, 1.209]	0.486	[0.087, 2.709]	0.294	[0.021, 4.063]	2.481	[0.667, 9.233]	1.498	[0.145, 15.489]	0.604	[0.060, 6.041]