A Personal Social Media Ecosystem Framework

By

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DISSERTATION

Submitted in partial satisfaction of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

Communication

in the

OFFICE OF GRADUATE STUDIES

of the

UNIVERSITY OF CALIFORNIA

DAVIS

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2022

ABSTRACT

The present dissertation proposes a new way to think about social media in a way that flips the problem of platform diversification on its head: the Personal Social Media Ecosystem Framework (PSMEF). This perspective defines social media as a type of user-centric digital environment (i.e., personal social media environment [PSME]) made up of various types of generalized mediated spaces (i.e., user interface classes) that transcend platform updates over time. Chapter 1 introduces the PSMEF. Two studies are then presented that evidence the types of user interface classes that exist, how social media use is consolidated across certain user interface classes (e.g., Chats/Messages, Search Pages, Home Pages), and detail a methodological framework to quantify user interface classes themselves (i.e., Study 2). In conclusion, outstanding questions, strengths, and limitations of the PSMEF are discussed, in addition to novel methodological inroads to advance the framework moving forward (Chapter 4). *Keywords*: Social media use, social media elements, user interface classes, affordances

Table of Contents

Acknowledgements

I have had the privilege of spending time with an array of very smart people. Some provided support throughout my time as a graduate student, others in passing conversations. Many people stand out as warranting acknowledgement for their support, kindness, reassurance, critiques, and collaboration through the course of my academic journey. Thus, while I only list a few key people below by name, many more deserve acknowledgement. I hope they recognize this for themselves, knowing that they have both my gratitude and deep appreciation. The following people named served as key mentors, advocates, and role models of mine over the last five years. They went out of their way to support me in my growth.

Drew P. Cingel

Jeanette B. Ruiz

Jingwen Zhang

Laramie Taylor

Wang Liao

Chapter 1: Social media use in the context of the Personal Social Media Ecosystem Framework

Social media is fundamentally intertwined into people's experience in modern society. For example, use of social media is nearly ubiquitous in most industrialized countries (e.g., Anderson & Jiang, 2018) and social media platforms function as a place wherein people, in part, come to negotiate their social relationships, sense of identity, and understanding of the world (Marwick & boyd, 2014; Moreno & Uhls, 2019; Nesi et al., 2018). As a result, investigating how social media relates to the health and development of social media users is critical.

In particular, the prominence of social media has cultivated attention towards uncovering the relationship between social media use and many aspects of users' lives, like their psychological health. Recent research investigating social media's impact on adolescent users' psychological well-being, for example, suggests that the strength and direction of these relations vary from individual to individual (Beyens et al., 2020; Pouwels et al., 2021; Valkenburg et al., 2021), based on specific patterns of use and the technological characteristics of platforms (e.g., Beyens et al., 2020). It is also likely that these relationships vary as a function of individual characteristics (e.g., Cingel et al., 2022; Valkenburg & Peter, 2013).

Together, conceptual and empirical work has signaled the need for a shift in social media-related theorizing. Indeed, person-specific effects solidify calls for a differential media effects paradigm when investigating social media use correlates (Valkenburg et al., 2021). Such a focus requires consideration of both micro (e.g., salient social identities) and macro environmental factors (e.g., timing effects in platform adoption; e.g., Nesi et al., 2018; Valkenburg & Peter, 2013). Also, as the commercial social media landscape matures, researchers will need to consider more superordinate technological variables (e.g., profiles, content streams, social networks) to organize and generalize effects (Bayer et al., 2020). However, to systematically assess how particular types of generalized social media features impact users, a means to explicate similarities and differences in these features as they come to contextualize users' social media environments is needed. After all, features and platforms have become more technologically nuanced at the user-level (e.g., personalized algorithms; Bhandari & Bimo, 2022).

Therefore, to account for different individual susceptibilities to (social) media effects (e.g., Valkenburg & Peter, 2013), longer-term research needs to generalize correlates and effects across platform design components and consider social media as a personalized environment (e.g., Bayer et al., 2020; DeVito et al., 2018). This would suggest that a theoretical framework allowing researchers to make predictions on the correlates of social media use, at an individualized level and across social media platforms over time, is needed for findings to be useful as platforms change in the years to come. Without such a framework, advancements across the commercial social media landscape will continue to outpace theoretical insights needed to help shape policy and regulation of social media systems.

Therefore, this article aims to build from and extend key conceptual paradigms used to study the correlates of social media use. To do so, it first reviews (1) central conceptualizations and operationalizations of social media, before examining (2) prominent theoretical frameworks used to bolster the generalizability of evidenced social media effects (e.g., features and affordances, social media elements). After, it (3) introduces the *Personal Social Media Ecosystem Framework (PSMEF)*, which presents new ways to define social media constructs. The PSMEF also proposes a new approach to comparing social media constructs across social media contexts and promotes an empirical definition of social media as a user-centric environmental context (i.e., a personal social media ecosystem). In conclusion, the theoretical and practical implications of this work is discussed, as well as the ways that researchers can leverage the conceptual framework to better understand the outcomes of social media use moving forward.

In terms of technological structure, social media is often defined as a type of platform, particularly social networking sites (SNS; Bayer et al., 2020; boyd & Ellison, 2007; Ellison & boyd, 2013). Early definitions of SNS included three main criteria: they represent “web-based services that allow individuals to (1) construct a public or semi-public profile within a bounded system, (2) articulate a list of other users with whom they share a connection, and (3) view their list of connections and those made by others within the system,” (boyd & Ellison, 2007, p. 211).

While initially informative in helping to differentiate between various types of platforms, the rapid maturation and evolution of social media systems has limited this definition’s utility. For instance, updates and cross-platform integrations (e.g., Facebook authentication on a third-party app) have fundamentally impaired the definition’s discriminant validity, because newer social media components often fall outside of this definition. This has necessitated multiple reformulations of the definition over the past decade (e.g., Bayer et al., 2020; Ellison & boyd, 2013; Kane et al., 2014). Further, platform updates have blurred the boundaries between any single digital platform (Ellison & boyd, 2013; Kane et al., 2014), making it hard to distinguish social media platforms from other types of platforms (e.g., video games) or one even from each other (e.g., cross-app messaging over Facebook, Messenger, and Instagram). Thus, platform-bounded definitions of social media remain less useful in describing social media as a dynamic, environmental landscape.

Operational and Conceptual Definitions of Social Media Use

Due to the complexity of social media, researchers are often left to selectively study popular social media platforms (e.g., Facebook, Instagram, TikTok) or "social media" in a subjective sense (e.g., based on what people consider to be social media; Kaye, 2021). While the selective study of social media is common in the assessment of social media use (e.g., Cingel et al., 2022), this practice brings about other conceptual challenges to understanding social media effects across time.

Self-report measures of social media use limit the ability to extrapolate evidenced relationships to future iterations of social media because these findings are tied to generalized patterns of use or user-platform relationships. This is because aggregate platform-level measures of browsing behavior will always vary in their replicability as a function of in-app updates. For example, recently evidenced effects evidenced by measures of passive Instagram use (Beyens et al., 2020) would not hold to the updates made to Instagram as a platform over time. One example of this would include the introduction of the *Favorites* feed on Instagram, launched in 2022. While Instagram's conventional *Following* feed enable users to access content from those they follow on the platform, the *Favorites* feed allows users to curate an even more selective content stream representative of a set of self-designated "favorite" users. Apart from the application of a more nuanced measure of passive Instagram use, a replication study assessing the effects of passive Instagram use on users' psychological health (e.g., Beyens et al., 2020) would provide little clarity regarding how the update may have impacted users' psychological health.[1] Platform updates require measures of social media use to differentiate between platform features, rather than only considering use patterns at the platform level.

[1] The problem rests with the fact that higher or lower rates of passive Instagram use falls short in informing on differential content exposure across Favorites and Following as potentially distinct content environments.

Similarly, measures of social media engagement often remain fragmented across select platform features (e.g., likes), such that they inadequately generalize to newly introduced features (e.g., reactions). A universal measure of social media use could help alleviate some of these issues, but this would require a measure that transcends distinct types of content environments and platform features (Trifiro & Gerson, 2019). A guiding framework can help to provide some clarity on how to map use patterns over time, but currently common measures of social media use inadvertently position evidenced effects in a historical and technological context (e.g., specific platform version).

Social Media as a Collection of Features and Affordances

One way that researchers seek to circumvent some of these issues is through mapping effects to affordances (Bayer et al., 2020; Ellison & boyd, 2013; Meier & Reinecke, 2021). *Features* represent the specific attributes of an object or environment and *affordances* reflect the action potential of environments in combination with user capabilities (Evans et al., 2017). Affordances generalize across technological contexts because different communication channels support affordances as a function of their features. Essentially, the same affordances may be possible as a function of different features (Bayer et al., 2020; Evans et al., 2017).

Feature- and affordance-based theoretical frameworks have certain benefits. Some frameworks leverage affordances to understand the role that mediated settings, like social media, play in driving various social phenomenon (e.g., peer interactions; Nesi et al., 2018; identity development; Moreno & Uhls, 2019). These frameworks are also parsimonious in their focus on a smaller set of affordances as opposed to a focus on a multitude of features. Nevertheless, a significant limitation of the feature and affordance framework is that it does not parameterize social media as an environmental context and it is difficult to identify all the affordances for social media as a technology (Bayer et al., 2020).

Social Media Defined as a Personal Social Media Ecosystem

Without a standard definition of social media, researchers often conceptualize social media in broader terms, like *Internet channels facilitating mass personal forms of communication* (Carr & Hayes, 2015) or *social interaction* (Bayer et al., 2020). These perspectives position social media as a type of digital ecology comprised of a bundle of mediated communication channels with social characteristics. However, social media as a digital ecology is increasingly nuanced and largely user-specific (Bayer et al., 2020; DeVito et al., 2018). People use the complex structure of social media systems to negotiate their online presence and manage their heterogeneous, digital connections—adopting platforms or settings based on perceived audiences, user norms, and/or their underlying technological function (DeVito et al., 2018). DeVito and colleagues (2018) coined this phenomenon a *personal social media ecosystem*.

Conceptualizing social media in terms of a personal social media ecosystem has significant benefits. First, it extends channel-based conceptualizations of social media by situating individual users at the center of their own social media environment. It also highlights how users' perceived experiences (e.g., perceived audiences) partially define aspects of social media as a type of space. Second, conceptualizing social media as user-specific ecologies helps to inform on relevant aspects of social media for studying the correlates of social media use. Despite these strengths, conceptualizing social media in terms of personal social media ecosystems still has some limitations. Mainly, this view requires a broader focus on general media ecologies (e.g., the Internet; Bayer et al., 2020) and individuals' offline environments to account for mutual influence between the different environmental systems theorized to impact media effect processes (e.g., social context; Valkenburg & Peters, 2013). Lastly, when considering the relevance of different technological innovations, it becomes necessary to map effects to technological variables (Naas & Mason, 1990). Thus, a link between personal social media ecosystems and more general technological constructs is required to advance an understanding of social media correlates over time.

Social Media Elements

One solution to increasing the theoretical utility and generalizability of social media correlates is to map them onto persistent yet generalized technological components that exist across platforms (Bayer et al., 2020). Such *social media elements* represent standard units/components of social media that exist across different communication channels and are made up of a commonly understood *set* of features and affordances. The concept thus creates a unit of analysis that maps onto the underlying building blocks of social media itself, spanning profiles, messages/chats, content streams, and social networks (Bayer et al., 2020). While *profiles* represent interfaces that "enable users to maintain unique collections of personal attributes created by the user, their network, and/or the platform" (Bayer et al., 2020, p. 474), *messages/chats* depict components that allow "users to engage in directed social interaction using text, video, photo, or other media" (Bayer et al., 2020, p. 475). Similarly, *content streams* encapsulate features that enable users "to consume and/or engage with feeds of user-generated content provided by their network" (Bayer et al., 2020, p. 474) and *social networks* summarize features "representing social connections, such as contacts created via mutual 'friending' or one-way 'following'" (Bayer et al., 2020, p. 474). Considering social media elements help to characterize persistent features that underpin social media systems over time (Bayer et al., 2020).

Construing social media in terms of social media elements helps to advance social media-related theorizing. Bayer and colleagues (2020) argue that when certain relationships are exhibited in relation to particular social media elements, they should generally apply to those same elements on other platforms. After all, certain components are often re-used across different technologies (Naas & Mason, 1990), with social media elements representing types of technological components that permeate across platforms over time (e.g., profiles; Bayer et al., 2020). Social media elements also provide a means to identify generalized technological constructs that exist across social media. For instance, navigational (e.g., networks of in-app links; Benevenuto et al., 2012) and semantic networks (e.g., hashtags networks; Zappavigna, 2015) share a common set of features and affordances and also exist across various channels of communication. Thus, navigational and semantic networks constitute social media elements based on Bayer and colleagues' (2020) definition.

The concept of social media elements has its own limitations, however. Although the concept of social media elements characterizes central aspects of social media (e.g., Bayer et al., 2020), it largely fails to provide a means for studying social media as a type of user specific ecology. While Bayer and colleagues (2020) rightfully acknowledge the complexity of studying social media elements when considering dynamic media ecologies, historical effects, and person-specific factors, the question of what constitutes the basic environmental units that define social media as a type of personal social media ecosystem remain. This is critical as theories of ecology span diverse environmental systems and explicate different types of environmental units (e.g., Bronfenbrenner, 2005); the concept of social media elements seemingly reflects just one generalized aspect of such a system.

Further integrating the concepts of user-specific ecologies and social media elements would be theoretically beneficial, as understanding what constitutes the basis of an individual's environment is central to ecological theories (e.g., Bronfenbrenner, 2005). The Personal Social Media Ecosystem Framework (PSMEF) seeks to address this gap by providing a heuristic theoretical framework to study social media elements as they come to form user-centric environments (see Figure 1). The PSMEF defines social media as an environmental context to further maximize the *ecological validity* and *generalizability* of established social media research by integrating the concept of social media elements with personal social media ecosystems.

The Personal Social Media Ecosystem Framework: Extending Ecological Systems Theory

The PSMEF posits that assessing social media through the lens of social media elements (Bayer et al., 2020) and Ecological Systems Theory (EST; Bronfenbrenner, 2005), can help to structure social media as a digital context (e.g., Nesi et al., 2018). EST describes environmental systems in terms of a mutually reinforcing, yet nested environmental structure centered around the individual (Bronfenbrenner, 2005). Thus, EST would consider social media as a type of user-centric ecosystem (e.g., Bayer et al., 2020; DeVito et al., 2018), if it were an offline context (Bronfenbrenner, 2005). EST defines several environmental constructs. Four are pertinent to defining social media as a context: *offline settings*, *microsystems*, *mesosystems, and exosystems*. To help differentiate between the mediated environmental systems proposed by the PSMEF and ESTs offline contexts, the PSMEF defines each construct using distinct nomothetic labels (e.g., digital microsystem, digital mesosystem). In this way, the PSMEF extends EST explicitly to the context of interactive media using distinct construct labels. This would capture the unique properties of mediated environments (Nesi et al., 2018), in addition to integrations between offline and mediated environments (e.g., metaverse, augmented reality) by conceptualizing them as separate constructs.

Digital User Interfaces as Mediated Settings. Social media is multidimensional in its structure with human-computer interfaces and applications as two primary dimensions. While a *user interface* is a two-way medium by which computer systems and users symbolically communicate, an *application* represents all other aspects of a program (Myers, 1995). Thus, it is possible to divide social media platforms into its user interface aspects (e.g., representation of inputs, symbolic feedback), and application features (e.g., data pipelines, algorithms).

However, the user interface concept does not differentiate between many user-specific spaces that exist across a live platform. For example, each Facebook profile represents a user-specific interface with a distinct combination of features and affordances. Yet, users' Facebook profiles are structurally similar even though they each represent distinct locations on Facebook. This suggests that a more specific definition of a user interface is needed to capture this type of nuance. Thus, social media engagement takes place over a *digital user interface*, or a specific mediated environment. This mediated environment is comprised of a set of platform objects, features, and affordances that facilitate symbolic interaction between user(s) and/or a user and their environment over a live platform. The digital user interface concept is meant to be analogous to EST's *offline settings* (Bronfenbrenner, 1977), in that it is reflective of the spaces in which users exist and engage (e.g., a home, a school, a Facebook profile page). Thus, digital user interfaces represent the most primitive environmental unit in the PSMEF; an array of mediated environments (e.g., in-app pages) that exist across social media at any given time.

Digital Microsystems and Digital Exosystems. Individuals also access digital user interfaces within the context of more superordinate environmental constraints, like settings and accounts (e.g., Rideout & Robb, 2018), which allow users to change or set aspects of their digital user interfaces in unique ways. Such application-based components revolve around an individual (e.g., DeVito et al., 2018) mirroring EST's concept of an *exosystem*, or superordinate environmental structures which:

> "do not themselves contain the developing person, but impinge or encompass the immediate settings in which that person is found, and thereby influence, delimit, or even determine what goes on there" (Bronfenbrenner, 1977, p. 515).

Thus, it is possible to theorize that social media is housed within a type of *digital exosystem*, or a generalized multi-platform application specific to an individual. This digital exosystem reflects aspects of a platform's systems (or the broader Internet) that exist outside of an individual digital user interface. The aspects of the digital exosystem also influence the individual digital user interfaces. Accounts; semantic, social, and navigational networks; tailored algorithms; data pipelines; and the Internet would all fall within this definition of a digital exosystem.

While useful, digital user interfaces and digital exosystems as constructs fail to fully encapsulate all aspects of the most immediate environmental system to the individual (i.e., microsystem). Specifically, users also comprehend social media spaces as a function of their own psychology (Bayer et al., 2020; DeVito et al., 2018). This makes social media contexts akin to a *microsystem* in EST, which comprises a:

> "pattern of activities, social roles, and interpersonal relations experienced by a developing person… with particular physical, social, and symbolic features that invite, permit, or inhibit engagement in sustained… interaction with, and actively in, the immediate [setting]" (author adaptations in brackets; Bronfenbrenner, 2005, p. 5).

Therefore, I define a *digital microsystem* as a digital user interface an individual engages with that is characterized by certain roles and perceived audiences. This digital microsystem exists within a broader digital exosystem (e.g., accounts, settings, application). Digital microsystems fundamentally differ from digital user interfaces because they represent an environmental structure rooted with the individual, which is subjected to more superordinate environmental constraints (e.g., digital exosystem) defined by a user (e.g., settings) *in combination with* platform systems (e.g., tailored feed).

Digital Mesosystems, Social Media, and Personal Social Media Ecosystems. Lastly, social media encapsulates multiple channels of communication that facilitate social interaction (Bayer et al., 2020; Carr & Hayes, 2015). These channels often exist within and across multiple distinct digital microsystems for any given user. Offline, EST conceptualizes the intersection of microsystems as a *mesosystem*, or "the linkages and processes taking place between two or more settings containing the developing person," (Bronfenbrenner, 2005, p. 6). When conceptually transposed to the context of social media, social media and platforms reflect a type of *digital mesosystem*—or an interrelated set of digital microsystems for any given individual. After all, at its most fundamental level, a mesosystem represents all the microsystems in which a person engages—the individual represents the initial link between such systems (Bronfenbrenner, 1979). Thus, it is possible to more concretely explicate concepts, like personal social media ecosystems (DeVito et al., 2018), in terms of *personal social media environments* (PSMEs). It is possible to think of PSMEs as a user-centric digital mesosystem that is centered around a subset of digital microsystems. These microsystems facilitate social interaction, which are embedded in one or more live platforms, a digital exosystem, device(s), and an individual's offline social contexts (e.g., microsystem, mesosystem).

The PSMEF as an Extension to Communication Theory

The PSEMF's conceptualization of social media as PSMEs extends existing work in this research area. First, a PSME is more specific than former conceptualizations of social media (Bayer et al., 2020; boyd & Ellison, 2007; Carr & Hayes, 2015; DeVito et al., 2018; Ellison & boyd, 2013; Kane et al., 2014; McCay-Peet & Quan-Haase, 2017) because it explains social media in terms of digital microsystems. In doing so, it bypasses issues of conceptualizing social media too broadly and therefore, limiting the specificity and ecological validity of its operational and empirical definition. PMSEs also inherently reflect discrete environmental structures which consolidate over particular popular "social media" platforms within users' respective regional markets. For instance, in the United States, platforms like Facebook, Instagram, Twitter, and Snapchat remain popular among user demographics (e.g., Anderson & Jingjing, 2018), suggesting that the platforms themselves function as core contexts underpinning individuals' PSMEs.

PSMEF Classes and Social Media Elements. Further, the PSMEF also integrates the concept of social media elements with PMSEs. For example, in EST, prototypical environmental structures (e.g., classrooms) represent the product of larger sociological characteristics of a society. This *macrosystem* includes the values, standards, and traditions of a given cultural group (Bronfenbrenner, 1977; 2005). Social media also has a macrosystem (Nesi et al., 2018) that is shaped by user norms and pre-existing technological structures, such as commercial design standards (boyd, 2015). Consequently, it is possible to group social media environments into *environmental classes* based on sets of shared environmental features (Rauthmann & Sherman, 2020). For instance, Profiles and Chats/Messages, as social media elements (Bayer et al., 2020), represent two ways to define a *user interface class*—a set of user interfaces with a shared set of platform features and affordances that exist across multiple platforms. Thus, the concept of user interface classes in the context of the PSMEF maps the concept of social media elements onto the technological structures underpinning individuals' PSMEs (see Figure 1).

Comparing Social Media Contexts. Lastly, the PSMEF also outlines criteria for the validity of different types of comparisons across social media contexts. For example, digital user interfaces (e.g., posts, updates, stories) exist as embedded and inter-networked structures that together form more superordinate environmental structures (e.g., a content feed on a home page). This would suggest that internal validity is maximized when digital user interfaces/digital microsystems under comparison share more consistent structures, whereas external validity is increased when comparison points span heterogeneous instances of digital user interfaces/digital microsystems. Lastly, ecological validity is maximized when social media contexts under investigation more closely match digital microsystems themselves or as they come together to form users' PSMEs as a type of digital mesosystem.

The Theoretical Utility of the PSMEF. The PSMEF, in providing language contextualizing social media environments at a user-specific level and social media in terms of transcendent types of environmental contexts, can aid theorizing and prediction by helping to inform on relevant facets of social media for study. For example, work investigating how social network characteristics impact users can extend from studying general elements, like "friend lists", to social contact based on exposure or interaction within specific user interface classes. Using environments as parameters for social networks would provide insight into how unique forms of social contact *afforded* by different user interface classes may conditionally influence outcomes of interest. This approach is also consistent with social network-based accounts of EST (e.g., Neal & Neal, 2013). Furthermore, by using alternative constructs outlined by the PMSEF, studies can also investigate how distinct environmental systems interrelate to create conditional media effects, whether resulting from PSME composition or user disposition (I expand upon this notion in the Discussion section). In all, the PSMEF provides a flexible theoretical framework that can help to inform on the study of social media effects over time, with particular attention to conditional social media effects based on individual-level factors, environmental context, and certain patterns of engagement.

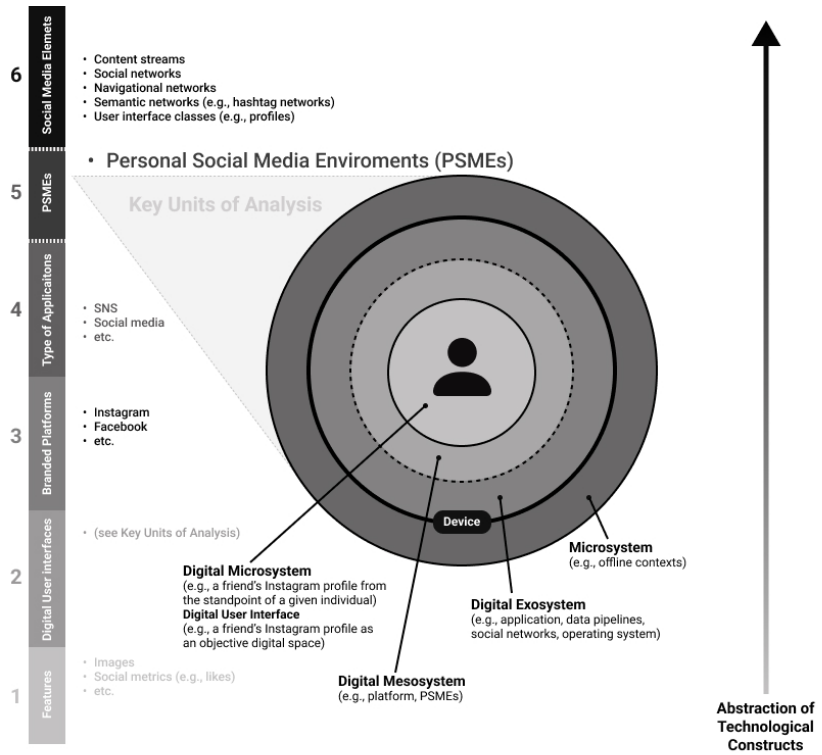


Figure 1. The Personal Social Media Ecosystem Framework (PSMEF) as an extension to the Hierarchical CMC Taxonomy (Meier & Reinecke, 2021). *Notes.* See the original paper for more information about the Hierarchical CMC Taxonomy, which organized devices, types of applications (e.g., social media), branded platforms, and features as a hierarchical set of units for analysis for the study of computer-mediated communication (Meier & Reinecke, 2021). The PSMEF formally adds personal social media environments and feature classes as more superordinate types of technological constructs. In addition, it illustrates that devices remain embedded in broader environmental systems (e.g., microsystem)—essentially, extending into EST. Units of analysis within PSMEs represent nested structures.

Discussion and Future Directions

In this article, I reviewed key paradigms used to study social media, their strengths and limitations, and proposed a heuristic framework—the Personal Social Media Ecosystem Framework (PSMEF)—to help advance social media research. I believe that this framework can be applied to the study of social media use, its correlates, and effects by guiding how social media use is operationalized, and effects extrapolated, as a function of the populations under study. Specifically, the PSMEF provides a flexible definition of social media as a user-centric digital environment (i.e., PSMEs), one partially defined by users' psychology (e.g., perceived audiences), users' actions (e.g., user settings), and platforms systems (e.g., data pipelines). At the core of these PSMEs rest digital user interfaces, or mediated interfaces that facilitate symbolic interaction between users and their digital environment, which themselves exist as a set of subordinate, nested structures in a broader set of superordinate environmental systems (e.g., digital microsystem, digital exosystem, macrosystem). While this re-conceptualization of social media brings additional theoretical complexity, it also provides scaffolding to help model the complexity that is already inherent within social media systems. In addition, it aids in the partitioning of individuals' PSMEs in terms of social media elements, providing novel opportunities to study social media in more generalizable ways. Finally, the PSMEF uses the same language to define offline contexts as mediated contexts—effectively extending EST to provide a holistic ecological framework, one perhaps more apt to address future permutations of social media systems (e.g., metaverse).

Explicating Causal Predictions. Finally, pairing the PSMEF and the Differential Susceptibility to Media effects Model (DSMM; Valkenburg & Peters, 2013) could generate useful predictions given their ability to probe these relationships. Specifically, the DSMM provides concise causal predictions related to how dispositional, socio-contextual, and developmental factors interrelate with media use and effects. According to the DSMM, user engagement in particular user interface classes could solicit transactional effects over time. This occurs when patterns of use (e.g., passive use, selective exposure) and corresponding effects (e.g., depression, internalization of the thin-ideal) remain self-reinforcing, potentially contingent on other factors (e.g., presence of a mental disorder). The PSMEF posits that investigating such relationships across an array of user interfaces with similar environmental compositions (i.e., user interface class) will help to identify potential boundary conditions and assess their level of robustness. Investigating the underlying structure of PSMEs across particular social and situational contexts should also yield insights into the socio-contextual influences driving certain patterns of social media use and effects (Rauthmann & Sherman, 2020; Valkenburg & Peter, 2013). This could include how parents/guardians interact with adolescents to regulate their use of social media and how social media literacy intermediates effect outcomes (see Schreurs & Vandenbosch, 2021).

Building a Foundation for Social Media Theorizing. The adoption of the PSMEF as a research paradigm should help facilitate a program of research that better illuminates the prospective effects of emerging social platforms long-term. In part, this is because the PSMEF, in guiding the identification and distillation of user interface classes, should help to characterize interactive platforms, despite inherent differences in their underlying features. User interface categories could help justify different comparison points (e.g., different realizations of the same or separate user interface class) on some standardized set of features and affordances. In addition, when new user interface classes are identified, evidenced effects in relation to pre-existing user interface classes with similar characteristics may help to inform on the prospective effects of future iterations of social media (Bayer et al., 2020).

Building a Methodological Framework. To accomplish the above, future work should focus on evidencing user interface class categories using multiple methods. This would help to solidify certain user interface classes and help to motivate organized research efforts. Asking participants to describe their PSMEs using open-ended questions (e.g., DeVito et al, 2018) would help to identify emerging or a preliminary set of user interface class categories. Another possibility is to investigate how user interfaces associate with other constructs (e.g., platforms) or technological affordances; such methods have been used to contrast the similarity of different communication technologies using open-ended text data by plotting concepts in a multidimensional vector space (e.g., Chang et al., 2008). Lastly, a set of inductive, yet quantitative tools to evidence user interface classes is needed to help account for thresholds/cutoffs between different user interface classes themselves (see Figure 2). This would help to inform on points of theoretical inquiry, like differential effects as a function of user interface class composition. Lastly, as there is inherent variability between studies and methods, a consistent set of metrics is needed to help inform on study design (e.g., selection of comparison points) and theorizing of user interface classes over time. Given its flexibility (see Doerfel, 1998), semantic network analysis is an attractive theoretical and methodological framework to evidence user interface class categories. This is because forms of network analysis can model the meaning of concepts based on their association with other concepts inductively (Doerfel, 1998; Carley, 1993).

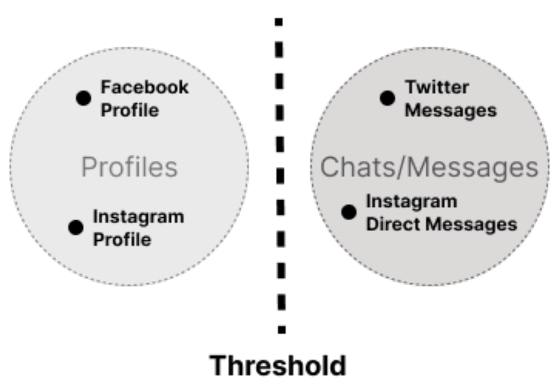


Figure 2. Theoretical boundaries between user interface class categories. *Notes.* User interface class boundaries (dashed circle) reflect a fuzzy boundary. Exemplar user interfaces are depicted in bold.

Limitations. Despite its many benefits, the PSMEF also has challenges. First, because the PSMEF conceptualizes social media as a user-centric structure, users' PSMEs may not sufficiently cover the types of social media environments needed for a particular study. While between subject designs should help to facilitate a range of comparisons across different user interface class categories, individual-level factors can drive selective patterns of engagement across certain environmental contexts (Rauthmann & Sherman, 2020). This would indicate that there is a need to account for individual-level confounders when assessing such relationships. Finally, naturalistic comparison points also remain limited to those that exist as a part of the broader social media landscape. This makes it easier to assess more common (e.g., *Stories*) compared to more idiosyncratic environmental structures (e.g., *Snap Maps*).

Conclusion

The PSMEF offers a broader organization of platform features to explore social media effect outcomes, despite an everchanging social media landscape. As a conceptually guided approach to study social media, the advancement of a standardized set of quantitative methods in the context of the PSMEF is likely to provide significant inroads to further our understanding of social media design and its correspondent relationship with effect outcomes of interest.

Chapter 2: Applying the Personal Social Media Ecosystem Framework to Adolescents' Understanding of Social Media

While at times viewed as a broad set of platforms, social media reflects more of a cultural phenomenon, co-constructed by business models and users, than any set of platforms in particular (boyd, 2015). Social media is also complex. For instance, in real-time, popular social media apps (e.g., Instagram) take multiple forms as new features are piloted and rolled out to the broader public; often occurring across user-segments to vet the underlying capacity of back-end infrastructure (e.g., computational load) in a way that is quick, secure, and scalable (Guo, 2017). In this way, at any given time platforms can inherently differ in their underlying structural composition between users. This complexity is further compounded as platforms naturally change over time through feature updates as well (boyd, 2015; Ellison & boyd, 2013), having become increasingly interconnected over the last two decades (e.g., cross-platform integrations [e.g., Facebook authentication on Spotify]) and much more advanced compared to preceding types of Internet platforms (Devon, 2022).

Despite such complexities, for methodological reasons, studies investigating the relationship between social media and correlates of its use often treat social media platforms as unitary concepts in a way that assumes internal consistency in platform structure (for a review Cingel et al., 2022). On one hand, such an approach helps facilitate the study of popular social media platforms and their correlates (e.g., mental health) by treating each platform as a standardized unit of analysis. On the other hand, such an approach limits the generalizability of evidenced effects by contextualizing the interpretability of findings to particular historical contexts (e.g., certain in-app versions; see Chapter 1; Carter et al., in revision).

One way to account for feature variability is to study social media in terms of more generalized technological constructs in consideration of users' unique social media environments (Carter et al., in revision; Bayer et al., 2020). For instance, the Personal Social Media Ecosystem Framework (PSMEF; Carter et al., in revision) proposes that social media is made up of a set of generalized types of mediated environments—particularly, user interface classes—that transcend platforms over time and underwrite users' social media experiences. Investigating user interface classes and other types of *social media elements*, or commonly understood sets of features that permeate social media platforms (e.g., social networks, profiles), should help to increase the generalizability of evidenced effects by helping to organize effects across the unique realizations of more transcendent technological constructs (Bayer et al., 2020; Naas & Manson, 1990). Thus, just as meta-analyses compute aggregated statistics that account for variability across studies to estimate the robustness of evidenced effects (Field & Gillett, 2010), social media elements provide an overarching conceptual structure to facilitate such computations by guiding how social media is operationalized in and effects extrapolate across studies (Carter et al., in revision; Bayer et al., 2020).

While advantageous, the social media effects literature has only started to advocate for the study of social media elements (e.g., Cingel et al., 2022; Parry et al., 2021). Furthermore, while frameworks, like the PSMEF, formally integrate and extend on the concept of social media elements with the introduction of user interface classes (i.e., Carter et al., in revision), studies have yet to evidence the types of user interface classes that underwrite users' contemporary social media experiences. Thus, while Chats/Messages and Profiles operate as characteristic types of user interface classes permeating in different forms across various platforms over time, other user interface classes likely exist to contextualize social media as an evolving technological structure (Carter et al., in revision; Bayer et al., 2020). Addressing this gap would represent a significant step towards advancing the PSMEF (see Limitations outlined in Chapter 1).

Therefore, the primary objective of the present study is twofold. First, it sought to explore the types of user interface classes that characterize social media experiences among a sample of adolescent social media users. Although I believe the PSMEF can be applied to all social media users regardless of age, this study's research questions are addressed using data collected from adolescent participants, given that this age group are among the earliest adopters of social media (boyd & Ellison, 2007) and report high rates of social media use (Anderson & Jingjing, 2018). Second, as social media elements can help characterize platforms as they change over time (Bayer et al., 2020), the present study also sought to investigate how users associated various user interface classes with four popular platforms: Facebook, Twitter, Instagram, and Snapchat. To do so, it analyzed a set of transcripts derived from eight adolescent focus groups (N = 59; ages 13-17) by extracting social media-related concepts from statements they made about social media. Using these concepts, a classification scheme for user interface classes is proposed and subsequently leveraged to model how adolescents psychologically interrelated the identified user interface class categories with specific platforms (e.g., Facebook, Snapchat) through two complementary quantitative methods. Results provide an interesting first look on the expanse of user interface classes that shape youths' contemporary experiences over social media. In conclusion, practical considerations relating to the measure of social media use are also discussed, including how these findings signpost the potential utility of leveraging language models to quickly glean insights about social media use trends.

The Personal Social Media Ecosystem Framework: A Novel Paradigm

The integration of social media elements in the context of the PSMEF offers opportunities to explore novel questions regarding social media systems. For instance, what types of user interface classes contextualize individuals' understanding of social media? How are user interface classes distributed over platforms? Understanding such would help to provide a stronger theoretical basis to subsequently investigate how engagement in certain user interface classes may impact individuals over time.

Importantly, the PSMEF proposes that social media is unique for each person, contextualized by the various platforms, settings, and perceived audiences that color their social media experiences (Chapter 1; Carter et al., in revision). Underlying each user's personal social media environment (PSME), however, is a set of mediated spaces that users can generally navigate to and engage within; such *digital user interfaces* represent the foundation of users' PSMEs and represent unique instantiations (e.g., User A's Facebook Profile) of broader types of user interfaces (e.g., Facebook Profile's Interface, Profiles generally; Chapter 1; Carter et al., in revision). Altogether, this suggests that investigating how individuals understand their PSMEs could shed light onto the core user interface classes underpinning their experiences over social media as an environmental context—especially, when assessed in relation to popular social media platforms (e.g., Facebook, Twitter, Instagram, Snapchat).

While Chats/Messages, Profiles, and various types of user generated content will likely represent salient components of PSMEs for social media users, the breadth of salient user interface classes remain less clear. Individuals may identify a few or many user interface classes when reflecting on their social media experiences and understanding of social media as a function of the underlying composition of their PSMEs. Furthermore, although the number of digital user interfaces remains potentially vast, activity over social media platforms has been evidenced to consolidate across a subset of user interfaces (Benevenuto et al., 2012). One explanation for the different trends in user navigation across user interfaces relates to the underlying navigational network which interlinks the user interfaces housed within a platform (Benevenuto et al., 2012). Together, this suggest that the underlying navigational structure of platforms and users' use behaviors may lead youth generally to differentially associate user interface classes with platforms. How these associations between platform concepts and user interface classes will manifest remain less clear, however. Therefore, I propose the following research questions:

RQ1: What types of user interface classes contextualize participants' understanding of social media?

RQ2: What social media platforms do participants cognitively associate with certain user interface classes?

Method

Participants

Eight semi-structured group interviews were conducted to examine how an ethnically diverse sample of adolescents (ages 13-17, M = 14.50, SD = 1.47) understand social media (N = 59; 66% Caucasian/White, 14% African American/Black, 15% Hispanic, 2% Middle Eastern, 2% Asian, 2% Biracial; Male 50%). Participant recruitment and interviews were conducted through an independent research marketing firm, *Focuscope Inc,* in summer 2019. *Focuscope* contacted people from their the participant pool who are parents of children in the target age range. If the parents consented and the adolescents were interested in participating, adolescents could sign up for a focus group. All participants had at least one active social media account on Facebook, Instagram, Twitter, or Snapchat. Participants reported on which account(s) they used within the previous month; 35.6% reported using Facebook (*n* = 21), 94.9% reported using Instagram (*n* = 56), 39.0% reported using Twitter (*n* = 23), and 100% reported using Snapchat (*n* = 59). On average, participants reported having 2.69 active social media accounts. The interviewer specifically asked about these four social media platforms because they are the most popular among this age group (Rideout & Robb, 2018). However, in the focus groups, participants were prompted to talk about other social media platforms and social media in general.

Procedure

Participation occurred at the offices of the research marketing firm, which is located in a suburb of a large metropolitan area in the Midwestern United States. Upon arrival, parents provided written consent for their adolescent's participation, and adolescents provided their assent prior to completing a short demographic survey. Participants were organized in groups ranging from 6-8 members. There were four all-male groups and four all-female groups. Each 90-minute session was video- and audio-recorded for analysis. The moderator used a semi-structured questionnaire to lead the session. Questions were developed to encourage participants to discuss all of the social media platforms they used and their perceptions of differences between these platforms. At the end of each session, participants were thanked for their time and received $100 in compensation.

Concept Identification and Transcript Annotation

First, I leveraged a combination of human coding and natural language processing (NLP) techniques to extract concepts from the eight focus group transcripts to identify distinct user interface classes. Transcripts were minimally pre-processed (e.g., hyphen separated words were linked to reflect single concept units). The first author and a research assistant screened the transcripts to identify social media-related terms that spanned key theoretical domains of interest: (1) social media features, (2) social media platforms, and (3) generalized interactive media concepts (e.g., apps, social media, platforms). These conceptualizations of social media mapped onto constructs defined by the Hierarchical Taxonomy of Computer-Mediated Communication (HCMC; Meier & Reinecke, 2021) and provided an initial basis to identify digital user interface concepts (Coding Scheme 1; see also Figure 1). The first author and one research assistant then manually coded each statement to create a gold standard set of annotations to assess the accuracy of our custom NER algorithm. Coding discrepancies were settled based on unanimous agreement.

Identifying Digital User Interfaces and Interface Classes. Second, using the manually annotated statements (N = 3,017), a custom named entity recognition (NER) model was trained in spaCy, an open-source python module. Performance metrics were calculated using 20% of the sample against the manually annotated, gold standard annotations in Prodigy (version 1.11.6), an annotation program. While precision reflects the number of tagged components accurately identified by our algorithm, recall reflects the ability of the algorithm to effectively capture all the relevant components present within the transcripts themselves. The F-score metric, which reflects the algorithm's performance more globally, is a combination of precision and recall metrics (see Manning & Schutze, 1999). Accuracy metrics indicated sufficient performance for each category: features (P = 90.12, R = 81.11, F_{Score} = 85.35), platforms (P = 98.35, R = 95.21, F_{Score} = 96.76), and generalized media concepts (P = 91.54, R = 95.20, F_{Score} = 93.33).

Next, using spaCy's English parts-of-speech model, I thematically reviewed noun phrases including HCMC concepts to derive a generalizable set of user interface categories in line with the concept of social media elements (e.g., chats, profiles; Bayer et al., 2020) to address RQ1.

Particularly, I identified different user interface classes based on if a concept or set of concepts represented a distinct type of user interface (i.e., had a common set of features and affordances, existed across multiple platforms; Coding Scheme 2). User interface class categories were determined by the authors based on background knowledge and their interpretation of context provided by participants. For the top 25 terms for HCMC concepts and noun phrases see Figures 2 and 3.

Figure 2. Named Entity Recognition Tagged HCMC Concepts Identified in Participant Statements ($N = 1,991$)

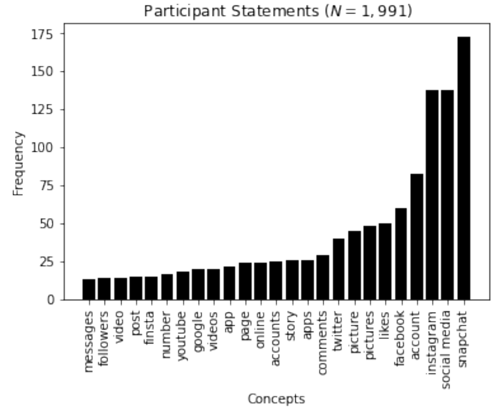
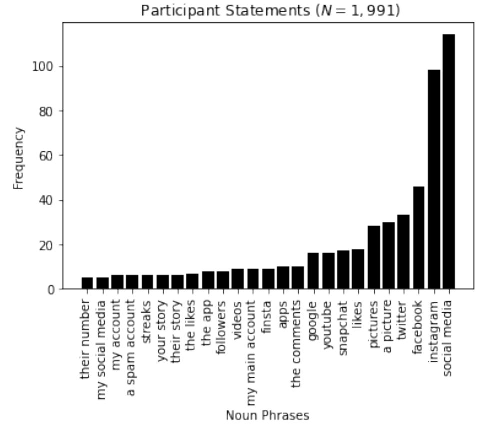


Figure 3. Named Entity Recognition Tagged HCMC Noun Phrases Identified in Participant Statements ($N = 1,991$)



Calculating Concept Contingencies

Lastly, user interface class and platform concepts were manually coded by the first author and one research assistant on a statement-by-statement basis as either present or absent to create a contingency matrix (see Osgood, 2009). Coders relied on the presence or absence of references to each concept across nouns and referential noun phrases (e.g., it, the app). Coding in this way afforded a standardized procedure, whereas using available automated tools would have necessitated additional finetuning.[2] Noun phrases operated as coding units and coding relied on a mutual interpretation between coders, given the diversity of the underlying sample and conversational format of the interviews. User interface class concepts were coded according to

[2] While language models to automatically resolve co-references exist (e.g., spanBert using Allennlp in Python), such software is not always accurate. The study opted for human coding as it yielded results exhibiting a higher degree of accuracy (e.g., face validity).

the categories of user interface classes identified (see RQ1 in Results). For example, based on language conventions used by participants, terms like “post”, “pictures”, “videos” were mapped onto posts as a user interface class. Similarly, “my account”, “profile”, and “finsta” were mapped onto profiles as a user interface class. Content feeds (e.g., trending) that mapped onto discernible in-app pages (e.g., Search Tab on Twitter) were coded according to their corresponding user interface class (e.g., search page). References to in-app pages (e.g., Explore page on Instagram) were coded based on their corresponding features to the most representative user interface class (e.g., search page). Platform concepts were limited to the four focal platforms of interest: Twitter, Facebook, Snapchat, and Instagram.

All interviewer statements (n = 1,374) were screened out to better address our proposed objectives. This yielded a final sample of participant statements for further analysis (n = 1,991). The contingency matrix served as the basis for our second primary analyses and reflected the degree to which participants psychologically associated concepts (Osgood, 2009).[3]

Correspondence Analysis

Correspondence analysis (CA) assesses how nominal variables interrelate to provide a means to investigate the similarity of concepts by plotting them in a low-dimensional Euclidean space (e.g., 3D, see Figure 4). Platform concepts’ proximity to user interface class concepts suggest, but do not directly indicate, that they frequently occur together within participants’ statements. Squared cosine values indicate the importance of a particular dimension for a given observation (i.e., concept), similar to factor loading. Variance contributions provide an indication of how observations contributed to the dimensions themselves (i.e., percent of variance a user

[3] The data underlying this article will be made available on request.

interface class accounted for). I reduced the contingency matrix to a cross-tabulated frequency table between the two nominal categories of interest (i.e., platforms, user interface classes) and used the "FactoMineR" library in R (version 2.4) for our CA analysis.

Map Analysis and Network Construction using Concept Contingency Probabilities

Map analysis complements CA by providing a means to both quantitatively and qualitatively explore how participants schematically interrelate platform and user interface class concepts via the application of network analysis and the generation of graph visualizations (Carley, 1993). Map analysis visualizes how youth associate certain platform concepts psychologically. CA assesses whether platform concepts are similar based on their association with user interface concepts.

Networks represent a collection of nodes and their relationships, or ties. Our network mapped an adjacency matrix of platform and user interface concepts. Node size is reflective of concept frequency or prominence. Concept contingency probabilities were calculated using our contingency matrix (see Osgood, 2009). Obtained contingencies reflected, $P(Concept_{AB})$, and the expected contingencies, $P(Concept_{A})\ x\ P(Concept_{B})$. Obtained contingency probabilities between concepts greater than their corresponding expected contingencies were included as ties in our network; thicker ties imply a stronger cognitive association between concepts, whereas a lack of connection between concepts implies non-association based on the rate of co-occurrence within statements. Network visualizations and metrics were produced using Gephi (Bastian, Heymann, & Jacomy, 2009).

Results

RQ1 asked what user interface classes contextualize participants' understanding of their PSMEs. Several user interface classes were identified based on our second coding scheme. These included Chats, Home Pages, Profiles, Search Pages, Posts, Group Pages, Comments/Comments Sections, Location Pages, and Stories. Each of these user interface classes represent navigable and generalized digital space across multiple social media platforms. Chats and Profiles directly mapped onto previously identified social media element categories (Bayer et al., 2020). Posts encapsulate a class of persistent, mediated interfaces embedded in users' home pages and profiles. Stories are a multi-media, ephemeral mediated interface, visible for only a set period. Home Pages index mediated pages where users access content from their social network, among other content streams, typically situated as the root page of a platform. Group Pages represent a type of mediated interface (public or exclusive) that allows users to network with select audiences for distinct purposes, often managed by a set of administrative users (Facebook, 2021). Search Pages represent a type of mediated interface that functions as a space for users to search/explore content, often including content external to users' social networks. Comments and Comment Sections encapsulated segmented mediated interfaces that allow for public replies to a published piece of content, customarily on user posts. Lastly, Location Pages reflected mediated interfaces that aggregate user content to offline geographical locations (e.g., Snap Maps).

RQ2 asked about the popular social media platforms that participants associate with certain user interface classes. To address this, two complementary modes of analysis (i.e., correspondence analysis, map analysis) and a chi-squared test were used to assess their interdependence. When assessing the interrelationship using the frequency table, the expected and observed frequency distributions of user interface classes and platforms within statements significantly differed from chance ($\chi^2 = 121.3$, $p < .001$).[4] This implies a meaningful pattern of associations between platform and digital user interface concepts.

[4] *p*-value is based on a Monte Carlo simulated estimate using 2,000 replicates.

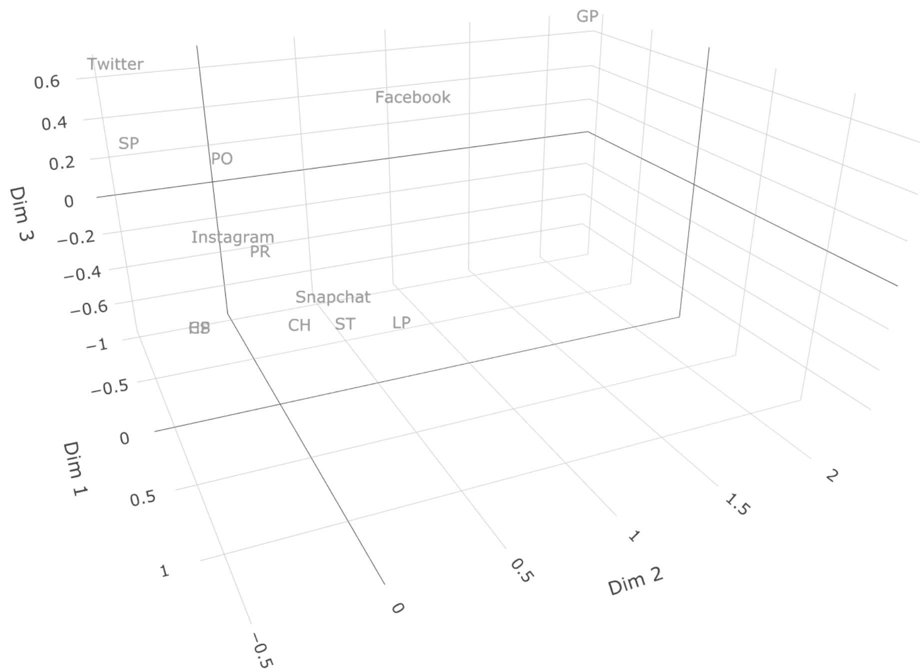


Figure 4. Correspondence Analysis: 3D Plot *Notes.* User interface concept labels were abbreviated to increase the graph's readability: Post (PO), profile (PR), search pages (SP), chats (CH), stories (ST), group pages (GP), home pages (HP), and comment sections (CS). I used the R package "plotly" (version 4.10.0) to create the 3d representation using concept coordinates from our correspondence analysis. Platform concepts closer in proximity maintain a more similar compositional profile across the user interface class concepts. Proximity between user interface class concepts and platform concepts imply, but does not indicate, that they often occurred together across our observations. The model was based on an adjacency matrix derived from platform and user interface concept co-occurrences rates across all participant statements (N = 1,991).

The first two dimensions of our CA accounted for 88.9% of the variance between concept categories; approximately, 72.8% for Dimension 1 and 16.1% for Dimension 2. Figure 4 plots specific platforms as a function of their association with the identified user interface classes, wherein platform proximity indicates a higher degree of similarity in platforms' pattern of association with certain user interface class categories. The squared cosine of Instagram (.81) and Snapchat (.99) was highest on Dimension 1. Stories (40.70%) and Location Pages (26.56%) accounted for the most variance for Dimension 1, suggesting that they explained the closer proximity between Snapchat and Instagram. The squared cosine values indicated that Facebook loaded primarily on Dimension 2 (.61), with Group Pages accounting for the most variance across Dimension 2 (75.35%). In contrast, squared cosine values indicated that Twitter loaded across the three dimensions (Dimension 1 [.34], Dimension 2 [.21]), with the highest loading on Dimension 3 (.43). Variance contributions of Posts (20.58%), Home Pages (8.01%), Comment Sections (8.01%), and Profiles (30.42%) were highest on Dimension 3. In addition, Search Pages contributed equally to Dimension 2 (19.66%) and Dimension 3 (19.98%). Together, this suggests that Posts and Profiles seemed to account for the Instagram's similarity to Twitter, with Search Pages accounting for Twitter's similarity with Facebook. Chats contributed marginally to each of the three dimensions (< 3.5%).

Table 1

Map Analysis: Network Metrics

Concept	Frequency	Degree	Weighted Degree	Eigencentrality
Snapchat	180	8	.069	.772
Instagram	164	11	.091	1.0
Profiles	148	9	.061	.904
Posts	144	9	.051	.853
Facebook	65	6	.021	.673
Twitter	47	6	.012	.717
Stories	45	6	.027	.689
Chats	15	4	.006	.483
Location Pages	13	1	.006	.113
Comment Sections	10	3	.004	.402
Search Pages	9	6	.011	.719
Home Pages	5	2	.003	.270
Group Pages	3	3	.003	.375

Notes. Degree represents the number of edges a concept has in our network. Weighted degree is a normalized measure of degree. Eigencentrality reflects the prominence of a concept in our network, with higher values indexing greater prominence as a function of the number of connections a node has, in addition to the connections of the nodes immediately connected to it in the network. Frequency indexes how many times a concept occurred across adolescents' statements (N = 1,991).

The map analysis offers a complementary pattern of results (see Figure 5). The observed contingencies between Snapchat and Instagram (.03, co-occurring across 3% of statements) were larger than with any other platform (< 1% of statements), implicating that participants associated the two platforms with one another (more so than any other platform examined). Snapchat and Instagram also maintained higher observed contingencies with Profiles than Twitter and Facebook. This affirms the proximity between Snapchat and Instagram illustrated by our CA, suggesting that these two platforms are conceptually similar among our participants. The platforms' associative relationships with the identified user interface concepts evidence that the similarity between Snapchat and Instagram is likely the result of participants' cognitively associating the platforms with Chats, Search Pages, and Stories. There was a lack of association between Instagram and Location Pages; Twitter and Chats; and Snapchat and other user interface concepts, like Home Pages and Comments Sections. This indicates that participants largely did not associate these user interface classes with the specified platforms. Search Pages associated with all four platforms. Lastly, the relationships between Twitter and Instagram appear to relate as a function of individuals' cognitively associating the platforms with Posts, Search Pages, and Profiles, rather than Home Pages and Comment Sections. The latter two only related with Instagram. Interestingly, Posts and Profiles maintained the highest association (observed contingency = .02, co-occurring across 2% of statements) than any other pairing of user interface class (< 1% of statements). Posts and Profiles were also among the most frequently mentioned. Graph density was .47, suggesting that platform and user interface concepts were moderately interconnected. Network metrics are included in Table 1.

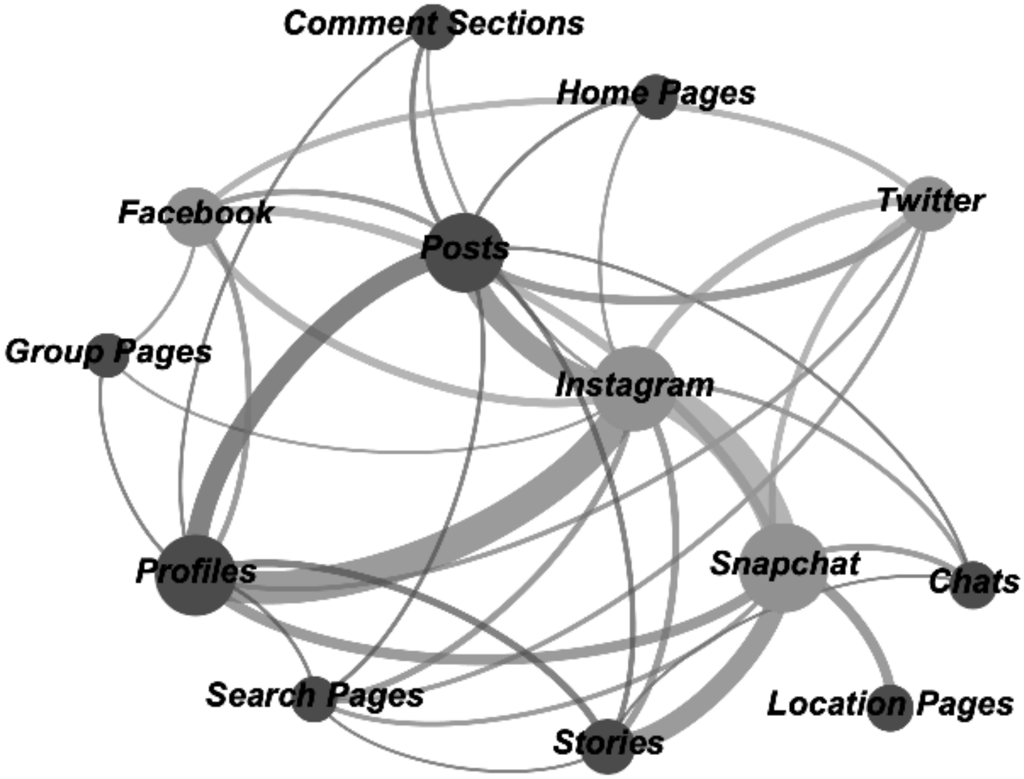


Figure 5. A Generalized Cognitive Representation of Adolescents' Mental Model of their Personal Social Media Environments. *Notes.* Node size is scaled to concept frequency. Tie width reflects the observed contingencies between concepts; wider ties reflect a higher degree of cognitive association (see Osgood, 2009). Representative of only participant statements (N = 1,991).

Discussion

Building from the concept of social media elements and the PSMEF, the present study sought to identify distinct types of user interface classes—user interfaces with a commonly understood set of features and affordances—that underpin experiences over social media platforms over time. Extending the initial explication of the PSMEF (see Chapter 1), our data illustrated additional, generalized types of user interfaces that represent salient aspects of youths' PSMEs. These included Posts, Stories, Home Pages, Search Pages, Group Pages, Location Pages, and Comments/Comments Sections. These user interface classes provide insights for systematically probing how social media use patterns and effects vary and/or converge across distinct, yet generalized types of mediated environments. For example, characterizing effects across Twitter's Search Tab and Instagram's Explore Tab would help to extrapolate how engagement on Search Pages generally impact users. Using common social media elements as a unit of analysis would streamline statistical techniques like meta-analysis (Bayer et al., 2020).

Interestingly, our data also showed that youth associated particular social media platforms with a distinct constellation of user interface classes. Some platforms related more closely with one another based on their inclusion of specific types of user interfaces, whereas others remained more distinct. For example, Instagram and Twitter, and Instagram and Snapchat, shared the most similar compositional profile across the user interface classes. Facebook was seemingly the most different. This would imply that it is possible to characterize particular platforms based on different user interface classes. Lastly, youth more strongly associated Profiles and Posts with Instagram, Location Pages and Stories with Snapchat, and Group Pages with Facebook. Thus, while some user interface classes represent more common spaces across platforms (e.g., Posts, Profiles, Chats), some appeared more specific to particular platforms (e.g., Location Pages, Group Pages).

Modeling PSMEs: Advancing the Study of Social Media

Self-Report Measures: Targeting PSMEF Constructs. Pragmatically, these findings carry important implications for the study of social media. For instance, while it is common for studies to focus on prominent platforms (Cingel et al., 2022), our data and the PMSEF indicate that more assessment within these platforms is needed. In particular, measures of social media use should map to Posts and Stories as distinct types of content streams. Moreover, self-report measures seeking to understand psychological or behavioral correlates associated with types of content streams should formulate items based on how users access them. Considering user interface classes as nested and internetworked structures would allow researchers to assess effects at different levels of abstraction (e.g., Stories vs. Posts; Home Pages vs. Search Pages). Exploring passive use (e.g., browsing), or other behavioral dimensions (Kaye, 2021), at this level could produce new insights by enabling researchers to extrapolate results to different PSMEF constructs, including certain user interface classes and other social media elements. Potential comparison points include TikTok's Following Page and Instagram's Home Tab; both provide users with access to in-network Stories and Posts. Snapchat's Stories Tab also provides an additional point of comparison for Stories (e.g., in-network content stream of stories).

Leveraging Language Models to Evaluate Social Media at Scale. Our results also provide a path to investigate social media at scale by modeling language. For example, people associate things closer in space and time more closely psychologically (Fiedler et al., 2012), which would account for the pattern of cognitive associations made by participants exhibited within our map analysis. For example, findings from large-scale behavioral analyses show that users more frequently switch between similar (e.g., browsing photos, looking at photo comments) compared to distal types of social media activities (e.g., visiting user settings, browsing photos; Benevenuto et al., 2012). Similarly, our data evidenced that users psychologically associate user interface classes (e.g., Posts, Comments/Comment Sections) that facilitate related social media activities (e.g., browsing photos in posts, looking at post comments). As such, individuals may be more likely to transition between specific user interface classes, like Comments/Comment Sections, when they are engaging with Posts. When considered in joint, it may be possible to more quickly assess aspects of platform structure and general social media use trends through open-ended user reports than through close-ended self-reports. Direct verification is needed to validate the degree to which platform navigation and psychological distance associate to inform on use trends across user interface classes, however.

Contextualizing Person-Specific Effects. The uses of multiple levels of analysis when operationalizing social media measures can also help advance a more fundamental theoretical understanding of social media (Meier & Reinecke, 2021), including person-specific effects (e.g., Beyens et al., 2020; Valkenburg et al., 2021). For example, researchers can pair methods used to assess person-specific effects (e.g., experience sampling) with additional measures that tap into the composition of participants' PSMEs. In this way, researchers could compare the PMSEs of individuals who experience no effect of social media use on self-esteem (Valkenburg et al., 2021) with users who report experiencing positive or negative effects. By combining these two approaches, researchers could gain a better understanding of why and how social media use may contribute to user mental health and well-being, among other outcomes.

Limitations and Future Directions

Conclusions made by our analysis remain limited to the nature of our sample and methodology. First, the present study does not represent an exhaustive listing of user interface classes or platforms. Second, the user interface class categories need additional empirical verification. When addressing this in future research, TikTok warrants special attention given the TikTok For You Page, which presents users with an individually curated algorithmic content stream of short videos. This feature has been widely replicated by other platforms (e.g., Instagram's Reels Tab, Spotlights Tab on Snapchat, and Shorts Tab on YouTube), suggesting the emergence of a new user interface class. Third, our results can only speak to the aspects of social media salient to our participants, which only captures part of their social media experiences (Bayer et al., 2020). Thus, while the use of focus groups helped to facilitate a more comprehensive assessment of environmental components, this method relies on participant recall and their understanding of social media (Rauthmann & Sherman, 2020). Lastly, the replicability of our analysis will vary as a function of trends in social media use across time (see Nesi et al., 2018), changes to platforms, and by user demographics. Future work is needed among larger and more diverse samples to more objectively capture the interrelationships between user interface class concepts and platforms.

Conclusion

Over the last two decades the rapid maturation of commercial social media platforms has cultivated a great deal of attention towards understanding how to study social media effects. While the future evolution of social media systems serves to further compound social media's complexity, researchers' capacity to generate formative insights regarding social media use will hinge on whether existing communication theory is fit to help accommodate the generalizability of research across such transitions. In helping to structure the study of social media in terms of generalized classes of mediated environments, the PSMEF will aid researchers in conceptually navigating broader changes across social media as a contemporary landscape with the aim of advancing scientific understanding that can help benefit the public at large.

Chapter 3: A Replication and Extension of the Personal Social Media Ecosystem Framework

The question of for whom, under what conditions, and by what means social media comes to impact focal outcomes of interest, like mental health, has remained difficult to fully address. In part, this is due to the rapid maturation and diversification of social media platforms as a type of communication technology (boyd, 2015; Bayer et al., 2020). In response to changes seen across the commercial social media landscape, researchers have broadened their methodological approaches and theorizing to accommodate the increasingly dynamic, multiplatform social media reality experienced by users to assess social media use correlates. This includes transitions from single (e.g., Facebook) to multiplatform studies (e.g., Beyens et al., 2020), in addition to an emphasis on studying more contextually transcendent constructs (e.g., affordances) over platform features within the context of social media—particularly, as individual features differ widely across platforms as distinct technologies and themselves change over time (Ellison & boyd, 2013; Evans et al., 2017; Bayer et al., 2020).

In line with these efforts to increase the generalizability of evidenced effects, recently introduced conceptualizations of social media have helped to advance novel ways of approaching the study of social media design and their corresponding effects. This includes theoretical frameworks, like the Personal Social Media Ecosystem Framework (PSMEF; Carter, Cingel, Ruiz, & Wartella, in revision) and the concept of social media elements (Bayer et al., 2020),[5] which outline innovative ways to conceptualize, and thus operationally define, social media constructs to increase the generalizability of evidenced social media effects over time. For example, the PSMEF proposes that evidencing effects across certain user interface classes—that

[5] A *social media element* represents a common set of transcendent technological components that exist across multiple communication channels over social media (e.g., profiles, content streams; Bayer et al., 2020).

is, different instantiations of user interfaces with similar underlying features and affordances—can help increase the generalizability of evidenced effects (Carter et al., in revision). This is because mapping effects in this way will facilitate the computation of aggregated and comparative effect sizes by helping to pair effects across the various environmental contexts over social media wherein people navigate to (e.g., Home Tab on Instagram, Newsfeed on Facebook) and engage over time (e.g., Home Pages; Bayer et al., 2020; Carter et al., in revision).

Despite these conceptual advancements, few studies investigating social media leverage the PSMEF due to its recent introduction. One used an early iteration of the framework to organize a thematic review of the literature on social media use and adolescents' mental health (Cingel et al., 2022). Another study leveraged the PSMEF to explore the salient aspects of youths' personal social media environments (see Chapter 2; Carter et al., in revision) and evidenced that adolescents psychologically associated certain classes of user interfaces (i.e., Profiles, Posts, Chats/Messages, Stories, Location Pages) differentially with particular popular platforms (i.e., Instagram, Snapchat, Facebook, Twitter). This study also identified several salient types of user interfaces classes that functionally characterize adolescents' social media environment, including Profiles, Posts, Chats/Messages, Stories, Location Pages, Search Pages, Group Pages, Home Pages, and Comments/Comment Sections (see Chapter 2 for definitions).

While informative in helping to identify generalized technological spaces that underpin users' experiences over social media, previous work leveraging the PSMEF left open a few outstanding questions for future research (i.e., Carter et al., in revision). Foremost, Study 1 (see Chapter 2) thematically coded transcripts to identify distinct user interface classes, which requires the specification a-priori categories (Doerfel, 1998; Carley, 1993). Thus, while helpful in establishing a preliminary basis for theorizing, the use of a pre-defined set of user interface class categories inherently limited evidencing the validity of user interface classes themselves. After all, explicating a quantitative framework for validating user interface classes represents a central outstanding challenge of the PSMEF (see Limitations outlined in Chapter 1).

Therefore, the present study (i.e., Study 2) maintains two primary objectives. First, it sought to extend previous work on the PSMEF by inductively exploring the types of user interfaces classes that exist over six popular social media brands: Snapchat, Facebook, Twitter, Instagram, YouTube, and TikTok. Second, Study 2 sought to also introduce a new computational approach to study users' social media environments—particularly, a structured form of semantic network analysis, schematic semantic network analysis (SSNA). To do so, open-ended descriptions of interfaces, derived from a sample of college students ($N = 380$, ages 18 to 34), were analyzed to identify distinct user interfaces classes over six popular social media platforms using two complementary methods: SSNA and a popular form of text analysis (i.e., Latent Dirichlet Allocation). After, interfaces were contrasted to explore how they converged or diverged in similarity to form unique user interface classes as a function of their association with the semantic features (e.g., posts, picture, family, search, peers) participants used to describe them. In doing so, this study extended and replicated previous work conceptually and methodologically on the PSMEF (e.g., Chapter 1, Chapter 2 [i.e., Study 1]; Carter et al., in revision). Results provide insight into social media as an increasingly heterogeneous environmental context, outlining how the PSMEF can help researchers operationalize social media constructs in a way that capitalizes on the increasing diversity of the commercial social media landscape. The theoretical and practical implications of SSNA are also discussed in the context of comparable close-ended computational techniques (i.e., Galileo Method; Woelfel & Fink, 1980).

The Personal Social Media Ecosystem Framework

The Personal Social Media Ecosystem Framework (PSMEF) allows researchers to study social media in a way that capitalizes on the diversity of social media systems. To do so, the framework conceptualizes social media in terms of users' personal social media environments (PSMEs) using constructs derived from Ecological Systems Theory (EST), a prominent theory of environmental systems in the context of human development (Bronfenbrenner, 2005). Particularly, following EST's conceptualization of environmental systems as individual-centric set of nested environmental structures, the PSMEF explicated concepts like digital user interface, digital microsystem, digital mesosystem, digital exosystem, and user interface classes (Carter et al., in revision). As a result, the PSMEF both extends on and mirrors EST's initial formulation of its nested human ecology through its adaptation of constructs like an offline setting, microsystem, mesosystem, and exosystem to interactive media environments.

According to the PSMEF, at a broad level, social media is an expansive digital landscape made up of the various mediated spaces that serve to underwrite users' experiences, centered around those that facilitate social interaction (Carter et al., in revision). Often this is conceptualized in terms of channels of communication, platforms, features, or user interfaces (e.g., chat room, Facebook profile; Carr & Hayes, 2015; Meier & Reinecke, 2020). However, to provide a basis for theorizing about social media as an environmental context, the PSMEF conceptualized distinct instantiations of particular user interfaces over a live platform as a primitive environmental unit (i.e., digital user interfaces). Thus, while user interfaces (e.g., Instagram's Profile Interface) operate as a template for certain segments within popular apps, digital user interfaces represent realizations of those interfaces wherein users can navigate (e.g., a given Instagram Profile). Such digital user interfaces remain analogous to the idea of an offline location, but over mediated spaces (Carter et al., in revision). Digital user interfaces in the context of the PSMEF, thus, function as the basis of social media as a contemporary digital landscape.

Building from digital user interfaces, digital user interfaces come together to form a more superordinate sprawl of mediated environments (e.g., the Internet, a platform), with each representing a seemingly unique space from the standpoint of each user. To account for this, the PSMEF proposed that for any given user, each digital user interface reflects a *digital microsystem*, a digital location characterized by the unique roles, norms, and perceived audiences contextualizing that space for them as an individual (Carter et al., in revision).

Personal Social Media Environments (PSMEs). The PSMEF's conceptualization of constructs like digital user interfaces and digital microsystems provides a theoretical basis for defining users' personal social media environments (PSMEs). Particularly, by integrating these concepts, the PSMEF defines *PSMEs* as a user-centric digital environment, centered around a subset of digital microsystems that facilitate social interaction, embedded in one or more live platforms, broader applications (e.g., data pipelines), device(s), and an individual's offline social contexts (see Figure 1 in Chapter 1; Carter et al., in revision). As a result, the PSMEF, in making linkages between interactive media and EST, provided a theoretical foundation for the study of social media as a digital ecology in extension to EST (Bronfenbrenner, 2005).

Social Media Elements and User Interface Classes. Lastly, the PSMEF affords new ways to conceptualize social media in terms of more generalized technological structures, and thus, social media as a dynamic environmental context. The primary way it accomplishes this is by directly mapping the concept of social media elements to users' PSMEs (Carter et al., in revision). Theoretically, all digital user interfaces (e.g., user A's profile on Facebook) and digital microsystems (e.g., user's A's profile on Facebook from the standpoint of a particular observer) represent a derivative of a user interface class (e.g., Profiles as a general type of user interface). User interface classes operate as the primary conceptual basis for the study of social media use correlates over time in the PSMEF (Chapter 1; Carter et al., in revision).

Leveraging Semantic Network Analysis to Quantitatively Model User Interfaces

One way to quantitatively evidence the validity of certain user interface classes categories would be to model users' understanding of the user interfaces they use across their PSMEs. After all, working or conceptual models aid people in understanding computing systems and inherently represent a set of schema and sub-schema—psychological structures detailing objects (e.g., platform features, actions) and how they interrelate (Shehata et al., 2021). Importantly, people rely upon schema to successfully navigate various situational contexts by helping them conceptually model situationally relevant information with a schema's salience and context (Shehata et al., 2021). As people come to understand user interfaces in terms of system objects, their relationships, and potential object operations (i.e., conceptual model; Foley & Van Dam, 1982), interface cues should associate with certain mental heuristics and behavioral representations (e.g., Sundar, 2015). This makes investigating schema across groups of people a seemingly ideal basis to explore user interface class categories. Group-level mental representations afford a more accurate model of the world as it objectively exists (Rauthermann et al., 2020; Woelfel & Fink, 1980) and user interface classes reflect a *commonly understood* set of generalized technological components (Bayer et al., 2020; Carter et al., in revision). How user interface concepts map onto particular social media features and other related concepts as a function of individuals' schematic understanding of their PSME is less clear, however. Nevertheless, the types of user interface classes identified, in addition to their features, should remain consistent with the types of user interface classes evidenced by previous work (e.g., Chapter 2 [i.e., Study 1]; Carter et al., in revision). Therefore, I propose and ask the following:

H1: User interfaces across each of the six social media platforms will group together to represent previously identified user interface classes (e.g., Messages/Chats, Home Pages, etc.).

RQ1: What other types of user interface classes exist across Facebook, Instagram, Twitter, Snapchat, and TikTok?

Method

Participants

Participants were recruited to complete an online questionnaire. A total of 380 participants were recruited from an online sample pool of college students and completed the open-ended social media questions. All participants received extra credit in exchange for their participation in the online survey. Seventy-one percent of participants identified as female (n = 270), 25% male (n = 95), 1% non-binary (n = 5), and the remaining other/prefer not to answer (n = 10). Seventy-five percent identified as heterosexual (n = 285), 8% bisexual (n = 31), 5% asexual (n = 18), and 2% lesbian/gay (n = 9); 10% fell outside of these categories or preferred not to answer (n = 22). Participants ranged from ages 18 to 34 (M = 19.41, SD = 2.01). The majority identified as Asian (57%, n = 215), followed by White (22%, n = 85), Hispanic/Latino (17%, n = 64), Black (5%, n = 19), and American Indian or Alaska Native (4%, n = 16).

Procedure

Participants were recruited via an online sample pool of college students. After viewing a set of experimental stimuli and completing a set of dependent variables for a separate study, subjects were asked to report on their use of social media. This included three primary measures (see below). Participants concluded their participation by completing a set of demographic questions and were thanked for their time. The project was approved by the Internal Review Board at the primary investigator's sponsoring institution.

Measures

Platforms Used. Participants were asked to report on the social media platforms they use, spanning a set of popular social media platforms (i.e., Instagram, Facebook, Twitter, Snapchat, YouTube, TikTok, Reddit, Tumblr, WeChat, Messenger, and WhatsApp), in addition to other not listed. Use rate listed by percentage of participants who reported using an app: Instagram (92%), YouTube (84%), Snapchat (69%), Tik Tok (67%), Facebook (53%), Twitter (48%), Messenger (39%), Reddit (25%), WhatsApp (24%), WeChat (20%), Tumblr (6%), and other (3%).

Table 1.

Marginal Frequencies of Top Ranked Platforms by Use Over Last Month

Platform	1st App	2nd App	3rd App	4th App	5th App
Instagram	109	118	70	39	8
YouTube	61	39	65	69	53
Snapchat	39	57	62	38	33
TikTok	100	73	36	22	10
Facebook	1	18	30	39	42
Twitter	7	21	34	36	37
Messenger	1	3	2	5	5
Reddit	4	8	8	15	17
WhatsApp	2	3	12	16	17
WeChat	46	7	4	5	2

Notes. Platforms represented ranked across each of the top five ranks at least one. Ranks were truncated at 5th to illustrate top ranked apps. A chi-squared test of independence on marginal frequencies across the top five ranks indicated that platforms significantly varied in their prominence of use over the last month, χ^2 (435.47), $p < .001$, using 2000 bootstrapped replicates in R via the chisq.test() function.

Rank of Platforms by Use Over Past Month. Participants were asked to rank the platforms they reported using over the last month from most (ranked first) to least (ranked last). Marginal frequencies across the first five ranks are listed in Table 1: Instagram ($\bar{x}_{Rank}$= 2.27, median = 2), Tik Tok ($\bar{x}_{Rank}$= 2.27, median = 2), Snapchat ($\bar{x}_{Rank}$= 3.36, median = 3), YouTube ($\bar{x}_{Rank}$= 3.45, median = 3), Twitter ($\bar{x}_{Rank}$= 4.39, median = 4), Facebook ($\bar{x}_{Rank}$= 4.84, median = 5), Messenger ($\bar{x}_{Rank}$= 5.38, median = 5), Reddit ($\bar{x}_{Rank}$= 5.27, median = 5), WhatsApp ($\bar{x}_{Rank}$= 5.54, median = 5), WeChat ($\bar{x}_{Rank}$= 2.71, median = 1), Tumblr ($\bar{x}_{Rank}$= 6.29, median = 6), and other ($\bar{x}_{Rank}$= 3.18, median = 3).

Pages/Sections Used by Platform. Lastly, participants completed an open-ended question asking them to detail the social media pages/sections they typically navigate to over each social media app they reported using. For each, they were also prompted to detail in a short paragraph its attributes and features, who they encounter while in the space (e.g., strangers, celebrities, acquaintances, friends, family), and what generally occurs on the platform while they are using it. Subjects were also asked to demarcate each page/section from its corresponding description using syntax (e.g., colon) to facilitate coding by clearly outlining what respondents conceptualized as distinct navigable segments of the platforms themselves (see below).

> *Please list the in-app pages or sections you typically navigate to over the [PLATFROM NAME] app. For each page/section, describe its attributes, features, and characteristics. In addition, please describe who you typically interact with and/or encounter in the page/section (e.g., close friends, family members, peers, acquaintances, strangers, influencers, celebrities, news outlets), how you interact in the space, and what generally happens there based on your experience. Please format your response by listing information about each page or section in the form of a short paragraph (illustrated below).*
>
> **Page/Section Name:** Description……………………………………………… ………………………………………………………………………………………… ………………………………………………………………………………………… …………… etc.

Open ended responses for each social media brand were screened to identify entries designating a particular in-app user interface using syntax as indicated in the question's prompt for further analysis. Multiple entries were screened out (Instagram, n = 145; TikTok, n = 117; Snapchat, n = 134; Facebook, n = 105; YouTube, n = 146; Twitter, n = 84) due to participants' failure to provide a clear label for a section/page description or description itself for a reported section/page. This yielded a final set of participants for analysis with at least one self-reported entry: Instagram (N = 202), Facebook (N = 97), Snapchat (N = 125), Twitter (N = 94), Tik Tok (N = 132), and YouTube (N = 165).

Identifying and Coding User Interface Classes

Each page/section entry provided by participants and its corresponding description were screened and subsequently coded for the top used platforms in the sample: Instagram (N = 474), Facebook (N = 162), Snapchat (N = 286), Twitter (N = 154), and Tik Tok (N = 248), and YouTube (N = 287). Reference frames used by subjects to demarcate different pages/sections comprising each platform spanned digital user interfaces (e.g., particular Facebook group page), primary pages (e.g., home page) listed within platforms' navigation menus (e.g., navigation bar), content streams (e.g., my feed on Instagram, For You Page on TikTok, Trending on Twitter), and individual content structures (e.g., videos). While each could operate as a unit of analysis to derive thematic categories for distinct feature classes (e.g., user interfaces, content streams), user interfaces partially internetworked into fixed aspects of platform systems' navigational structure, like a navigation bar or menu, provided a seemingly ideal point of reference to derive distinct user interface classes from. This is because menus operate as a primary organizing structure across platforms (Shneiderman et al., 2018).

The first author and another co-author reviewed each page/section description to derive a set of thematic categories reflective of prominent user interfaces over each platform for coding. User interfaces tended to map onto most of the primary navigation icons listed in across each platform's navigational bar (e.g., *Direct Messages* on Instagram, *Home* on TikTok). For a listing of each user interface category by platform, see Table 2. A subset of page/section entries (approx. 20%) were selected at random to assess intercoder reliability for each platform across the identified user interfaces categories. Krippendorff's alpha indicated a high degree of intercoder reliability across each platform: Instagram ($\alpha = .958$), Snapchat ($\alpha = .974$), TikTok ($\alpha = .967$), YouTube ($\alpha = .975$), Twitter ($\alpha = .949$), and Facebook ($\alpha = .917$). Remaining entries were split and coded independently. For frequency distributions across individual user interfaces, see Figure 1. Categorizations produced for the reliability set were resolved for analysis by randomly selecting code values across the two coders.

Table 2.

User Interfaces by Platform

Platform	User Interfaces
Instagram	Home, Explore, Create, Activity, Profile, Direct Messages, Reels, Shop, Other
YouTube	Home, Search, Library, Explore, Comment Sections, Subscriptions, Shorts, Create, Other
Snapchat	Chat, Camera, Stories Page, Spotlight, Memories, Snap Maps, Other
Tik Tok	Home, Discover, Record, Inbox, Profile
Facebook	Home, Watch, Profile, Notifications, Menu, Messenger, Search, Groups, Marketplace, Reels, Dating, Other
Twitter	Profile, Search, Home, Notifications, Messages, Spaces, Other

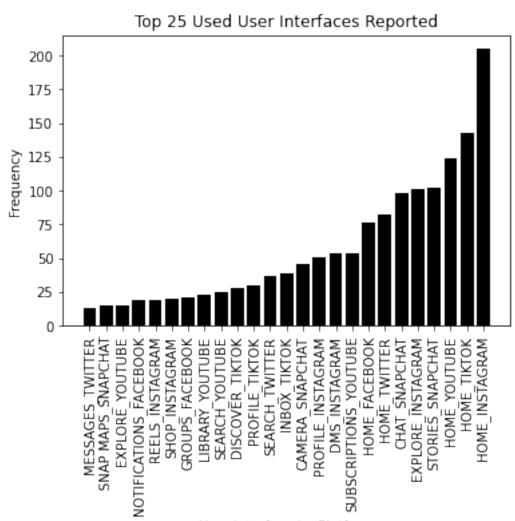


Figure 1. Top 25 Primary User Interfaces Reported. *Notes.* Individual user interfaces were aggregated to primary navigational tabs for each platform.

Plan for Analysis

As results can vary by methods and data processing decisions, it is important to validate findings using multiple approaches (Grimmer, Roberts, & Stewart, 2022). To do so, I employed two complementary forms of text analysis to demonstrate the robustness of our results: Latent Dirichlet Allocation (LDA) and Schematic Semantic Network Analysis (SSNA). Taken together, LDA provides a means to evidence initial user interface classes represented across participant descriptions using probabilistic modeling techniques. In contrast, SSNA provides a means to explore, in more nuanced detail, user interface classes and their corresponding attributes via network analysis.

Latent Dirichlet Allocation. LDA, as a popular method to extract latent structures (i.e., topics) from text data (Grimmer et al., 2022), inductively models distributions of topics across units of text (e.g., descriptions) and can simultaneously model topics as a probabilistic distribution of words (Blei, 2012). Topics are selected based on a multinomial language model estimated by word frequencies across text units as a function of word co-occurrences (Grimmer et al., 2022); words with high levels of co-occurrence across user interface descriptions should more likely map onto the same topic. LDA, thus, provides a means to evidence user interface classes and their key attributes by modeling latent structures from open-ended descriptions.

Schematic Semantic Network Analysis. In addition, the present study introduced SSNA as a mixed methods approach to both classify and probe user interfaces, in addition to user interface class attributes. Based on the Galileo Method, which takes a matrix of pairwise similarity ratings between a set of concepts to compute concept similarity (Woelfel & Fink, 1980), SSNA uses semantic features derived from text descriptions as a general psychological subspace for the target population to model similarities between mental constructs (e.g., a person's conception of their Home Tab on Instagram). This takes the form of an adjacency matrix, c x f, wherein a primary concept, c_i, is defined by a vector, $\vec{c_i}$, derived from semantic features present across its corresponding descriptions. Each feature represents a single dimension of a broader mental subspace that is reflective of a schematic manifold, $\mathbb{R}^f$, and can classify primary concepts as more or less similar as a function of their associative relationships among some set of semantic features, $f_{i \ldots n}$. In this way, SSNA is consistent with cognitive schema theory such that it defines mental constructs hierarchically as a function of their association with subordinate concepts (Shehata et al., 2021). As a user interface is represented as a set of semantic vectors (i.e., $\vec{c_i}$) across $\mathbb{R}^f$, a user interface class (UIC), UIC_i, can be defined as a set of user interfaces (UI), UI_{ij}, with more intra-group connections to a set of semantic features (i.e., edges), $f_{i \ldots n}$, than some other subset of UI.

LDA: Topic Model. The number of topics (*k*) for LDA is specified a-priori and can lead to more or less meaningful representations at varying levels of *k*. Topic coherence—a measure of a topic's semantic interpretability (Srinivasa-Desikan, 2018)—was used to determine *k* for our final model; higher topic coherence values equate to more meaningful topics. Descriptions were pre-processed (i.e., removed stop words and punctuation, lowercased entries) and lemmatized given the size of our corpus (Grimmer et al., 2022) using spaCy, an open-source natural language processing pipeline in python.

SSNA: Network Construction, Analysis, and Visualization. Two networks were constructed using SSNA. The first allowed for the verification of UICs determined by our topic model. Parts of speech labels were appended to each lemmatized semantic feature to account for homonyms (e.g., post|VERB, post|NOUN) using spaCy to further contextualize UIC attributes. To increase the accuracy of the SSNA representation, semantic features with frequencies below the mean were dropped. This allowed us to model predominant semantic structures across our sampled population, one more reflective of shared meaning structures (e.g., culturally endowed concepts). The resulting graph provides a group-level representation (Woelfel & Fink, 1980). This yielded a set of 283 semantic features for the first SSNA network. In our second network, topics generated from our LDA model were used to inform on UIs to aggregate and further probe the semantic attributes of our identified UICs (n = 242, semantic features). User interfaces falling within each of the clustered groupings yielded by our first SSNA network were collapsed into a single node in our second SSNA network. The latter SSNA network allowed for the exploration of UIC attributes. User interface categories categorized as "other" were dropped from the visualization and analysis of both SSNA networks.

Network analysis methods, like clustering and community detection, can also be applied in SSNA to identify groups of primary concepts, including UICs and their attributes, based on the primary concepts' degree of intra-group connections with particular semantic features. To do so, modularity analysis using the Louvain method, a community detection algorithm was leveraged; nodes that cluster together maintain more intra-group associations than nodes external to the clustered group (Blondel et al., 2008).

Multiple indicators exist to inform on a node's position in the network. Centrality denotes the importance, prominence, or power of a concept in a network or how central a concept is within a body of text (Barnett et al., 2010). In line with graph theory, various centrality measures function to calculate the importance of any given network node (e.g., primary semantic concept) based on its connections to other nodes (e.g., descriptive semantic features). For example, the simplest form of centrality, degree centrality, indexes the number of links for each node. Eigenvector centrality was selected as it is a generalized form of degree that includes a node's extended connections (i.e., edges of the nodes its connected with) to calculate node prominence (Bonacich, 1987). Prominent user interfaces falling with certain modalities or groupings, indexed by higher eigenvector centrality values, should denoted a potential type of user interface class that functionally demarcates users' understanding of social media based on their PSMEs. This is because eigenvector centrality can identify concepts with influence more globally over the whole network as opposed to only nodes directly linked to the focal node; it is a scaled value expressed as a percentage and is often used to identify important thematic concepts in text data (e.g., Ruiz & Barnett, 2015). UIs with high eigenvector centrality scores across each cluster should maintain the same qualitative attributes of groupings seen by the LDA model.

Network visualizations and metrics were produced using Gephi (Bastian, Heymann, & Jacomy, 2009). Nodes are colored by modularity class, with the same color among UIs denoting stronger intragroup connections across the same-colored semantic features. Tie width is reflective of concept co-occurrence such that wider lines denote higher rates of co-occurrence across individual page/section descriptions.

Results

H1 predicted that user interfaces across each of the six social media platforms would cluster together to represent previously identified user interface classes (e.g., Messages/Chats, Home Pages, etc.) and RQ1 asked what other types of user interface classes exist across Facebook, Instagram, Twitter, Snapchat, YouTube, and Tik Tok more generally. To initially assess H1 and RQ1, I first ran several topic models to determine the number of topics most suitable for our data. Topic coherence scores peaked at three topics (see Figure 2) and then subsequently diminished in value. Thus, three topics were used to estimate our LDA model. See Table 3 for top words by topic. Topics 1 and 2 mapped onto Chats/Messages and Home Pages as previous identified UICs, supporting H1. Topic 3 appeared to map onto in-app pages indexing overly algorithmic content (e.g., recommended videos), suggesting the emergence of a distinct, yet previously unidentified UIC. I will refer to this grouping as Overt Algorithmic Content Pages (OACP).[6]

Table 3.

User Interface Class Topics

Topic #	**Top Words by Topic (ordered by probability)**	**Topic Label**
1	Friends, use, people, send, tweets, content, page, close, usually, interact	Chats/Messages
2	Posts, people, friends, follow, stories, post, like, page, look, interact	Home Pages
3	Videos, watch, page, people, like, usually, shows, recommend, subscribe, based	Overly Algorithmic Content Pages

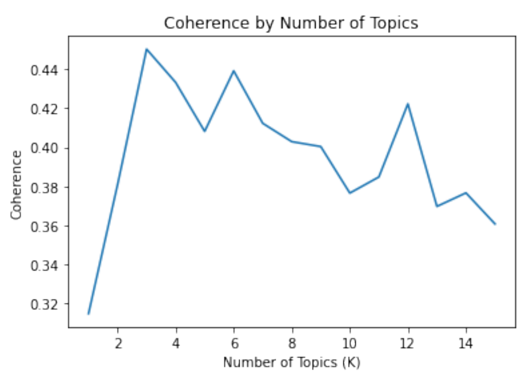


Figure 2. Topic Coherence by Topic Number.

[6] The nomothetic label denotes the overt nature of algorithms across the UIs represented in this grouping (see SSNA results and LDA key terms). Thus, while algorithmic curated content is widespread across different UICs, users index recommendation algorithms as a primary characteristic of OACPs.

To further validate, H1 and RQ1, modularity was applied to our first SSNA network multiple times to assess the consistency of modularity groupings. This yielded four primary clusters 90% of the time, indicating a consistent solution. For a listing of all user interfaces by their modality class, see Table 3. Cluster 1 encompassed 28.98% of the semantic concepts across the network and mapped onto Topic 3 (i.e., OACPs). User interfaces in this cluster included Home on Tik Tok, Home on YouTube, Reels on Instagram, Shorts on YouTube, and Spotlight on Snapchat; each contain a tailored algorithmic content stream of videos. Cluster 2 spanned 27.21% of the semantic concepts across the network and mapped onto Topic 2 (i.e., Home Pages). This included Home on Instagram, Stories on Snapchat, and Home on Facebook—user interfaces prototypical to home pages. Cluster 3 spanned 21.20% of the semantic concepts across the network, indexing Search Pages as a user interface class grouping; it included Explore on Instagram, Search on Twitter, Discover on Tik Tok, Search on YouTube, and Search on Facebook. Cluster 4 spanned 18.73% of the semantic concepts across the network, with the user interfaces representative of Chats/Messages characterizing it as a grouping (i.e., Topic 1). This cluster included Chat on Snapchat, Direct Messages (DMS) on Instagram, Inbox on Tik Tok, Messenger on Facebook, Messages on Twitter. The groupings of the aforementioned UIs mapped onto the same groupings between 60%-100% of the time across modularity iterations: Cluster 1 (100%), Cluster 2 (60%), Cluster 3 (60%), and Cluster 4 (100%).[7] In all, our SSNA analysis also supported H1 and evidenced four stable classes of user interfaces (RQ1).

Lastly, to explore the types of features/attributes characterize prominent user interface classes among participants' PSMEs, I took two additional steps. First, our initial LDA model illustrated key attributes of three UICs (see Table 3). To further validate and contextualize UIC attributes,

[7] Minor deviations typically resulted from one of the user interfaces loading on a different cluster across iterations.

the identified, predominant groupings of UI concepts for each cluster (see bolded user interfaces in Table 4) were collapsed into single nodes to investigate their common features as a type of UICs in a separate SSNA network based on our LDA topics. The cluster analysis across the secondary SSNA network (see Figure 3) resulted in four primary clusters of semantic features for each user interface class concept.

Table 4.

User Interfaces by Cluster

Platform (UIC)	User Interface (Platform, Eigenvector Centrality)
Cluster 1	**Home** (TikTok, .89), **Home** (YouTube, .84), Subscriptions (YouTube, .54), **Reels** (Instagram, .49), Library (YouTube, .42), Profile (TikTok, .38), Explore (YouTube, .37), **Shorts** (YouTube, .29), Record (TikTok, .18), **Spotlight** (Snapchat, .13)
Cluster 2	**Home** (Instagram, 1.0), **Stories** (Snapchat, .86), **Home** (Facebook, .84), Profile (Instagram, .52), Profile (Twitter, .23), Activity (Instagram, .22), Profile (Facebook, .17), Notifications (Twitter, .11), Create (Twitter, .08)
Cluster 3	**Explore** (Instagram, .89), **Search** (Twitter, .51), **Discover** (TikTok, .46), Groups (Facebook, .38), Shop (Instagram, .35), **Search** (YouTube, .34), Marketplace (Facebook, .24), Menu (Facebook, .21), Comment Section (YouTube, .15), **Search** (Facebook, .12), Watch (Facebook, .04), Dating (Facebook, .02)
Cluster 4	**Chat** (Snapchat, .65), **Direct Messages** (Instagram, .58), **Inbox** (TikTok, .43), Camera (Snapchat, .41), Notifications (Facebook, .39), **Messenger** (Facebook, .23), **Messages** (Twitter, .23), Memories (Snapchat, .22), Snap Maps (.21), Create (Instagram, .18), Reels (Facebook, .09), Create (YouTube, .03)
Cluster 5	Home (Twitter, .82)

Notes. Bolded user interfaces index those included in the second network analysis. Clusters were based on the Louvain method. A sensitivity analysis was conducted by running modularity 10 separate times.

For a full listing of attributes by grouping, see Table 5. Cluster 1 accounted for 27.69% of concepts and the UIC, OACPs. Semantic attributes for OACPs as a UIC benchmarked UIs containing a tailored algorithmic content stream that exposed users largely to out-of-network (e.g., stranger, influencer), yet curated video content. Cluster 2 accounted for 20.25% of concepts and the UIC, Search Pages. Together, semantic attributes for Search Pages as a UIC indexed that it encompassed UIs including a search bar and topically curated out-of-network content streams which users use to access information (e.g., news, fashion). Cluster 3 accounted for 16.12% of concepts and the UIC, Chats/Messages. UIs characteristic of Chats/Messages indexed user interfaces that mediate private, yet directed forms of reciprocal forms of social interaction (e.g., text, send, receive). Cluster 4 accounted for 35.12% of concepts and the UIC, Home Pages. In all, Home Pages served as a set of UIs containing in-network content streams (e.g., acquaintances, family) indexing recent events, which users generally construe as public.

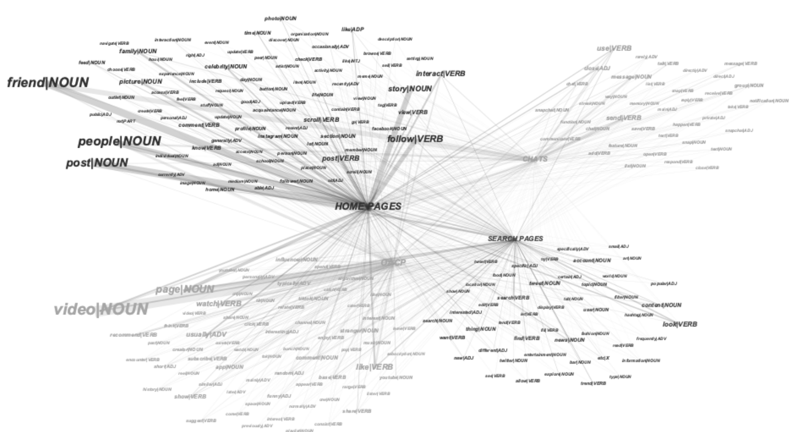


Figure 3. A Network Representation of Users' Schema of Prominent User Interface Classes.
Notes. Node size is indexed by concept frequency to highlight frequently occurring semantic concepts. Concepts within the same shade maintained more intra-group connections to the respective user interface class concept. The top left cluster corresponded to Home Pages; the top right cluster, Chats/Messages; the bottom left, OACPs; and the bottom right, Search Pages.

Table 5.

User Interface Class Attributes across Prominent User Interface Groupings

UIC	Verbs	Nouns	Modifiers
Overtly Algorithmic Content Pages (OACP)	Like, watch, show, recommend, base, subscribe, share, click, think, enjoy, relate, spend, encounter, suggest, appear, consist, pop, come, cater, leave, catch, video, interest, range, curate, listen	Video, page, app, comment, stranger, influencer, tiktok, interest, youtube, creator, algorithm, music, channel, share, history, like, tik, tok, past, clip, subscription, one, reel, watch, space, youtuber, playlist, bunch	Random, funny, short, interesting, similar, usually, typically, mainly, personally, normally, previously, later
Search Pages	Look, find, search, want, trend, allow, tend, see, fill, read, display, edit, tweet, let, try	Content, tweet, news, account, thing, user, search, bar, topic, twitter, information, filter, explore, entertainment, food, world, location, type, fashion, hashtag, tab, show, art	New, different, interested, specific, popular, certain, small, specifically, frequently,
Chats/Messages	Use, send, save, add, talk, message, chat, open, happen, communicate, receive, list, reply, respond, text, snap, close, take	Message, group, snapchat, chat, notification, feature, list, snap, way, text, function, memory, streak	Close, direct, main, snapchat, private, rarely, directly
Home Pages	Follow, interact, post, scroll, view, comment, know, include, check, choose, browse, contain, access, tag, go, feel, create, update, sell, upload, navigate	Friend, people, post, story, picture, family, celebrity, section, photo, time, instagram, feed, profile, home, lost, facebook, like, follower, person, outlet, member, day, button, acquaintance, interaction, scroll, peer, update, school, place, hour, individual, stuff, event, activity, image, item, setting, artist, view, experience, discover, meme, medium, description, ad, access, request, organization	Able, recent, personal, public, good, old, right, like, generally, occasionally, recently, currently

Notes. Modifiers include adjectives and adverbs. Part-of-speech labels were based on spaCy's English model.

LDA Validation of UIC Attributes. When investigating topic distributions among the semantic attributes grouped to particular UICs,[8] semantic features grouped to each class (i.e., secondary SSNA network, Figure 1) contained percentages of words that corresponded highest with their corresponding latent topic, except for Search Pages. Ninety-six percent of the semantic attributes mapped to Chats/Messages cluster in our second SSNA network corresponded to the Chats/Messages latent topic, 83% OACPs to the OACP latent topic, and 70% Home Pages to Home Page latent topic. For Search Pages, 59% of the clustered semantic attributes mapped onto the OACP latent topic. When collapsed across relevant UI concepts (see bolded UI concepts, Table 3) on a description by-description basis, mean topic distributions corresponded highest with their respective latent topic, except for Search Pages. Sixty-eight percent of descriptions of Chat/Message UIs mapped onto the Chat/Messages latent topic, 67% percent of descriptions for Home Page UIs mapped onto the Home Page latent topic, and 71% percent of OACPs mapped onto the OACP latent topic. For Search Pages, topic distributions across descriptions of Search Page UIs were highest for OACPs at 53%. In all, our results were largely consistent across methods.

Discussion

Social media represents a "moving target" for study due to technological (e.g., platform updates) and cultural shifts (e.g., divergent patterns or conventions of use) that often affect its general composition as a type of mediated environment (Ellison & boyd, 2013; Bayer et al., 2020). To account for this fluctuation, the PSMEF seeks to map social media effects to more generalized social media constructs that structurally compose the mediated spaces users engage within (e.g., Chats/Messages, Home Pages). Building from Study 1, this study quantitatively

[8] Word lemmas were used to investigate topic distribution scores across groups UIC attributes for each UIC class by dropped POS labels.

analyzed a set of open-ended survey responses indexing the user interfaces (i.e., pages/sections) a sample of young adults reported commonly using over six popular platforms: TikTok, Instagram, Snapchat, YouTube, Facebook, and Twitter. In addition to evidencing the validity of previously identified types of user interface classes (e.g., Chats/Messages, Home Pages) using two inductive analytical methods (e.g., Carter et al., in revision; Bayer et al., 2020), our data clearly exhibit the theoretical and methodological benefits of schematic semantic network analysis (SSNA) and Latent Dirichlet Allocation (LDA) in the context of the PSMEF. Results suggest that social media use is largely consolidated across set of four general user interfaces classes that facilitate varying forms of social interaction, supporting the PSMEF.

A Replication and Extension of the PSMEF: Six Prominent Social Media Apps

Perhaps the most promising aspect of the PMSEF is its replicability and the underlying utility of its constructs, like user interface classes. In Study 1, references made about user interfaces were grouped into a set of thematically derived user interface class categories as a function of user interfaces' similarity across certain features and affordances. Taking a more inductive approach, the present study (i.e., Study 2) (a) had participants report on the pages/sections they typically navigate to when using social media and (b) describe their understanding of each in detail. Each reported page/section was then classified to one of several primary user interfaces exhibited on each app's navigational menus (e.g., Home on Instagram, Search on Twitter, Chats on Snapchat) and then (c) quantitatively modeled each user interface using the semantic features participants used to simultaneously describe them as mediated spaces. In this way, through SSNA and LDA, this study used the semantic features derived from text descriptions as a general mental model of social media to benchmark user interfaces groupings and their attributes.

On one hand, as inductive analytical techniques, LDA and SSNA afforded the capacity to assess user interface similarity both quantitatively and qualitatively across platforms without any a-priori constraints (e.g., thematic categories) and provided further evidence for the validity of Chats/Messages, Home Pages, and Search Pages as previously identified user interface classes. For instance, each emerged as predominant types of user interfaces based on users' understanding of their PSMEs, with Home Pages and OACPs representing the most referenced types of user interface used (see Figure 1). Characteristic attributes of each user interface class, in addition to patterns of social media use associated therein, were also clearly exemplified. Chats/Messages related to more reciprocal types of social media use behaviors (e.g., text, chat, communicate), whereas passive (e.g., view, browse) and reactive (e.g., commenting) social media activities contextualized Home Pages (see Kaye, 2021). In contrast to Home Pages and Chats/Messages, Search Pages related to more targeted forms of social media use (e.g., look, search, find), content discovery via topically curated content streams (e.g., news, hashtag, topic), and a search bar that users use to access specific content (e.g., user).

Moreover, our results also evidenced the existence of a new, yet prominent user interface class—particularly, Overly Algorithmic Content Pages (OACPs). OACPs represented one of the primary dimensions across our network analyses and topic model, and this user interface class reflected a major reformulation in design across the commercial social media landscape. While the Home Tab on YouTube has conventionally served as an access point to a tailored algorithmic feed, a subset of OACPs characteristically emerged in response to Tik Tok's Home Tab—particularly, the "For You" algorithm under TikTok's For You Page. Preliminary assessment of Tik Tok's For You Page denoted that youth remain highly cognizant of the algorithm and the personalized nature of the content they receive via the algorithm itself; they also associated it with improved content consumption experiences (Bhandari & Bimo, 2022). Our data further affirmed these preliminary findings across replicated OACPs pages, including Reels on Instagram, Spotlights on Snapchat, and Shorts on YouTube, in addition to Tik Tok's Home Page (see Figure 3). For instance, semantic features participants cognitively associated with OACPs included algorithm, curate, and recommend, in addition to concepts reflective of an array of experiential states (e.g., funny, think, relate) and particular user groups (e.g., creator, stranger, influencer). The latter contrasted Home Pages and Chats/Messages, which were associated with more in-network connections (e.g., family, friends, acquaintances), and seemingly refined how users interfaced with out-of-network content. The latter is conventional of Search Pages. Nevertheless, OACPs related to a similar pattern of use behaviors with Home Pages (e.g., watch, subscribe).

While our results were largely consistent, there were some slight inconsistencies by method of analysis. Our LDA analysis evidenced three user interface groupings, whereas our SSNA analysis evidenced Search Pages, in addition to the remaining three categories. The difference seemingly resulted from a lower level of reporting for user interfaces characteristic of Search Page within our sample compared to OACPs (see Figure 1). This may have led the LDA analysis to interrelate the two user interface groupings given their similarity (see LDA Verification of UIC Attributes); both provide users access to tailored, out-of-network content streams. SSNA's utilization of more nuanced semantic information likely enabled it to differentiate between the two groupings, however. For instance, "search" as a semantic feature associated most strongly with Search Pages in our second SSNA analysis, whereas the term weighted highest with OACP latent topic compared to the remaining topics based on our topic model. The latter is surprising considering that many OACPs do not afford users the capacity to search. Thus, whether Search Pages and OACPs represent the same or distinct types of user interface class categories needs further empirical verification. Nevertheless, our results suggest that they represent two related, but distinct types of user interface groupings.

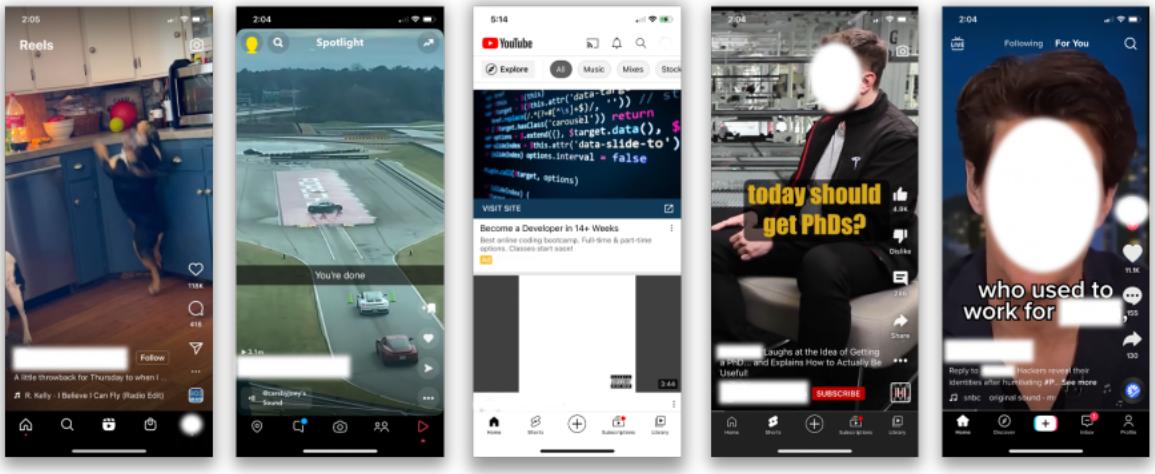


Figure 3. Screenshots of Overtly Algorithmic Content Pages (OACP). *Notes.* OACP pages were screenhotted May of 2022. Blurred overlays were added to mask individuals and poster affiliations. OACPs by name from left to right are as follows: Instagram's Reels Tab, Snapchat's Spotlight Tab, YouTube's Home Tab, YouTube's Shorts Tab, and the For You Page on TikTok's Home Tab.

PSMEF, User Interfaces Classes, and User Interface Genres

Beyond these insights, SSNA and LDA also provides an approach to further map out social media as an evolving landscape. For instance, Search Pages, Home Pages, OACPs, and Chats/Messages represented the most characteristic dimensions of social media as user-centric mediated environment (see eigenvector centrality metrics in Table 4). As a result, each of these user interface classes may function as a type of reference point to help characterize user interfaces maintaining complimentary, yet unique underlying attributes, just like genres help to organize our understanding of media content. This is because user interfaces less characteristic of users' engagement over social media map on more or less similarly to these predominant types of user interface classes. Chats/Messages, OACPs, Home Pages, and Search Pages may then represent superordinate types of user interface groupings with a weighted set of characteristic features, making them a seemingly ideal benchmark for user interface similarity metrics as new user interfaces are introduced over time.

The PSMEF and Person-Specific Social Media Effects: Moving Forward

While understanding the primary antecedent factors driving person-specific social media effects remain ongoing (Valkenburg et al., 2022), it is evident that the PSMEF provides an opportunity to explore qualitative and quantitative aspects of users' PSMEs across sub-groups exhibiting positive, negative, or non-significant effects (Carter et al., in revision). For instance, using SSNA it is possible to compare the semantic associations between distinct effect groups to contextualize potential effect pathways (e.g., differences in associated cognitions, behaviors, etc.) or differences in the underlying compositions across users' PSMEs (e.g., differences in the salience of platform features) potentially driving certain social media effect outcomes. If benchmarked across certain user interface classes, the qualitative differences in situational features between distinct, yet common types of user interfaces would help to inform on the types of environmental factors that may partially drive such differential effects between groups with shared dispositional characteristics over time (see Rauthermann et al., 2020; Valkenburg & Peter, 2013). Themes inductively derived (e.g., LDA) from open-ended content descriptions could also function as a primary independent variable to explore content effects across user interface classes as well (see Grimmer et al., 2022).

Theoretical and Pragmatic Implications of Schematic Semantic Network Analysis

SSNA and Galileo. As a structured form of SNA, SSNA provides a means to probe schematic structures quantitatively, qualitatively, and at scale using a flexible methodological framework. While the number of semantic features included in the final model were reduced by dropping semantic features occurring in frequency below the mean to increase the accuracy of the resulting network (Woelfel & Fink, 1980), the representation spanned 283 primary and descriptive semantic concepts in total to initially evidence user interface groupings. For comparison, an *equivalent* close-ended Galileo measure would require just over 80,000 pairwise similarity comparisons to model the same number of semantic features to evidence user interface similarity.

Whether SSNA is more accurate as a function of its capacity to include more semantic features compared to other multidimensional modeling techniques, like the Galileo method (see Woelfel & Fink, 1980), is a question of future research. Nevertheless, SSNA clearly maintains a high degree of theoretical utility. This is made evident by the conceptual consistency between SSNA and cognitive schema theory. For instance, cognitive schema theory presumes that schema are hierarchical cognitive structures made up of a set of interrelated concepts (e.g., events, people, objects; Shehata et al., 2021). In line with this conceptualization of schema, SSNA defines primary concepts as a function of their hierarchical interconnections with subordinate semantic concepts, rather than doing so based on pairwise similarity ratings as in Galileo. Despite these differences, the two approaches highly complement one another. For instance, the original Galileo method affords the capacity to calculate similarity metrics across all concepts modeled, whereas SSNA permits such across primary concepts, but not directly between descriptive concepts. Further, Galileo is a highly sensitive form of psychometric measurement (Woelfel & Fink, 1980), which strongly underscores its methodological utility. On the other hand, SSNA can help to inform on semantic reference points to construct a self-report Galileo measure in a theoretically informed manner. Specifically, semantic features derived from our SSNA that bridge distinct user interface class groupings (e.g., video|NOUN, like|VERB) should serve as ideal cognitive anchor points for a Galileo measure to further validate user interface categories, in addition to other semantic features unique to particular user interface classes (e.g., search|VERB). Thus, researchers should consider using the methods in-joint when investigating PSMEs.

Limitations and Future Directions

Despite its strengths, this study maintained some limitations. First, the present methodology partially relied on thematic coding. Nevertheless, the primary analysis used two forms of automated computer analysis (SSNA, LDA) to quantitatively classify user interface classes inductively. Further, in contrast to previous work which coded for the presence/absence of user interface concepts across text descriptions (e.g., Carter et al., in revision), the present study thematically mapped reported pages/sections to navigable locations over each app indexed by a navigational icon in the app's primary navigational menus. Mapping reported sections/pages to prominent navigational icons provided a unitary basis for the comparison of user interfaces across different platforms—specifically, given platforms' hierarchical structure (e.g., Newsfeed is embedded in the Home Tab on Facebook) and their role as primary in-app navigational components (Shneiderman et al., 2018). However, the resulting pattern of associations may differ when mapped onto other technological structures (e.g., content streams vs. primary tabs), as they also function as types of user interface classes (e.g., Stories, Posts).

Lastly, given the low level of reporting for particular platforms and certain types of user interfaces, the present study did not have sufficient power to assess the unique characteristics of all user interfaces participants reported using to evidence prospective types of user interface classes. Nevertheless, through this approach it was possible to model the most centrally used user interfaces reported by participants. Results imply the existence of alternative groupings of user interfaces, including Notification Pages (e.g., Notifications on Twitter, Activity on Instagram), Digital Marketplaces (e.g., Shop on Instagram, Marketplace on Facebook), and Creation Pages (e.g., Create on Instagram, Record on Tik Tok). Participants just reported using them less frequently. Additional work is needed to model users' PSMEs at scale to further validate proposed user interface classes and their corresponding attributes.

Conclusion

Social media has evolved into an increasingly pluralistic, multi-platform reality. Today's social media landscape will likely look very different from tomorrows, however. I hope that the methodological and theoretical contributions of this work will help researchers further organize social media effects research and keep pace with the continual updates seen across the commercial social media landscape—particularly, by mapping correlates of social media use onto user interface classes, among other social media elements.

Chapter 4. A Review of the Personal Social Media Ecosystem Framework: Advancing the Study of Personal Social Media Environments as Evolving Structures

How should researchers approach the study of social media? Over the last two decades, the answer to this question has been largely outpaced by the rapid development of the commercial social media landscape. For instance, as of February 2022, Facebook services 2.91 billion monthly active users internationally (Statista, 2022). This acquisition of users grew rapidly, representing a near 29000% increase in monthly active users compared to the platform in 2008, when Facebook initially eclipsed Myspace—another popular platform at that time (Statistica, 2021). Since Facebook's rise in popularity, the social media landscape has only gotten more diverse. Today, among nationally representative surveys in the United States, platforms like YouTube, Facebook, Instagram, Snapchat, and TikTok remain among the most popular, with some variation in rates of platform adoption across user demographics (Auxier & Anderson, 2021).

The increasing diversification of the commercial social media landscape has led to numerous challenges to studying social media effects. The introduction of new apps and features has largely subverted definitions of what constituted social media (e.g., boyd & Ellison, 2007; Ellison & boyd, 2013) and simultaneously promoted continual shifts in how social media is itself studied (see Carter et al., in revision). For example, self-report measures of social media use often focus on different types of features as platforms have changed (e.g., likes, social networks, reactions); the use of heterogeneous measures, however, has led to mixed patterns of effects in relation to social media use correlates, like well-being (Trifiro & Gerson, 2019; Cingel et al., 2022). Further, common social media use measures (e.g., browsing behavior at the platform level; Beyens et al., 2020) often limit the interpretability of finings to a particular historical context (e.g., certain app version), carrying minimal indication of how platform design relates to social media use outcomes as platforms change over time (Carter et al., in revision). In all, to remain relevant for future permutations of social media and better uncover the effects of social media use more generally as platforms change, research on social media needs to methodologically and theoretically account for the variation inherent to social media as a type of technological structure itself. After all, social media represents an everchanging, mediated landscape (Bayer et al., 2020).

The Next Wave of Social Media Theorizing

While often framed as problematic (e.g., Bayer et al., 2020; Ellison & boyd, 2013), the growing technological diversity across the commercial social media landscape has brought about newfound opportunities to study social media in more generalizable ways over time. For instance, recently introduced theoretical frameworks, like the Personal Social Media Ecosystem Framework (PSMEF), and the concept of social media elements (Bayer et al., 2020), outlined ways to explicate and define social media in light of the generalized technological structures permeating social media as a complex mediated context for social interaction. Initially, this included common types of user interfaces, like profiles and chats/messages, content streams, and global technological components, like social networks (e.g., friend's list; Bayer et al., 2020). Mapping effects to such *social media elements*, or commonly understood technological structures that exist across multiple channels of communication, will arguably help to organize evidenced effects as platforms continue to change (Bayer et al., 2020). This is partially because social media elements, as conglomerations of platform features, often iterate across platforms in unique ways and generalize beyond individual features (see Chapter 1).

Building from the concept of social media elements, two studies were presented (i.e., Study 1 & 2) that explicated and subsequently advanced the PSMEF (Carter et al., in preparation; Carter et al., in revision). Provided these recent developments, the present article highlights how emerging work on the PSMEF is re-characterizing ways to study of social media over time—both theoretically and methodologically. In conclusion, ways to further advance the PSMEF using the Galileo method (Woelfel & Fink, 1980), a largely underappreciated research paradigm, are discussed—especially provided limitations with current methodological approaches used in the development the PSMEF (e.g., Schematic Semantic Network Analysis; Study 2; Carter et al., in preparation).

The Personal Social Media Ecosystem Framework: An Abbreviated Overview

The crux of the PSMEF rests on the notion that over any live platform, there exist numerous instantiations of user interfaces (e.g., Obama's profile as a derivative of Instagram's profile interface), serving as unique mediated environments for users to engage within. The PSMEF coined these spaces as digital user interfaces (Carter et al., in revision). Importantly, in certain combinations, digital user interfaces can form a generalized type of environmental structure—particularly, a user interface class (see Study 2 for an example, see Chapter 1 for a definition). According to the PMSEF, user interface classes serve as an organizing structure to investigate the dimensions and characteristics of the primary environmental units (i.e., digital user interfaces) underwriting users' PMSEs. This is because each instantiation of a user interface (i.e., digital user interface) represents a derivative, in some form, of a user interface class. As a result, the PSMEF argues that evidencing the types of user interface classes that exist and their dimensionality can help to functionally characterize users' social media experiences. This makes evidencing user interface classes the most pressing aspects of studying social media as a dynamic mediated landscape in the context of the PSMEF. Without a means to identify, classify, and map user interfaces that make up popular interactive platforms to user interface classes, researchers will continue to lack a coherent grounding to study social media as a type of naturalistic environment over time, in addition to correlates of its use.

User Interface Classes: Initial Evidence. Two previous studies have directly sought to identify a core set of user interface classes in line with the PSMEF (Study 1 & 2; Carter et al., in preparation; Carter et al., in revision). Initial evidence suggested a set of primary user interface classes spanning Chats/Messages, Profiles, Stories, Posts, Comment/Comment Sections, Location Pages, Search Pages, Home Pages, and Group Pages as prospective types of user interface class categories (Study 1; Carter et al., in revision). While Chats/Messages and Profiles mapped onto initial conceptual definitions of social networking sites (boyd & Ellison, 2007; Bayer et al., 2020), the remaining reflected token, but largely unintegrated types of generalized social media structures within extant conceptual frameworks (e.g., Bayer et al., 2020). In all, the explication of user interface classes, helped to extend the concept of social media elements and better formalize the study of these characteristic mediated spaces by outlining an initial set of generalized spaces underwriting users' contemporary social media experiences. Though informative, it remained unclear how classify user interface class quantitatively to facilitate their systematically study as platforms change over time.

Advancing Quantitative Methods to Study User Interface Classes. To provide a stronger methodological foundation to the PSMEF, Study 2 introduced a novel computational approach (i.e., schematic semantic network analysis) that enabled the systematic study and identification of user interface classes (Carter et al.., in preparation). Specifically, it outlined a way to inductively quantify and project the meaning of user interfaces within a simple mathematical framework using schematic semantic network analysis (SSNA), a structured form of semantic network analysis that analyzes the meaning of concepts provided a set of corresponding text descriptions. Through a simple set of preprocessing steps, SSNA converts words present in descriptions into a psychological subspace (i.e., multidimensional vector space) by treating words as unique dimensions of cultural meaning; the meaning of primacy concepts (e.g., user interfaces) is then determined by their pattern and strength of association with the descriptive semantic concepts (e.g., people, photo, search) used to describe them. Through the application of network analysis (e.g., community detection), the method also provided a means to evidence the dimensionality of user interfaces, in addition to identify user interfaces class groupings, based on the underlying associations users make between user interfaces with certain defining semantic features (e.g., search, image, post, picture, stranger, algorithm).

Using this inductive approach, along with a form of topic modeling,[9] four primary classes of user interface were identified (three of which were replicated), including Chats/Messages, Home Pages, Search Pages, and Overly Algorithmic Content Pages (OACPs). The latter represented an emerging class of user interfaces stemming from TikTok's initial For You Page—an algorithmic content stream made up of short videos, characterized by a tailored algorithm (Bhandari & Bimo, 2022). The initial commercial introduction and later replication of OACPs across several mainstream platforms has seemingly recharacterized how users can engage with out-of-network content, an activity more conventional of Search Pages (see Chapter 3 Discussion Section). Home Pages, which characteristically provide users with in-network content streams (e.g., acquaintances), along with OACPs, represented the most reported type of user interface classes used; highlighting their prominence as mediated spaces underpinning individuals' social

[9] A computational method that identifies latent meaning structures (e.g., topics) using word frequencies and co-occurrence rates inductively from text units (e.g., documents, sentences, descriptions) (Grimmer et al., 2022).

media experiences (Study 2; Carter et al., in preparation). Chats/Messages associated with more directed, yet private forms of communication with in-network ties (e.g., friends). Search Pages associated with curated forms of content, like fashion, news, topics, or particular users, implicating their role as spaces for more directed forms of information acquisition and uncertainty reduction (Study 2; Carter et al., in preparation). Similar to Search Pages, OACPs indexed a stream of tailored content largely falling outside of users' known social contexts (e.g., associating with strangers, creators) (Study 2; Carter et al., in preparation).

Creating a Foundation for Social Media Research. The PSMEF, in facilitating the identification and distillation of user interface classes, has helped to characterize social media platforms, despite differences in their underlying features. In this case, emerging work illustrated the characteristic mediated spaces underpinning contemporary social media experiences; users' social media activities remain consolidated across Chats/Messages, Search Pages, Home Pages, and OACPs as generalized types of mediated environments (Carter et al., in preparation; Carter et al., in revision).

Importantly, adoption of the PSMEF as a paradigm to study social media should help facilitate a program of research that better informs on the potential effects of emerging platforms long-term. By replicating the methods outlined in Study 2, researchers could quickly derive a set of theoretically motivated, yet preliminary set of potential effect outcomes for emerging platforms by quantifying similarities between emerging and existing user interfaces classes themselves. After all, it would be reasonable to expect user interfaces from any new platform to elicit a similar pattern of effects to those existing that they share attributes with (Bayer et al., 2020). Similarity metrics could be calculated by taking the cosine of each user interface and its edges (e.g., a vector of associated descriptive semantic features) across a SSNA adjacency matrix.[10] In this way, understanding where user interfaces available on the new platform fall in association with pre-existing user interface classes would outline an agenda for the new platform's systematic study in light of extant work on the PSMEF (e.g., identifying relevant user interfaces to use as a comparison point for scientific investigation) and inform on theoretically-relevant predictions.

The Personal Social Media Ecosystem Framework: Moving Forward

While the PSMEF has progressed understanding of social media, several outstanding challenges for the framework remain. First, according the PSMEF, an individual's experience of any particular location over a platform varies person-to-person. As most techniques applicable to the PSMEF (e.g., SSNA) rely on group-level representations to assess more globalized technological structures (e.g., user interface composition), it is less clear how to model PMSEs on an individualized basis accurately and at scale to capture their differences. While group-level approaches (see Study 2; Carter et al., in revision) help to circumvent the need to model PMSEs individually by modeling PSMEs across groups of interest (e.g., those exhibiting positive compared to non-significant effects as a function of social media use), increasing the accuracy of measures at an individualized-level will only aid theorizing by increasing the precision of available PSME modeling approaches.

Chronosystem. Lastly, PSMEs will evolve over time as the broader social media landscape changes and additional methodological tools are needed to help map their trajectory. For instance, the *chronosystem* in EST represents broader historical effects that interact to guide developmental trajectories and culture, among other environmental systems (Tudge et al., 2009). As the most superordinate environmental system, the chronosystem governs all aspects of each

[10] An alternative approach would include calculating similarity metrics using Galileo (Woelfel & Fink, 1980).

subordinate environmental system in EST (Bronfenbrenner, 2005; Tudge et al., 2009), and as a byproduct PSMEs. An example would include timing effects with the emergence of TikTok in the United States (e.g., potential differences in its rate of adoption across different generational cohorts [e.g., Generation Z, Millennials]), in addition to its potential impact across Generation Z and Millennials provided differences in their stage of development.[11]

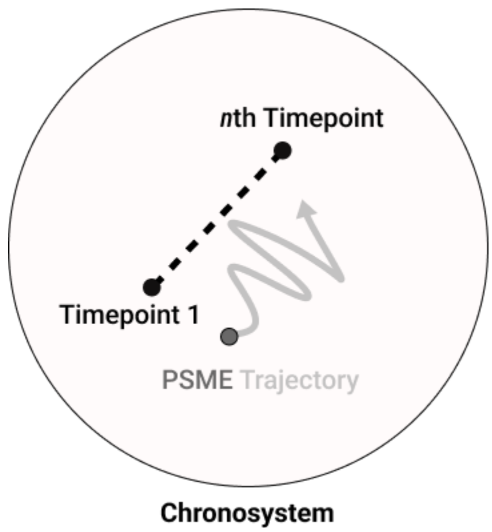


Figure 1. Modeling PSMEs Over Time. *Notes.* A personal social media environment (PSME) is listed at Timepoint 1. The grey line represents a hypothetical course of variation in the substance of the PMSE over time. Variation may occur at any level of the PSMEF.

Need for Direct Measures. Specifically, as shifts in language conventions can hamper the generalizability of SSNA,[12] close-ended measures to study PSMEs over time are necessitated. This is because close-ended measures would provide a consistent means to benchmark user interface class similarity in using a fixed set of cultural/theoretical concepts to index similarity metrics, rather than a variable set of concepts (as in SSNA). Below, I explore Galileo Method, a close-ended self-report measurement technique (Woelfel & Fink, 1980), as a methodological solution to study PSMEs over longer periods of time and cross-culturally. After,

[11] Developmental factors have been theorized to moderate media effect processes (Valkenburg & Peters, 2013).
[12] This occurs as the edges of the network change, altering the base vectors defining user interface concepts.

a future program of work using the Galileo method to advance the study of PSMEs in the context of the PSMEF is outlined.

The Galileo Method. Although many multidimensional modeling techniques exist, the Galileo Method operates as a theoretical and methodological framework to investigate media effects (for examples, see Wang & Woelfel, 2021; for a framework see Woelfel & Fink, 1980). This makes it ideal for the study of PSMEs. Specifically, the Galileo Method is a multidimensional modeling technique, like factor analysis, that takes a set of pairwise similarity judgements between a set of concepts to relationally project concepts onto a multidimensional vector space (Woelfel & Fink, 1980). Theoretically, this makes the Galileo Method akin to SSNA; both methods define concepts as a function of their interrelationships with other concepts (Study 2; Carter et al., in preparation). Nevertheless, Galileo maintains important theoretical distinctions—especially, when considering behavior.

Leveraging Galileo to Measure Social Media Use. Using a Galileo subspace, distance metrics between concepts can be calculated and used to derive insights regarding a range of phenomenon, like identification and likelihood of behavioral engagement (e.g., Wang & Woelfel, 2021; Woelfel & Fink, 1980). According to the Galileo approach, behavioral engagement is thought to increase as behavioral concepts become more proxemic to one's self concept in a Galileo sample space (Woelfel & Fink, 1980). This would suggest that it is possible to employ a Galileo measure to assess rates of social media use by taking distance scores between the concept of YOURSELF and certain mediated environments (e.g., browsing posts on your Instagram Home Tab) as a proxy of their rate of use (see Figure 2). The advantage of this approach is that Galileo distance scores inform on the likelihood of use as a function of the psychological distance between concepts. In contrast, other self-report measures of social media use map onto recalled rates of use, which have been shown to be inaccurate compared to more objective behavioral measurements (Junco, 2013). While there is initial evidence to indicate that cognitive associations users make between different user interface classes map onto patterns of social media use (Study 1; Carter et al., in revision), the validity of leveraging language models to benchmark social media use patterns in this way still needs additional verification.

Using Galileo to Model Social Media Environments. Using the Galileo Method to measure user interface classes and PSMEs also warrants further consideration. The first step in creating a Galileo measure applicable to modeling PSMEs is to identify a set of reference concepts for similarity judgements. A combination of domain relevant and irrelevant concepts is ideal to increase the accuracy of the Galileo projection (Woelfel & Fink, 1980). While the selection of reference concepts is often done subjectively (e.g., Wang & Woelfel, 2021), it is possible to leverage SSNA to facilitate the identification of key domain concepts in a quantitative, yet theoretically informed manner (Study 2; Carter et al., in preparation). For instance, semantic features frequently used to describe user interfaces across multiple user interface class categories function as seemingly ideal reference points to include as a part of the Galileo reference frame. This is because the semantic concepts maintain high weights across distinct user interface class categories (see the Discussion Section in Study 2). Incorporating concepts theorized to differentiate between mediated spaces, like particular mass-personal dimensions (e.g., PRIVATE|ADJ; O'Sullivan & Carr, 2018), use patterns (e.g., BROADCASTING|VERB; Kaye, 2021), and other meta-constructs (e.g., PERSISTENT|ADJ; Walther, 2017) would also help to characterize PSME components by testing the proposed boundaries argued by extant communication theory. For instance, to my knowledge, no studies have quantitatively validated O'Sullivan's and Carr's (2018) mass-personal typology in the context of social media, even though the framework differentiates between various mediated spaces and communication technologies as a function of their degree of information access (e.g., public vs. private) and message personalization (e.g., impersonal vs. personal).

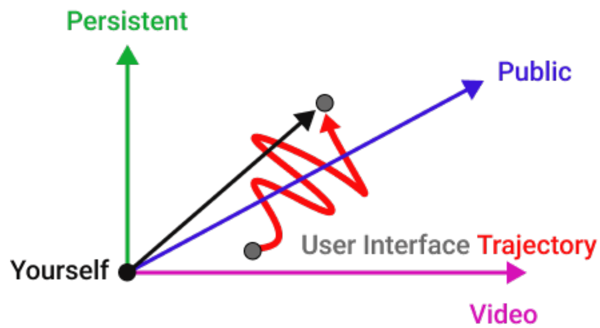


Figure 2. An Example Galileo Reference Frame. *Notes.* A user interface (e.g., Instagram's Home Page) is depicted in grey and follows a trajectory over time, illustrated in red. The redline represents a hypothetical course of variation in the substance of the user interface over time. Persistence, or the degree of storage and retrieval capacity (Walther, 2017), is depicted in purple. Public (blue) is reflective as a dimensional component of O'Sullivan and Carr's (2018) mass-personal typology. Lastly, video is illustrated (purple) as a platform feature/modality that generalizes across technologies (Meier & Reinecke, 2020).

Limitations of Galileo. Despite its potential for advancing the study of PSMEs and communication theory, the Galileo method maintains some limitations. A primary challenge relates to the selection of domain non-specific reference concepts from which to benchmark relevant domain concepts. This is because cultural meaning (e.g., language) changes over time and varies across populations (Bronfenbrenner, 2005; cf. Bayer et al., 2020). In turn, the utility of the Galileo Method is determined by a selected reference frame, which may not generalize well depending on the types of reference concepts selected. One solution to increase the utility of the Galileo Method would be to try to identify a set of concepts that remain more invariant over time and distinct populations (see Woelfel & Fink, 1980). Recent theoretical advancements in the context of social cognition provide inlets to accomplish such.

Construal Level Theory: A Generalized Psychological Reference Frame. To identify the invariant concepts ideally suited for a psychological reference frame, it is important to recognize how people come to understand the world using different frames of reference.

Foremost, psychological frames of reference exist at varying levels of abstraction (Soderberg et al., 2015). According to prominent theories of social cognition, like Construal Level Theory (Trope & Liberman, 2010), the level of abstraction of a particular mental representation maintains unique types of properties, but nevertheless can coincide simultaneously in mind. Low-level concepts tend to take on the variant, contextually nuanced, and specific attributes of an object, whereas abstract concepts take on more rigid, core, and goal orientated features of a mental representation (Soderberg et al., 2015; Trope & Liberman, 2010). Such concrete and abstract mental representations remain organized not only in their specificity, however, but also in their relative positioning across varying dimensions of psychological distance, including time, proximity, hypotheticality, and social distance (Soderberg et al., 2015; Trope & Liberman, 2010). Things closer to one's self concept, the present, and thought more probable or real remain closer in a psychological space with one another, with a person's self-conception operating as the most concrete and central psychological reference point (Trope & Liberman, 2010; Soderberg et al., 2015).

CLT and the Galileo Method. Importantly, CLT's primary tenets can inform on how to better model psychological concepts in a way that helps to increase the utility of a Galileo measure. While it is clear the use of subjectively selected collection of reference concepts may introduce added measurement error (e.g., Wang & Woelfel, 2021), selecting more abstract referent concepts should generate a more stable psychological reference frame. This is because these constructs should express less variability overall according to CLT (see discussion above).

Furthermore, leveraging different dimensions of psychological distance (e.g., time, hypotheticality, social distance) proposed by CLT should also improve the durability of a Galileo reference frame. Recent meta-analytical evidence demonstrated that manipulations of psychological distance maintain similar effect sizes across diverse situational contexts, methodologies, and between different cultural and gender demographics (Soderberg et al., 2015). This suggests that CLT's postulations about psychological distance remain consistent across diverse contexts, demographics, and cultural populations. Thus, incorporating CLT dimensions into a Galileo frame as reference concepts should help to contrast modelled associations across cultural populations and over time. Lastly, CLT's dimensions of psychological distance functionally map onto one's self-concept, serving as the most focal psychological anchoring point, akin to the Galileo method (see discussion above). This would suggest that the Galileo method could help to test CLT's dimensions as well. Together, extant theorizing would advocate that the psychological dimensions from CLT would provide a set of generalized, yet stable reference concepts uniquely apt for the Galileo Method.

The PSMEF, Construal Level Theory, and Galileo. Altogether, CLT provides a useful start to establishing a generalized psychological reference frame for the Galileo Method. In the context of the PSMEF, reference concepts identified using SSNA can be assessed for their utility by comparing them to concepts representative of CLT's dimensions. Changes in concept distance over measurement timepoints or populations between a focal concept across any of the CLT dimensions would imply a *shift in cultural meaning* of the referent concept.

Privacy as an Example. The concept of privacy is fundamental to communication theory (e.g., communication privacy management, mass-personal typology; O'Sullivan & Carr, 2018; Baruh et al., 2017) and is itself variant as a concept in its meaning across cultural contexts (cf. Baruh et al., 2017). For instance, different cultural groups ascribe distinct meanings, standards, and norms to the concept of privacy (cf. Baruh et al., 2017). Provided these differences, PRIVATE as a concept can be mapped onto a Galileo reference frame using CLT's dimensions to characterize the meaning of the concept over time and across distinct cultural populations. An example is illustrated in Figure 3. As cultural differences often emerge as a function of how people interrelate concepts psychologically (ojalehto & Medin, 2015), the goal would be to identify invariant networks of concepts to consistently benchmark meaning structures within populations, but also derive metrics to correct for cross-cultural differences (e.g., via matrix rotations; Woelfel & Fink, 1980). Altogether, understanding how concepts differ across populations and time would help to enable direct comparisons of PSME-related similarity judgements, despite inherent cultural variation, within the Galileo framework (see Woelfel & Fink, 1980).

Figure 3. An Example of Using CLT as a Galileo Reference Frame. *Notes.* Private (purple) is reflective as a dimensional component of O'Sullivan and Carr's (2018) mass-personal typology. The two purple hues represent different sample populations. The dashed line between the two groups is reflective of the approximated distance between two concepts in the multidimensional vector space (see Woelfel & Fink, 1980).

Applying the PSMEF at Different Levels of Abstraction

Lastly, at this point it should be clear that there exist several approaches to study PMSEs. Previously, a heavy focus was placed on user interface classes. Other work has placed emphasis on content streams, among other social media elements (e.g., Carter et al., in revision; Bayer et al., 2020). Beyond these, using platforms as a more globalize construct is also seemingly crucial to generate a foundation for future theorizing about social media—particularly, as they represent more complex technological structures (e.g., digital mesosystem; see Chapter 1) and function as the unit people (e.g., researchers, other stakeholders) generally seek to make predictions about (e.g., TikTok as an emerging platform; e.g., Cingel et al., 2022). While the PSMEF is still in its infancy, characterizing platforms by contrasting them with one another (e.g., Carter et al., in revision), other types of digital technologies (e.g., Brito, 2011), user interface classes (e.g., Carter et al., in revision), and other social media elements (Bayer et al., 2020) will likely help to advance this ambitious aim (for an example, see Study 1). A combination of each will likely be key to generating a body of research that adequately supports inferences across platforms as distinct technological contexts over time. One interesting inlet would be to investigate how default platform structures (e.g., root pages) impact rates of engagement over certain user interface classes.

Conclusion

Although social media will change, it is simultaneously becoming apparent how to measure and potentially account for this expected variation. On one hand, the PSMEF and concept of social media elements provide a flexible theoretical framework for studying social media. On the other, SSNA and the Galileo Method provide a clear roadmap on how to model social media systems as they continue to co-evolve along with broader cultural systems. The utility of these approaches rests in their complimentary nature; each provide unprecedented opportunities to map out social media as a dynamic environmental system over time. When paired with CLT, the Galileo Method may also provide a generalized means to model variation in psychological reference concepts, even among multicultural samples. After all, CLT's dimensions appear ubiquitous, irrespective of cultural differences (Soderberg et al., 2015). Using these methodological tools in line with the PSMEF warrant focused attention moving forward to keep pace with the perpetual changes often seen across the commercial social media landscape.

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