Designing and Evaluating General-Purpose User Representations Based on Behavioral Logs from a Measurement Process Perspective

A Case Study with Snapchat

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In human-computer interaction, understanding user behaviors and tailoring systems accordingly is pivotal. To this end, general-purpose user representation learning based on behavior logs is emerging as a powerful tool in user modeling, offering adaptability to various downstream tasks such as item recommendations and ad conversion prediction, without the need to fine-tune the upstream user model. While this methodology has shown promise in contexts like search engines and e-commerce platforms, its fit for instant messaging apps, a cornerstone of modern digital communication, remains largely uncharted. These apps, with their distinct interaction patterns, data structures, and user expectations, necessitate specialized attention. We explore this user modeling approach with Snapchat data as a case study. Furthermore, we introduce a novel design and evaluation framework rooted in the principles of the Measurement Process Framework from social science research methodology. Using this new framework, we design a Transformer-based user model that can produce high-quality general-purpose user representations for instant messaging platforms like Snapchat.

CCS Concepts: • Human-centered computing → Empirical studies in HCI; User models.

Additional Key Words and Phrases: Transformer, Representation Learning, Validity, Measurement Theory, Operationalization, Contrastive Learning, User Safety, Instant Messaging Apps, User Engagement

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1 INTRODUCTION

Instant messaging (IM) apps, such as WhatsApp, WeChat, Telegram and Snapchat, have become an indispensable part of our daily lives, shaping the way we communicate, share, and connect in the modern era [4]. For businesses running these platforms, understanding their users' needs and delivering a superior experience is paramount. Take *user safety* as an example. Instances of users being harassed, coupled with the increasing presence of scammers and bots, call for robust safety measures [25]. Timely identification and mitigation of such problematic accounts are crucial, not only for ensuring user safety but also for maintaining the platform's reputation. Furthermore, some IM apps offer services beyond mere communication functions. For instance, Snapchat and WeChat recommend content (e.g., news, photos, videos) to users. In this case, recommendations that resonate with individual user preferences are important.

To this end, many service platforms, including IM apps, leverage *user modeling* techniques. User modeling refers to the process of creating representations of users based on their behaviors, preferences, needs, and other attributes. These user representations are intended to capture and predict user actions, preferences, or intentions [19]. Various user modeling approaches exist, such as collaborative filtering¹ [40] and process mining² [7].



Fig. 1. Two examplar user behavior sequences in an instant messaging app.

In this paper, we focus on an increasingly popular *machine learning*-based user modeling approach: *learning user representations from user behavioral logs*. For convenience, we refer to this approach as **BLUM** (Behavioral Log-based User Modeling). BLUM systems leverage user behavioral log data³, which are records of high-resolution, low-level events triggered by user actions in an information system [1]. Examples of such events include clicking a button, swiping to the next page, viewing a video and sending a message. Figure 1 illustrates two chronological sequences of such events in IM apps. These sequences are commonly referred to as user behavior sequences and constitute input data for the user model to learn user representations. BLUM has been successfully applied to various domains, such as item recommendation in e-commerce platforms [46], content recommendation on social media [11, 45], conversion in search engines [31], and student grade prediction in massive open online courses [55].

BLUM-based systems have many advantages. For instance, within just a few minutes of interacting with an information system, a user may already generate a rich amount of log data necessary for effective user modeling. Also, modeling users based on behavior logs requires no active input from users (e.g., answering user surveys). The reduced user burden may improve user experience. Furthermore, BLUM does not require the use of features like user demographics, user-generated content⁴ (e.g., texts, images, videos) and user location, which are often non-anonymous and deemed sensitive and personal by users [20, 22, 32, 42].

¹Collaborative filtering (CF) models users based on user-item interaction data and assumes that users who agreed in the past will agree in the future about the preference for certain items. To apply CF, one can, for instance, compute the similarity between users based on their interactions with items, or use matrix factorization techniques to decompose user-item interaction matrices to multiple matrices representing latent factors of users [10]. ²Process mining is often used in e-learning platforms (among others). It can be used to identify clusters of students (e.g., over-, average-, and under-

performing students) by analyzing the sequences and patterns of resource access, quizzes, and interactions with the platform [43]. ³User behavior logs are also referred to as user interaction logs or user activity logs in the literature.

⁴Note that some researchers (e.g., [17]) also consider user-generated content like social media posts and product reviews as part of user behavior logs. We, however, do not share this view and consider user behaviors strictly as low-level user interaction events.

There are two main approaches to building BLUM systems. The first one is *task-specific*. That is, the user model is trained for specific downstream tasks (e.g., prediction of ad conversion or user churn) (e.g., [6, 29, 30, 53, 56, 58]). With this approach, the user model learns downstream task-specific information and consequently, the learned user representations would likely not transfer well to new tasks. The other, emerging approach is *General-purpose* BLUM (**G-BLUM**) (see Figure 2), which aims at learning general-purpose user representations that can be subsequently used for various downstream tasks, without the need to fine-tune the upstream user model for every new downstream task [57]. These user representations can also be directly incorporated into existing downstream models (e.g., spam detection systems) with minimal changes to the downstream models. Two arguments may explain G-BLUM systems's ability to learn general-purpose user representations, despite using only behavioral data. First, to the extent that users are more or less consistent in how they use an information system, we can expect similar representations for the same user based on behavioral sequences at different time points [12]. Second, to the extent that behavioral log sequences contain rich and complex patterns, nuanced user representations can be learned.

G-BLUM systems typically employ self-supervised learning to model users. One advantage of self-supervised learning (over supervised learning) is that it does not require (manually) labeled data, allowing for easier access to and collection of (abundant) training data. A common self-supervised training objective in G-BLUM systems is *Masked Behavior Prediction*, where parts of users' behavior sequences are randomly masked and the model learns by predicting the masked behaviors based on their context [11, 52, 57]. Another one is *Next Behavior Prediction*, where the model learns to predict the next user behavior, given the user's previous behaviors [8, 52, 61]. Both have been shown to work well on a variety of downstream applications (e.g., feed recommendation [57], ad conversion prediction [52], preferred product prediction [8]) without requiring further fine-tuning of the upstream user model .



Fig. 2. A typical G-BLUM system. First, user behavioral sequences are used to train a user model that learns general-purpose user representations. Then, the trained user model is used to generate user representations based on (new) behavioral sequences, which are then used for downstream tasks such as User Churn Prediction, Friend Recommendation, and Malicious Account Detection.

In this paper, we focus on *G-BLUM systems for IM apps* and contribute to the research literature in *three ways*. Manuscript submitted to ACM First, while prior studies have shown G-BLUM systems to work well for platforms like search engines and e-commerce services, the applicability of such systems to IM apps remains unclear; IM apps differ from these platforms in various aspects. For one, IM apps involve sustained and dynamic interactions among users, where conversations can span minutes to hours; IM app users also tend to engage multiple times a day [24]. This engagement rhythm stands in contrast to that of search engines where user interactions are often short-lived and focused (i.e., search-query-information) [27], and to that of e-commerce platforms which are visited only occasionally by users [28]. Furthermore, e-commerce platforms primarily focus on products, while search engines deal with a wide array of content types. In contrast, IM apps primarily handle personal messages, multimedia sharing, and sometimes, status updates. This personal touch makes user behavior on IM apps more nuanced [47]. In addition, on e-commerce platforms, users generally have a clear intent to browse or purchase; in search engines, they mostly seek information [26]. On IM apps, however, intentions vary widely from casual chats, sharing moments, to urgent communications [14]. Finally, IM apps handle personal conversations, making privacy paramount. This differs from search or shopping behaviors, where users might be more open to sharing data for better recommendations [33]. In sum, we believe that it cannot be simply assumed that the demonstrated successes of G-BLUM on other platforms would transfer to IM apps. We seek evidence for this assumption by designing and evaluating a G-BLUM system for a popular IM app: Snapchat.

Second, we introduce **COMUM** (Conceptualization, **O**perationalization and **M**easurement for User **M**odeling), a novel design and evaluation framework for G-BLUM systems (and other user modeling approaches). Previous studies on G-BLUM systems often lack clear conceptualization of their systems and evaluate them only on a few *specific* downstream tasks. This, in our opinion, does not provide sufficient evidence for the claim of "general-purpose". Therefore, we propose COMUM to help inform the design and evaluation of G-BLUM systems that align with the goals of such systems. COMUM is inspired by and adapted from the *Measurement Process Framework* from social science research methodology [49], which guides researchers through the process of conceptualizing a problem (e.g., What are "general-purpose user representations"?), operationalizing it into appropriate measures (e.g., What should the data and model architecture look like? How can user representations be extracted?) and assessing the quality of these measures (e.g., Are the resulting user representations actually general-purpose?). We describe COMUM and apply it to our G-BLUM system for Snapchat. Note that COMUM can also be adapted to other user modeling systems.

Third, by following the COMUM framework, we introduce and implement a novel Transformer-based [50] user model to learn user representations from behavioral log data of Snapchat users. This model has two training objectives that complement each other: Masked Behavior Prediction and User Contrastive Learning (see Section 3.3). To the best of our knowledge, we are the first to combine these two training objectives in G-BLUM systems. Furthermore, in developing G-BLUM systems, a key challenge concerns managing input sequences of varying lengths. User behavior logs might span mere minutes yet contain tens to hundreds of actions, depending on both the user and the nature of the interaction. New users also tend to have fewer behavioral log events than existing users. As users become more engaged, the length of their sequences can also grow. Consequently, user sequences can have a wide disparity in their lengths. Previous (G-)BLUM systems were trained with a fixed maximum length of user sequences (e.g., [8, 48, 57]). This restriction complicates handling sequences exceeding the predetermined length in downstream tasks. To accommodate longer sequences, which may help to create richer user representations, these systems are faced with two choices: either directly pre-train a model with very long sequences or modify the model architecture and then conduct further training. Both options are resource-intensive. In this work, we apply Attention with Linear Biases (ALiBi) [38], a novel modeling approach designed to handle input sequences of varying lengths efficiently and to achieve extrapolation for input sequences longer than those seen at training time. To the best of our knowledge, we are the first to apply ALiBi to Manuscript submitted to ACM

(G-)BLUM systems. Through our experiments and extensive evaluation based on our COMUM framework, we show that G-BLUM can be an effective approach to general-purpose user representation learning for Snapchat (and likely also other IM apps).

2 BACKGROUND

2.1 Typical G-BLUM Systems

Figure 2 from Section 1 illustrates the general setup of a G-BLUM system. The first step is to train a user model based on user behavior sequences with some predefined training objectives that enable learning of general-purpose user representations (i.e., they are not specific to a downstream task). Then, user representations are extracted from the trained user model. These representations serve as input for downstream task models. In subsequent downstream training, the upstream user model does not get updated; only the downstream models do, which are typically lightweight learners like linear regression [8, 13], logistic regression [8] and shallow neural networks (e.g., multilayer perceptron) [57].

2.2 Related Work

In the following, we review existing studies of G-BLUM systems. Note that we exclude studies where BLUM systems are downstream task-specific. We also exclude studies which, despite using techniques similar to G-BLUM systems, do not use behavior logs as main training data. This includes user-generated content (e.g., posts, images and videos) [2, 9], user and community networks [9, 35, 51], and mobile app usage data obtained from user surveys [57].

Most G-BLUM studies are motivated by recent advances in deep learning and natural language processing research. To start with, Yang et al. (2017) [54] applied the Continuous-Bag-of-Words (CBOW) algorithm [34] to behavior sequences of Adobe Photoshop users, where the training objective is to predict a user behavior given its neighboring behaviors. The trained model resulted in learned vectors for each user behavior, which are then aggregated (e.g., concatenated) for every user sequence. The aggregated vectors are treated as the final user representations, which are then evaluated on two downstream tasks: User Tag Prediction and Art Project Recommendation. Tao et al. (2019) [48] also investigated modeling Photoshop users based on their behavior sequences. They proposed and trained an innovative encoder-decoder model (named Log2Intent) with two simultaneous training objectives: Next Behavior Prediction and one that maximizes the semantic similarity between user behaviors and annotations for those behaviors. Similar to Yang et al. (2017) [54], the authors averaged the learned behavior vectors on the sequence level to generate user-level representations, and showed that these user representations achieved accurate downstream prediction of user interests. Chen et al. (2018) [8] used a recurrent neural network (RNN) to model user behavior sequences extracted from some commercial websites, with Next Behavior Prediction being the sole training objective. In addition, the authors made this model time-aware by incorporating temporal information (e.g., time difference between two events) as input to the model. Each user representation was computed by max pooling of all RNN states of the user's behavior sequence. The user representations were then evaluated on downstream tasks like user conversion prediction and preferred product prediction.

The above systems, however, have limitations. The CBOW algorithm used in [54] only learns static behavior representations that are independent of their context. The encoder-decoder model and RNN in [8, 48] only capture the context of a behavior from its left side in a sequence (i.e., prior user behaviors), instead from both sides (which can be beneficial for a richer understanding of user intents and behaviors).

More recent G-BLUM systems employed *Transformer-based user models* [50], which have been shown to be superior to previous approaches [13, 36, 57]. The main advantages of Transformers over earlier approaches are that their Manuscript submitted to ACM

self-attention mechanisms enable encoding of nuanced behavior-context interplay and that they do not suffer some of the problems that RNNs have [37], making them better suited to encode information in long, complex sequences.

Zhang et al. (2020) [57] were one of the first to implement a Transformer-based G-BLUM system. The authors modeled mobile phone users from their mobile app usage sequences (i.e., app installation, uninstallation, retention, and respective timestamps). They applied two training objectives to their Transformer-based model: Sequence Reconstruction and Masked Behavior Prediction. The learned user representations were evaluated on several downstream tasks including Next Week's App Installation Prediction, Look-alike Audience Extension and Feed Recommendation. In addition, Chu et al. (2022) [13] modeled users of Fusion 360 (professional software for computer-aided design), based on their behavioral sequences consisting of software commands. They applied a Transformer-based network coupled with a contrastive training objective, which maximizes the distance between vectors representing behavior sequences belonging to the same user and minimizes the distance of those belonging to different users. They evaluated the learned user representations by predicting user responses to customer surveys (e.g., product usage, areas, expertise, learning interests). Finally, Pancha et al. (2022) [36] modeled Pinterest users from their pin engagement sequences (e.g., saves, clicks, and reactions) and the related temporal information (e.g., timestamps and event duration). They applied a Transformer-based model with the primary training objective being predicting user behaviors over a 14-day window. They also included a metric learning objective, which aims to maximize the similarity between user representations and pin representations (which are generated daily from an proprietary process in the company). The learned user representations were subsequently evaluated on Future Pin Engagement Prediction, Feed Recommendation, and Ad Conversion Prediction.

While G-BLUM systems have been shown to work well for these platforms, little is known about the applicability of such systems to IM apps. IM apps differ from those platforms in various aspects, such as interaction dynamics, nature of content, user intention, and privacy concerns (as elaborated in Section 1). Our paper thus explores the applicability of G-BLUM systems for an IM app: Snapchat. Snapchat offers functionality beyond communications, such as Snaps (i.e., messages that disspear by default after being viewed), Maps (where you can discover public posts of other users and locate your friends if they enable location-sharing) and Stories (where users can see visual stories created by their friends), making it even more distinct from those systems where G-BLUM has been applied.

To implement our G-BLUM system, we adopt the Transformer architecture like in [13, 36, 57]. However, our approach differs from these earlier studies in various aspects, such as training objectives, methods for encoding positions in a sequence, and representation extraction methods. We delineate them in Section 3.3. Furthermore, we design and evaluate our G-BLUM system following COMUM, our own proposed framework, which is rooted in the principles of the Measurement Process Framework from research methodology in social sciences. For details, see Section 3.

3 SYSTEM DESIGN AND EVALUATION WITH COMUM

In this section, we introduce COMUM (Conceptualization, Operationalization and Measurement for User Modeling), a novel design and evaluation framework for G-BLUM systems. First, we describe the Measurement Process Framework from social science research methodology, which COMUM is based on. We also discuss, on a high-level, how this framework can be adapted to G-BLUM systems (Section 3.1). Then, we describe in three sections (Section 3.2, Section 3.3, and Section 3.4) details on how we leverage each step of COMUM (i.e., Conceptualization, Operationalization, and Measurement) to design and evaluate our G-BLUM system.



Fig. 3. The Measurement Process Framework from social sciences vs our CUMUM framework (Conceptualization, Operationalization and Measurement for User Modeling).

3.1 Measurement Process in a Nutshell

Social scientists frequently seek to measure theoretical and abstract concepts like personality traits, emotions, and prejudice [18]. Such concepts are intangible and cannot be directly measured [49]. For this reason, researchers approach measurement of such variables indirectly, leveraging a systematic approach: the Measurement Process Framework, which consists of three key stages: conceptualization, operationalization, and measurement [49] (see Figure 3).

3.1.1 Conceptualization. At this stage, the researcher identifies and defines the (abstract) concept they wish to measure. This involves providing a clear and concise theoretical definition. Without a clear definition, research can become ambiguous, as the meaning of concepts can differ between individuals, cultures, and contexts. Proper conceptualization ensures that the researcher and the audience share a common understanding of what is being studied. Take Emotional Intelligence (EI) as an example, where different definitions exist despite sharing terminology. According to Goleman [23], EI concerns the ability to recognize, understand, and manage one's own emotions, as well as the ability to recognize, understand, and influence the emotions of others. Goleman's EI consists of five components: self-awareness, self-regulation, motivation, empathy and social skills. Bar-on [5], in contrast, defines EI as non-cognitive capabilities, competencies, and skills that influence one's ability to cope with environmental pressures and demands. The corresponding key components are: interpersonal skills, stress tolerance, adaptability and mood. Differing definitions like these, if not clearly laid out, can impede efficient scientific discussions and progress.

For G-BLUM systems, the main concept of interest is "general-purpose user representation learning based on behavioral log data". A clear, proper, operationalizable definition for this concept would serve the foundation for the design and evaluation of G-BLUM systems. We discuss conceptualization of G-BLUM systems in detail in Section 3.2.

3.1.2 Operationalization. At this stage, the previously defined concept of interest gets turned into tangible, concrete measures. The researcher defines the specific methods and procedures necessary to measure the concept. This step bridges the gap between abstract theory and empirical study. By specifying how a concept will be measured, operationalization allows for consistency across studies, making findings more comparable and replicable. Take EI for instance. This concept can be operationalized in different ways, such as asking participants to solve emotional problems (e.g., Manuscript submitted to ACM

identifying emotions in faces) and to complete self-report EI questionnaires. Regardless of the form of operationalization (e.g., questionnaires, practical tasks), it is important to document clearly the operationalization procedure and ensure that the design of the EI measure follows from its definition. For example, when operationalizing Goleman's EI theory, one should not implement measures for mood, as mood is not part of Goleman's EI theory but Bar-on's.

When applying operationalization to G-BLUM systems, we should make sure that the design of our user model, as well as the training data, follows from the key concept's definition. We discuss this in detail in Section 3.3.

3.1.3 Measurement (Validity Assessment). After operationalizing a concept, the researcher must ensure that their measurements are valid (i.e., they measure what they claim to measure)⁵. Valid measurements are foundational for credible research. If a measurements are not valid, any conclusions drawn from the research can be questionable. Furthermore, ensuring the validity of measurements enhances the research's utility, as others can confidently build upon or reference the findings. To assess measurement validity, social scientists typically break it down into several validity indicators and investigate them individually [49]. These indicators commonly include *content, convergent, discriminant,* as well as *predictive* validity⁶. Note that among them, only predictive validity looks at performance in the traditional machine-learning sense. Thus, with COMUM, we place the idea of "performance" in a wider framework, as one of several possible *indirect* evaluations of whether a measure has "validity".

Content validity concerns whether a measure comprehensively addresses all pertinent aspects of a concept [18]. For instance, a valid measure of Goleman's EI should encompass all five key components of the concept. To assess its content validity, social scientists can seek expert opinions, or use latent variable models to quantify the fit of EI measurements with the structure of the EI theory (e.g., how many and what components?). For G-BLUM systems, content validity can correspond to, for instance, whether user representations encode relevant information like user behaviors and traits that differentiate one user from another.

Convergent validity concerns whether a measure aligns with other measures that it can be theoretically expected to resemble [18]. Again, take EI for example. Because of the theoretical overlap between Goleman's EI and Bar-on's, the respective measurements for these two EI concepts should show a strong (but not perfect) correlation. For G-BLUM systems, convergent validity can be considered as whether user representations strongly correlate⁷ with other measures of user representations based on similar behavioral data. Note that the notion of "high correlation" can be subjective. One solution to this is to compare the finding from convergent validity analysis to that from discriminant validity analysis, which is introduced next.

Discriminant validity, on the other hand, concerns whether a measure is distinct from other measures it should not resemble [18]. For example, EI is theorized to be different from concepts like IQ and personality traits. As such, EI measurements should not show strong correlations with those of IQ or personality traits. For G-BLUM systems, discriminant validity can pertain to whether user representations do not highly correlate with user characteristics *not* based on behavioral data, such as demographics. For example, age and gender are two demographic factors that can sometimes correlate with user behavior [41]. If user representations are highly correlated with demographics, it becomes difficult to say whether they are actually capturing meaningful differences among users or simply reflecting

⁵Note that in addition to being valid, measurements also need to be reliable (i.e., they are consistent across different situations or repetitions). In Section 6, we provide some discussion on reliability analysis for G-BLUM systems. However, we do not further engage with this topic, due to the large scope of reliability analysis possible that can warrant its own separate paper (see [16], for instance).

⁶*Face validity* is another commonly used validity indicator in social science research. It concerns whether, at first glance, a measure appears to accurately operationalize the intended concept. In our humble opinion, for G-BLUM systems, face validity can and should already be taken into account during the operationalization step. Therefore, we consider face validity analysis redundant for the measurement validity assessment step in G-BLUM systems.

 $^{^{7}}$ Note that when we use the term "correlate", we are referring to a non-zero relationship between two variables, which can be evidenced through methods like Pearson's correlation coefficients and cluster analysis.

demographic differences. Furthermore, we should expect the correlation between user representations and demographics (i.e., discriminant validity) to be lower than the correlation between user representations and other measures of user representations based on similar behavioral data (i.e., convergent validity).

Predictive validity concerns a measure's capacity to forecast relevant future outcomes [18]. For instance, Goleman [23] posited in his EI theory that EI is pivotal for life success. Thus, measurements of Goleman's EI should effectively anticipate outcomes such as future academic and professional accomplishments. To assess the predictive validity of G-BLUM systems, we can check how well the learned user representations based on historical user event logs can predict future user events like churn and engagement. This is similar to testing the performance of a G-BLUM system on downstream tasks, which is the most used approach in existing studies (see Section 2.2). Note that it is important to create a diverse set of downstream tasks (to support the claim of "general-purpose" user representations). Meanwhile, the selected tasks should also be relevant (to the application contexts), feasible (in terms of workload and privacy issues) and sensible (i.e., you have concrete expectations).

We discuss validity assessment for G-BLUM systems in further details in Section 3.4.

3.2 Conceptualization: General-purpose User Representations

While previous studies have demonstrated the success of G-BLUE systems for a few downstream tasks and platforms (see Section 2.2), the work on the conceptualization of G-BLUM systems has been limited. In those studies, G-BLUM systems were typically considered as BLUM systems that learn user representations generalizable to distinct downstream tasks. While this conceptualization is intuitive and describes G-BLUM systems correctly, we argue that a more precise conceptualization is necessary, which would pave way for the subsequent steps of operationalization and measurement validity analysis under the COMUM framework.

To begin with, we break G-BLUM systems down into two key concepts: "general-purpose user representations" and "behavior-based user modeling". For the former concept, we agree with earlier studies of G-BLUM systems [e.g., 13, 36, 57] that the user model should not be trained for specific downstream tasks and the resulting user representations should be applicable to distinct downstream tasks. As for the latter concept, building upon the definition of user modeling in [19] (see Section 1), we suggest defining it as "the process of creating user representations based on their behaviors, which capture and can predict user actions, preferences, or intentions."

Following from these two definitions, we can come to a more precise and practical conceptualization of G-BLUM systems. We define G-BLUM systems as a user modeling approach that fulfills the following five minimum criteria:

- (1) The user model is only trained on user behavioral data.
- (2) The user model's training objective is not directly connected to specific downstream tasks.
- (3) The learned user representations encode behavioral information.
- (4) The learned user representations capture user-specific information that can distinguish one user from another.
- (5) The learned user representations should generalize across distinct downstream tasks.

In the next section, we detail how we operationalize our conceptualization of G-BLUM system for Snapchat.

3.3 Operationalization: Transformer-Powered User Modeling

3.3.1 Data. Criterion 1 concerns the training data for user models. User behavioral log data usually needs to be extracted from raw platform logs, which are noisy, containing not only logs of user actions (e.g., clicks, swipes) but also many other events (e.g., app notifications, error reports, network requests). Therefore, it is important to ensure that Manuscript submitted to ACM

the final log data used for training a G-BLUM system consist of only user behaviors, as the goal of the system is to learn user representations from *only* behavioral data. In our G-BLUM system for Snapchat, we examine all log events and make a shortlist of events that are purely behavioral and triggered by user actions. Furthermore, it is important to consider whether the user community (that the G-BLUM system aims to serve) is well represented by the training data. To this end, we use a *large* and *random* sample of Snapchat users and their behavioral sequences for our G-BLUM system (see Section 4.1 for details).

3.3.2 User Model. To fulfill the second, third and fourth criterion for G-BLUM systems, we adopt two training objectives: *Masked Behavior Prediction* and *User Contrastive Learning.* Masked Behavior Prediction randomly masks parts of users' behavior sequences and forces the model to predict the masked behaviors based on their context.⁸ In this way, the user model learns to encode user behavioral information (fulfilling Criterion 3). User Contrastive Learning uses a contrastive loss function [21] to maximize the distance between representations of different users and minimize the distance between representations of the same user based on behavioral sequences from different time points. In this way, the user model learns user-specific information that sets one user apart from another (fulfilling Criterion 4). As these two training objectives are not specific to a downstream task, Criterion 2 is also fulfilled. Note that our paper is the first to apply both Masked Behavior Prediction and User Contrastive Learning training objectives to G-BLUM systems. See Section 4.2 for details on our implementation of these two training objectives.

Criterion 5 concerns that the learned user representations should generalize to different downstream tasks. To achieve this, the user model should be able to handle complex patterns in behavioral sequences (e.g., the interplay between behavior and context) such that nuanced, precise user representations can be learned. To this end, we adopt the Transformer architecture for our user model, as previous studies have demonstrated the benefit of Transformer-based models for effective user representation learning [13, 36, 57, 60]. Furthermore, to encode order information in behavioral sequences and to overcome the limitation of fixed-length input sequences in previous G-BLUM systems, we apply a novel position encoding method, Attention with Linear Biases (ALiBi) [38]. ALiBi is designed to not only encode positional information in sequences, but also accommodate long sequences, train more efficiently and achieve extrapolation at inference time for sequences longer than those seen at training time (see Appendix A for more information about ALiBi). To the best of our knowledge, our paper is the first to apply ALiBi to (G-)BLUM systems.

3.4 Measurement: Validity of User Representations

3.4.1 Content Validity. Following Criterion 3 and 4, we would expect user representations from a G-BLUM system to encode behavior-related information and user-specific information. For behavior-related information, we check whether our G-BLUM system can accurately predict a masked user behavior given the other user behaviors in a sequence (i.e., *Masked Behavior Prediction*). For user-specific information, we check whether the G-BLUM system can 1) generate similar user representations for the same user (based on the user's behavioral sequences from different periods) and dissimilar user representations for different users, and 2) among behavioral sequences of different users, retrieve the two that belong to the same user. We refer to the first one as *User Representation Similarity Analysis*, and the second one as *User Retrieval*.

3.4.2 Convergent and Discriminant Validity. For G-BLUM systems, we would expect the resulting user representations, which are behavior-based, to correlate more with other behavior-based measures of users (i.e., convergent validity) than

⁸Masked Behavior Prediction is analogous to Masked Token Prediction in some large language models, such as BERT [15]. Manuscript submitted to ACM

with non-behavioral measures (i.e., discriminant validity). To assess our system's convergent validity, we hypothesize that the learned user representations should exhibit stronger relationships with *an alternative behavior-based measure of users* than with two demographic variables: gender and age. We name this alternative bahavior-based measure of users as *behavior-based user tags*, which assigns labels to users based on their engagement preferences, such as chatting, content consumption and friending. ⁹ We examine this hypothesis by projecting the learned user representations onto a two-dimensional plane and checking the extent to which they show patterns that correspond to the aforementioned behavior-based user tags and demographics.

3.4.3 Predictive Validity. For predictive validity analysis, we expect user representations from a G-BLUM system to be able to predict relevant future user events. For IM apps, such events are typically related to user engagement and user safety. This is analogous to testing the performance of a G-BLUM system on downstream tasks, which is the most used approach in previous studies. For our G-BLUM system, we evaluate it on three distinct downstream tasks that span multiple use cases, including user safety, monetization, and user retention. These tasks are *Reported Account Prediction*, ad *Ads View Time Prediction* and *Account Self-deletion Prediction*¹⁰.

Specifically, Reported Account Prediction concerns whether an account is going to be reported by others for displaying undesirable behaviors, such as spamming and sexually harassment. Ads View Time Prediction concerns whether a user is going to engage with an ad for a duration longer than a specified threshold. Account Self-deletion Prediction concerns whether an account is going to be deleted by its owner.

4 EXPERIMENTS

The main goal of our study is to investigate whether G-BLUM systems can effectively model users of IM apps. To this end, we follow the COMUM framework where we train a Transformer-based user model on behavioral sequences of Snapchat users, and evaluate the user model and its user representations across different validity indicators. We detail below our experiments that serve these aims.

4.1 Snapchat and Data

Snapchat is a popular multimedia IM platform with close to 400 million daily active users as of the second quarter of 2023 [44], making it a suitable case study to explore the applicability of G-BLUM systems to IM apps. We identify 577 unique user behaviors and use them to construct user behavior sequences. These user behaviors are, for instance, sending a chat, viewing a video, swiping up or using a filter. They do not contain any identifiable information about the users or any information about chat content, video content, or filters. In addition, we insert a "new_session" *token*¹¹ into each sequence wherever a new user session begins. Such a user behavior sequence can look like: "open_chat, read_message, new_session, send_message, close_app". We construct different datasets based on Snapchat user behavior logs. Note that we restrict our study population to US-based adult users. While this means that our data may not be representative of all Snapchat users, our findings can still provide valuable insights.

Training Dataset. For training our user models, we randomly sample users who were *active* during the two weeks between April 1, 2023 and April 14, 2023. "Active" is defined as using Snapchat for at least 1 minute during this period. This resulted in a sample of 766,170 users and their behavior sequences (one sequence for each user).

⁹Due to the proprietary nature of this alternative measure, we cannot disclose its full and exact details.

¹⁰We report results from only these three tasks due to policy restrictions (e.g., user privacy, commercial interests).

¹¹The term "token" typically refers to words, subwords or characters in a sequence of text. Here, it simply refers to an element in a user behavioral sequence that indicates the beginning of a new user session.

Evaluation Datasets. We evaluate the measurement validity of our G-BLUM system across the following tasks: Masked Behavior Prediction, User Representation Similarity Analysis, User Retrieval, Reported Account Prediction, Ads View Time Prediction, and Account Self-deletion Prediction. Due to space limitation, we present the dataset statistics and construction procedure in Appendix D.

4.2 User Model Training

We train our user model from scratch on our sample of behavior sequences from US-based and active adult users. We truncate each behavioral sequence to a maximum length of 128 tokens¹². The user model has two training objectives that complement each other: Masked Behavior Prediction and User Contrastive Learning.

Specifically, we extract a random pair of non-overlapping sequences from each user, perform Masked Behavior Prediction on each sequence independently (with 15% random masking and trained on cross-entropy loss), and perform User Contrastive Learning within each mini-batch of behavior sequences. Let $\mathcal{B} = \{(s_i, s_{i^+})\}_{i=0}^n$ define a mini-batch of behavior sequences, where (s_i, s_{i^+}) are the sequence pair extracted from the same user's behavioral logs and n is the batch size. The User Contrastive Learning loss on each sequence pair (s_i, s_{i^+}) is defined as $t^{i,i^+} = -\log \frac{\exp(\sin(e_i, e_{i^+})/\tau)}{\sum_{j \neq i} \exp(\alpha_{ij} \cdot \sin(e_i, e_j)/\tau)}$, where e_i and e_{i^+} are the vectors of sequences s_i and s_{i^+} that belong to user *i*, e_j is the vector of sequence s_j from a different user *j*, and τ is the temperature hyperparameter¹³. We obtain each user (i.e., sequence) vector *e* by aggregating all the behavior (a.k.a., token) vectors in the last layer of the Transformer-basd user model. The User Contrastive Learning loss over the entire batch is calculated as $\mathcal{L}_{\text{UCL}} = \frac{1}{n} \sum_{i} t^{i,i^+}$. We optimize our G-BLUM model with the sum of Masked Behavior Prediction and User Contrastive Learning losses: $\mathcal{L} = \mathcal{L}_{MBP} + \mathcal{L}_{UCL}$.

Our user model consists of 12 Transformer Encoder layers with a hidden size of 768 and 12 attention heads per layer¹⁴. It is trained with a batch size of 512 and a learning rate of 4e-4 for 20 epochs. 95% of the user sequences are used for training while the rest 5% of users are for validation. Training a model takes about 8 hours on 8 Nvidia V100 GPUs.

4.3 Baselines and User Representation Extraction Methods

For the analysis of content and predictive validity, we compare our model with a series of baseline models, including:

- Term Frequency (TF) and Term Frequency Inverse Document Frequency (TF-IDF), which generate user representations by counting the frequency of each unique user behavior in the user behavior sequence. TF-IDF also assigns higher weights to behaviors that appear less frequent in other user behavior sequences.
- Skip-Gram with Negative Sampling (SGNS) [34], a popular Word2Vec algorithm that can learn fixed vector representation for each user behavior by using a shallow, two-layer neural network to predict context behaviors from a given target behavior. The vectors associated with the behaviors can then be aggregated for every user sequence to form user representations.
- Untrained user representations, where a fixed vector is randomly generated for each unique user behavior in the entire dataset. Then, like SGNS, the fixed vectors associated with the behaviors are aggregated to form a user representation. This can be considered as a "high-dimensional" TF approach, and is shown to be a competitive baseline in different downstream tasks [3].

¹²According to our preliminary analyses, longer sequences increase computational overhead while providing only minimal additional benefit. ¹³The temperature parameter in contrastive loss adjusts the sensitivity of distinguishing between similar and dissimilar data: a higher value makes the distinctions softer, while a lower value makes them sharper. ¹⁴This structure is similar to BERT-base, a large language model with many proven successful applications [15].

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• Transformer Encoder (**Enc**) and Decoder (**Dec**) are our implementation of BERT [15] and GPT2 [39] for user modeling, which respectively have the same architecture as BERT-base and GPT2-117M. We train them respectively with Masked Behavior Prediction and Next Behavior Prediction on the same data as our model.

User Representation Extraction. TF and TF-IDF are fixed-length vectors that directly summarize user behavior on the sequence level. We use these vectors directly as user representations. In contrast, our main user model and the other baseline models (i.e., SGNS, Untrained, Enc, Dec) learn vector representations on the token/behavior level (instead of the entire behavior sequence). Therefore, aggregating (i.e., pooling) the behavior-level vectors to a sequence-level vector (i.e., a user representation) is necessary. We experiment with four different pooling strategies, including mean pooling, max pooling, weighted mean pooling, and weighted max pooling (see Appendix C for details). We then select the best performing pooling strategy for each of the user models. Based on our analysis results reported in Table 4 of Appendix C, we perform weighted mean pooling for Dec and mean pooling for the other modeling approaches.

4.4 Content Validity Evaluation

To evaluate our user model's content validity, we first check how it performs Masked Behavior Prediction on unseen user behavior sequences. For this, we obtain a random sample of user sequences from 10,000 active users between May 29, 2023 and June 4, 2023. We randomly mask one behavior for each user event sequence and check how accurately the model can predict the masked behavior. Because some user behaviors are much more prevalent than others, we also compute balanced accuracy using a stratified masking procedure, which masks each behavior equally frequently across user sequences. The better the model performs masked behavior prediction relative to always guessing the most frequent user behavior, the more evidence for content validity.

Then, we check how well the model learns user-specific information. To this end, we implement two types of analyses. The first one is User Representation Similarity Analysis, where we check whether randomly chosen behavior sequences from the same user would be more similar (based on cosine similarity) than those from different users. The larger the difference in similarity scores, the more evidence for content validity. The second one is User Retrieval, which concerns, given a random user's behavior sequence and a sample of sequences from both that user and other users, whether the same user's sequences can be retrieved. We evaluate retrieval performance using Mean Reciprocal Rank (MRR), a metric that assesses retrieval quality based on the ranking of retrieved user sequences. The higher the MRR score, the better the retrieval performance and hence, the more evidence for content validity. Implementation details about User Retrieval can be found in Appendix D.

4.5 Convergent and Discriminant Validity Evaluation

Using the same sample of unseen users as in content validity evaluation, we apply t-SNE to project the extracted user representations to a two-dimensional plane. We then check to what extent the projections form patterns that correspond to users' gender, age group and behavior-based user tags. If the patterns are clearer for behavior-based user tags than for user demographics, then we are more confident in the model's convergent and discriminant validity.

4.6 Predictive Validity Evaluation

We evaluate how well the model performs Reported Account Prediction, Ads View Time Prediction and Account Self-deletion Prediction. We vary the gap between the labels and the user behavior sequences (i.e., features) from 0 to 7 days. We then use a multilayer perceptron (MLP; with 5-fold nested cross-validation for hyperparameter tuning) to Manuscript submitted to ACM perform these downstream prediction tasks based on past user behavior sequences. The better the prediction (indicated by AUC scores), the more evidence for predictive validity. More implementation details can be found in Appendix D.

4.7 Ablation Analysis

Lastly, we conduct an ablation study to investigate the influence of the two training objectives (i.e., Masked Behavior Prediction training and User Contrastive Learning) and ALiBi on our user model across all the evaluation tasks.

5 RESULTS

5.1 Training

We evaluate our user model every 500 training steps and plot the validation losses in Figure 7 of Appendix E. The figure shows that the validation loss steadily decreases over training steps, indicating model learning.

5.2 Content Validity

5.2.1 Masked Event Prediction. Table 1 summarizes performance of our user model (*Ours*) and the baseline model (*Enc*) on Masked Behavior Prediction across the two masking strategies (i.e., *Random* and *Stratified*). Note that we do not include the other baselines listed in Section 4.3, as they do not have a Masked Behavior Prediction training objective. *Majority Vote* refers to predicting all masked behaviors as the most frequent behavior in the training data. We can see that our user model achieves substantially higher prediction accuracy than Majority Vote for both masking strategies. Remarkably, even when stratified masking is used, our model's Masked Behavior Prediction performance only goes down by about 5 percentage points. Furthermore, we see that Enc has the best performance for both masking strategies. This is as expected, as Enc is trained exclusively with the Masked Behavior Prediction training objective and is thus optimized for this evaluation task. The fact that our model compares with Enc gives us confidence in our model's ability to encode behavioral information.

 Accuracy of Masked Behavior Prediction Different Models and Masking Strategies. 		Model	Within	Between	Differen	
			TF	0.7607	0.5610	0.1997
	Random	Stratified	TF-IDF	0.6572	0.3811	0.2762
	Tunidoni		Untrained	0.7563	0.5540	0.2023
rity Vote	0.2450	0.063	SGNS	0.8880	0.7908	0.0972
	0.9379	0.8908	Enc	0.8046	0.6350	0.1696
	0.9221	0.8693	Dec	0.6761	0.4589	0.2172
			Ours	0.5960	0.1910	0.4050

Table 2. Within-user vs Between-user Cosine Similarity.

5.2.2 User Representation Similarity Analysis. Table 2 summarizes the results from User Representation Similarity Analysis across our model and other baselines. The *Within* column shows the cosine similarity scores for user representations based on behavior sequences belonging to the same user. The *Between* column shows the cosine similarity of user representations based on behavioral sequences belonging to different users. Because users are not always performing exactly the same actions, one would expect the within-user cosine similarity to be smaller than 1 on average. Likewise, because sometimes different users can have similar behavioral sequences, we would expect the between-user cosine Manuscript submitted to ACM

similarity to be higher than zero on average.¹⁵ Moreover, it is possible that both within-user and between-user cosine similarity scores are high, due to the existence of overlapping user behaviors (between users) that might be meaningless for distinct user representations. Therefore, directly interpreting either within-user or between-user cosine similarity values can be misleading. Instead, we focus on the difference between *within-user* and *between-user* cosine similarity (i.e., the *Difference* column), which is a better reflection how well user representations encode user-specific information such that one user's representation is distinguishable from another user's. As we can see in the table, our user model outperforms the best baseline approach (TF-IDF) by about 13 percentage points, which is a substantial difference. Therefore, our model demonstrates the most evidence for this aspect of content validity among all the approaches. Furthermore, note that the naive implementations of BERT (Enc) and GPT2 (Dec) have led to cosine differences even lower than some other simpler approaches (e.g., TF-IDF, Untrained). This suggests that naively applying BERT/GPT2 in G-BLUM systems should be avoided.



Fig. 4. Our model and baselines' performance on the User Retrieval task across different input sequence lengths. Supplementary numerical results can be found in Appendix E.

5.2.3 User Retrieval. Figure 4 summarizes the performance of our user model and baselines on the User Retrieval task. Note that we also vary the length of the user sequences (from 32 to 1024 by a progression ratio of 2). The figure shows that our user model consistently and substantially outperforms all the baselines. Furthermore, we observe overall increasing performance as the input sequence becomes longer. This improvement is most pronounced and consistent for our model, suggesting that our model not only benefits from longer user sequences but, thanks to the ALiBi component, can also effectively conduct inference on sequences longer than those it encountered during training.

5.3 Convergent and Discriminant Validity

Figure 5 shows t-SNE visualizations of user representations from our model, color- and shape-coded by gender, age groups and behavior-based user tags. We can see that both different genders and age groups are randomly scattered across the vector space. In contrast, the clustering pattern is much clearer for behavior-based user tags. For instance, the light green triangles are concentrated on the right side of the space, the pink plus signs are mostly on the top, and most

¹⁵The minimum value for cosine similarity is -1, but in our analysis, it does not go below zero. Therefore, we opt for the zero threshold here.



Fig. 5. The t-SNE visualization of our model's user representations (based on mean pooling) color- and shape-coded by different gender groups, age groups and behavior-based user tags. Note that we omit the figure legend for Behavior-based User Tags on purpose, due to the proprietary nature of the labels.



Fig. 6. Our user model and baselines' performance on Reported Account Prediction, Ads View Time Prediction, and Account Self-Deletion Prediction. We use AUC as the evaluation metric. The x-axis indicate the time gap (in days) between the timestamp of the last behavior in an input behavior sequence and the time when the prediction target happened (i.e., when an account is reported; when a user views an ad for a long duration; when a user deletes their account).

yellow crosses are on the left. This pattern aligns with our expectation that our behavior-based user representations would exhibit a stronger relationship with another behavior-based user measure than with user demographics. Therefore, this indicates evidence for convergent and discriminant validity of our model's user representations. Note that we find this pattern to hold for the baseline models as well. This is not surprising, as those models also learn behavior-based user representations. However, as this is a visual, qualitative analysis, it is difficult to rank our model's performance here with other models. Therefore, we do not conduct further model comparison here.

5.4 Predictive Validity

Figure 6 shows our user model and baselines' performance on three downstream tasks: Reported Account Prediction, Ads View Time Prediction, Account Self-deletion Prediction, across different *time gaps*. "Time gaps" refers the number of days between the last timestamp of a user's behavior sequence and the (first) timestamp of the downstream event. Note that these two timestamps do not overlap. We can make three observations. *First*, our model consistently outperforms all other baselines (except for time gap of 1 and 5 in the Reported Account Prediction task), indicating higher predictive validity of our model compared to the rest. *Second*, our model can detect (likely) malicious accounts (reported by other users) and predict user account self-deletion with a high AUC score up to one week in advance. In contrast, our model predicts ads view time less well (but still better than the baselines and chance). Nevertheless, this is expected, as ads Manuscript submitted to ACM

view time also depends on other important factors, such ad length, ad content and user states (e.g., if users are fatigue or busy), which are not present in our model's user representations. *Third*, for Reported Account Prediction and Ads View Time Prediction, prediction performance goes down as the time gap becomes larger. Interestingly, however, performance on Ads View Time Prediction does not seem to correlate with the size of time gap. This indicates that temporal information is likely also important for this task.

5.5 Ablation Analysis

We also conducted an ablation study, where we strip our G-BLUM user model of only the Masked Behavior Prediction training objective, only ALiBi, and both User Contrastive Learning and ALiBi, respectively. Note that in the last ablation condition, the user model is equivalent to our baseline model Enc. To comprehensively understand the effectiveness of each component, we study the impact of the ablations on all the downstream evaluation tasks. For each task, we report the averaged results across different settings (e.g., different input lengths in the User Retrieval task).

Table 3 shows that without the User Contrastive Learning training objective, the user model would benefit from a small performance improvement on Masked Behavior Prediction. This is expected, as now the model has Masked Behavior Prediction as its sole training objective. Meanwhile, the model suffers from a significant performance drop on all the other tasks. This suggests the importance of User Contrastive Learning for training user models. The Masked Behavior Prediction training objective also contributes slightly to the model's overall performance. Without ALiBi, the model would suffer across all evaluation tasks. These ablation results further confirm the benefit of using User Contrastive Learning and ALiBi for G-BLUM systems.

Table 3. Ablation Study on All the Main Components of Our Model: Masked Behavior Prediction (MBP), User Contrastive Learning (UCL), and ALiBi. We evaluate the (ablated) models on the averaged results across different settings on 6 evaluation tasks: Masked Behavior Prediction (MBP), User Representation Similarity Analysis (URSA), User Retrieval (UR), Reported Account Prediction (RAP), Ads View Time Prediction (AVTP), and Account Self-deletion Prediction (ASP). The evaluation metrics are: ACC (accuracy), COS (cosine difference), MRR (Mean Reciprocal Rank), and AUC. Note that these evaluation scores are converted to the same scale.

	MBP ACC	URSA COS	UR MRR	RAP AUC	AVTP AUC	ASP AUC	
Our Model	92.21	40.50	90.77	89.07	66.30	89.85	
- MBP	N/A	-0.27	-1.28	+0.23	-0.80	-1.53	
- UCL	+1.61	-28.38	-4.66	-0.34	-3.98	-0.49	
- ALiBi	-0.47	-1.05	-0.43	-1.01	-3.52	-1.53	
- UCL & AliBi	+1.58	-23.54	-4.53	-1.15	-6.76	-1.34	

6 CONCLUSION

In this paper, we show that G-BLUM systems are likely a promising strategy to learn general-purpose user representations for IM apps. We also introduce COMUM, a design and evaluation framework for G-BLUM systems. COMUM is inspired by and adapted from the established Measurement Process Framework in social science research methodology. We use it to guide the conceptualization, operationalization and measurement quality assessment of our G-BLUM system.

Specifically, we conceptualize a G-BLUM system as a user modeling approach that consists of five minimum criteria. We then implement a Transformer-based user model with architecture and training data that fulfill these criteria. Across Manuscript submitted to ACM various measurement validity analyses, our model and its user representations demonstrate medium to high levels of validity and consistently outperform various baselines. Among others, a few findings are worth highlighting. *First*, our user model achieves high predictive validity for two important downstream domains: user safety and user churn. *Second*, we show that sequences as short as consisting of only 128 events can already be used to create user representations of medium-to-high measurement validity. This has the potential to replace traditional user representation approaches that rely on months worth of (sensitive) user data. *Third*, we find that simply using out-of-the-box Transformer-based models (e.g., BERT/GPT2) will not learn the best user representations. Lastly, we also compare different aggregation approaches for user representation extraction (see Appendix C), and find mean pooling to be overall the best one.

Despite many insights, our paper has limitations. For one, we did not conduct any online evaluation. Consequently, the performance of our user modeling approach in real production environments, in terms of both efficiency and efficacy, remains unclear. Also, we did not investigate the reliability of our user G-BLUM system and the learned user representations, which is another important measurement quality criterion to consider. The Measurement Process Framework from social sciences traditionally assesses reliability using multiple indicators, such as test-retest reliability, internal consistency and inter-rater reliability (see [16] for more details). However, they do not readily apply to user models and user representations, necessitating significant modifications. We advocate research in this area. Finally, our proposed COMUM framework is not strictly prescriptive. For instance, researchers may not agree on the definition of key concepts, specific model designs and evaluation strategies. Nevertheless, we still consider COMUM a step forward in advancing user modeling theories and practices. We hope it proves valuable to researchers in user modeling, and we encourage them to adapt COMUM for their own G-BLUM systems and potentially other user models.

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A ALIBI: ATTENTION WITH LINEAR BIASES

ALiBi adds a linear bias to the attention scores in a Transformer model. This bias is calculated as a function of the distance between the query and key tokens. This distance can be calculated in a variety of ways, but a common approach is to use the absolute difference between token indices. The bias is then added to the attention scores before the softmax function is applied. Specifically, let \mathbf{q}_i define the *i*-*t*h query in the input sequence of length *L*. Let **K** defines the key matrix, the attention score of query *i* is calculated as: softmax($\mathbf{q}_i\mathbf{K} + m * [-(i-1), ..., -2, -1, 0, -1, -2, ..., -(L-1-i)]$), where *m* is a fixed head-specific constant. Following previous studies [38, 59], we set the values of different *m* as a geometric sequence (*i.e.*, $\frac{1}{2^i}$, $\frac{1}{2^2}$, ..., $\frac{1}{2^n}$). The effect of the linear bias is to penalize attention between tokens that are far apart. This helps to prevent the model from attending to tokens that are outside of its context window and generalizing to sequences longer than seen previously. As a result, ALiBi can improve the performance of Transformer models on long sequences.

B EVALUATION LOSS DURING USER MODEL TRAINING

Figure 7 shows the evaluation loss of our model during the training stage. As shown in the figure, the evaluation loss converges smoothly through the training process.



Fig. 7. Evaluation loss of the left-out validation set during the training procedure.

C COMPARISON OF DIFFERENT POOLING METHODS FOR USER REPRESENTATION SIMILARITY ANALYSIS

Model	Within ↑	Between \downarrow	Difference ↑
Untrained (mean)	0.7563	0.5540	0.2023
Untrained (max)	0.9880	0.9857	0.0023
Untrained (weighted mean)	0.7265	0.5375	0.1889
Untrained (weighted max)	0.9766	0.9709	0.0057
S GN (mean)	0.8880	0.7908	0.0972
SGN (max)	0.9062	0.8679	0.0383
SGN (weighted mean)	0.8729	0.7806	0.0922
SGN (weighted max)	0.9019	0.8638	0.0381
Enc (mean)	0.8046	0.6350	0.1696
Enc (max)	0.9635	0.9479	0.0156
Enc (weighted mean)	0.7848	0.6232	0.1616
Enc (weighted max)	0.9359	0.9165	0.0193
Dec (mean)	0.7237	0.5224	0.2013
Dec (max)	0.9553	0.9393	0.0160
Dec (weighted mean)	0.6761	0.4589	0.2172
Dec (weighted max)	0.9246	0.9025	0.0222
Dec (last token)	0.9279	0.8992	0.0287
Ours (mean)	0.5960		0.4050
Ours (max)	0.9373	0.9042	0.0332
Ours (weighted mean)	0.5743	0.1861	0.3882
Ours (weighted max)	0.8981	0.8556	0.0424

Table 4. Comparison of Different Pooling Methods for Each User Model.

For our user model and several baselines, we experimented with different pooling methods to create user representations. Specifically, for Transformer-based models, we obtain the vector of each behavior in a user sequence from the last Transformer layer of the model. Then, we aggregate the behavior vectors for a sequence to obtain a sequence-level representation (i.e., the final user representation). Four different aggregation strategies were considered: mean pooling, max pooling, weighted mean pooling, weighted max pooling. "Weighted" refers to assigning higher weights to behaviors towards the end of a sequence (i.e., more recent behaviors) and lower weights to those towards the beginning of the sequence. From left to right, the weights increase linearly and sum up to one. As Table 4 shows, mean pooling consistently outperforms other aggregation methods for the User Representation Similarity Analysis task in most models except for Dec. Since the masked self-attention mechanism used in Dec allows the later tokens to access more context than the previous tokens, it makes sense to assign higher weights to the later tokens when pooling sequence embedding from Dec.

D TASK DEFINITION AND DATASET STATISTICS

For fair comparison, users do not overlap between training and evaluation datasets.

Masked Behavior Prediction and User Representation Similarity Analysis. Description of the two tasks can be found in Section 4.4. A random sample of 23,596 users were used for Masked Behavior Prediction and 2,000 users were used for User Representation Similarity Analysis.

User Retrieval. This task aims to evaluate the models' capability in distinguishing and grouping users based on user behavior sequences. To this end, we construct a dataset with 2,001 samples from user data between May and June, 2023. Each sample consists of 101 user behavior sequences: 1 *query* and 100 *candidates*. Within the 100 candidates, there is 1 *positive candidate* that belongs to the same user as query and 99 *negative candidates* that belongs to other users. We directly apply each model to this task without task-specific training. When evaluating each sample, we obtain vector representation for each behavior sequence, and rank the 100 candidates based on their cosine similarity with the query. We measure the models' performance with Mean Reciprocal Rank (MRR) defined as MRR = $\frac{1}{N} \sum_{i=1}^{N} \frac{1}{r_i}$, where N represents the number of samples and r_i represents the rank of the positive candidate in the *i*-th sample. Each behavior sequence contains 1024 (2¹⁰) user behaviors. To evaluate the models' capability with different input lengths, we run 6 different experiments with the first 2⁵, 2⁶, 2⁷, 2⁸, 2⁹, 2¹⁰ behavior of each sequence as input. For models with an input length limitation, we split each behavior sequence into non-overlapping 128-length segments, obtain vector representation for each segment, and take the average as the final user representation.

Reported Account Prediction, Ads View Time Prediction, and Account Self-deletion Prediction. These tasks aim to predict accounts/users that get reported by other users (e.g., due to malicious behaviors), view an ad for above a duration threshold, and voluntarily delete their own accounts. We collected data across 20 different dates between May and June, 2023 and construct three balanced datasets with sample sizes of about 13,000, 10,000, and 13,000, respectively. We formulate these tasks as binary classification problems (e.g., a reported user v.s. not a reported user). We calculate user representations using their latest 128-length behavior sequence as input. The user representations and binary labels are then used to fit a multi-layer perception (MLP) classifier. The hyperparameters of the MLP classifier are determined with random search in 5-fold cross validation for fair comparison across different models. We evaluate the classification results using AUC scores.

E DETAILED NUMERICAL RESULTS

This section includes tables containing numerical results supplementary to Figure 4 and Figure 6. Specifically, Table 5 details numerical results of the User Retrieval task. Table 6 details numerical results of the Reported Account Prediction task. Table 7 details numerical results of the Ads View Time Prediction task. Table 8 details numerical results of the Account Self-deletion Prediction task.

Model	2 ⁵	2 ⁶	27	2 ⁸	2 ⁹	2 ¹⁰	Average
TF	80.20	81.41	82.27	82.64	84.19	86.12	82.81
TF-IDF	80.90	81.81	82.86	83.20	84.84	86.67	83.38
Untrained	80.28	81.22	82.28	82.64	84.25	86.06	82.79
SGN	79.40	80.99	81.61	82.34	83.70	85.56	82.27
Enc	82.24	84.16	86.02	86.36	88.38	90.28	86.24
Dec	81.68	84.14	86.34	85.19	87.57	89.16	85.68
Ours	83.79	87.35	90.54	92.71	94.61	95.63	90.77

Table 5. Detailed Results of User Retrieval (UR) with Input Sequence Length Ranging from 32 (25) to 1024 (210).

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Table 6. Detailed Results of Reported Account Prediction across Different Input-Target Time Gaps (in Days).

Model	0	1	2	3	4	5	6	7	Average
TF	90.00	86.90	86.60	86.70	85.70	84.60	84.90	86.20	86.45
TF-IDF	89.70	87.70	86.30	85.80	86.10	86.10	84.10	86.20	86.50
Untrained	90.60	88.60	85.70	86.40	85.20	86.50	84.50	85.60	86.64
SGN	90.40	86.60	86.60	84.50	85.80	84.70	85.20	85.50	86.16
Enc	90.60	89.70	87.70	87.50	87.40	87.20	86.10	87.20	87.92
Dec	91.70	88.80	88.50	89.00	88.20	88.50	86.70	87.30	88.59
Ours	91.80	89.30	89.00	89.80	88.70	87.90	88.60	87.50	89.08

Table 7. Detailed Results of Ads View Time Prediction (AVTP) across Different Input-Target Time Gaps (in Days).

Model	0	1	2	3	4	5	6	7	Average
TF	61.20	61.30	52.00	60.20	50.40	64.50	62.70	55.40	58.46
TF-IDF	59.90	60.00	60.20	59.70	63.20	63.20	60.00	<u>64.30</u>	61.31
Untrained	58.30	56.70	55.70	55.80	54.00	57.20	57.40	55.50	57.86
SGN	58.10	56.00	56.70	55.80	62.90	58.20	57.40	57.80	56.33
Enc	58.80	57.70	58.70	58.00	63.30	61.50	59.00	59.30	59.54
Dec	59.80	60.70	60.20	<u>61.10</u>	59.90	62.90	61.10	61.50	60.90
Ours	66.90	65.70	65.40	65.90	66.80	67.50	66.80	65.40	66.30

Table 8. Detailed Results of Account Self-deletion Prediction across Different Input-Target Time Gaps (in Days).

Model	0	1	2	3	4	5	6	7	Average
TF	96.80	89.10	88.00	85.70	83.20	85.60	85.50	84.80	87.34
TF-IDF	95.90	88.10	85.70	85.20	85.20	85.60	83.70	85.90	86.91
Untrained	97.10	89.10	86.30	85.90	85.90	86.70	85.20	86.60	87.85
SGN	97.20	89.20	87.50	86.20	84.70	84.90	85.20	85.40	87.54
Enc	96.40	89.70	87.90	86.90	86.90	87.50	85.50	87.20	88.50
Dec	97.80	90.30	87.30	85.90	85.20	87.10	83.20	86.60	87.92
Ours	97.50	92.00	89.70	88.20	87.60	88.30	86.90	88.60	89.85