Event Distribution in Daily Life: A Replication Study.

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Abstract

Research in event cognition highlights the crucial role of event segmentation in shaping perceptions and memories. Anticipation of event boundaries is influenced by characteristic duration, often assumed to follow normal distributions in daily events. This study replicates recent investigations into event duration using a nightly segmentation approach with continuously captured daily images. Forty-one participants collected images over fourteen days, segmenting them into events. Event durations for various activities were modelled using truncated normal, exponential and gamma models. Our findings align with prior research in event distribution, revealing that overall, an exponential or gamma distribution provides a superior fit compared to a truncated normal distribution. This suggests that when daily events are studied in an ecological context at a fundamental level, most of them have little sign of a typical duration. Consequently, duration estimation is unlikely to play a large role in anticipating event boundaries.

Keywords: Event duration, Event Cognition, Nightly segmentation.

Introduction

Despite the constant stream of activity in our lives, we tend to interpret our actions in distinct event-based units. The division of ongoing activities into meaningful segments is a natural aspect of perception, understanding, and memory processes (Zacks, Speer, Swallow, Braver, & Reynolds, 2007). These event units are not solely determined by the physical structure of the activity itself; rather, event segmentation represents an active cognitive process, shaping how individuals perceive and divide their experiences (Sastre, Defina, Garrett, Zacks, & Dennis, 2022).

Recent investigations into event boundaries have primarily delved into how these boundaries are identified and how ongoing events evolve (Doherty & Smeaton, 2008; Zwaan, Langston, & Graesser, 1995; Zacks et al., 2007; Reynolds, Zacks & Braver, 2007; Franklin et al., 2020; Kumar et al., 2023). Some studies have demonstrated peoples' capacity to anticipate upcoming event boundaries. For example, Zacks et al. (2011) observed reduced accuracy and confidence in predicting future activities just before an event boundary in paused videos, indicating an anticipation of forthcoming changes.

Anticipation of event boundaries is also evident in research employing the dwell time paradigm (Hard et al., 2006; Hard, Recchia, & Tversky, 2011; Kosie & Baldwin, 2019). These investigations, involving self-paced progression through static images, demonstrate increased dwell time before an event boundary, reaching a peak at the boundary and subsequently decreasing. Baldwin and Kosie (2021) propose that this dwell time pattern signifies an anticipation of event boundaries, indicating sensitivity to cues for detecting such boundaries.

There are at least four ways by which individuals could anticipate an upcoming event boundary. One potential strategy involves recognising alterations in perceptual stimuli that transpire in anticipation of an event boundary, such as an increase in the rate of change of the stimulus features. Notably, the fluctuations in physical change and looking time (manifesting as extended dwell time) exhibited concurrent increases at breakpoints (Hard et al., 2011).

A second way that an individual may also could anticipation of event boundaries is based on knowledge of the goal and causes (Baldwin et al., 2001; Zacks & Tversky,

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2001; Zacks, 2004; Saylor, Baldwin, Baird, & LaBounty, 2007; Hard et al., 2011). For instance, people nearing a goal or in the final stages of a process are likely to anticipate the event's end.

Moreover, entropy, signifying uncertainty in future predictions, presents another means of anticipating event boundaries. Recent research (Kumar et al., 2023) underscores that models integrating uncertainty better align with human segmentation, surpassing those focusing solely on prediction accuracy. Computational event segmentation models have frequently integrated entropy (e.g., Chen et al., 2007; Brand & Kettnaker, 2000).

Finally, people may also anticipate event boundaries based on the typical duration of events. For instance, when attending a theatre play, spectators often have an idea of the usual duration of a play, influenced by the play's genre, playwright, or similar productions they've seen, enabling them to anticipate roughly when the performance might conclude (similar to time-based prospective memory; McDaniel, 2007). This possibility has received little scientific attention. Neural network simulations by Hanson and Hanson (1996) suggest it could be a plausible mechanism for anticipating event boundaries: the network's expectations of event duration influenced its response to new information, similar to how uncertainty affects individuals' sensitivity to change, as proposed by Baldwin & Kosie (2021). It is this potential usefulness of duration information for event boundary anticipation that this paper aims to explore through a replication.

The usefulness of duration information for event boundary anticipation crucially depends on the extent to which events have typical durations and that people are aware of them. Previous research by Griffiths and colleagues (2006) demonstrated that people can accurately estimate the durations of specific common events. In their studies (Griffiths & Tenenbaum, 2006; Lewandowsky, Griffiths, & Kalish, 2009), participants predicted durations for routine activities baking times for cakes and watching a movie. The results indicated that people's estimations were normally distributed. However, these studies focused only on a limited number of events that likely had clearly defined durations and endpoints.

Moreover, daily events like making a cake involve more than just the duration of baking. They encompass a range of preparatory and complementary tasks like ingredient gathering, batter mixing, and decorating. Hence, embracing a broader viewpoint in event analysis offers a more comprehensive framework for understanding the durations of daily events within their natural context.

In contrast, a study of more wide-ranging event types in daily life showed durations to have a skewed distribution. Zhuang et al. (2012) explored various daily life event types, using lifelogging devices to track activities over seconds, minutes, and hours. Participants wore smartphones for four weeks, capturing GPS, audio, and images. The results revealed skewed duration distributions. A related study by Sastre et al. (2022) echoed these findings, investigating how perceptions of typical durations inform expectations of event boundaries. This study highlighted that the majority of daily events lack a characteristic duration, and events from multiple activities tended to favour mixture models like normal exponential or gamma exponential mixtures.

In terms of methodologies, existing research on cognitive events, particularly in event boundary anticipation from a duration perspective, has tended to focus on shorter timeframes (seconds to minutes). This emphasis on shorter durations may arise from methodological constraints in laboratory experiments (Yates, Sherman, & Yousif, 2023). Limited exploration exists for events on longer time scales, with only a few researchers delving into this area (Zhuang et al., 2012; Sreekumar et al., 2018; Sastre et al., 2022; Sastre et al., under review).

For instance, in Sreekumar and colleagues' study (2018), a nightly segmentation approach was applied, asking nine participants to review daily images captured via a mobile phone over a two-week period and segment them into distinct episodes. This method minimises reliance on memory by providing a comprehensive stream of pictures, offering precise time duration information through image stamping, and revealing the exact timing of specific activities. Moreover, in recent research involving ecological momentary assessment (EMA) (Sastre et al., under review), participants completed micro-surveys using an EMA application over 14 consecutive days, with seven semi-random survey notifications daily. Participants provided the start times of the events while the end time was taken as the time when they started filling out the survey; nevertheless, reliance on manual time inputs raises concerns about the accuracy of daily event duration subjective calculations.

To overcome the methodological limitation observed in Sastre et al.'s (under review), the present study employs nightly segmentation methods with time-stamped pictures to collect accurate time duration information, as observed in a previous study (Sreekumar et al., 2018). To facilitate a rigorous comparison between our present study and Sastre et al.'s study (under review), participants were given consistent instructions for event categorisation, and the same analysis method was used to address the same research questions related to the temporal duration of daily events.

Methods

Participants

Forty-one participants were recruited from three sources. The first source was a participant pool hosted at www.unforgettable.me. Unforgettable is a platform, similar to Mechanical Turk or Prolific Academic, for experience sampling that allows users to collect private data from their daily lives and make it available for researchers (Dennis et al., 2019). The second source consisted of Facebook posts made in various student groups. Researchers posted weekly advertisements on these pages until the recruitment target was met, with each post containing study details and a contact email for research inquiries. The third resource was a local flyer around the university campus.

The eligibility criteria specified individuals over 18 years old who own an Android phone and reside in Australia. Participants were compensated between AUD $103.65 and AUD $112.70 based on the number of completed surveys and the amount of data collected. Among 230 potential recruits, 74% declined participation due to privacy concerns, job limitations, disinterest, or time constraints. Initially, 58 joined, but 17 withdrew due to technological problems.

The final sample consisted of 41 participants aged between 18 and 67 years (26 females, 15 males, mean age = 32.1, SD = 10.1). Participants represented diverse racial and ethnic backgrounds: 27 (66%) identified as Hispanic/Latino, 4 (10%) as East Asian, 4 as White Mexican (10%), 3 (7%) as White/Caucasian, 2 (5%) as South Asian, and 1 (2%) as White/Sephardic Jew. All provided written consent and received study information and instructions in English.

Materials and Procedure

Participants in this study were instructed to wear Android phones with front-facing cameras hung around their necks, as shown in Figure 3. These cameras automatically captured the surroundings at 10-minute intervals, from 8 am to 8 pm, aligning with the participants' daily routines over a 14-day period.

Figure 3. Demonstration of Phone Positioning: Around Neck, Camera Uncovered.

Using an event segmentation interface, participants reviewed daily photos, either each evening or the following morning. This interface provided them with the capability to mark the start and end of events by selecting images with timestamps, offering the flexibility to unselect and delete pictures as needed. Their primary task was to identify the start and end images of events and complete a survey for each established event throughout the entire 14-day period. Participants were instructed to complete each section for every event selected from the photo carousel, as depicted in Figure 4, the designated interface.

Additionally, alongside the nightly segmentation survey, participants undertook five socio-demographic surveys through the Unforgettable.me website.

Selecting Event Categories The nightly segmentation survey, integrated into the event segmentation interface, followed the framework established by Hamm et al. (2013) and Sastre et al. (2022). Hamm et al. (2013) conducted preliminary research wherein undergraduate participants were assigned to identify tags that effectively encapsulated the essence of episodes from their daily lives. For each event that they identified, they provided three tags. They were free to choose the tags as they wished, but were aware that these tags would be used for a later memory study in which they would be given two of the tags and be required to retrieve the remaining tag. Hamm et al (2013) retained the tags that related to activities, locations and people and clustered similar tags under these domains.

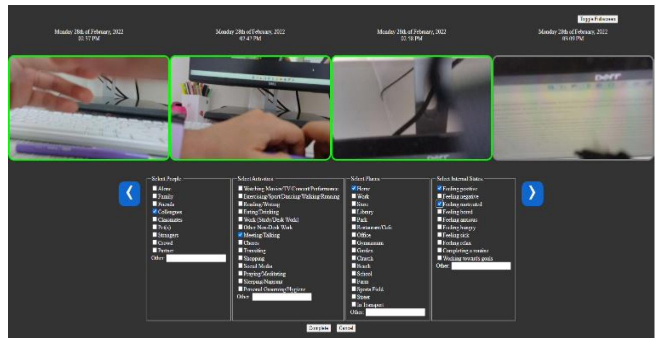

Figure 4. Nightly segmentation interface.

In Hamm et al.'s (2013) study, they categorised daily events into 15 activities, nine locations, and six people domains. Building upon this foundational work, Sastre et al. (2022) conducted a pilot study, they noticed a recurring tendency among participants to utilise the "Other" response option provided in the survey. Consequently, Sastre et al. (2022) included additional categories to capture the most frequent of these additional tags.

Moreover, recognising the need to encompass additional dimensions, we introduced a fourth domain in our study, focusing on mood, bodily states, and goal structure labelled as Internal States. Our study comprised 15 categories in the activity domain, 17 in the location domain, 10 in the people domain, and 11 in the Internal States domain (see Table 1). Importantly, participants were provided with an "other" option in each section for providing free-text descriptions. While participants had the flexibility to select multiple options for Activity, People, and Internal State sections, they were limited to choosing only one option for the Location section. For the purpose of our analysis, we focused only on image selection and the activity category for this study.

Data analysis

We fit three distributions to each activity type, as well as to the overall distribution. First, a truncated normal distribution was used, aligned with studies suggesting certain daily occurrences follow normal distributions (Griffiths & Tenenbaum, 2006). Second, we utilised an exponential distribution to capture the skewed patterns seen in data from Zhuang et al. (2012) and Sastre et al. (2022). The choice of an exponential model assumes the most probable event duration is zero. Third, we employed a gamma model for its ability to capture a rapid increase from zero.

Table 1: Nightly segmentation survey categories.

Categories	Tags
Activity type (15)	Watching movies/TV/listening to a concert/other performance Exercising/playing sport/ dancing/walking/running Reading/writing Eating/drinking Work (studying, working at a desk) Other non-desk work (e.g. bar-tending, paramedic, carpenter, vendor) Meeting/talking/chatting/discussing Chores (cooking, cleaning, laundry) Transiting (drive/fly/bus/taxi, other vehicles) Shopping Using social media Praying/meditating Sleeping/napping Personal grooming/hygiene (e.g. brushing teeth, showering, doing hair) Other activity
People (10)	Alone, Family, Friends, Colleagues, Classmates, Pet(s), Strangers, Crowd, Partner, Other People.
Places (17)	Home, Work, Store, Library, Park, Restaurant/café, Office, Gymnasium, Garden, Church, Beach, School, Farm, Sports field, Street, In transport (car/airplane/ship/truck and rail), Other places.
Internal States (11)	Feeling positive, Feeling negative, Feeling motivated, Feeling bored, Feeling anxious, Feeling hungry, Feeling sick, Feeling relax, Completing a routine, Working towards goals, Other internal states.

For each type, we fit three models as follows:

Truncated Normal:

$$\text{duration}[i] \sim \text{Norm}(\mu,\sigma)$$
$$\mu \sim \text{Norm}(400)$$
$$\sigma \sim \text{Norm}(100)$$

Exponential:

$$\text{duration}[i] \sim \text{Exp}(\lambda)$$
$$\lambda \sim \text{Exp}(1)$$

Gamma:

$$\text{duration}[i] \sim \text{Gamma}(\alpha,\beta)$$
$$\alpha \sim \text{Exp}(2)$$
$$\beta \sim \text{Gamma}(1,0)$$

The estimation was conducted using the Nimble package in R, version 0.12.1 (Nimble, 2021). For each model, 10 chains of 101,000 MCMC samples were taken. The first 1000 samples of each chain were discarded. The widely applicable information criterion (WAIC) was used to select the best model (Watanabe, 2013). In addition, model convergence was evaluated visually using trace plots of the posterior chains (Depaoli & Van de Schoot, 2017) and with R-hat (Moins, Arbel, Dutfoy, & Girard, 2022; Brooks & Gelman, 1998). All R-hat values should be close to 1, and values greater than 1.1 indicate that one or more chains have failed to converge for individual models. When a chain fails to converge, the draws returned by the sampler are not a sample from the posterior distribution and cannot be used for estimation (Brooks & Gelman, 1998).

Results and Discussion

In the initial phase, 4,773 events were gathered, and 1,474 were subsequently excluded from the analysis. Activities with fewer than 40 data points, such as 'Reading/Writing' (n = 35), 'Other Activity' (n=38), as well as those exceeding 700 minutes (n = 1.389), were omitted to align with the analytical approach of Sastre and colleagues (under review). Consequently, the final dataset for our study comprised 3,299 events. Table 2 provides a comparative analysis of dataset sizes, specifically delineating the Experience Sampling Study (Sastre et al., under review) and the Nightly Segmentation (current study).

Table 2. Breakdown of Daily Events.

Events	n	
	Experience Sampling	Nightly Segmentation
Watching movies/TV /listening to a concert	330	117
Using social media	294	185
Sleeping/napping	230	463
Eating/drinking	583	366
Desk work	768	427
Meeting/talking/chatting	466	167
Chores	225	200
Personal grooming/ hygiene	151	276
Shopping	96	98
Exercising/play sport	135	212
Transiting	240	669
Other non-desk work	87	119

Table 3 illustrates the WAICs scores between the truncated normal and exponential models across various activities in both the Experience Sampling (ES) and the Nightly Segmentation (NS) study. Bolded outcomes within the table highlight the superior-fitting model for each activity. Instances where differences between models fell within five units are also bolded, indicating ambiguity in model distinction. Furthermore, for the current study, a trace plot analysis was conducted for all events, revealing overlapping samples and demonstrating consistency in model outputs. Moreover, R-hat values across all parameters for each model consistently remained below 1.0, affirming the convergence of individual models.

Table 3. WAIC score for Truncated Normal and Exponential distribution models in the Experience Sampling (ES) and the Nightly Segmentation study (NS).

Events	Truncated Normal Model		Exponential Model	
	ES	NS	ES	NS
All data	36,21	54,23	**35,01**	**52,24**
Watching movies/TV/ listening to a concert	3,613	**1,967**	**3,476**	**1,970**
Using social media	3,203	1,750	**3,088**	**1,739**
Eating/drinking	6,076	3,482	**5,965**	**3,444**
Desk work	8,599	**4,975**	**8,473**	5,001
Meeting/talking/chatting	5,102	1,684	**4,947**	**1,649**
Chores	2,320	2,053	**2,241**	**2,011**
Personal grooming/hygiene	1,579	2,787	**1,557**	**2,496**
Shopping	1,060	983	**1,033**	**957**
Exercising/play sport	1,455	2,112	**1,438**	**2,087**
Transiting	**1,199**	6,622	1,218	**6,404**
Other non-desk work	1,028	1,375	**1,015**	**1,367**

Note: Numbers in **bold** indicate the better-fitting model (lower WAIC). Four events were excluded the analysis model process: 'Reading/writing", 'Other activity' due to lack of data, and 'Sleeping/napping' on the basis that participants were unable to anticipate event boundaries during sleep.

As can be seen in Table 3, in the Nightly Segmentation study (NS), a preference for the exponential model is evident not only in the aggregated data but also for most individual activity types (nine out of eleven events), suggesting that events do not generally have a typical duration. Moreover, the truncated normal model demonstrates a better fit for Desk Work activity than the exponential distribution.

In comparison to the Experience Sampling (ES) study, two activity categories—Transiting and Desk work,—exhibited disparities, the discrepancy in the 'transit' event type was attributed to COVID-19 restrictions during that study, limiting prolonged transit events. Contrarily, our nightly segmentation (NS) study, conducted post-pandemic, revealed prolonged transit events favoured by an exponential distribution, as our participants did not experience lockdowns or mobility restrictions imposed during the pandemic. Consequently, this observation aligns with a strong preference for an exponential distribution.

In the nightly segmentation study, desk work events exhibited characteristics aligned with the truncated normal distribution, differing from the Experience Sampling study's emphasis on the exponential distribution. The current disparity may also be from the influence of the COVID-19 pandemic, fostering more fragmented routines, and frequent transitions into and out of desk work. Notably, desk work in the nightly segmentation study averaged 128 minutes, compared to the Experience Sampling study reported 91 minutes. These discrepancies highlight the necessity for further research replicating daily event durations under similar circumstances to comprehensively understand the variations in daily event durations.

Similar to concerns in the Experience Sampling study (Sastre et al., under review), our nightly segmentation study questioned the appropriateness of the exponential distribution for comparison, given its bias towards zero-length events. We also explored the gamma distribution. Table 4 presents the WAICs for both models.

Table 4. WAIC score for Exponential and Gamma distribution models in the Experience Sampling study (ES) and the Nightly Segmentation study (NS).

Events	Exponential Model		Gamma Model	
	ES	NS	ES	NS
All data	35,01	52,24	**34,99**	**52,17**
Watching movies/TV /listening to a concert	**3,476**	**1,970**	**3,475**	**1,968**
Using social media	**3,088**	**1,739**	**3,091**	1,745
Eating/drinking	**5,965**	3,444	**5,967**	**3,426**
Desk work	**8,473**	5,001	**8,468**	**4,972**
Meeting/talking/ chatting	**4,947**	**1,649**	**4,948**	**1,654**
Chores	**2,241**	**2,011**	**2,244**	**2,015**
Personal grooming /hygiene	**1,557**	**2,496**	**1,561**	**2,502**
Shopping	**1,033**	**957**	**1,035**	965
Exercising/play sport	**1,438**	**2,087**	**1,042**	**2,092**
Transiting	**1,218**	6,404	**1,217**	**6,393**
Other non-desk work	**1,015**	**1,367**	**1,018**	**1,369**

Note: Numbers in **bold** indicate the better-fitting model (lower WAIC).

Results indicate that in the Nightly Segmentation study (NS), the gamma model was favoured in four cases (all data, eating/drinking, desk work, and transiting), while the exponential model was preferred in two cases (using social media and shopping). Six categories (watching movies/TV/listening to a concert, meeting/talking/chatting, chores, exercising, personal grooming, and other non-desk work) showed no clear dominance for either model. This challenges the distinction between exponential and gamma models in most events, aligning with the Experience Sampling study's findings (Sastre et al., under review).

Conclusion

Our primary aim was to address the identified methodological limitation observed in Sastre et al.'s (under review) research, where participants reported the start times for events, and the end time was deduced as the moment they initiated the survey. However, concerns arose about the precision of calculations for daily event durations due to reliance on participants' time inputs. To overcome this limitation, our study conducted a replication of Sastre et al.'s (under review), employing nightly segmentation methods with time-stamped pictures inspired by a previous study (Sreekumar et al., 2018) to collect accurate time duration information.

In order to enable a thorough comparison between our current investigation and the study by Sastre et al. (currently under review), participants were provided with uniform guidelines for categorising events and the same analysis approach was employed to explore the research questions concerning the time duration of daily events. Specifically, we were motivated by the possibility that people may use typical duration information to anticipate an upcoming event boundary.

This possibility is grounded in the finding that people acquire and use knowledge about different classes of events, which can be described as scripts or event schemas (Bower, 1982; Baldwin et al., 2001; Zacks & Tversky, 2001; Zacks, 2004; Saylor, Baldwin, Baird, & LaBounty, 2007), and in particular that event knowledge includes information about typical duration (Hanson & Hanson, 1996; Baldwin & Kosie, 2021). These components could play a vital role in estimating when an event ends, as discussed within the framework of time-based prospective memory (McDaniel & Einstein, 2007).

Whereas earlier research (Griffiths & Tenenbaum, 2006; Lewandowsky et al., 2009) focused on specific everyday event durations, revealing their adherence to a typical distribution. However, our findings indicated that the event duration data from daily life did not fit well with a typical distribution; indeed, most activity types displayed skewed distributions, aligning with the results of studies conducted by Sastre et al. (under review), Zhuang et al. (2012), and Sreekumar et al. (2018). Thus, when daily events have been studied from a general perspective, there is a broader tendency for event durations in daily life to follow an exponential pattern, with a few exceptions, as observed in the analysis of all data.

We agree with the findings that reported event durations spanned from seconds to hours, displaying a significant exponential component. This suggests a lack of typical duration for many daily events. This indicates that, at least at a general level of categorisation of events, they lack a typical duration (Sastre et al., under review). We found that people did not adhere to a single event duration distribution. Some events skewed exponentially; others were normally distributed with an exponential component. Our results reconcile discrepancies in prior reports on event duration distributions (Griffiths & Tenenbaum, 2006; Lewandowsky et al., 2009; Zhuang et al., 2012; Sreekumar et al., 2018). Moreover, our study indicates the utility of event duration as a distinguishing feature of event types appears to be more pronounced in studies with fine-grained events, akin to those conducted by Griffiths (2006; 2009). Overall, these findings imply that typical duration information in anticipating event boundaries might be applicable only in a limited number of cases and is, therefore, not likely to contribute to event segmentation on these timescales in everyday activity.

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