Utilizing Players' Playtime Records for Churn Prediction: Mining Playtime Regularity

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Abstract—In the free online game industry, churn prediction is an important research topic. Reducing the churn rate of a game significantly helps with the success of the game. Churn prediction helps a game operator identify possible churning players and keep them engaged in the game via appropriate operational strategies, marketing strategies, and/or incentives. Playtime related features are some of the widely used universal features for most churn prediction models. In this paper, we consider developing new universal features for churn predictions for long-term players based on players' playtime. In particular, we measure playtime regularity using the notion of *entropy* and *cross-entropy* from information theory. After we calculate playtime regularity of players from data sets of six free online games of different types. We leverage information from players' playtime regularity in the form of universal features for churn prediction. Experiments show that our developed features are better at predicting churners compared to baseline features. Thus, the experiment results imply that our proposed features could utilize the information extracted from players' playtime more effectively than related baseline playtime features.

Index Terms—churn prediction, data mining, feature engineering, free-to-play games, supervised learning

I. Introduction

FREE online games allow players to access games for free. As in other freemium products and services, the revenue of a free online game company depends on in-game purchases, and a larger player base indicates greater potential revenue. Retaining current players is usually much easier and less costly than recruiting new players. Therefore, these game companies strive to identify potential churners in order to retain them via proper operational strategies and incentive mechanisms.

Recent efforts on churn prediction in the game industry have employed various methods and models, such as binary predictions, survival ensembles, and the Cox model, and have utilized different features, including playtime, login frequency, player in-game state, and player in-game activity, such as

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purchases; see, e.g., [1]–[12]. In [13], a churn prediction model is built based on user-app relationships in a game launcher platform.

Playtime is widely selected as a universal churn prediction feature. Unlike game-specific features that are different for different games or may exist in one game but not in others, which limits their applicability, playtime is one of the most fundamental records in any game database, irrespective of game-specific characteristics. It is also more reliable than other records, such as the players' login data that sometimes depends on network conditions instead of the players' behavior. By playtime, we mean the records of when a player play the game and for how long.

However, there is a lack of research in further utilizing players' playtime. Thus, in our previous work [14], we considered utilizing the players' playtime to measure their playtime regularity for churn prediction. Specifically, we considered long-term players, who stay in the game for a sufficiently long period of time and calculate the empirical distributions and related entropies of these players' playtime. After observing the differences of related entropies of these players' playtime between churners and non-churners, we developed playtime related features for churner prediction based on these distributions and entropies. However, when [14] examined how each player compares to the entire game community that he/she is playing with, the results varied if the proportion of churners/non-churners changed in the dataset. Our previous work only tested the developed playtime related features on two games in the same type and the generality of our result might be a limit.

In this paper, we have improved the way of examining how each player compares to the entire game community that he/she is playing with. And we have tested our developed playtime related features for churner prediction on more games of different types to show the generality. We present a deeper and more thorough analysis of how churners and non-churners differ in their playtime regularity, thereby expanding our prior work [14].

The main contributions of our work are listed below.

- We have improved the model of long-term players' playtime regularity based on the data of players' playtime distribution from [14].
- We inspect churners' and non-churners' evolvement of playtime regularity across six free online games of different types. Then we propose features based on players' playtime regularity for long-term players.

- We conduct experiments to evaluate our developed features across those six free online games' data sets and show that these features could help achieve a better prediction performance than the baseline features. The experiments results imply that our proposed features could utilize the information extracted from players' playtime more effectively than the baseline playtime related features.

The rest of the paper is organized as follows. Section II describes the game data sets we use. Section III explains how we split up the playtime of a player into periods and how different distributions of players' playtime can be defined to capture the players' playtime regularity of a player. Section IV illustrates how churners and non-churners evolve differently over time. Section V presents the process of feature engineering from players' playtime regularity and Section VI evaluates the performance of our proposed features. Section VII concludes the paper.

II. FREE ONLINE GAME DATA SETS

This work utilizes non-game-specific playtime data. The effectiveness of the proposed methods are evaluated using the datasets of six free online games: *Thirty-six Stratagems (TS)*, *Thirty-six Stratagems Mobile (TSM)*, *Game of Thrones Winter is Coming (GOT)*, *Womanland in Journey to the West (WJW)*, *League of Angels II (LOA II)*, and *Era of Angels (EOA)*.

A. Background of the Selected Games

The above games are free online games published by Yoozoo Games.[1] These games are published on PC and mobile platforms and are designed for different game types. The reasonable number of active players and the diverse in-game mechanisms make the data from these six games highly suitable to extract and evaluate our proposed features and churn prediction algorithms.

B. Data Selection

Since a short-term players' playtime provides little information, we consider those long-term players who have played the game for at least 15 days.

To define churners and non-churners in the free online games, notice that the churners are unlikely to withdraw their accounts even if they stop playing the game for a long time. We thus define a churner as a player who does not access the game consecutively for a certain number of days. Motivated by [9], in these games, we define a churner as a player who stops playing for more than 3 days, because we find that in our data sets, over 95% of such players do not return to the game.

For our numeric analysis, we randomly select a set of long-term players with the same numbers of churners and non-churners for each game. The game platform, the game type, and the number of players, including churners and non-churners for each game, are listed in Table. I.[2]

TABLE I
DETAILS OF SELECTED GAME DATA SETS

Selected Games	Platform	Type	#Churners	#Non-churners
Thirty-six Stratagems (TS)	PC	Strategy	7238	7238
Game of Thrones Winter is Coming (GOT)	PC	Strategy	2718	2718
Thirty-six Stratagems Mobile (TSM)	Mobile	Strategy	4217	4217
Womanland in Journey to the West (WJW)	Mobile	RPG	2768	2768
Era of Angels (EOA)	Mobile	MMORPG	8171	8171
League of Angels II (LOA II)	Mobile	Card Game	3383	3383

III. PLAYER TIME SPENDING DISTRIBUTION

The players' playtime distribution describes how a player allocates his/her time spent in a given game. In this section, we consider the playtime distributions at different aggregation levels during the latest playing periods of a player. As will be seen later, these distributions will be the basis for the proposed feature engineering and churn prediction method.

A. Latest Playtime and Periods

We consider the latest n days of playtime of a player. Let $t_{u,d,r}$ be the playing time spent by player u, on day d, within hour r, where $d = 1, 2, ..., n$, and $r = 1, 2, ..., 24$. For example, for $n = 15$, if player 2 kept playing the game for 15 days continuously and his/her latest playing date is December 15th, then $t_{2,15,1} = 0.1$ means player 2 spent 0.1 hour on December 15th between 0AM and 1AM. Similarly, $t_{2,1,2} = 0.4$ means player 2 spent 0.4 hour on December 1st between 1AM and 2AM. A different player may have a different latest playing date. For example, if player 3's latest playing date is November 20th, then $t_{3,15,4} = 0.7$ means player 3 spent 0.7 hour on November 20th between 3AM and 4AM. Formally, d indexes the $n + 1 - d$-th day to the latest playing date.

We partition n days into m periods of equal days. For example, if $n = 15$, $m = 5$, then each period has 3 days and the first period includes days in the set $D_1 = \{1, 2, 3\}$ and the second period includes days in the set $D_2 = \{4, 5, 6\}$. Formally, the k-th period includes days in

$$D_k = \left\{ (k-1)\frac{n}{m} + i : i = 1, 2, ..., \frac{n}{m} \right\}, \ k = 1, 2, ..., m.$$

Based on the latest playing times, we will calculate the empirical probability distributions related to the in-game time spent by a player.

B. Daily Playtime Distribution

We first consider the total in-game time spent on each day and how each player distributes his in-game time over different days of a period. To this end, we define the individual (empirical) probability of the playtime for player u on day d within period k as

$$p_{\text{ind}}(d|u, k) = \frac{\sum_{r=1}^{24} t_{u,d,r}}{\sum_{w \in D_k} \sum_{r=1}^{24} t_{u,w,r}}.$$

For instance, consider the latest $n = 15$ days of playing the game for a certain player, with $m = 5$ periods of 3 days. Assume that during the first period player u spends 5 hour, 6 hours, and 8 hours on the 1st, 2nd, and 3rd days, respectively. Then within the first period, the probabilities of the daily playtime of this player over the 3 days are $p_{\text{ind}}(1|u, 1) = 5/(5 + 6 + 8)$, $p_{\text{ind}}(2|u, 1) = 6/(5 + 6 + 8)$, and $p_{\text{ind}}(3|u, 1) = 8/(5 + 6 + 8)$.

In addition, in order to capture the daily playtime distribution of the community of churners in set U, we introduce a "global" probability of the total daily playtime of all the churners on the d-th day within the k-th period as

$$p_{\text{global}}^{\text{churner}}(d|k) = \frac{\sum_{u \in U} \sum_{r=1}^{24} t_{u,d,r}}{\sum_{u \in U} \sum_{w \in D_k} \sum_{r=1}^{24} t_{u,w,r}}.$$

C. Hourly Playtime Distribution

We next consider the in-game time spent in each hour and how it is distributed over different days of a period. We define the empirical probability of the playtime for player u in hour r on day d within period k as

$$P_{\text{ind}}(d|u, k, r) = \frac{t_{u,d,r}}{\sum_{w \in D_k} t_{u,w,r}}.$$

For instance, consider the same example in the last subsection, and assume that during the first period player u spent 0.1 hour, 0.2 hour, and 0.3 hour in the hour from 8:00 - 9:00 on the 1st, 2nd, and 3rd days, respectively. Then within the first period, the probabilities of the playtime in the hour from 8:00 - 9:00 of this player over the first period are $P_{\text{ind}}(1|u, 1, 9) = 0.1/(0.1 + 0.2 + 0.3)$, $P_{\text{ind}}(2|u, 1, 9) = 0.2/(0.1 + 0.2 + 0.3)$, and $P_{\text{ind}}(3|u, 1, 9) = 0.3/(0.1 + 0.2 + 0.3)$.

Similarly, in order to capture the hourly playtime distribution of the churner community U, we introduce a global probability of the playtime of all the churners in hour r on the d-th day within the k-th period as

$$p_{\text{global}}^{\text{churner}}(d|k, r) = \frac{\sum_{u \in U} t_{u,d,r}}{\sum_{u \in U} \sum_{w \in D_k} t_{u,w,r}}.$$

The afore-introduced players' playtime distributions will be the basis to extract new features for churn prediction.

IV. TIME SPENDING REGULARITY: CHURNERS VERSUS NON-CHURNERS

Since we aim to predict churn in this paper, for each game, the data set is equally divided into a training data set and a test data set. In this section, we examine the playtime patterns of churners and non-churners from the training data set at different timescales for each game, with the aim of identifying possible differentiators between churners and non-churners.

A. Entropy and Playtime Pattern

Based on the players' playtime distributions introduced in Section III and motivated by [15], we use the notion of *entropy* from information theory as the metric to characterize variance and change in playtime [16]. Given a probability distribution $p(\cdot)$, its entropy is defined as

$$H(p) = \sum_x p(x) \log \frac{1}{p(x)}.$$

A higher entropy means a more even distribution and more regular playtime pattern, and a smaller entropy implies a less even distribution and more irregular/casual playtime pattern.

For each game and the data set described in Section II, we consider the latest $n = 15$ days playing time, which is the same as [14]. But we consider multiple periods to examine players' playtime patterns where [14] only considers a single period. In this paper, we divide the playtime into $m = 2, 3, 5$ periods, where the corresponding periods have $7, 5, 3$ days, respectively. We calculate the corresponding playtime distributions and entropies for each player of different periods.

The mean entropies and 95% confidence intervals of churners and non-churners (within the training set) in different periods are shown in Appendix A (Fig. 1, Fig. 4 - Fig. 21). Fig. 1 illustrates the entropy distributions of churners and non-churners in those games on a granularity of each day for all aforementioned games, while Fig. 4 - Fig. 21 illustrate the entropy distributions on a granularity of each hour.

We observe that non-churners have a higher mean value of entropy than churners for any selected number of periods m, in both daily and hourly playtime distributions and in those games. This implies that non-churners have much more regular playtime patterns than churners. Moreover, the entropies of non-churners exhibit a smaller decrease as time moves on, compared to churners. This implies that non-churners have a more regular playtime pattern than churners across different timescales, while churners spend their in-game time more and more casually as time moves on.

A further look at the hourly entropies in Appendix A (Fig. 4 - Fig. 21 and Fig. 58) shows that the above mentioned difference between churners and non-churners is more significant in the hours from early morning to late night and less significant from late night to early morning. In Fig. 58, we can see that the playtime entropy/regularity is higher from early morning to late night and lower from late night to early morning. This is consistent with the fact that late night to early morning is the most common sleep time, and it is hard for the majority of players (churners or non-churners) to maintain a regular playtime pattern during that period of time.

B. *Cross-entropy and Correlation with the Highest and the Lowest Regularity*

In our previous work [14], we examined how each player compares to the entire game community that he/she is playing with over the same corresponding playing period using the notion of *cross-entropy* from information theory. However, the examination results may vary if the proportion of churners/non-churners changes in the dataset. In this paper, instead of examining how the playtime distribution of each player compares to the average playtime distribution of the entire game community, we now examine how distributions of each player's playtime

compare to two certain types of distributions (uniform distribution $p_{\textbf{uniform}}$ which corresponds to the highest regularity, and degenerate distribution $p_{\textbf{degenerate}}$ which corresponds to the lowest regularity), using the notion of *cross-entropy* from information theory to characterize the purchase regularity of a player.

1) Cross-entropy with uniform distribution: **Given an individual player's daily playtime distribution $p_{\textbf{ind}}(d|u,k)$, and the uniform distribution**

$$p_{\textbf{uniform}}(d) = \frac{1}{\frac{n}{m}}, d \in \{1, 2, .., \frac{n}{m}\},$$

the cross-entropy between these two distributions is defined as:

$$H(p_{\textbf{ind}}(\cdot|u,k), p_{\textbf{uniform}}(\cdot)) =$$
$$\sum_d p_{\textbf{uniform}}(d) \log \frac{1}{p_{\textbf{ind}}(d|u,k)}.$$

Similarly, for hourly distribution, the cross-entropy between these two distributions is defined as:

$$H(p_{\textbf{ind}}(\cdot|u,k,r), p_{\textbf{uniform}}(\cdot)) =$$
$$\sum_d p_{\textbf{uniform}}(d) \log \frac{1}{p_{\textbf{ind}}(d|u,k,r)}.$$

For example, if the cross-entropy is smaller, it implies that the playtime distribution of the player is more similar to the uniform distribution, and thus indicates a larger playtime regularity.

For each game, we calculate the cross-entropies for daily and hourly distributions using the training datasets. There are four kinds of cross-entropies in this section, churner-uniform, nonchurner-uniform, churner-degenerate and nonchurner-degenerate. For example, a churner-uniform cross-entropy is the cross-entropy between a churner's $p_{\textbf{ind}}$ and the uniform distribution. For daily distribution, The mean cross-entropies and 95% confidence intervals are shown in Appendix A (Fig. 2). For hourly distribution, The mean cross-entropies and 95% confidence intervals are shown in Appendix A (Fig. 22 - Fig. 39). We observe from Fig. 2 and Fig. 22 - Fig. 39 that the mean daily and hourly churner-uniform cross-entropies are increasingly higher than those of nonchurner-uniform as the time moves on. It implies that churners' playtime distributions are less similar to the uniform distribution, hence they have less playtime regularity.

2) Cross-entropy with degenerate distribution: **Given an individual player's daily playtime distribution $p_{\textbf{ind}}(d|u,k)$, and the degenerate distributions $(i = 1, 2, .., \frac{n}{m})$**

$$p_{\textbf{degenerate},i}(d) = \begin{cases} 0, & d \neq i; \\ 1, & d = i. \end{cases}, d \in \{1, 2, .., \frac{n}{m}\}.$$

In order to measure how similar the distribution of playtime to the degenerate distribution, we pick the minimum cross-entropy between distribution $p_{\textbf{ind}}(d|u,k)$

and distribution $p_{\textbf{degenerate},i}$ as the cross-entropy with the degenerate distribution, i.e.:

$$H(p_{\textbf{ind}}(\cdot|u,k), p_{\textbf{degenerate}}(\cdot)) =$$
$$= \min_i(\sum_d p_{\textbf{degenerate,i}}(d) \log \frac{1}{p_{\textbf{ind}}(d|u,k)}).$$

Similarly, for hourly distribution, the cross-entropy between these two distributions is defined as:

$$H(p_{\textbf{ind}}(\cdot|u,k,r), p_{\textbf{degenerate}}(\cdot)) =$$
$$\min_i(\sum_d p_{\textbf{degenerate,i}}(d) \log \frac{1}{p_{\textbf{ind}}(d|u,k,r)}).$$

For example, if the cross-entropy is smaller, it implies that the playtime pattern of the player is more similar to a degenerate distribution, and thus indicates a larger playtime irregularity.

For each game, we calculate the cross-entropies for daily and hourly distributions using the training datasets. For daily distribution, The mean cross-entropies and 95% confidence intervals are shown in Appendix A (Fig. 3). For hourly distribution, The mean cross-entropies and 95% confidence intervals are shown in Appendix A (Fig. 40 - Fig. 57). We observe from Fig. 3 and Fig. 40 - Fig. 57 that the mean daily and hourly churner-degenerate cross-entropies are increasingly lower than those of nonchurner-degenerate as the time moves on. It implies that churners' playtime distributions are more similar to the degenerate distribution, hence they have less playtime regularity.

C. Players' Playtime Regularity for Churn Prediction

To summarize, churners and non-churners exhibit different playtime regularities or patterns as captured by the entropies and cross-entropies of the playtime distributions:

- Churners have lower entropies or larger playtime irregularity, as well as a larger decrease in entropy than non-churners as time moves on.
- Churners' playtime distributions have increasingly higher cross-entropies with uniform distribution as the time moves on, which represents churners' playtime distributions are less similar to the uniform distribution, hence they have less playtime regularity.
- Churners' playtime distributions have increasingly lower cross-entropies with the degenerate distribution as the time moves on, which represents paying churners' playtime distributions are more similar to the degenerate distribution, hence they have larger playtime irregularity.

In the next two sections, we will utilize these differences to engineer entropy-based features for churn prediction.

V. Feature Engineering

The observation in Section IV shows that churners and non-churners exhibit different playtime regularity that can be captured by the corresponding entropies. In this section, we propose several features based on entropies that will be used for churn prediction in the next section.

A. Static Feature and Rate Feature

For a given playtime distribution for player u in k-th period ($k \leq m$), we define a function $f(u,k)$ representing the corresponding entropy or cross-entropy. We call $f(u,k)$ a static feature. Based on the static feature, we define a rate feature:

$$g(u,k) = \frac{f(u,k) - f(u,k+1)}{f(u,k)}$$

to capture the change in entropy/cross-entropy as time moves on where $k < m$. Recall from the last section that churners exhibit smaller entropies but with a greater entropy decrease as time increases. The rate feature amplifies the differences between churners and non-churners.

B. Feature Selection

As seen in Section IV-A and Section IV-B, churners and non-churners exhibit differences in entropy of the daily play-time distribution and of hourly playtime distribution, as well as in cross-entropy of hourly playtime distribution. We therefore select four types of features as follows:

- The combination of the static feature and rate feature of entropy of the *daily* playtime distributions. We call this type of features the 1st type of the proposed features.
- The combination of the static feature and rate feature of cross-entropy of the *daily* playtime distributions. We call this type of features the 2nd type of the proposed features.
- The combination of the static feature and rate feature of entropy of the *hourly* playtime distributions. We call this type of features the 3rd type of the proposed features.
- The combination of the static feature and rate feature of cross-entropy of the *hourly* playtime distributions. We call this type of features the 4th type of the proposed features.

VI. CHURNER PREDICTION

In this section, we evaluate the efficacy of churn prediction using entropy features with several typical classifiers.

A. Evaluation Strategy

1) Baseline Features: To evaluate the effectiveness of our proposed features, we use following baseline features for comparison:

- The raw data of the playtime distribution of players.
- The daily total time spent, which we call the 1st type of baseline features.
- The combined feature of total time spent, the last day of login, and number of time slots played. This baseline feature is designed based on Recency, Frequency, Monetary Value (RFM) model [17]. We call this type of feature as the 2nd type of baseline features.
- Daily standard deviation of the playtime distribution of players in each period, which we call the 3rd type of baseline features.
- Hourly standard deviation of the playtime distribution of players in each period, which we call the 4th type of baseline features.

2) AUC Evaluation: Given the binary nature of prediction/classification, we use the area under the Receiver-Operating-Characteristics (ROC) [18] curve (AUC) [19] to evaluate the overall performance of a classifier. Note that, AUC has been used as a metric to evaluate the performance of a certain churn prediction model in many previous work, such as [1], [4], [6], [20].

B. Evaluation Results

We use multiple classifiers (Logistic Regression (LR), support vector machine (SVM), Random Forests (RF), regular Recurrent Neural Network (RNN), and Long Short-Term Memory network (LSTM)) and the aforementioned features for churn prediction. Motivated by [21], since heuristically using a larger dimension does not improve the predictions and may cause the model to overfit, the RNN (LSTM) consists of a RNN (LSTM) layer to handle the sequential data with an output dimension of 64. The RNN (LSTM) layer uses the default settings of PyTorch [22].

For each game, the data set is equally divided into a training data set and a test data set as we mention in Section IV. We train classifiers using the training data set and evaluate their performance using the test data set. We evaluate the performance of the classifiers that are trained with the data of the entire m playing periods on the test data set. The results are shown in Table.II (Not that: the raw data, 1st type and 2nd type of selected baseline features are not related to the choice of period m). The best AUC score for each game is shown in bold font in Table.II.

In our previous work [14], the proposed entropy features have the best performance as opposed to the baseline features for *Thirty-six Stratagems* and *Thirty-six Stratagems Mobile*. In this paper, we see that, our proposed entropy features have the best performance with the highest AUC for all six games, as opposed to the baseline features. We also find that the highest AUC is achieved when number of periods is $m = 5$ the for all these games, except *League of Angels II (LOA II)* where the highest AUC is achieved when number of periods is $m = 3$. This implies that a finer division on playtime may lead to a better predictive power. It's worth noticing that for *Womanland in Journey to the West (WJW)*, the achieved highest AUC is the lowest among all games (still higher than the AUC of baseline features). This is consistent with our observation in Fig. 1, Fig. 13 - Fig. 15 and Fig. 49 and Fig. 51: The entropy/cross-entropy difference between churner and non-churner is less significant here than in other games.

One thing we want to mention from Table.II is that, although the RNN and the LSTM help us achieve the best AUC for all these games (except *League of Angels II*) using the 1st type proposed feature, using the 4th type proposed feature leads the RNN and the LSTM to overfit in few cases when the dimension of the 4th type proposed feature grows larger. In this paper, we are focusing on mining players' playtime regularity instead of tuning the RNN and LSTM models to achieve better result, but it would be a good direction to build a better RNN framework to avoid overfitting in the future work as another project.

TABLE II
AUC FOR DIFFERENT PROPOSED FEATURES (CLASSIFIERS TRAINED WITH THE DATA WHERE PLAYING TIME IS DIVIDED BY $m = 2, 3, 5$ PERIODS)

			Period $m = 2$						Period $m = 3$						Period $m = 5$					
			LR	SVM	DT	RF	RNN	LSTM	LR	SVM	DT	RF	RNN	LSTM	LR	SVM	DT	RF	RNN	LSTM
TS	Proposed Features	1st Type	0.69	0.69	0.56	0.69	0.70	0.70	0.71	0.71	0.57	0.70	0.71	0.71	0.71	0.71	0.58	0.71	0.72	**0.72**
		2nd Type	0.64	0.64	0.54	0.64	0.65	0.65	0.68	0.68	0.55	0.69	0.69	0.69	0.68	0.68	0.56	0.68	0.68	0.69
		3rd Type	0.67	0.67	0.57	0.67	0.64	0.57	0.69	0.69	0.57	0.68	0.62	0.59	0.70	0.70	0.58	0.69	0.63	0.58
		4th Type	0.64	0.65	0.55	0.65	0.59	0.60	0.69	0.69	0.57	0.68	0.60	0.58	0.69	0.57	0.70	0.45	0.60	
	Baseline Features	Raw Data	0.66	0.66	0.56	0.67	0.56	0.58												
		1st Type	0.67	0.67	0.56	0.68	0.68	0.65												
		2nd Type	0.64	0.64	0.55	0.62	0.63	0.63												
		3rd Type	0.56	0.56	0.53	0.56	0.57	0.57	0.57	0.57	0.53	0.57	0.57	0.58	0.57	0.57	0.52	0.59	0.58	0.58
		4th Type	0.57	0.58	0.53	0.59	0.55	0.53	0.57	0.57	0.53	0.58	0.52	0.53	0.54	0.55	0.52	0.57	0.53	0.53
GOT	Proposed Features	1st Type	0.75	0.76	0.60	0.75	0.76	0.76	0.78	0.78	0.62	0.77	0.78	0.77	0.79	0.79	0.63	0.77	**0.79**	0.77
		2nd Type	0.65	0.65	0.54	0.65	0.66	0.65	0.68	0.68	0.57	0.69	0.69	0.68	0.68	0.68	0.56	0.68	0.70	0.70
		3rd Type	0.71	0.71	0.58	0.70	0.61	0.57	0.72	0.73	0.59	0.71	0.64	0.61	0.72	0.73	0.58	0.72	0.63	0.59
		4th Type	0.65	0.65	0.55	0.67	0.54	0.55	0.70	0.70	0.57	0.70	0.59	0.59	0.69	0.69	0.58	0.72	0.59	0.59
	Baseline Features	Raw Data	0.64	0.64	0.56	0.67	0.61	0.58												
		1st Type	0.73	0.73	0.59	0.72	0.73	0.69												
		2nd Type	0.67	0.67	0.54	0.66	0.65	0.65												
		3rd Type	0.63	0.63	0.53	0.61	0.62	0.61	0.64	0.64	0.54	0.62	0.64	0.63	0.63	0.63	0.52	0.63	0.62	0.62
		4th Type	0.65	0.65	0.56	0.64	0.56	0.56	0.63	0.63	0.53	0.63	0.54	0.56	0.58	0.58	0.52	0.60	0.56	0.53
TSM	Proposed Features	1st Type	0.77	0.77	0.63	0.76	0.78	0.78	0.79	0.79	0.66	0.78	0.80	0.80	0.80	0.80	0.65	0.79	**0.81**	0.81
		2nd Type	0.68	0.68	0.56	0.68	0.69	0.69	0.72	0.73	0.59	0.72	0.74	0.74	0.71	0.71	0.58	0.71	0.72	0.72
		3rd Type	0.75	0.75	0.61	0.73	0.69	0.61	0.75	0.76	0.60	0.73	0.70	0.63	0.76	0.76	0.62	0.74	0.70	0.65
		4th Type	0.73	0.72	0.58	0.72	0.60	0.60	0.75	0.76	0.61	0.74	0.62	0.63	0.77	0.77	0.61	0.76	0.66	0.66
	Baseline Features	Raw Data	0.71	0.71	0.59	0.72	0.69	0.70												
		1st Type	0.76	0.76	0.62	0.74	0.76	0.77												
		2nd Type	0.70	0.70	0.57	0.69	0.67	0.67												
		3rd Type	0.66	0.66	0.54	0.64	0.66	0.66	0.66	0.66	0.55	0.64	0.67	0.67	0.67	0.67	0.55	0.65	0.67	0.67
		4th Type	0.71	0.72	0.58	0.70	0.67	0.61	0.70	0.70	0.57	0.69	0.63	0.59	0.67	0.67	0.55	0.69	0.60	0.59
WJW	Proposed Features	1st Type	0.64	0.64	0.56	0.65	0.66	0.66	0.64	0.64	0.55	0.65	0.69	0.69	0.64	0.64	0.57	0.64	**0.69**	0.68
		2nd Type	0.61	0.61	0.54	0.60	0.60	0.61	0.59	0.59	0.51	0.61	0.60	0.62	0.58	0.58	0.51	0.59	0.58	0.59
		3rd Type	0.64	0.64	0.55	0.63	0.56	0.55	0.64	0.64	0.55	0.63	0.57	0.56	0.65	0.65	0.57	0.63	0.57	0.55
		4th Type	0.62	0.62	0.55	0.63	0.55	0.55	0.64	0.65	0.54	0.63	0.55	0.56	0.63	0.63	0.57	0.62	0.58	0.55
	Baseline Features	Raw Data	0.62	0.63	0.54	0.63	0.58	0.58												
		1st Type	0.64	0.64	0.55	0.63	0.66	0.63												
		2nd Type	0.62	0.62	0.53	0.61	0.62	0.62												
		3rd Type	0.60	0.60	0.53	0.60	0.60	0.60	0.60	0.60	0.51	0.60	0.60	0.60	0.61	0.61	0.52	0.61	0.61	0.60
		4th Type	0.62	0.62	0.54	0.62	0.56	0.55	0.61	0.61	0.53	0.62	0.53	0.55	0.59	0.58	0.54	0.59	0.54	0.53
EOA	Proposed Features	1st Type	0.68	0.68	0.56	0.68	0.69	0.69	0.70	0.70	0.56	0.70	0.71	0.71	0.71	0.71	0.58	0.71	**0.72**	0.72
		2nd Type	0.65	0.65	0.54	0.65	0.65	0.65	0.68	0.68	0.56	0.68	0.68	0.69	0.67	0.67	0.56	0.67	0.68	0.68
		3rd Type	0.68	0.67	0.57	0.67	0.66	0.60	0.70	0.69	0.59	0.69	0.64	0.59	0.70	0.71	0.60	0.69	0.62	0.60
		4th Type	0.65	0.65	0.56	0.65	0.62	0.59	0.69	0.69	0.57	0.68	0.63	0.60	0.70	0.70	0.59	0.70	0.61	0.59
	Baseline Features	Raw Data	0.65	0.65	0.57	0.67	0.59	0.57												
		1st Type	0.65	0.65	0.56	0.66	0.67	0.62												
		2nd Type	0.65	0.64	0.55	0.64	0.63	0.64												
		3rd Type	0.54	0.54	0.53	0.57	0.60	0.60	0.54	0.54	0.53	0.55	0.60	0.60	0.55	0.55	0.52	0.58	0.58	0.59
		4th Type	0.60	0.59	0.55	0.61	0.61	0.57	0.60	0.59	0.55	0.62	0.56	0.54	0.58	0.58	0.54	0.61	0.53	0.54
LOA II	Proposed Features	1st Type	0.70	0.70	0.55	0.69	0.70	0.70	0.71	**0.71**	0.56	0.70	0.71	0.70	0.70	0.71	0.56	0.70	0.70	0.68
		2nd Type	0.66	0.66	0.56	0.66	0.66	0.66	0.67	0.67	0.56	0.67	0.67	0.68	0.66	0.66	0.52	0.65	0.65	0.66
		3rd Type	0.67	0.68	0.55	0.68	0.59	0.56	0.67	0.67	0.56	0.70	0.55	0.56	0.65	0.65	0.56	0.69	0.59	0.57
		4th Type	0.62	0.63	0.55	0.66	0.60	0.56	0.65	0.65	0.55	0.67	0.58	0.54	0.65	0.64	0.58	0.70	0.55	0.55
	Baseline Features	Raw Data	0.60	0.59	0.55	0.65	0.56	0.58												
		1st Type	0.63	0.63	0.54	0.67	0.61	0.56												
		2nd Type	0.66	0.66	0.54	0.65	0.63	0.63												
		3rd Type	0.56	0.56	0.52	0.60	0.61	0.59	0.55	0.55	0.52	0.58	0.60	0.59	0.53	0.53	0.52	0.60	0.60	0.58
		4th Type	0.57	0.56	0.54	0.61	0.57	0.54	0.55	0.55	0.53	0.61	0.53	0.52	0.53	0.53	0.53	0.60	0.52	0.53

Overall, the evaluation shows that our proposed entropy features outperform the baseline features in churn prediction, and indeed capture the differences in the playtime between churners and non-churners. In other words, although players' playtime serves as an important feature in previous work, our proposed entropy features could utilize the information extracted from players' playtime more effectively.

VII. CONCLUSIONS

In this paper, we address the problem of better exploiting the information extracted from players' playtime records for predicting churners in free online games. The goal is to characterize and mine players' playtime regularity among churners and non-churners. We consider long-term players and understand their playtime regularity among churners and non-churners. We observe that there is a significant difference between churners and non-churners in terms of entropies exhibited in playtime regularity. Based on this observation, we propose some prediction models using new features extracted from mining players' playtime regularity. After experiments are conducted, the corresponding result shows that our proposed entropy/cross-entropy features are better at predicting

churners, compared to the baseline features. This implies our proposed features could exploit the information extracted from players' playtime records more effectively. It sheds light on a better way of utilizing player's playtime records. Thus, game companies can benefit from our algorithms by exploiting the information extracted from players' playtime records more effectively from the database. Our findings also help game developers design better in-game mechanisms by increasing players' playtime regularity to reduce churn rate.

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Appendix A
The Entropy/Cross-entropy Distribution on a Granularity of Each Day/Hour for Player Time Spending in Each Aforementioned Game
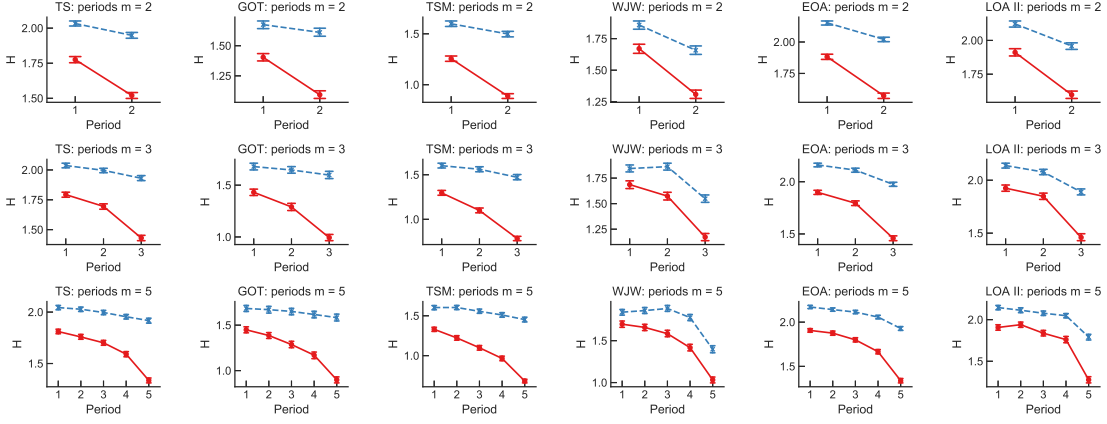
Fig. 1. The mean entropies of the daily distributions of playtime of aforementioned games players in different periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
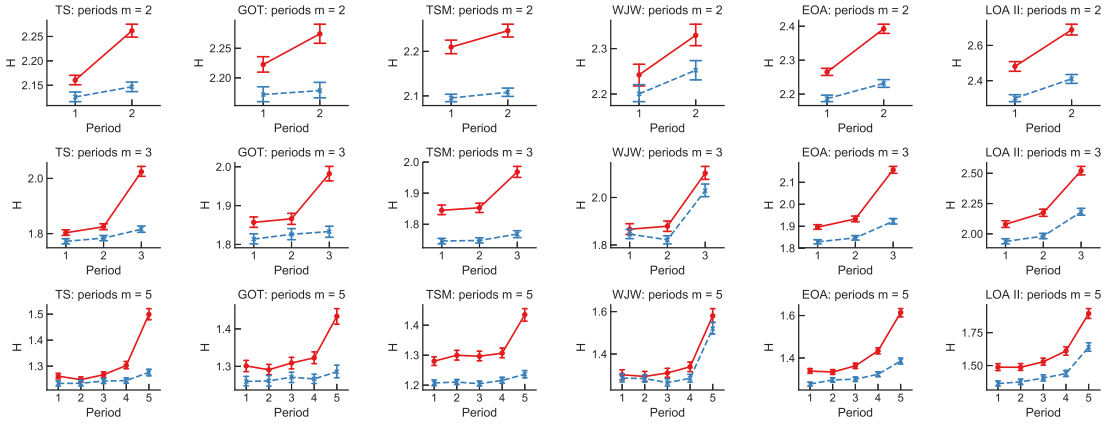
Fig. 2. The mean cross-entropies between the players' daily playtime distributions and the uniform distribution in aforementioned games. The blue dashed line shows the non-churners, while the red solid line shows the churners.
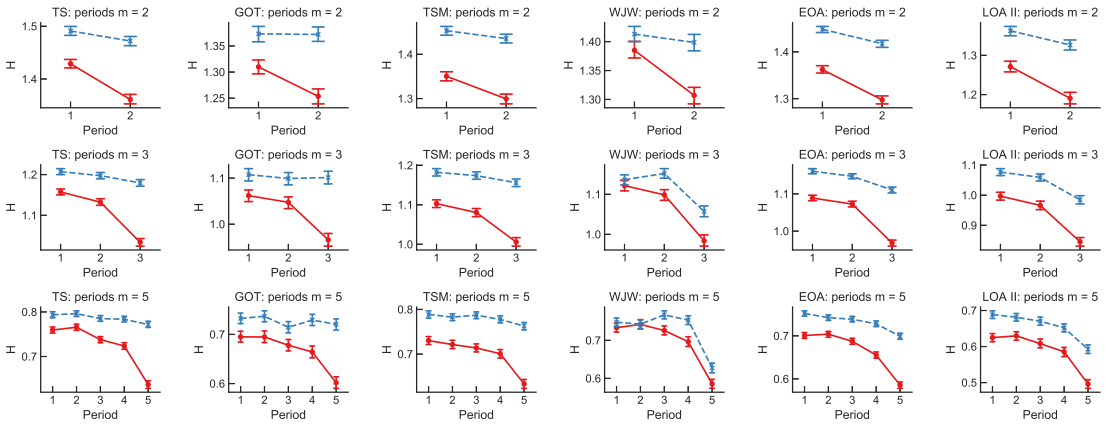
Fig. 3. The mean cross-entropies between the players' daily playtime distributions and the degenerate distribution in aforementioned games. The blue dashed line shows the non-churners, while the red solid line shows the churners.
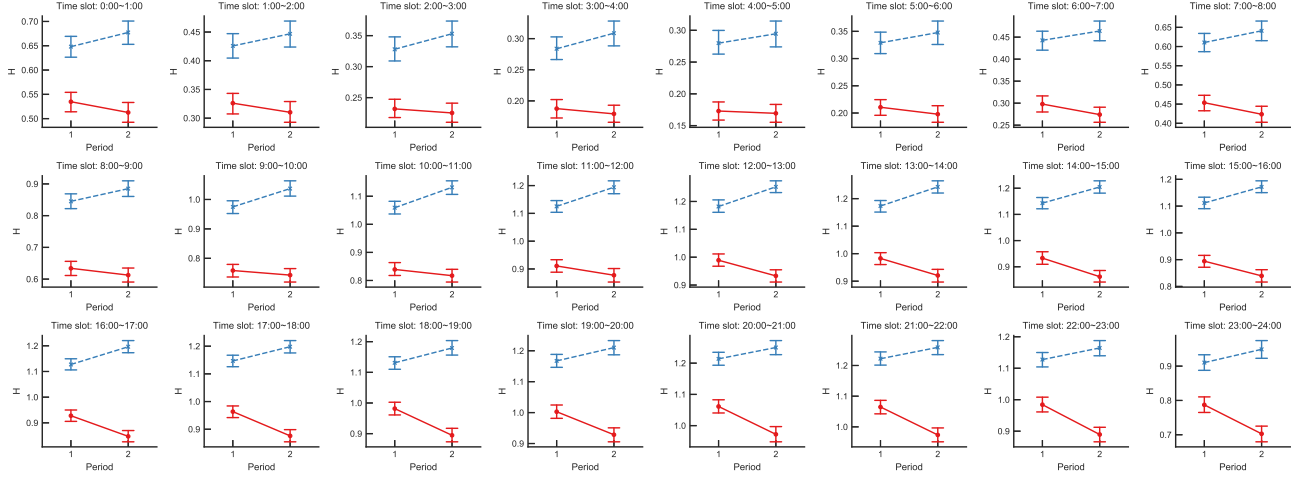
Fig. 4. The mean entropies of the hourly distributions of playtime of *Thirty-six Stratagems (TS)* players where the playing time is divided by $m = 2$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
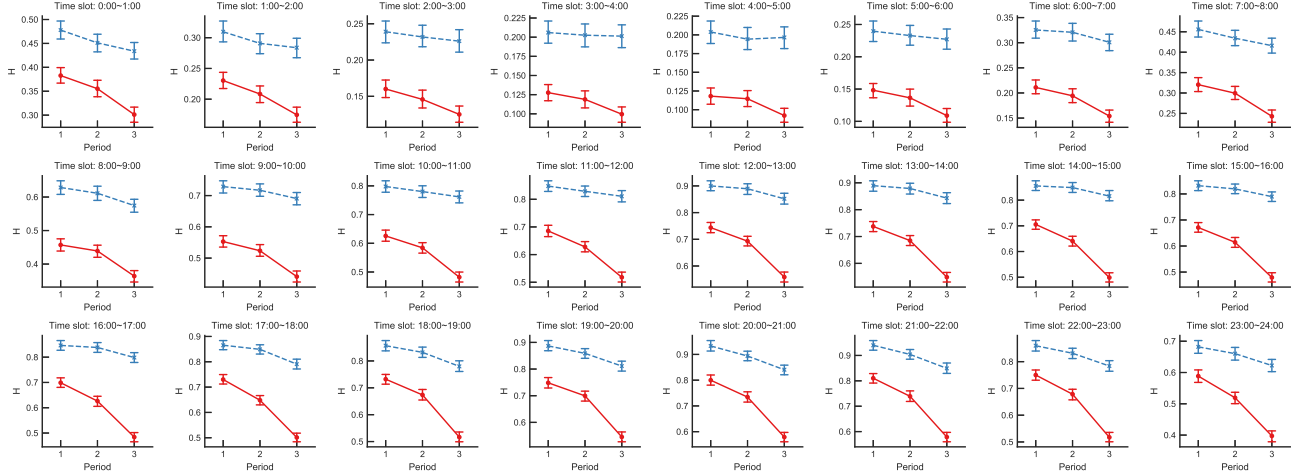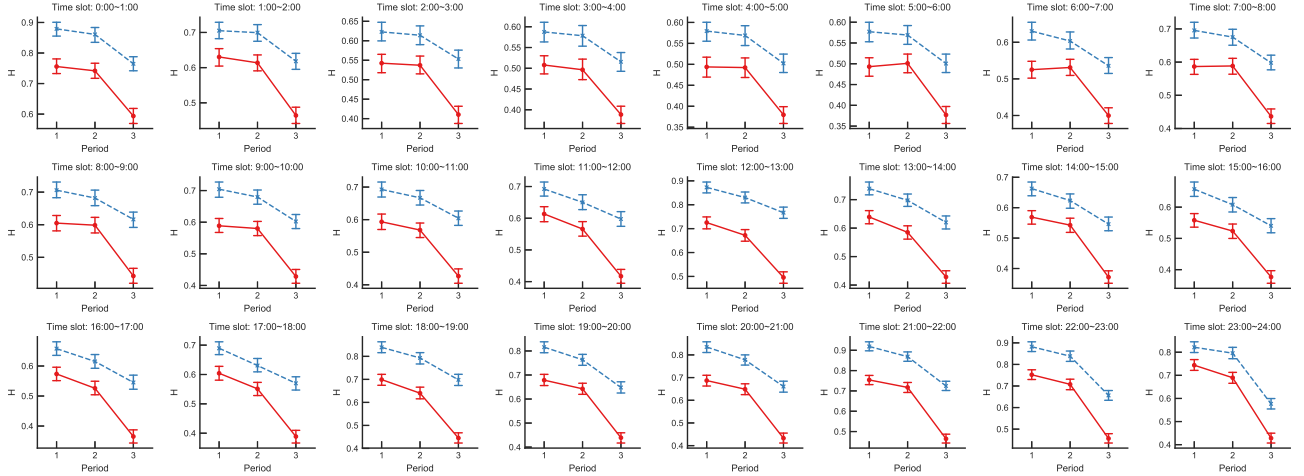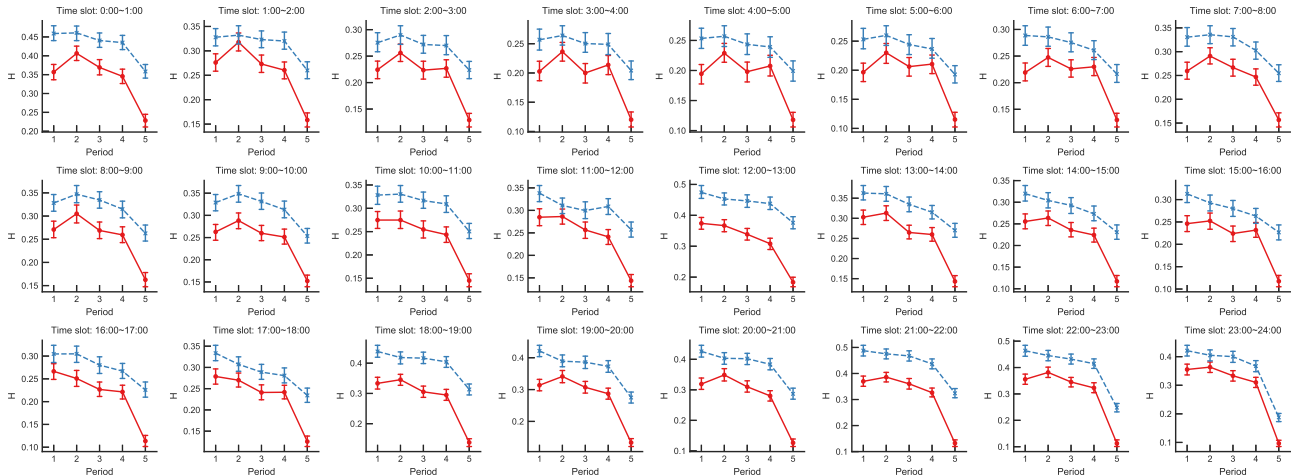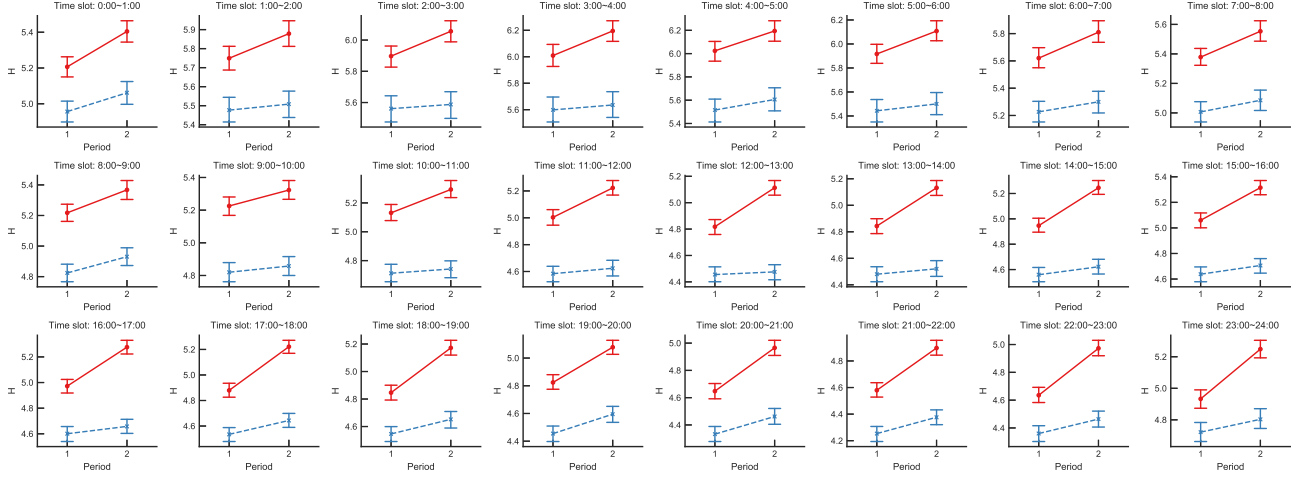

Fig. 5. The mean entropies of the hourly distributions of playtime of *Thirty-six Stratagems (TS)* players where the playing time is divided by $m = 3$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
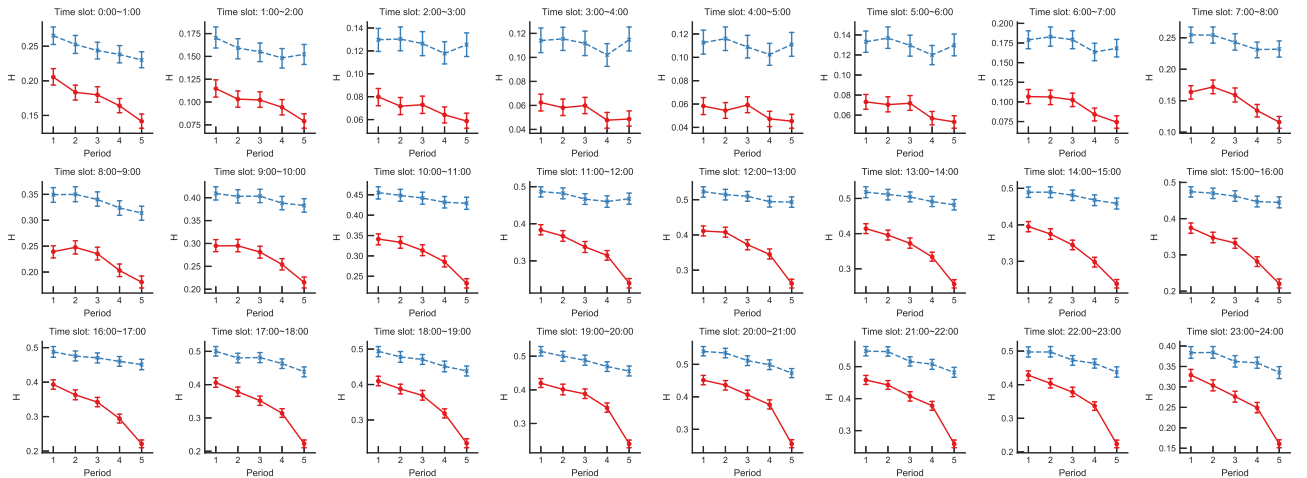
Fig. 6. The mean entropies of the hourly distributions of playtime of *Thirty-six Stratagems (TS)* players where the playing time is divided by $m = 5$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
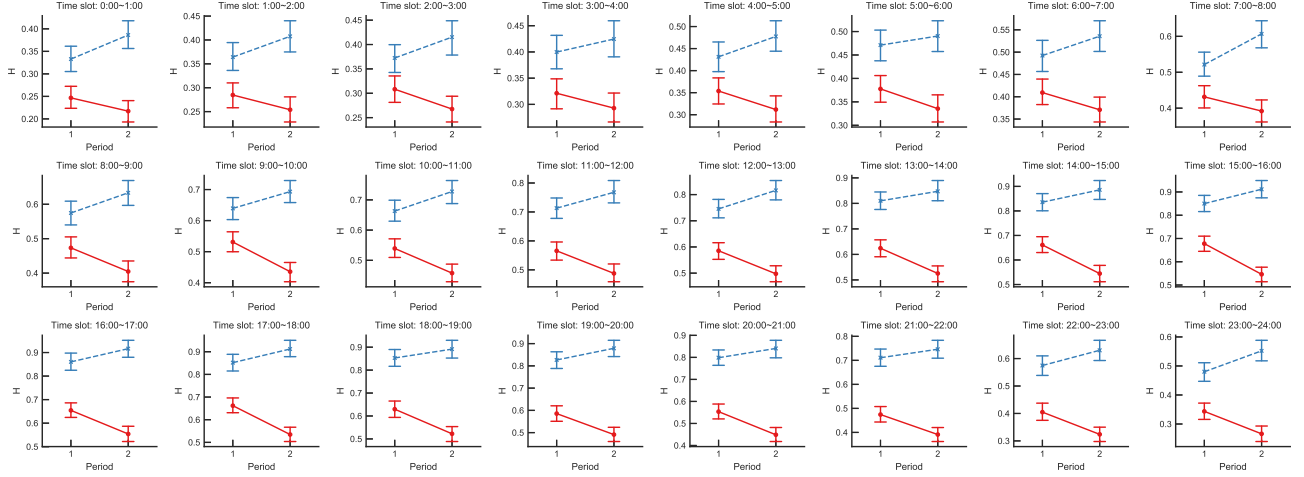
Fig. 7. The mean entropies of the hourly distributions of playtime of *Game of Thrones Winter is Coming (GOT)* players where the playing time is divided by $m = 2$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
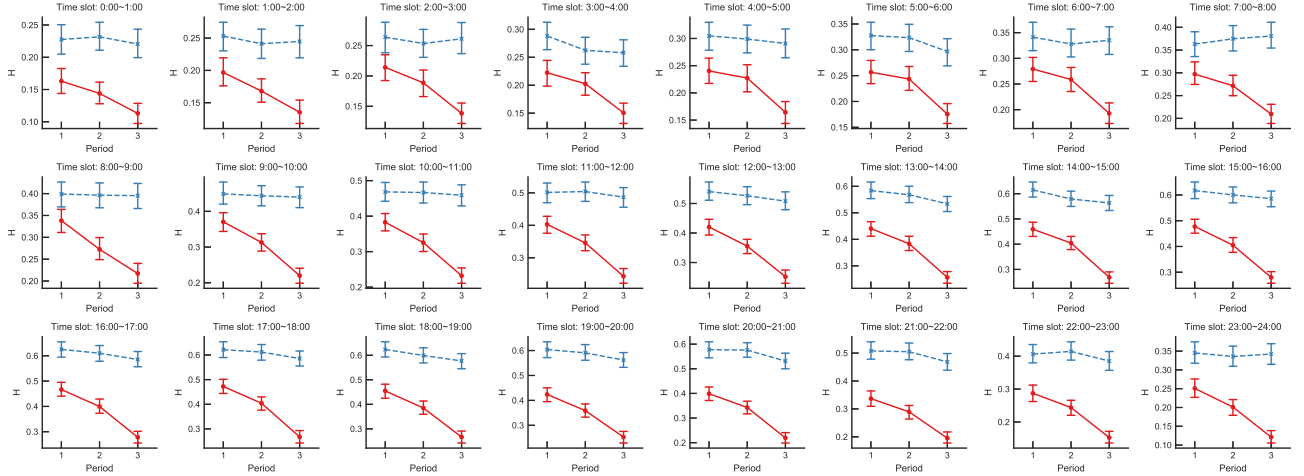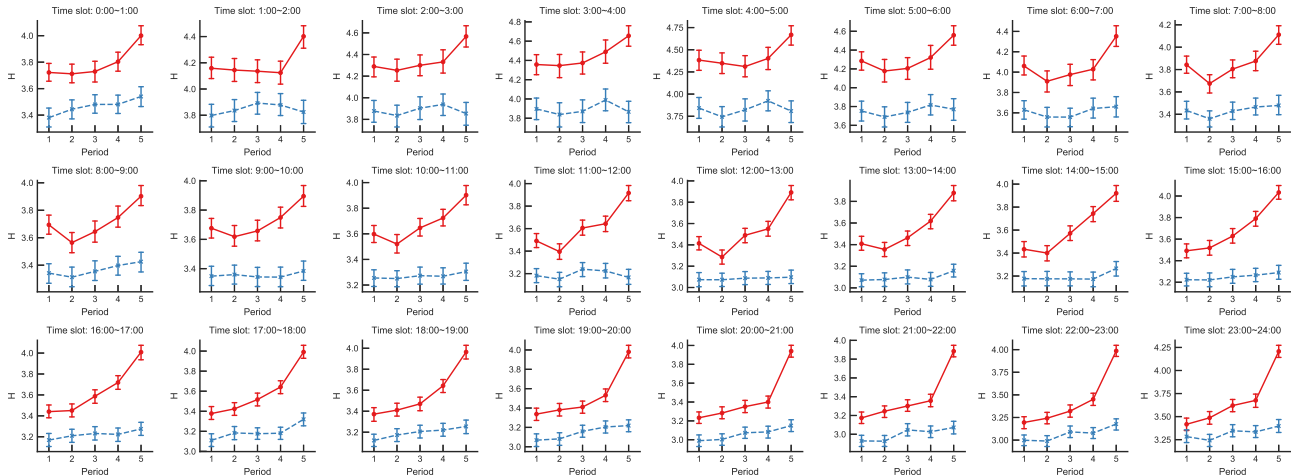

Fig. 8. The mean entropies of the hourly distributions of playtime of *Game of Thrones Winter is Coming (GOT)* players where the playing time is divided by $m = 3$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
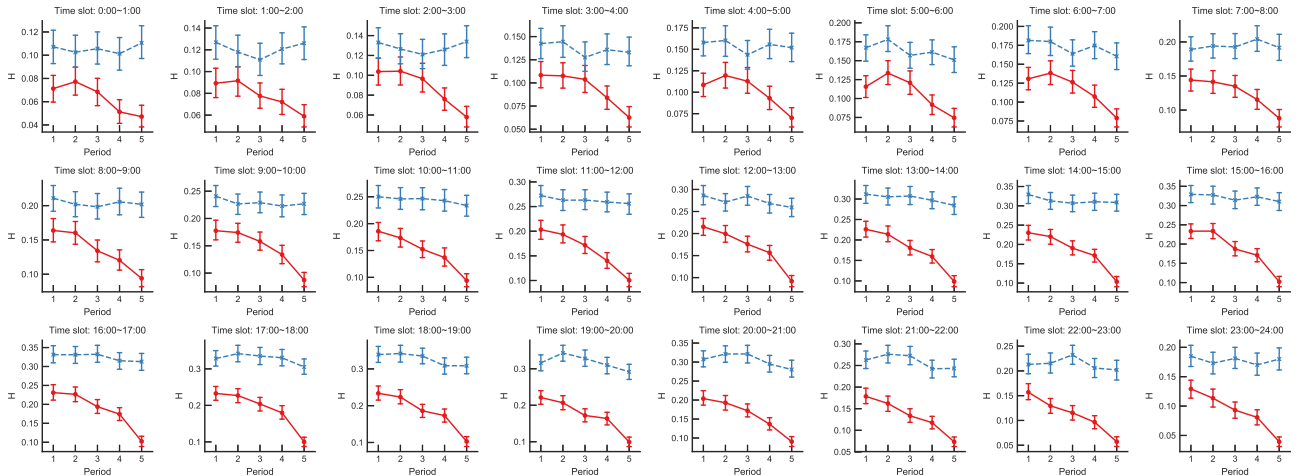
Fig. 9. The mean entropies of the hourly distributions of playtime of *Game of Thrones Winter is Coming s (GOT)* players where the playing time is divided by $m = 5$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
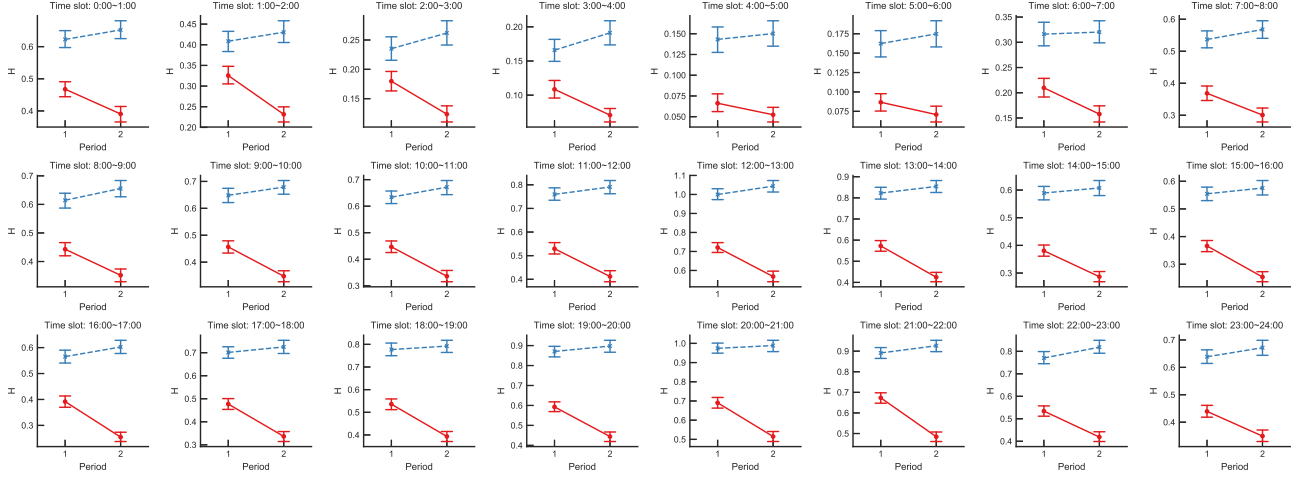
Fig. 10. The mean entropies of the hourly distributions of playtime of *Thirty-six Stratagems Mobile (TSM)* players where the playing time is divided by $m = 2$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
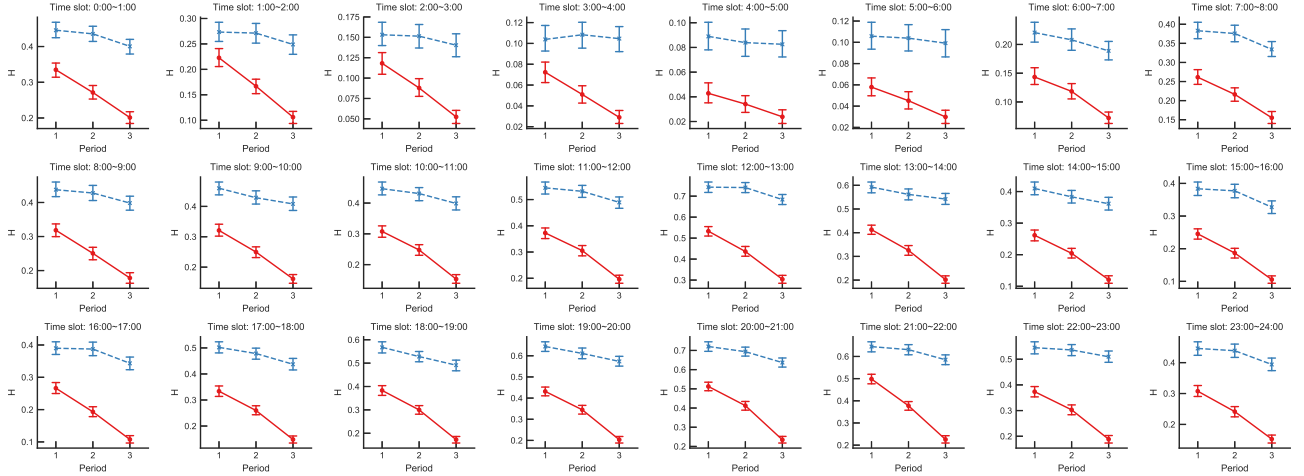

Fig. 11. The mean entropies of the hourly distributions of playtime of *Thirty-six Stratagems Mobile (TSM)* players where the playing time is divided by $m = 3$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
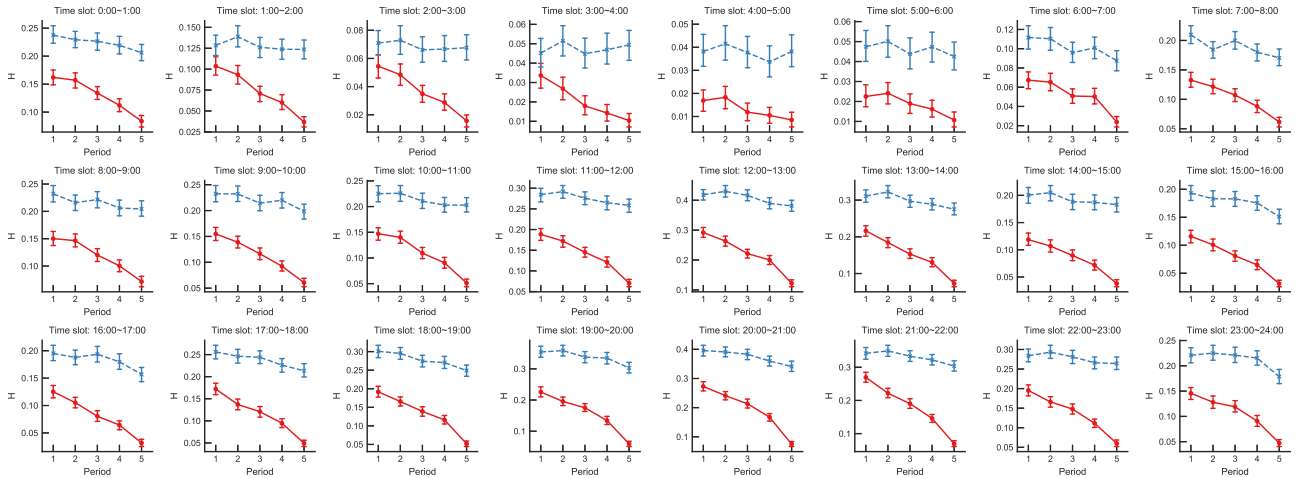
Fig. 12. The mean entropies of the hourly distributions of playtime of *Thirty-six Stratagems Mobile (TSM)* players where the playing time is divided by $m = 5$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
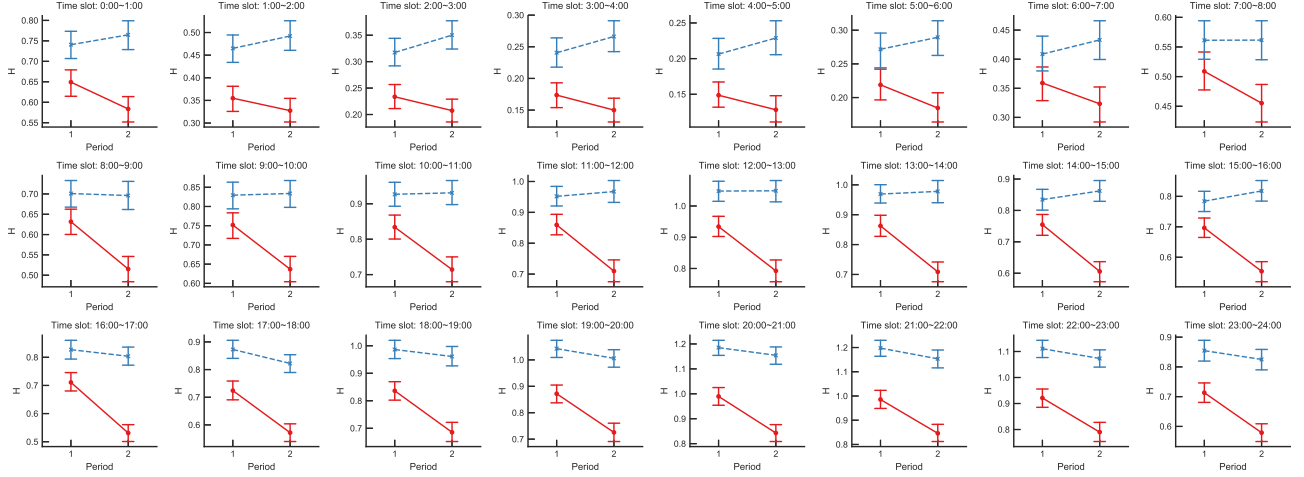
Fig. 13. The mean entropies of the hourly distributions of playtime of *Womanland in Journey to the West (WJW)* players where the playing time is divided by $m = 2$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
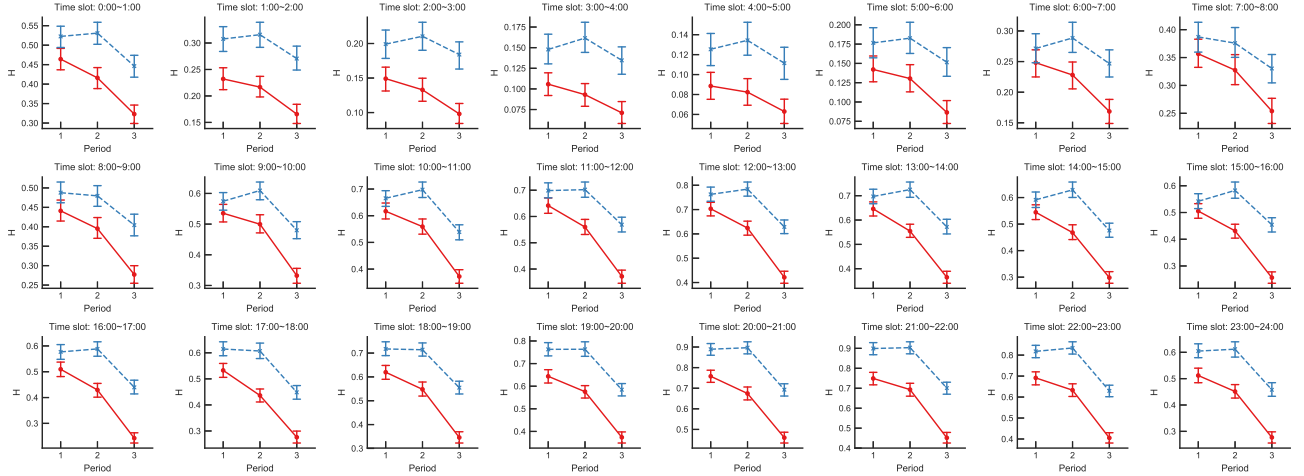
Fig. 14. The mean entropies of the hourly distributions of playtime of *Womanland in Journey to the West (WJW)* players where the playing time is divided by $m = 3$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
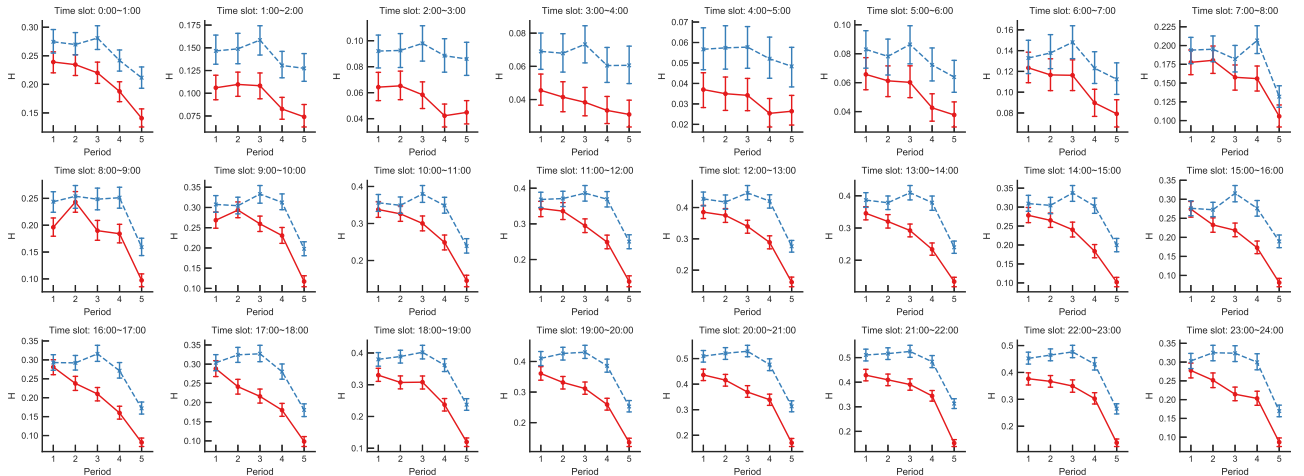

Fig. 15. The mean entropies of the hourly distributions of playtime of *Womanland in Journey to the West (WJW)* players where the playing time is divided by $m = 5$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
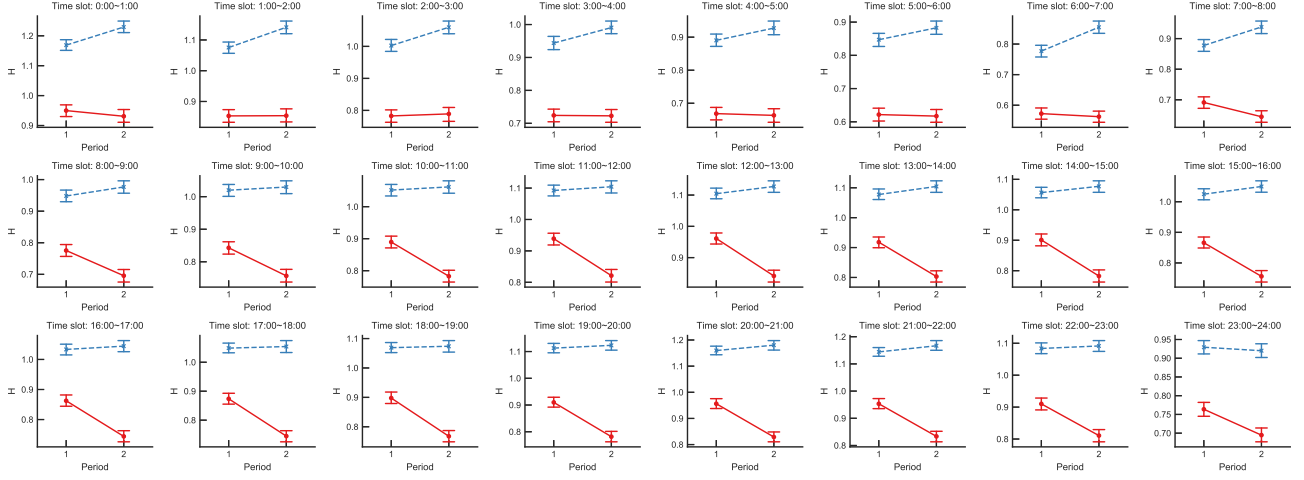
Fig. 16. The mean entropies of the hourly distributions of playtime of *Era of Angels (EOA)* players where the playing time is divided by $m = 2$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
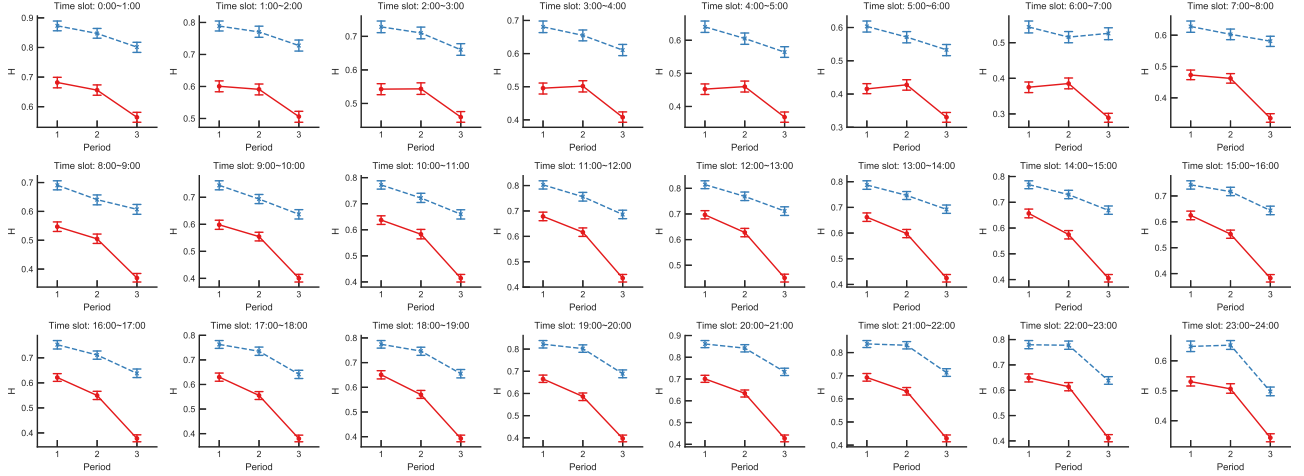

Fig. 17. The mean entropies of the hourly distributions of playtime of *Era of Angels (EOA)* players where the playing time is divided by $m = 3$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
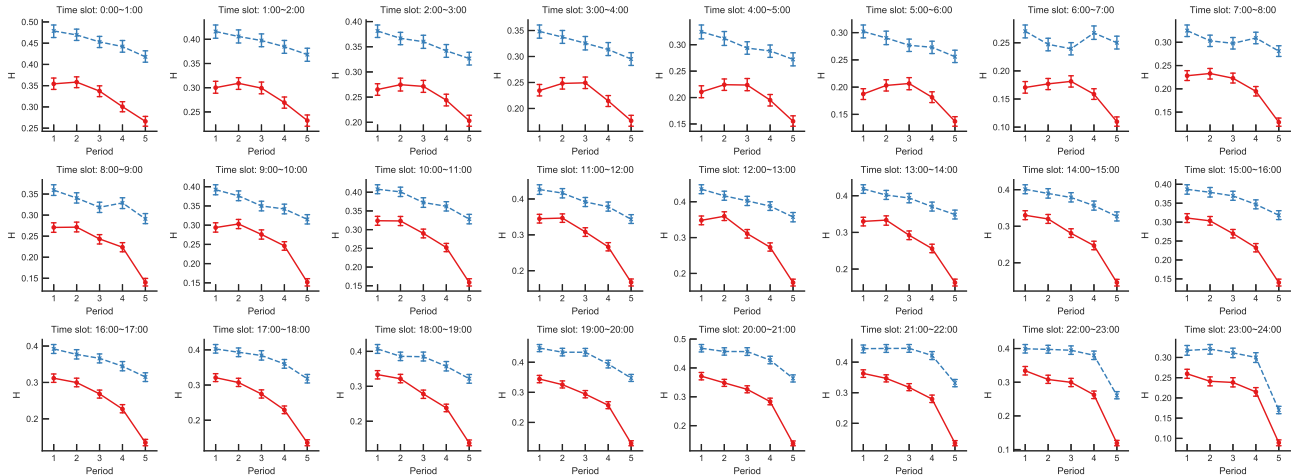
Fig. 18. The mean entropies of the hourly distributions of playtime of *Era of Angels (EOA)* players where the playing time is divided by $m = 5$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
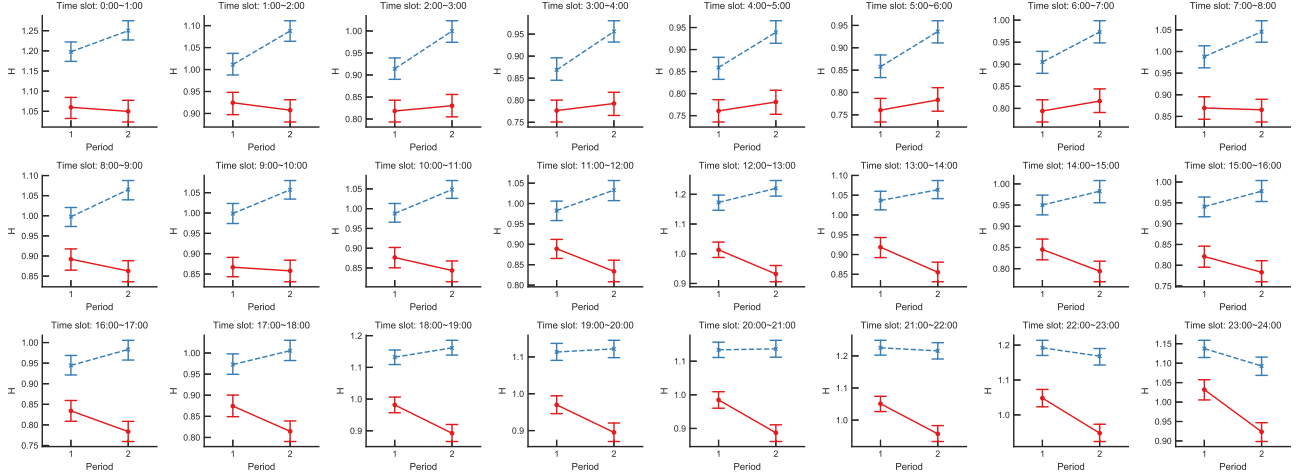
Fig. 19. The mean entropies of the hourly distributions of playtime of *League of Angels II (LOA II)* players where the playing time is divided by $m = 2$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.

Fig. 20. The mean entropies of the hourly distributions of playtime of *League of Angels II (LOA II)* players where the playing time is divided by $m = 3$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.

Fig. 21. The mean entropies of the hourly distributions of playtime of *League of Angels II (LOA II)* players where the playing time is divided by $m = 5$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.

Fig. 22. The mean cross-entropies between the players' hourly playtime distributions and the uniform distribution in *Thirty-six Stratagems (TS)* where the playing time is divided by $m = 2$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
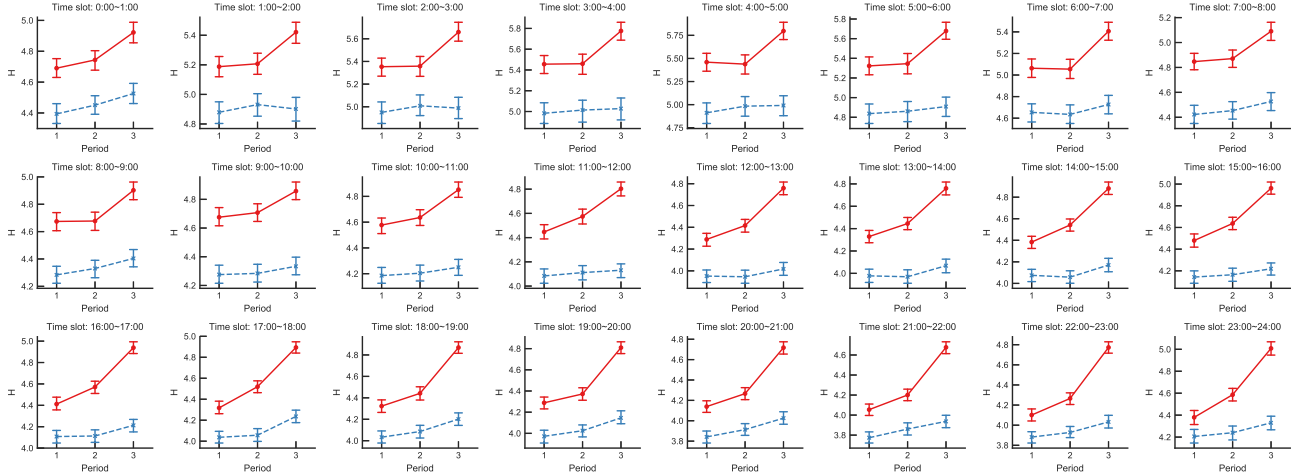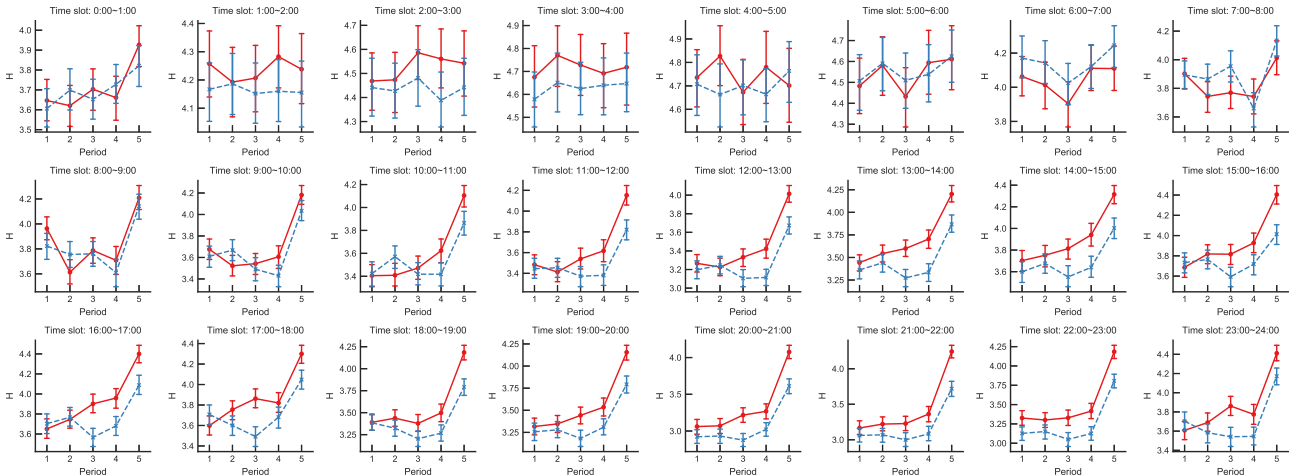

Fig. 23. The mean cross-entropies between the players' hourly playtime distributions and the uniform distribution in *Thirty-six Stratagems (TS)* where the playing time is divided by $m = 3$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
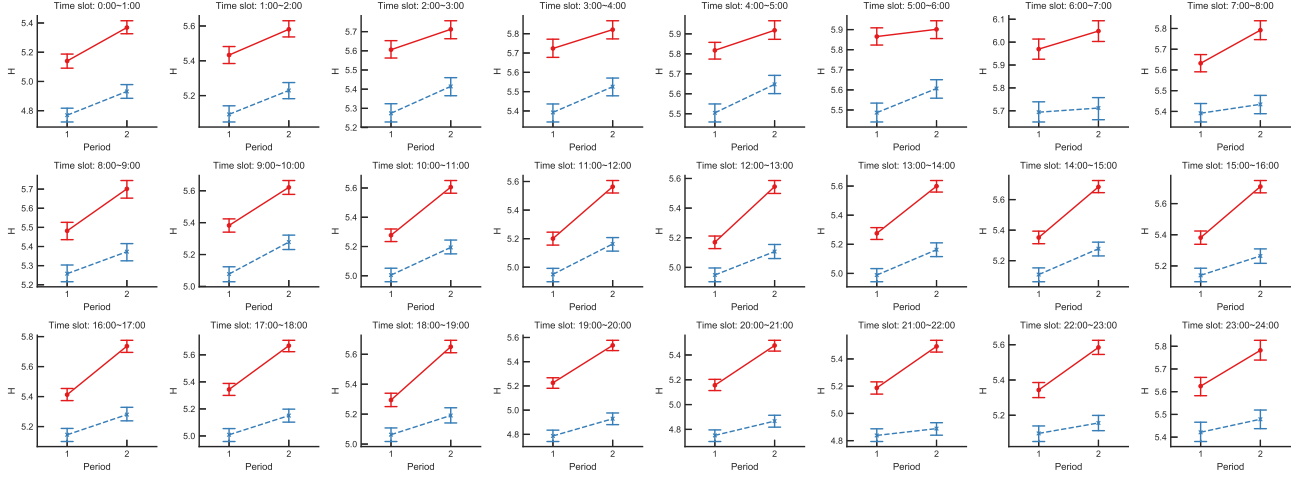

Fig. 24. The mean cross-entropies between the players' hourly playtime distributions and the uniform distribution in *Thirty-six Stratagems (TS)* where the playing time is divided by $m = 5$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
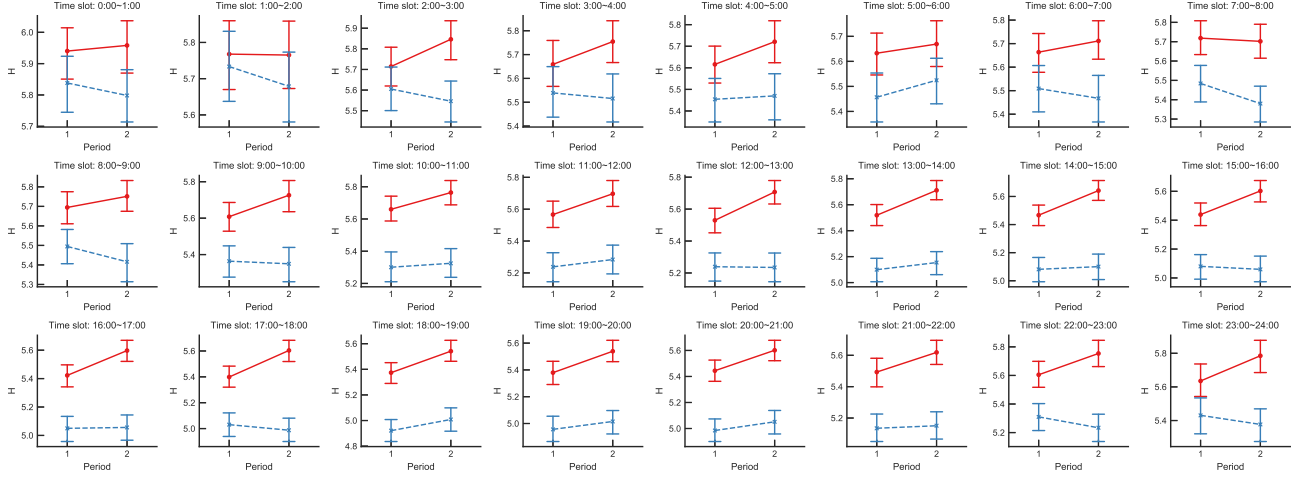
Fig. 25. The mean cross-entropies between the players' hourly playtime distributions and the uniform distribution in *Game of Thrones Winter is Coming (GOT)* where the playing time is divided by $m = 2$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
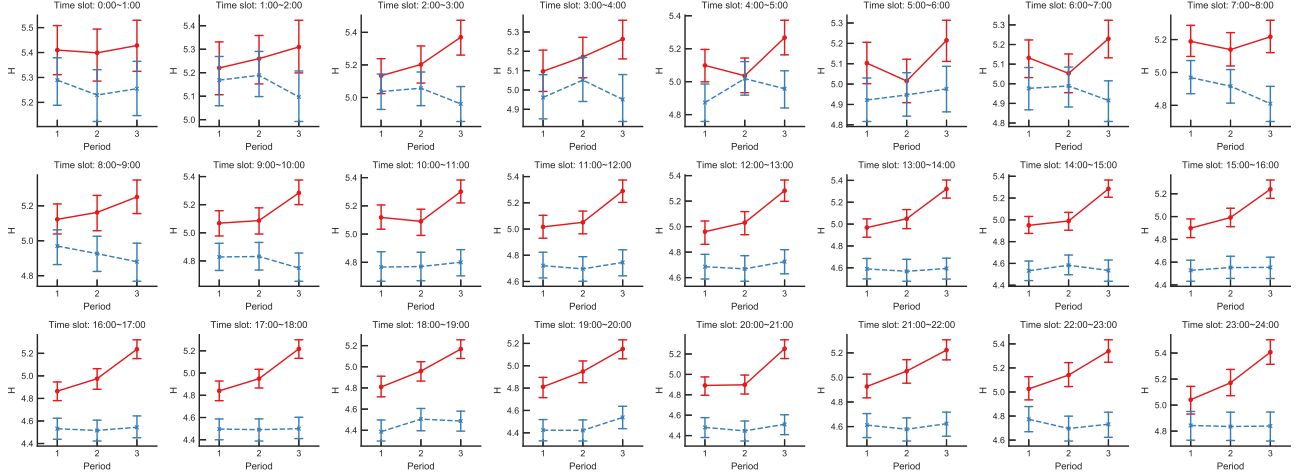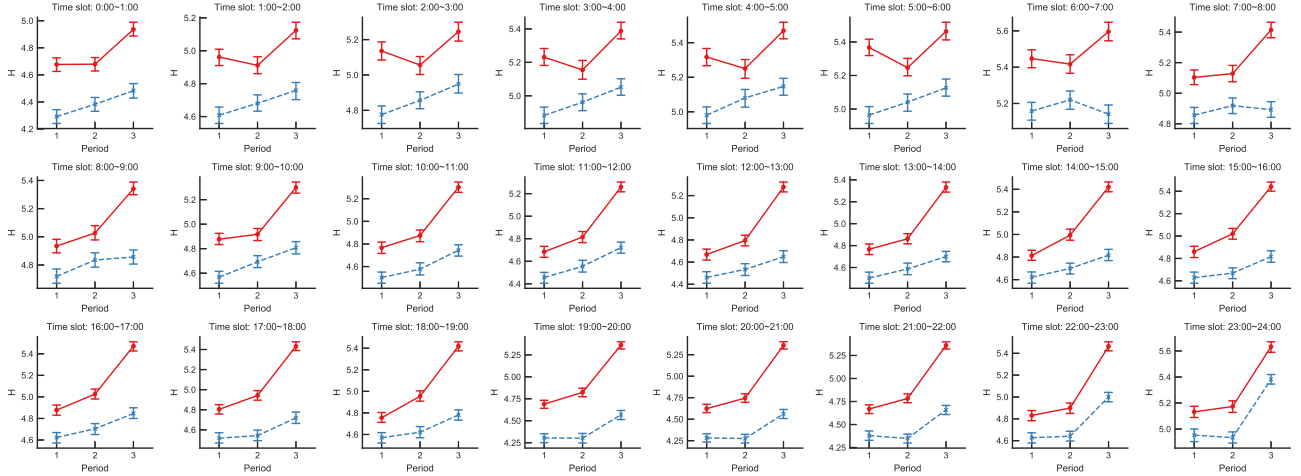

Fig. 26. The mean cross-entropies between the players' hourly playtime distributions and the uniform distribution in *Game of Thrones Winter is Coming (GOT)* where the playing time is divided by $m = 3$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
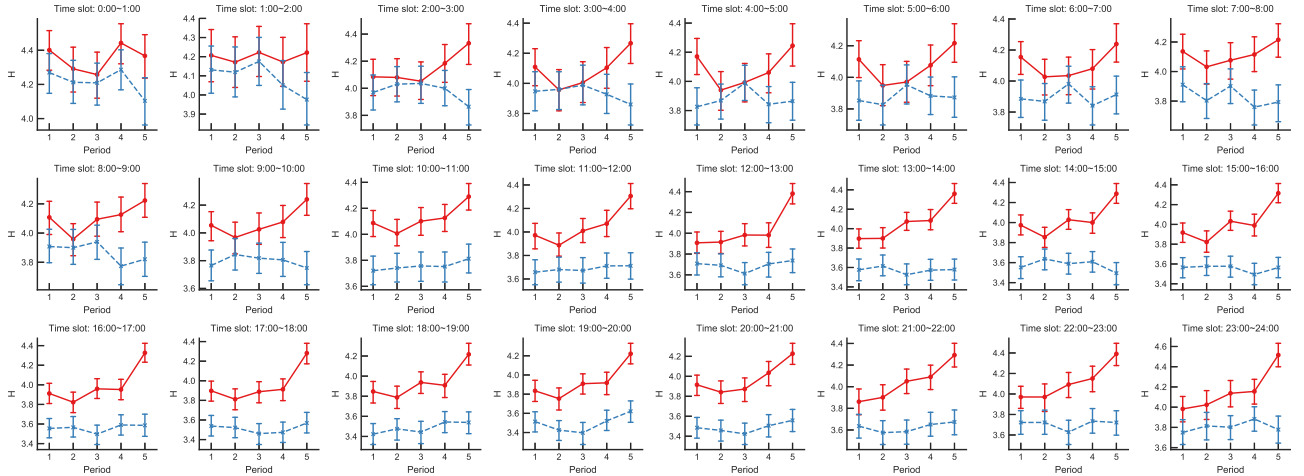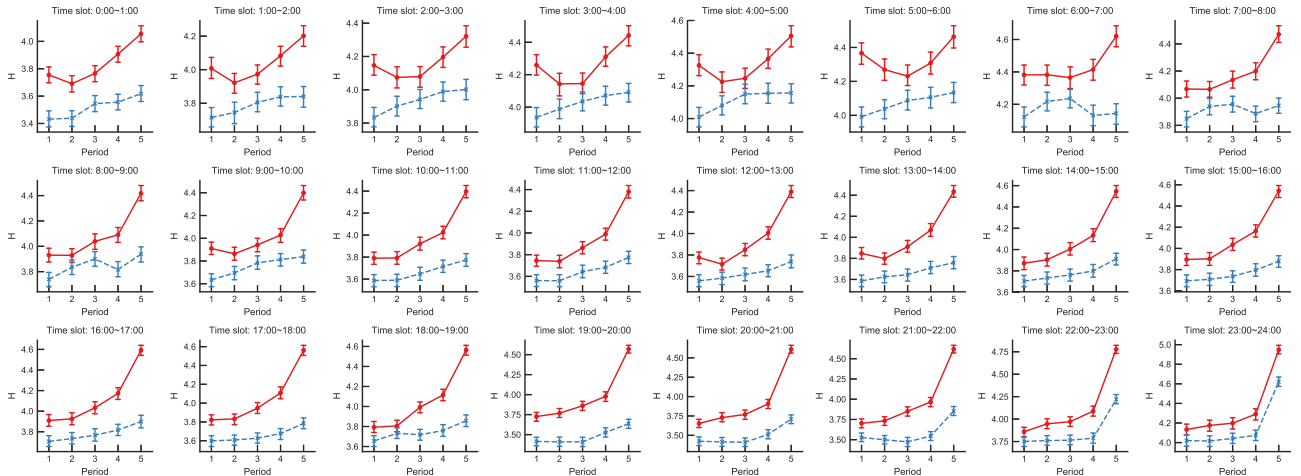

Fig. 27. The mean cross-entropies between the players' hourly playtime distributions and the uniform distribution in *Game of Thrones Winter is Coming (GOT)* where the playing time is divided by $m = 5$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
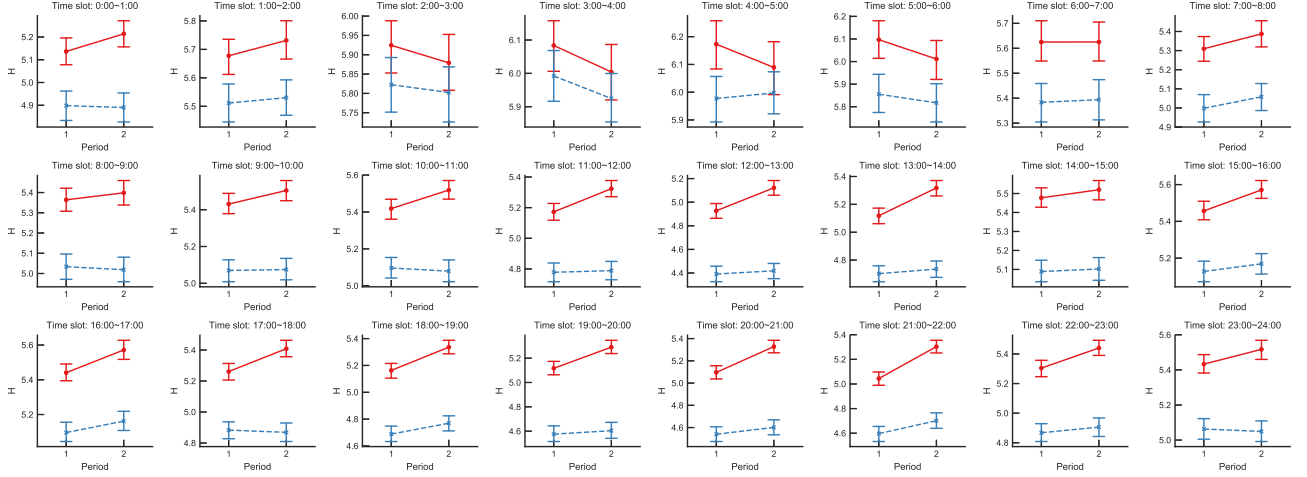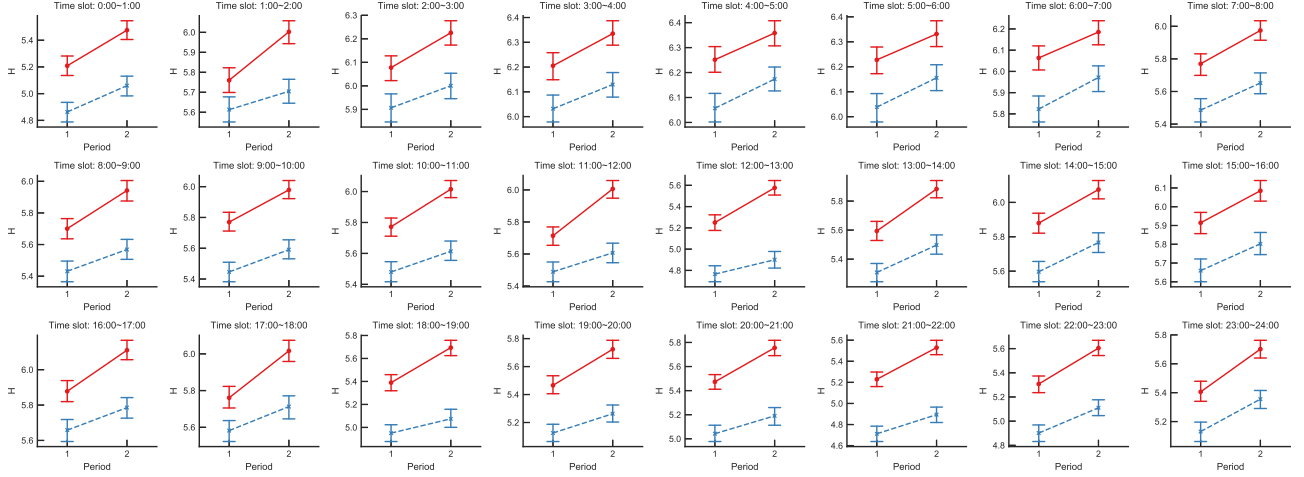
Fig. 28. The mean cross-entropies between the players' hourly playtime distributions and the uniform distribution in *Thirty-six Stratagems Mobile (TSM)* where the playing time is divided by $m = 2$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
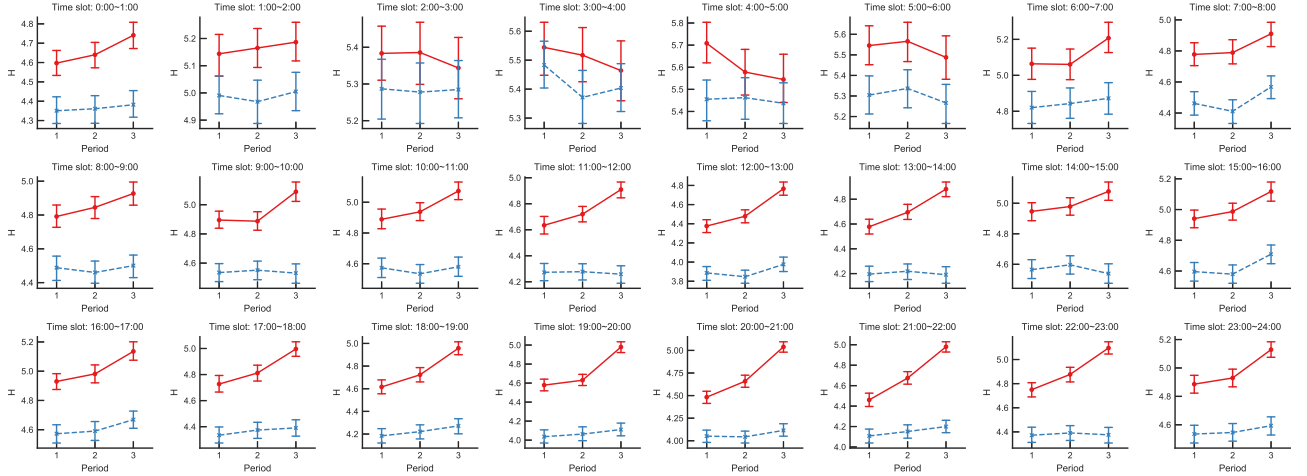
Fig. 29. The mean cross-entropies between the players' hourly playtime distributions and the uniform distribution in *Thirty-six Stratagems Mobile (TSM)* where the playing time is divided by $m = 3$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
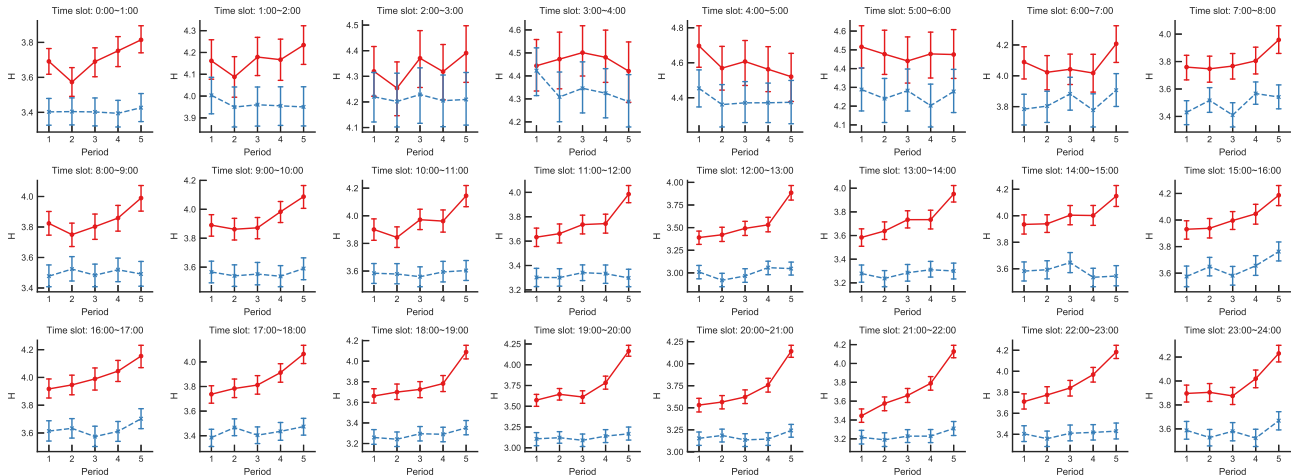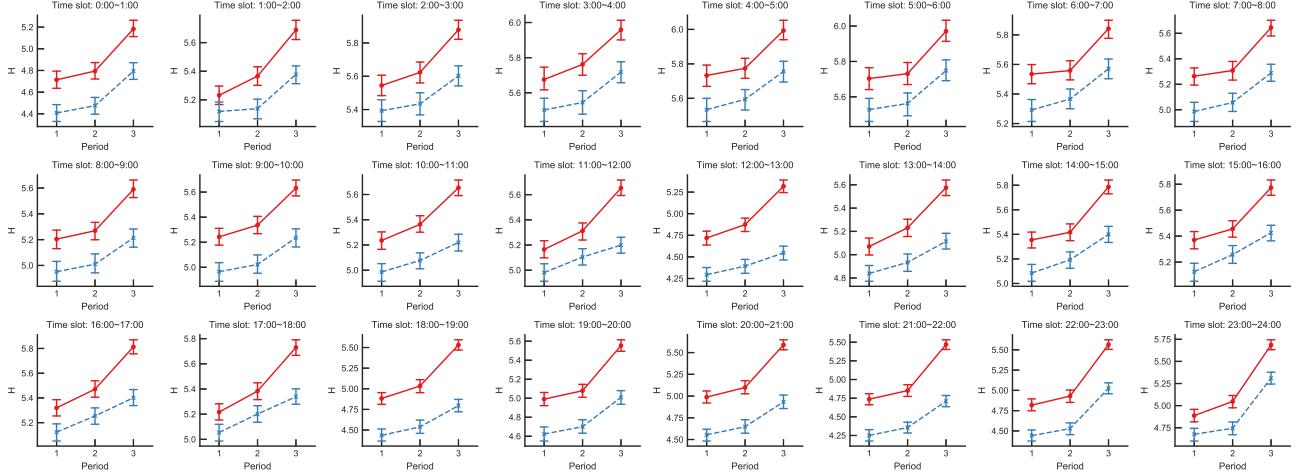

Fig. 30. The mean cross-entropies between the players' hourly playtime distributions and the uniform distribution in *Thirty-six Stratagems Mobile (TSM)* where the playing time is divided by $m = 5$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
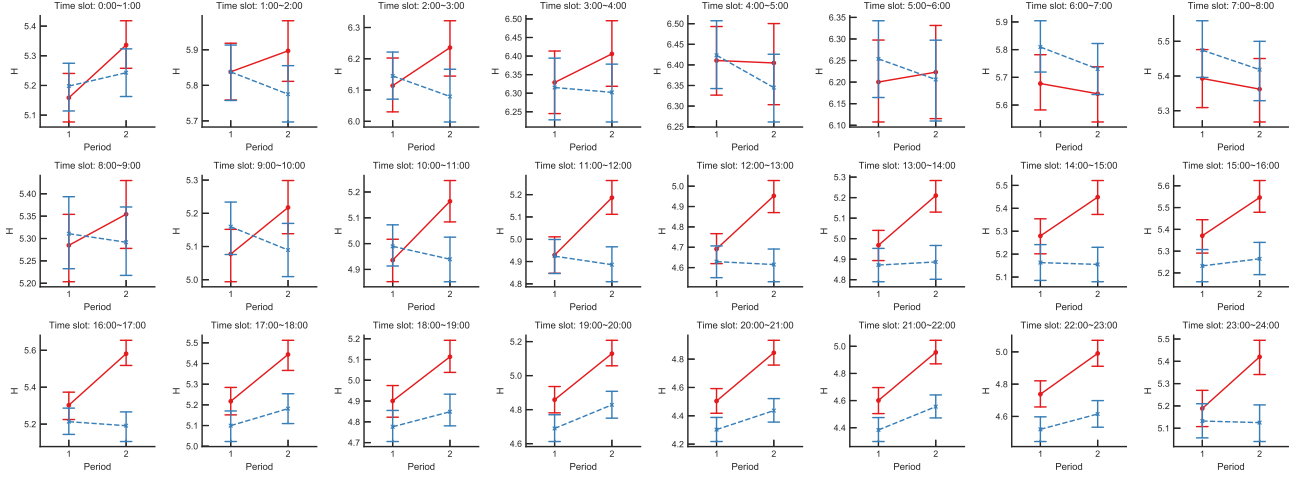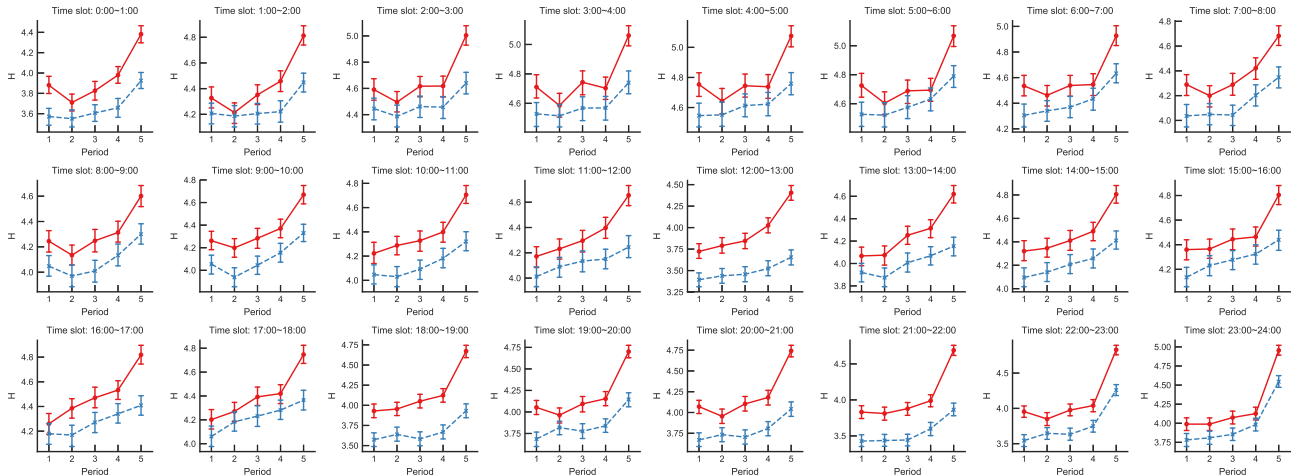
Fig. 31. The mean cross-entropies between the players' hourly playtime distributions and the uniform distribution in *Womanland in Journey to the West (WJW)* where the playing time is divided by $m = 2$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
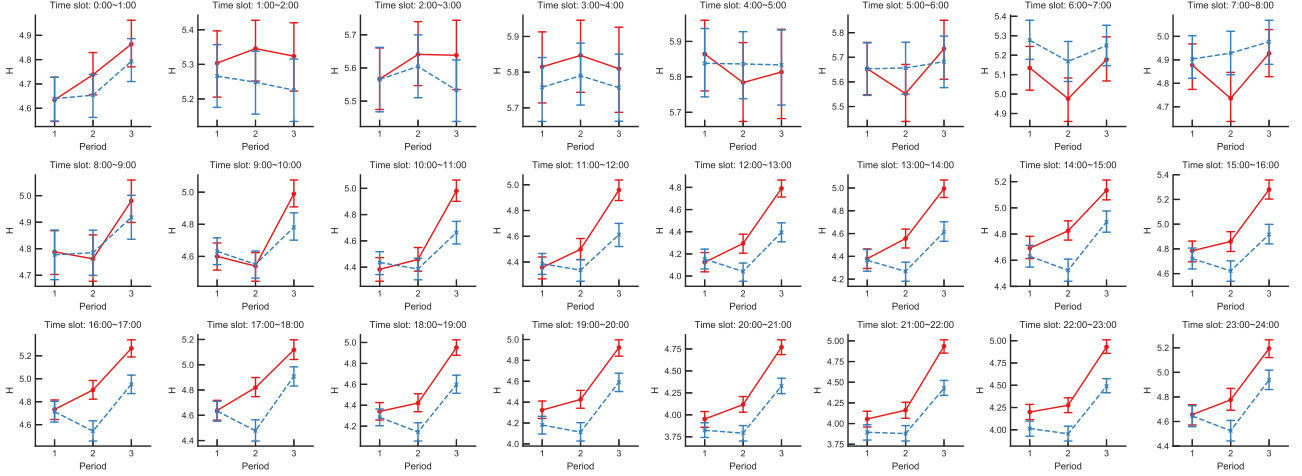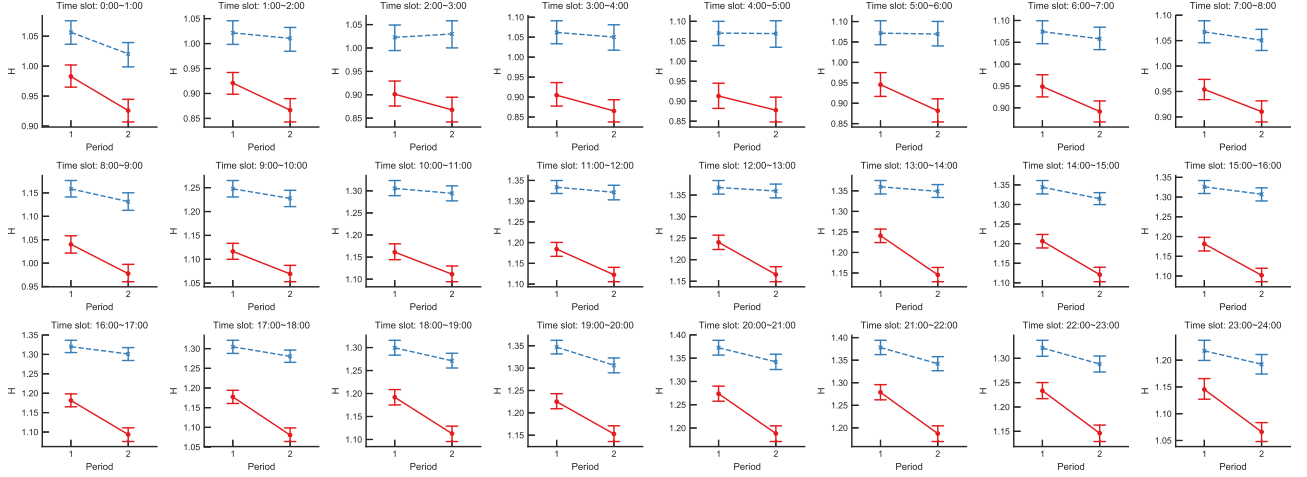

Fig. 32. The mean cross-entropies between the players' hourly playtime distributions and the uniform distribution in *Womanland in Journey to the West (WJW)* where the playing time is divided by $m = 3$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.

Fig. 33. The mean cross-entropies between the players' hourly playtime distributions and the uniform distribution in *Womanland in Journey to the West (WJW)* where the playing time is divided by $m = 5$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
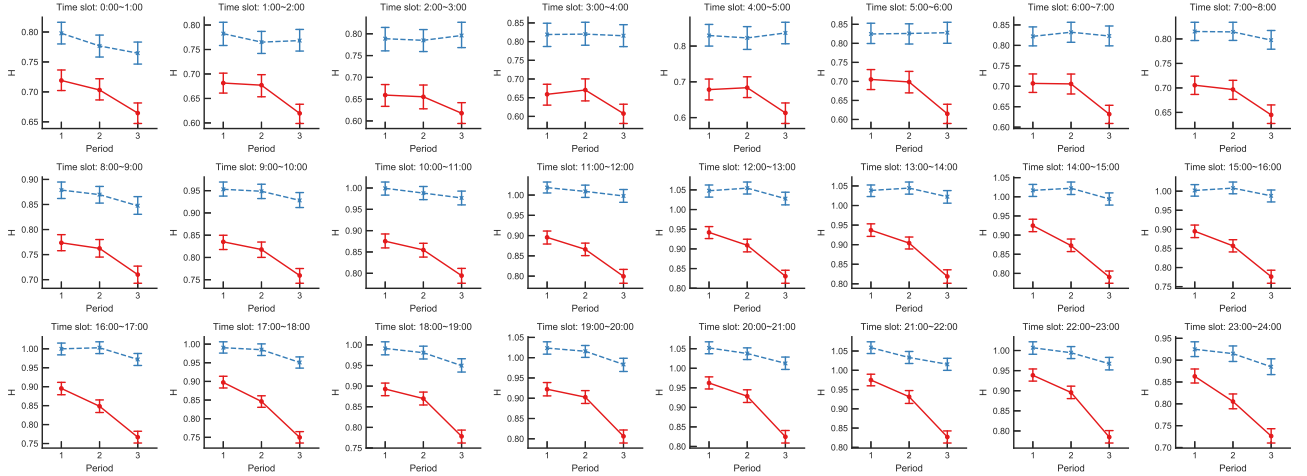
Fig. 34. The mean cross-entropies between the players' hourly playtime distributions and the uniform distribution in *Era of Angels (EOA)* where the playing time is divided by $m = 2$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
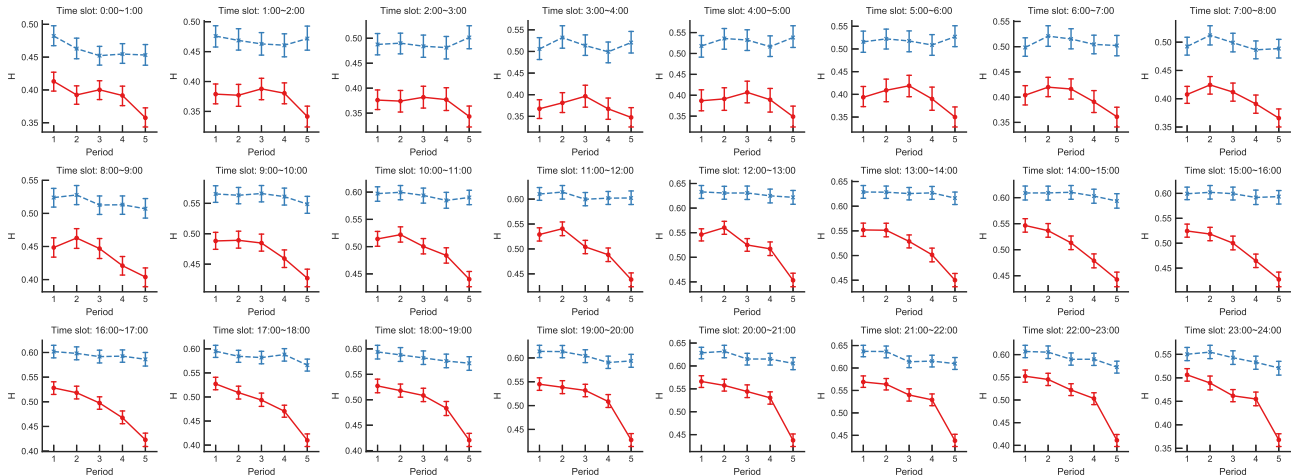

Fig. 35. The mean cross-entropies between the players' hourly playtime distributions and the uniform distribution in *Era of Angels (EOA)* where the playing time is divided by $m = 3$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.

Fig. 36. The mean cross-entropies between the players' hourly playtime distributions and the uniform distribution in *Era of Angels (EOA)* where the playing time is divided by $m = 5$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
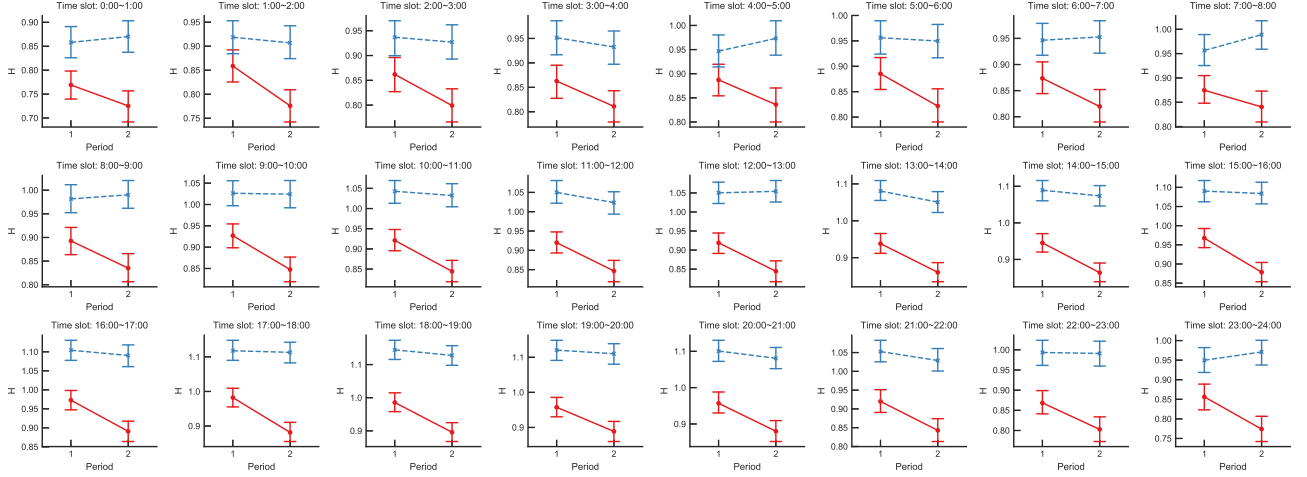
Fig. 37. The mean cross-entropies between the players' hourly playtime distributions and the uniform distribution in *League of Angels II (LOA II)* where the playing time is divided by $m = 2$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
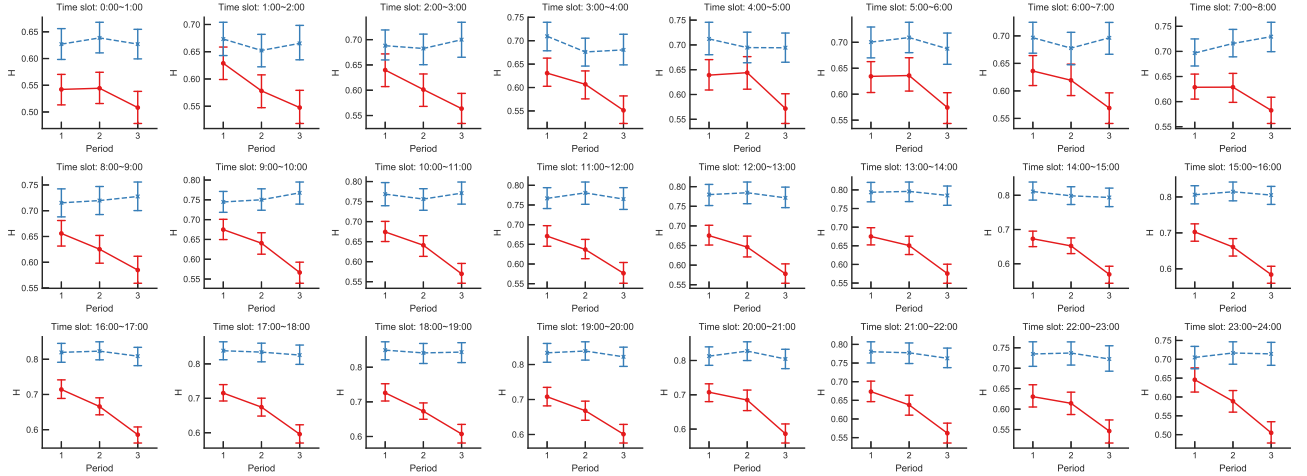

Fig. 38. The mean cross-entropies between the players' hourly playtime distributions and the uniform distribution in *League of Angels II (LOA II)* where the playing time is divided by $m = 3$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
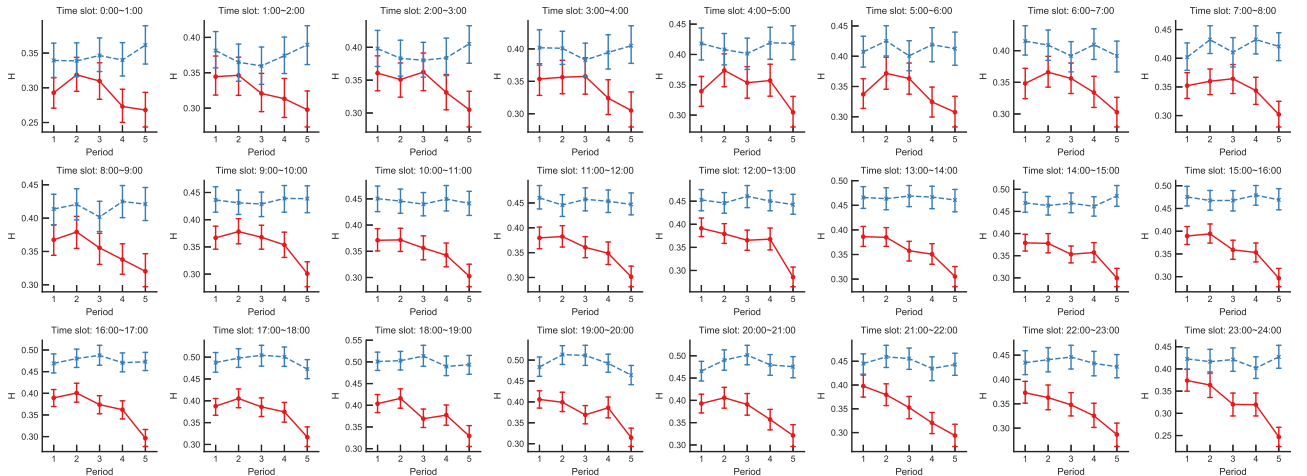

Fig. 39. The mean cross-entropies between the players' hourly playtime distributions and the uniform distribution in *League of Angels II (LOA II)* where the playing time is divided by $m = 5$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.

Fig. 40. The mean cross-entropies between the players' hourly playtime distributions and the the degenerate distribution in *Thirty-six Stratagems (TS)* where the playing time is divided by $m = 2$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
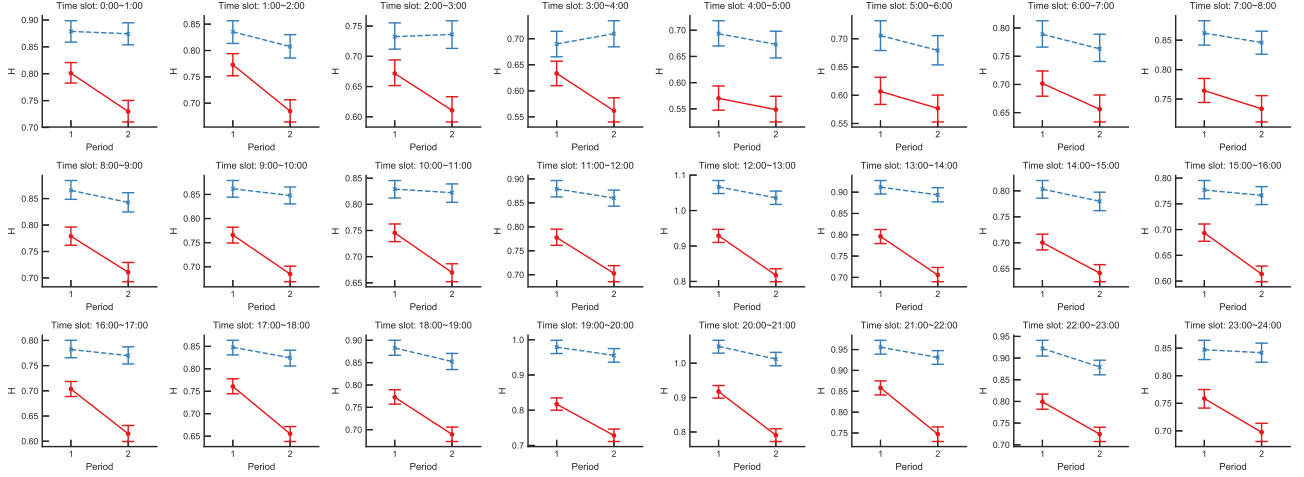

Fig. 41. The mean cross-entropies between the players' hourly playtime distributions and the degenerate distribution in *Thirty-six Stratagems (TS)* where the playing time is divided by $m = 3$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
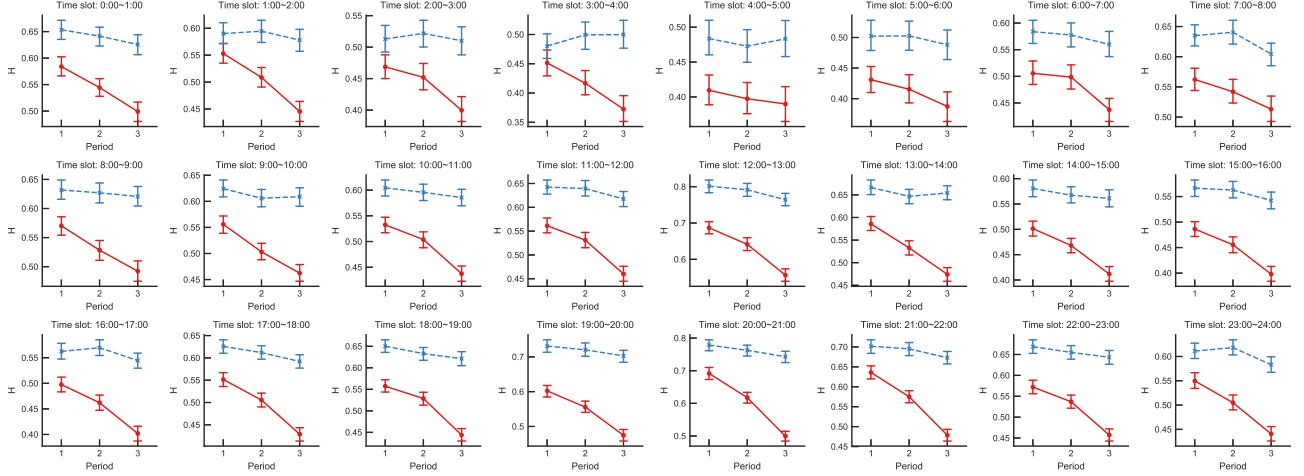

Fig. 42. The mean cross-entropies between the players' hourly playtime distributions and the degenerate distribution in *Thirty-six Stratagems (TS)* where the playing time is divided by $m = 5$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.

Fig. 43. The mean cross-entropies between the players' hourly playtime distributions and the degenerate distribution in *Game of Thrones Winter is Coming (GOT)* where the playing time is divided by $m = 2$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.

Fig. 44. The mean cross-entropies between the players' hourly playtime distributions and the degenerate distribution in *Game of Thrones Winter is Coming (GOT)* where the playing time is divided by $m = 3$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.

Fig. 45. The mean cross-entropies between the players' hourly playtime distributions and the degenerate distribution in *Game of Thrones Winter is Coming (GOT)* where the playing time is divided by $m = 5$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
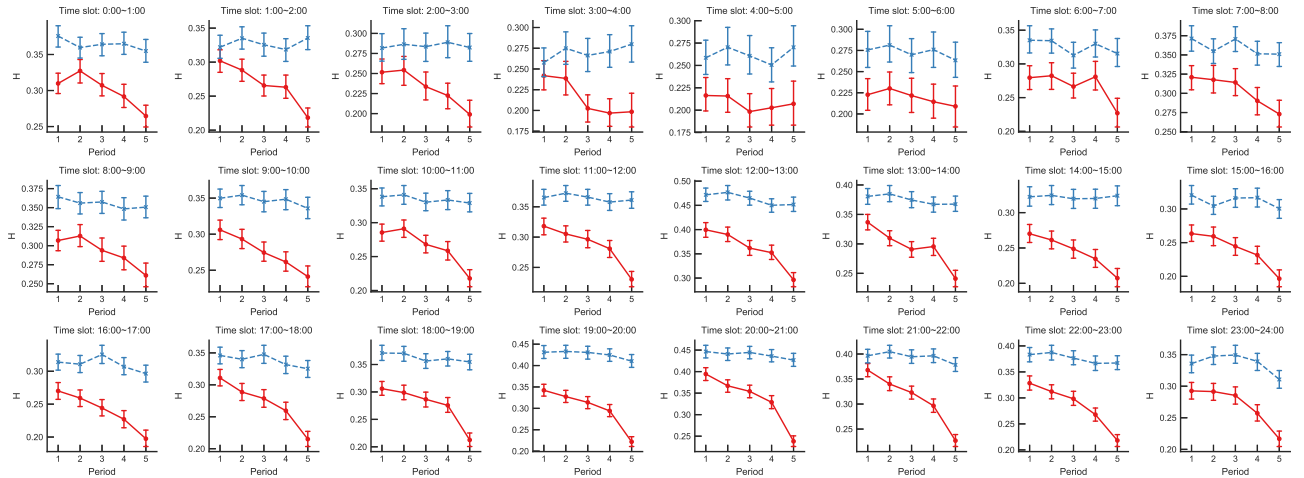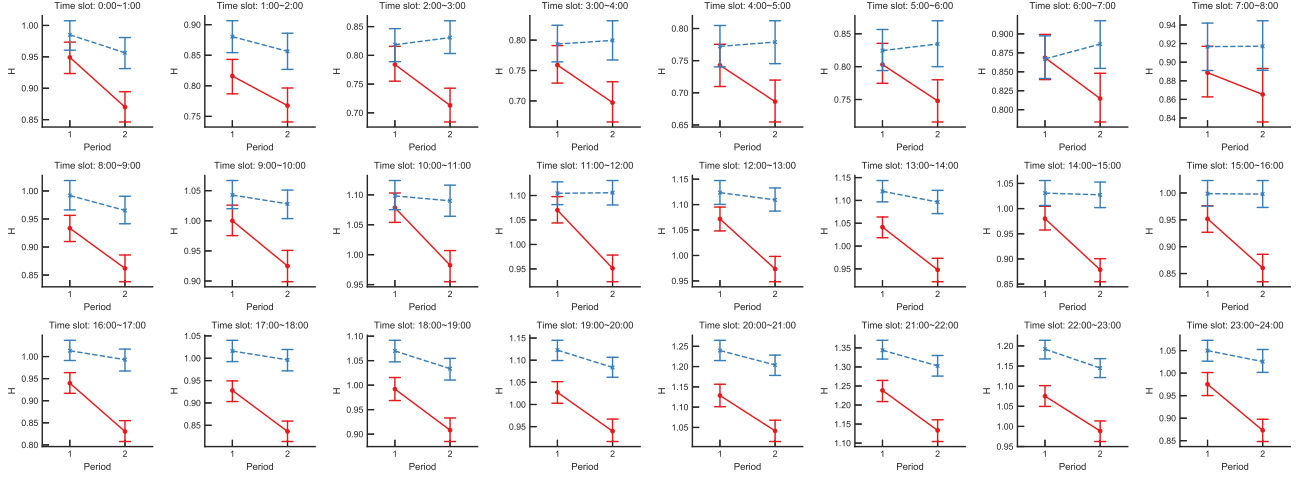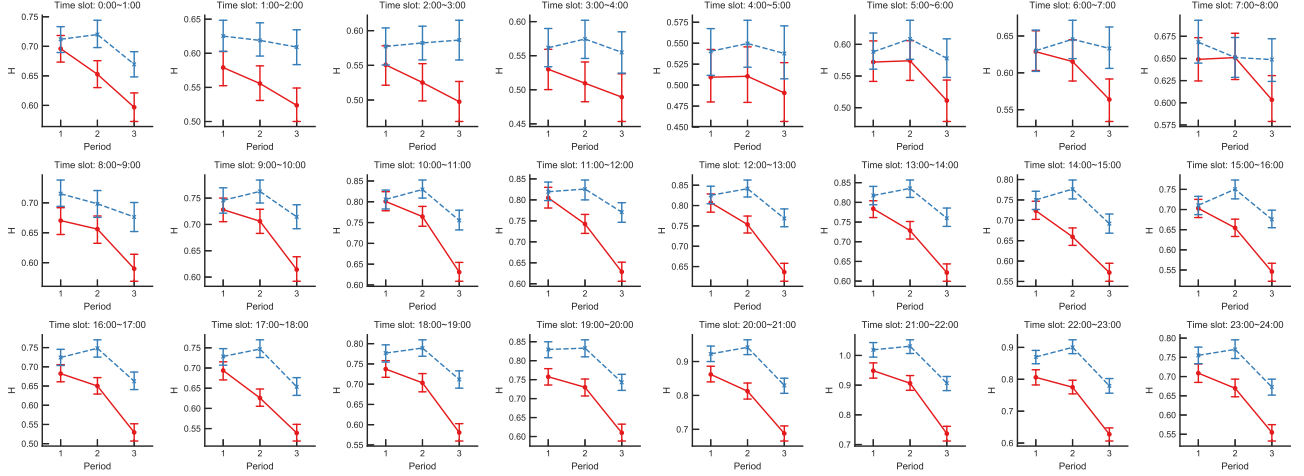
Fig. 46. The mean cross-entropies between the players' hourly playtime distributions and the degenerate distribution in *Thirty-six Stratagems Mobile (TSM)* where the playing time is divided by $m = 2$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.

Fig. 47. The mean cross-entropies between the players' hourly playtime distributions and the degenerate distribution in *Thirty-six Stratagems Mobile (TSM)* where the playing time is divided by $m = 3$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.

Fig. 48. The mean cross-entropies between the players' hourly playtime distributions and the degenerate distribution in *Thirty-six Stratagems Mobile (TSM)* where the playing time is divided by $m = 5$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
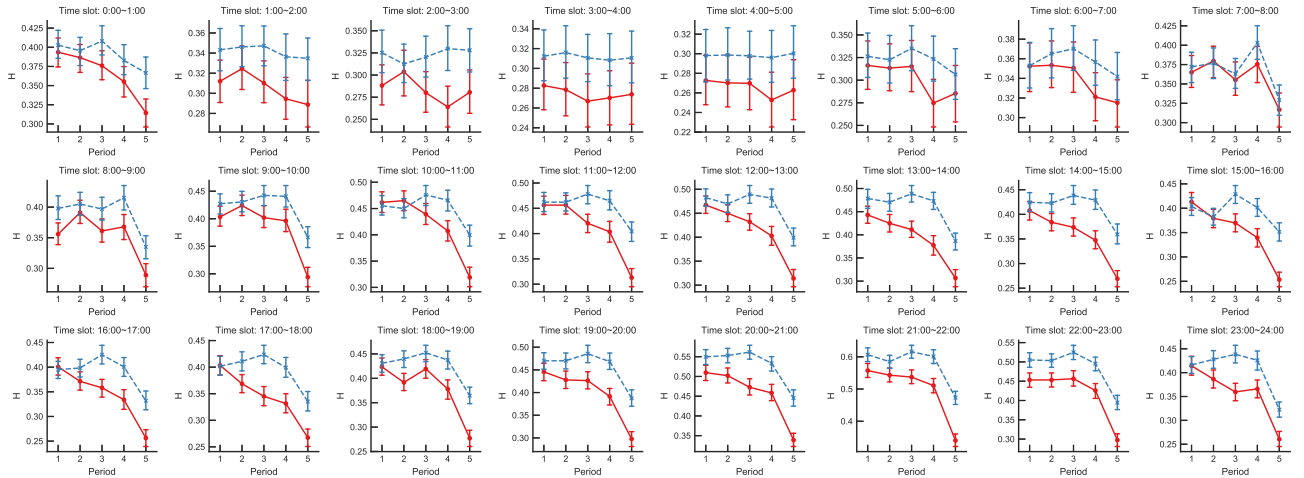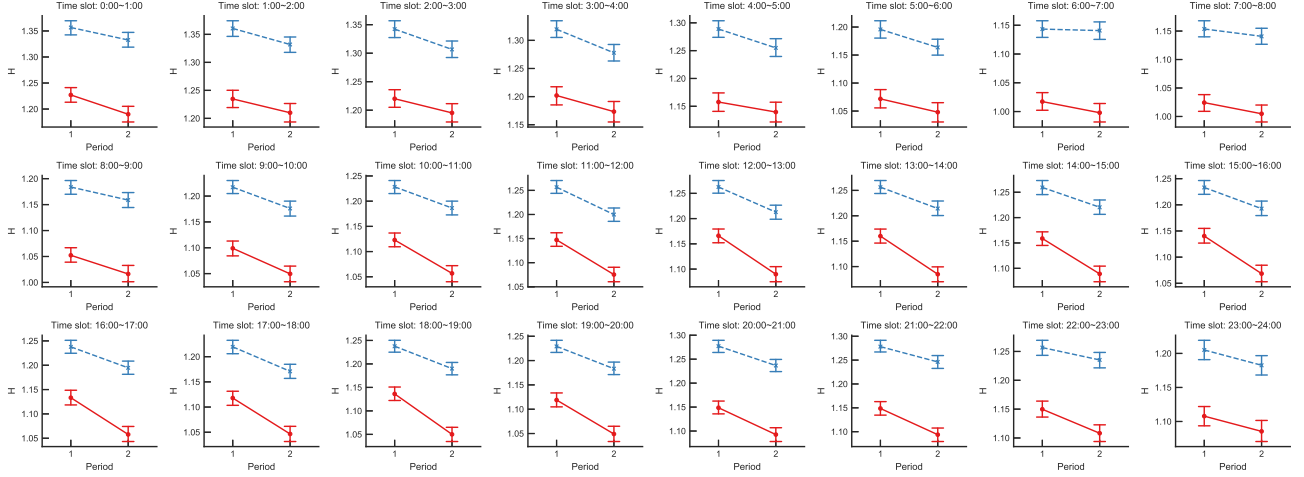
Fig. 49. The mean cross-entropies between the players' hourly playtime distributions and the degenerate distribution in *Womanland in Journey to the West (WJW)* where the playing time is divided by $m = 2$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.

Fig. 50. The mean cross-entropies between the players' hourly playtime distributions and the degenerate distribution in *Womanland in Journey to the West (WJW)* where the playing time is divided by $m = 3$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.

Fig. 51. The mean cross-entropies between the players' hourly playtime distributions and the degenerate distribution in *Womanland in Journey to the West (WJW)* where the playing time is divided by $m = 5$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
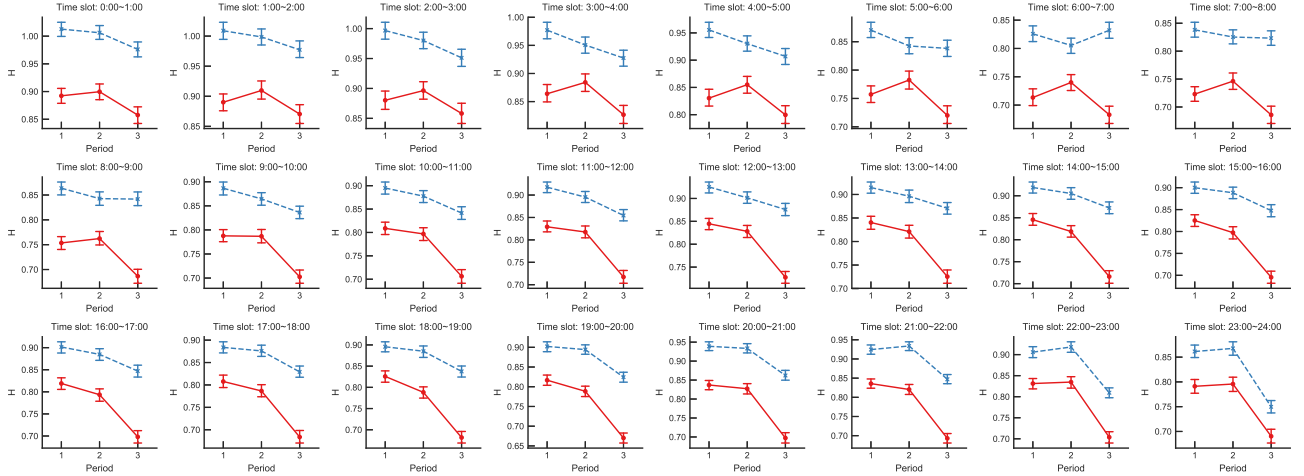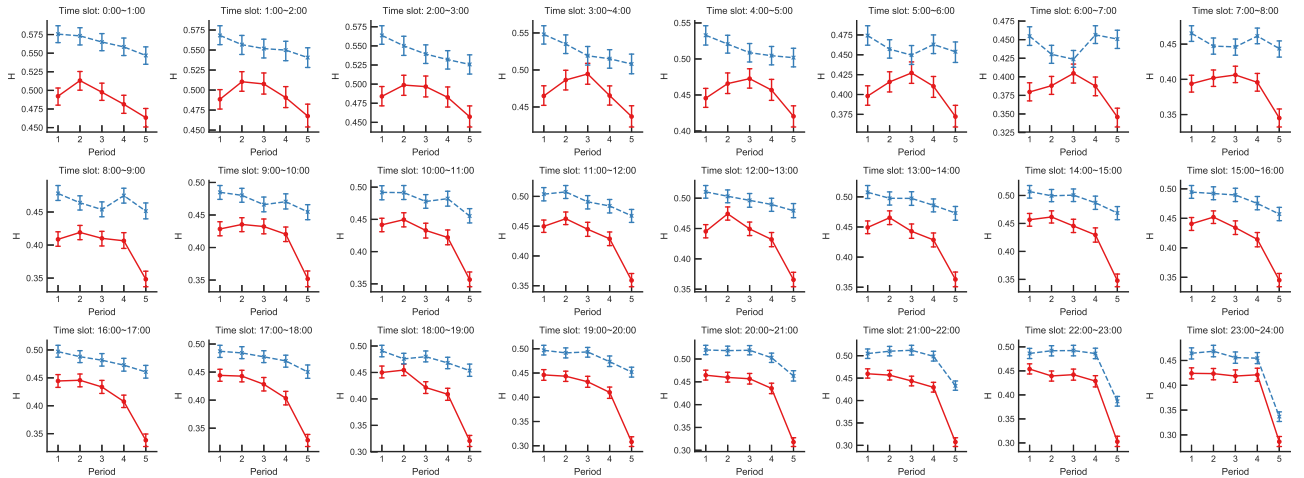
Fig. 52. The mean cross-entropies between the players' hourly playtime distributions and the degenerate distribution in *Era of Angels (EOA)* where the playing time is divided by $m = 2$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.

Fig. 53. The mean cross-entropies between the players' hourly playtime distributions and the degenerate distribution in *Era of Angels (EOA)* where the playing time is divided by $m = 3$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.

Fig. 54. The mean cross-entropies between the players' hourly playtime distributions and the degenerate distribution in *Era of Angels (EOA)* where the playing time is divided by $m = 5$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
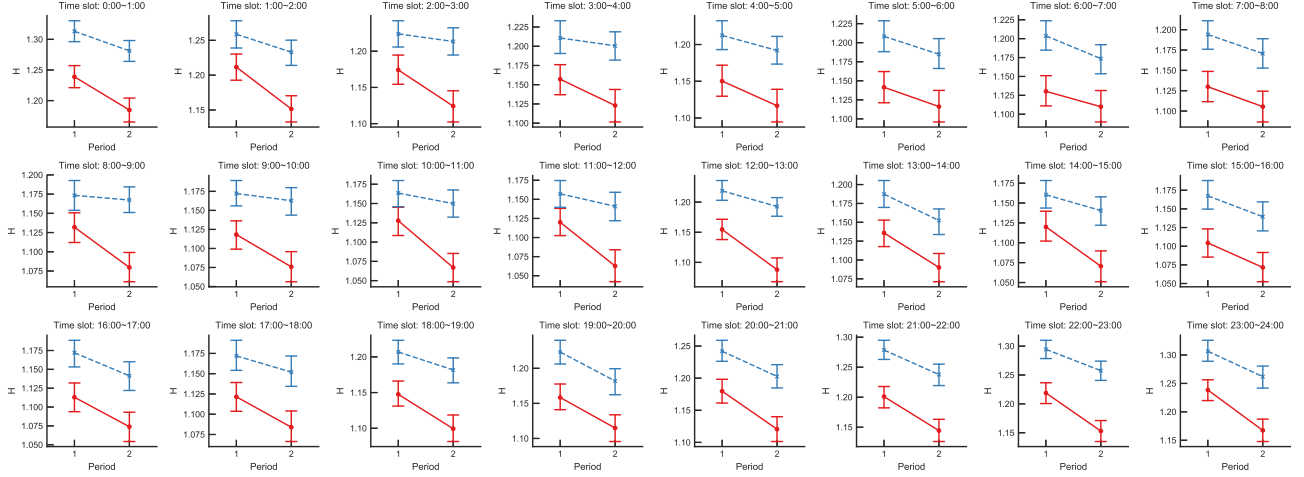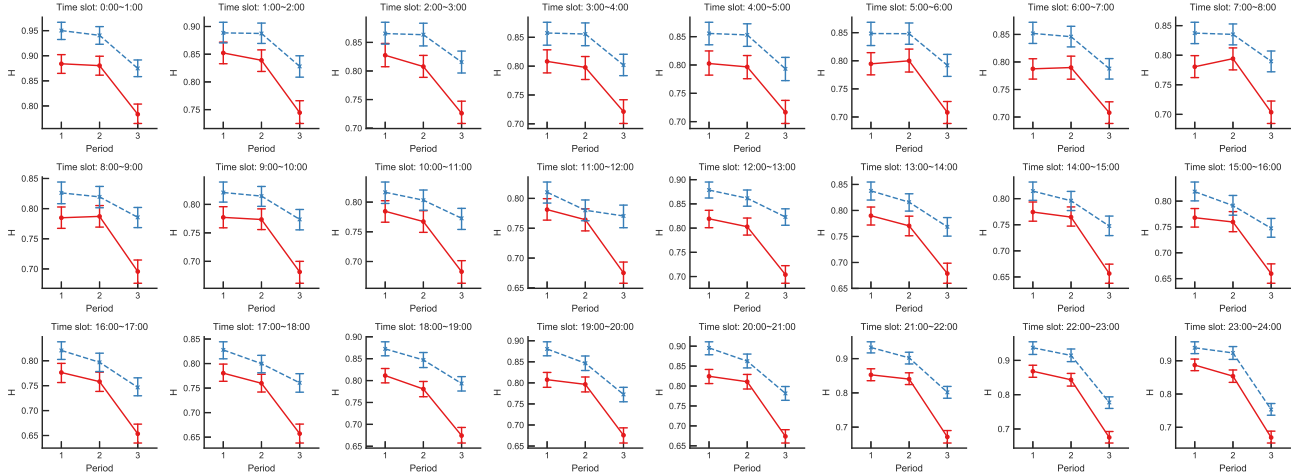
Fig. 55. The mean cross-entropies between the players' hourly playtime distributions and the degenerate distribution in *League of Angels II (LOA II)* where the playing time is divided by $m = 2$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
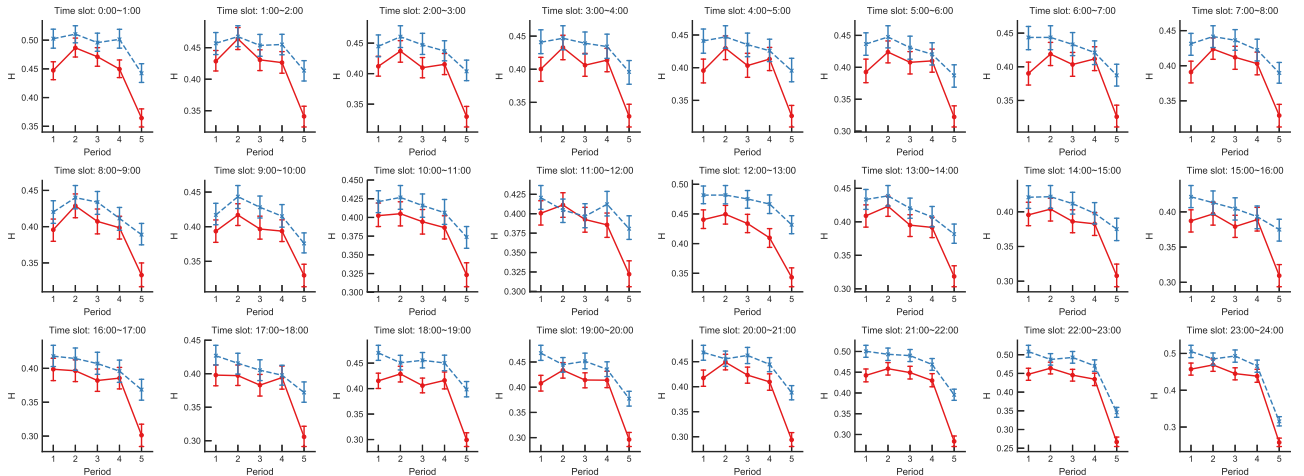

Fig. 56. The mean cross-entropies between the players' hourly playtime distributions and the degenerate distribution in *League of Angels II (LOA II)* where the playing time is divided by $m = 3$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.

Fig. 57. The mean cross-entropies between the players' hourly playtime distributions and the degenerate distribution in *League of Angels II (LOA II)* where the playing time is divided by $m = 5$ periods. The blue dashed line shows the non-churners, while the red solid line shows the churners.
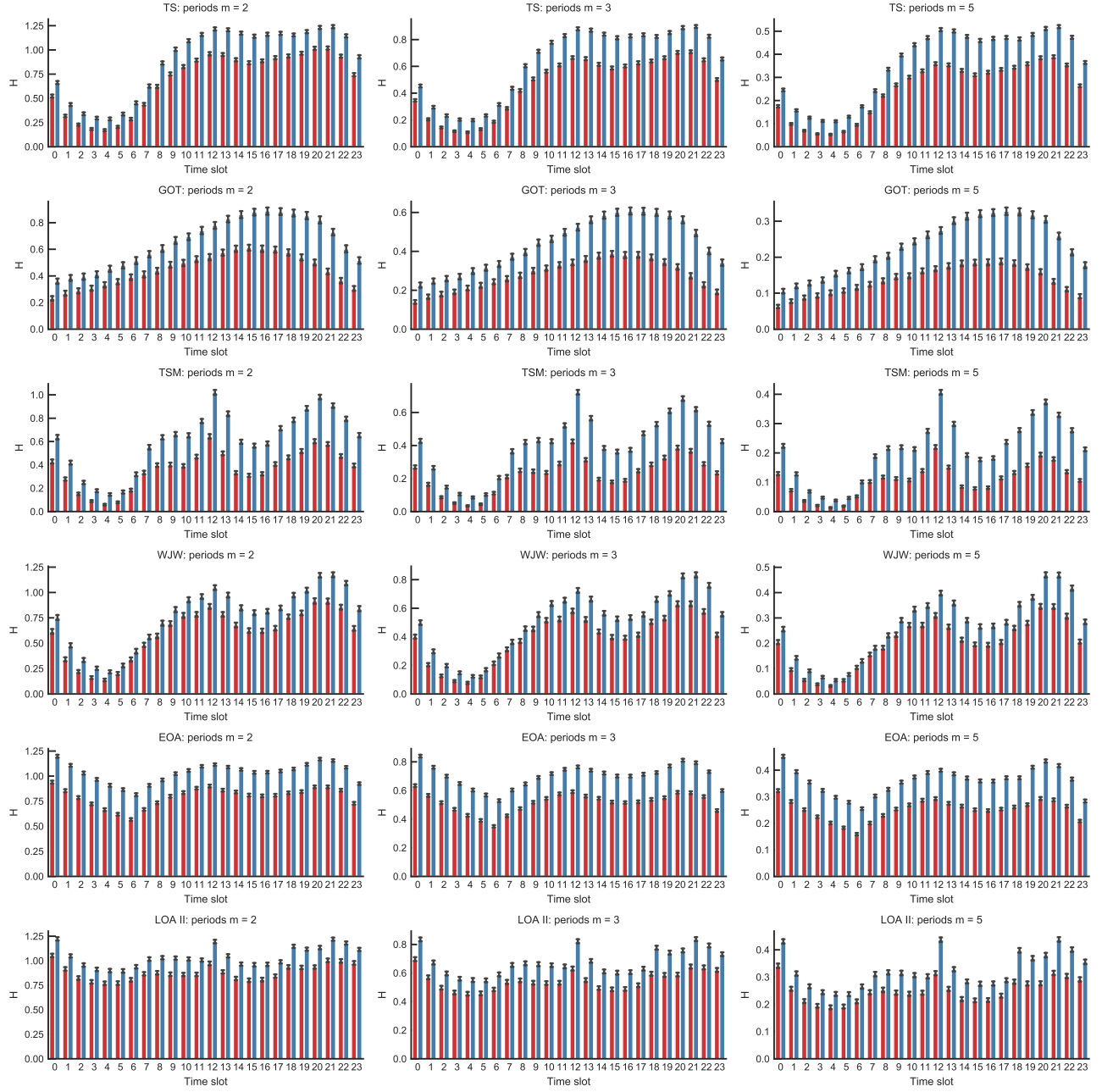
Fig. 58. The mean entropies of the distributions of hourly time spending of aforementioned games' players in different time slot (from 0:00 - 1:00 to 23:00 - 24:00, indexed from 0 - 23). The blue bar shows the non-churners, while the red bar shows the churners.
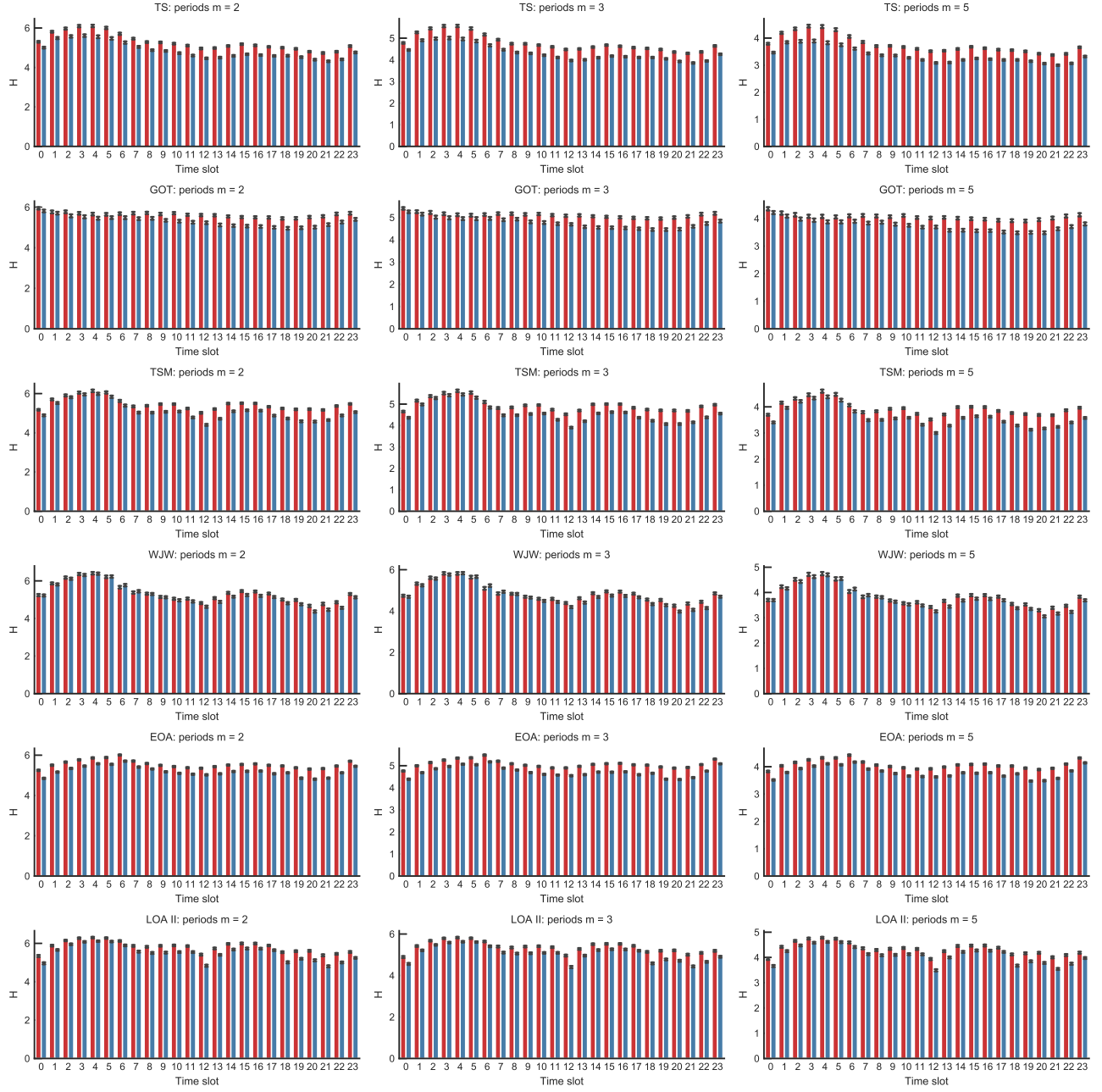
Fig. 59. The mean cross-entropies between the players' hourly playtime distributions and the uniform distribution in different time slot (from 0:00 - 1:00 to 23:00 - 24:00, indexed from 0 - 23) in the aforementioned games. The blue bar shows the non-churners, while the red bar shows the churners.
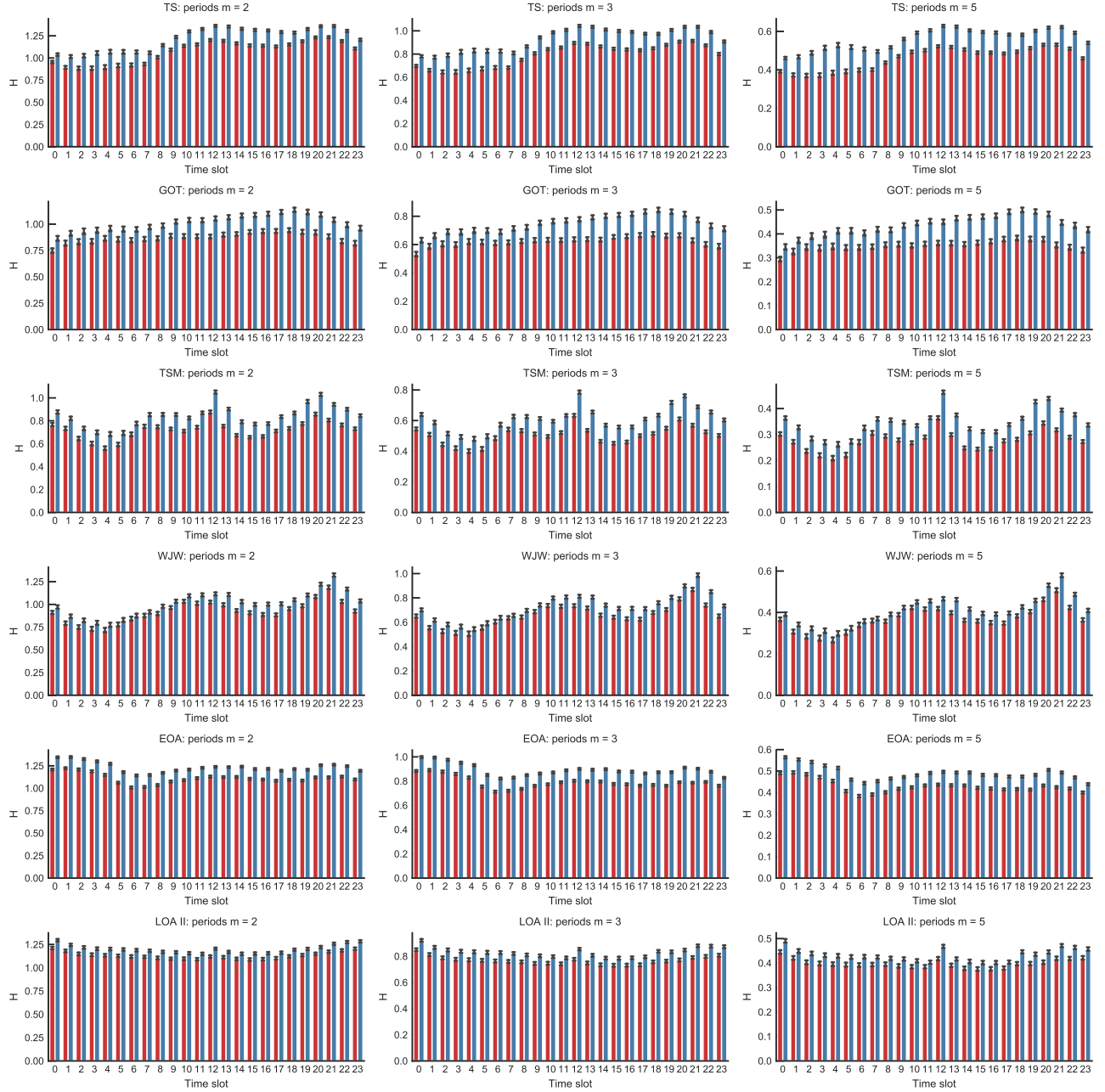
Fig. 60. The mean cross-entropies between the players' hourly playtime distributions and the degenerate distribution in different time slot (from 0:00 - 1:00 to 23:00 - 24:00, indexed from 0 - 23) in the aforementioned games. The blue bar shows the non-churners, while the red bar shows the churners.