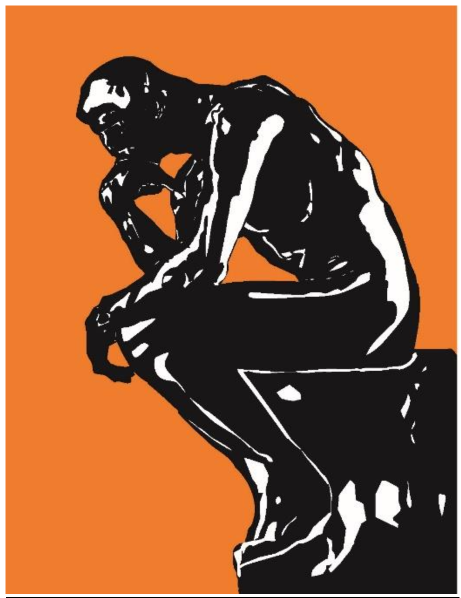
**Exploring the effects of paranormal belief and gender on precognition task: An application of the Bayesian Mindsponge Framework on parapsychological research**

Tam-Tri Le [1], Minh-Hoang Nguyen [1,*], Quan-Hoang Vuong [1]

[1] Centre for Interdisciplinary Social Research, Phenikaa University, Yen Nghia Ward, Ha Dong District, Hanoi 100803, Vietnam

* Corresponding: hoang.nguyenminh@phenikaa-uni.edu.vn



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## Abstract

Precognition is an anomaly in information transmission and interpretation. Extant literature suggests that paranormal beliefs and gender may have significant influences on this unknown information process. This study examines the effects of these two factors, including their interactions, on precognition performance by employing the Bayesian Mindsponge Framework (BMF) analytics. Using Bayesian analysis on secondary data of 60 participants, we found that men may have higher chances to score a hit in a precognition task compared to women. Interestingly, stronger beliefs in the paranormal may decrease the success probability in performing precognition tasks. Considering the interactions between the two factors, the effect of paranormal beliefs on precognition task performance is stronger in men than women. Using mindsponge-based reasoning, we argue that paranormal beliefs may increase the interference of imagination in the reception of hypothetical precognitive information. Women tend to rely more on intuition, which may lessen the interference effect of imagination on hypothetical psi reception. Based on the findings, we suggest that researchers should be careful when assessing

participants' psi potential for experiments. We also demonstrate some advantages of utilizing the BMF in parapsychological research.

**Keywords:** precognition; paranormal belief; gender; information processing; Bayesian Mindsponge Framework

## 1. Introduction

### *1.1. Beliefs in paranormal phenomena*

Paranormal forms of information transmission and reception regarding the human mind (e.g. telepathy, precognition, etc.), while not yet clearly understood nor confirmed, are widely believed worldwide (Irwin, 2009). Interestingly, besides the general population, scientists and engineers also have considerable degrees of belief about paranormal phenomena (Wahbeh et al., 2018). Beliefs in the paranormal, such as religious and spiritual concepts, can be integrated deeply into people's value systems, influencing their thinking and behaviors (Vuong et al., 2021). While the reality of parapsychological phenomena is still a mystery and highly debatable, experimental evidence so far overall supports the existence of such phenomena, which are unlikely to be explained by the quality of the studies, fraud, selective reporting, experimental or analytical incompetence, or other frequent criticisms (Cardeña, 2018). Thus, it is scientifically appropriate to keep an open mind when examining this field and develop novel, rigorous, and multidisciplinary approaches. But regardless of whether the objective anomalies exist or not, people's beliefs in the paranormal is quite prevalent in society and can be studied closely within the normal scope of psychology.

Among the demographic factors influencing paranormal beliefs, gender is often found to have a significant impact. Overall, studies have suggested that women are more likely to report paranormal experiences compared to men (Castro et al., 2014; Wahbeh et al., 2018). Women tend to have more paranormal beliefs than men (Lindeman & Aarnio, 2006; Mogi, 2014; Vyse, 1997), which may partially be due to their relatively higher intuitiveness (Aarnio & Lindeman, 2005; Ward & King, 2020). Interestingly, Spinelli et al. (2002) did not find an association between gender and belief in the paranormal. Still, they suggested that the masculinity trait may increase the likelihood of reported belief and experience related to the paranormal due to higher self-confidence.

Precognition is among the common notions in paranormal beliefs. For example, a study in Brazil reported that about 70% of the normal population believe in having experienced a precognitive dream at least once (Monteiro de Barros et al., 2022). However, recall and interpretation of dreams toward perceived precognition are subjected to biases (Watt et al., 2014). Culture is a major influencing factor on beliefs in precognition (Harris et al., 2022), which is intuitive since religious beliefs are often deep-rooted in the collective mindset, typically seen in the cultural evolution of East and Southeast Asian countries (Vuong et al., 2018). On the relationship between paranormal beliefs and precognition tasks, a study suggests that those with a higher level of belief in precognitive dreams may perform worse in predicting lottery results, probably due to the illusion of having influence over their luck interfering with probabilistic reasoning (Blagrove et al., 2006). Furthermore, theoretically, latent inhibition (filtering out familiar information due to pre-exposure) was proposed to be a factor influencing sensitivity to paranormal stimulus in precognition tasks. Still, supporting evidence was not found (Hitchman et al., 2015).

### *1.2. Examining the phenomenon of precognition*

In a normal information process, the mind is supposedly only able to be aware of qualia corresponding to represented information of the objective world existing in the past. Prospection is based on inferences from past experiences as well as mental simulations of future scenarios. However, the phenomenon of precognition suggests that it may be possible for the mind to absorb information corresponding to future objective occurrences under conditions and through currently unknown mechanisms. This is commonly considered to be a violation of physical laws due to the perceived unidirectionality of time. But some empirical evidence suggests that access to information from the future may be possible (Bem et al., 2016; Bem, 2011; Mossbridge & Radin, 2018).

It is not unexpected that precognition research is met with strong opposition along the way, theoretically and methodologically, including in recent criticisms (Branković, 2019; Reber & Alcock, 2020). The skepticism and cautiousness are understandable because the nature of information, awareness, and time are all largely unknown regarding the current human understanding. From a metaphysical viewpoint, the notions of time (as a direction of changes) and human awareness (as the act of observation) may be interdependent since information must interact with the human mind – an information processing system – in order to be "known". Recently, Muhmenthaler et al. (2022) replicated some of the earlier experiments with more than 2000 online participants but did not find any effect of precognition. However, it should be noted that precognition likely does not happen in normal conditions but rather in specific mental states, and thus simplified procedure may not be effective. For example, the Ganzfeld sensory deprivation technique is often employed in experiments involving extra-sensory perception, overall yielding significant yet debatable results (Bem & Honorton, 1994; Williams, 2011).

### *1.3. A new information processing approach to parapsychology*

Besides exploring the relationships between paranormal beliefs, gender, and precognition, the present study also aims to demonstrate the application of the Bayesian Mindsponge Framework (BMF) analytics on parapsychological research. Theoretical reasoning is based on the mindsponge mechanism of information processing (Vuong, Le, & Nguyen, 2022; Vuong, Nguyen, et al., 2022; Vuong & Napier, 2015), and Bayesian analysis follows the BMF analytics protocol (Nguyen et al., 2022b; Nguyen & Vuong, 2022). Since information transmission, reception, and processing are the basis of precognition, the information processing approach is highly compatible. Additionally, mindsponge-based reasoning is effective in exploring psychological processes in which many different mental values interact with each other to create subjective meanings and intentions (Nguyen et al., 2021; Vuong, Le, La, et al., 2022). The mindsponge theory's conceptual development is based on natural principles of living systems in the ecosphere (Vuong, 2022). The approach is in alignment with other highly effective frameworks in psychological research, such as the Theory of Planned Behavior (Ajzen, 1991), but also offers further flexibility and systematic investigation protocols.

Regarding the rationale for employing the analysis method, it is because Bayesian inference is fundamentally compatible with the mindsponge theory. Furthermore, considering various issues in parapsychology, such as overcomplicated models, unpersuasive findings, small sample sizes, replication crises, etc., Bayesian statistics is very helpful regarding the technical aspects of research endeavors (Jefferys, 1990). More detailed arguments on Bayesian statistical analysis are presented in the methodology section.

Beliefs are trusted values priorly accepted that can serve as references for related information processes. In the scope of the present study, paranormal beliefs can interfere with the hypothetical precognitive information reception and interpretation. Additionally, extant literature suggests that gender likely influences this information process. The study has the following research questions (RQs):

> RQ1: How does paranormal belief affect the probability of successfully carrying out a precognition task?
>
> RQ2: How does gender affect the probability of successfully carrying out a precognition task?

On top of these linear relationships, we want to examine the effects of the predictors in interactions. This can provide a clearer look at the probabilities of each case of both genders with different strength levels of paranormal belief. Thus, RQ3 is derived as follows.

> RQ3: How do the interactions between paranormal belief and gender affect the probability of successfully carrying out a precognition task?

## 2. Material and method

### *2.1. Materials*

The present study used secondary data, employing the dataset from the study by Watt et al. (2020). The dataset is deposited on the *Psi Open Data* server, which is publicly accessible. The sample has 60 participants primarily recruited from the Koestler Parapsychology Unit of the University of Edinburgh. All participants were volunteers, and the experiment was approved by the University of Edinburgh School of Philosophy, Psychology and Language Sciences ethics committee. The experiment was conducted from December 2017 to March 2018. Watt et al. (2020)'s study was pre-registered on the Koestler Parapsychology Unit Registry in 2017.

The sample consists of 28 males and 32 females, with a mean age of 34.2 (SD = 18.13). Most participants (about 80%) self-reported being creative/artistic, practicing a mental discipline, and/or having previous psi experience. The degree of belief in the paranormal was measured using the Australian Sheep-Goat Scale (ASGS) (Thalbourne, 1995). The scale has 18 items asking about the agreement of belief in various paranormal phenomena, each with three possible answers. Respondents must choose one answer of either "true" (2 points), "uncertain" (1 point), or "false" (0 points). The possible total score ranges from 0 (absolute disbelief) to 36 (absolute belief). In this dataset, the sample has a mean ASGS score of 16.17 (SD = 8.77).

In the experiment, Watt et al. (2020) prepared a suitable environment to induce the Ganzfeld effect in the participants, including many factors in the procedure, such as a windowless metal chamber, eye masks, red light, white noise, and other relaxation techniques. Participants were asked to rank four clips corresponding to how much each would match the target clip, which was randomly generated afterwards. The research team took precautions to minimize possible fraud and error, which are presented in more detail in their paper (Watt et al., 2020). If the target clip has the highest ranking, then it is a hit for the precognition task. In total, there were 22 hits out of 60 trials (37% hit rate, compared to the mean chance expectation of 25%).

### *2.2. Model construction*

Three variables used in the present study are described in Table 1.

**Table 1**: Variable description

| Variable | Description | Type of variable | Value |
|---|---|---|---|
| *HIT* | Whether the participant guessed the correct target clip (ranked highest). | Binary | 1 = Hit<br>0 = Miss |
| *ASGS* | The participant's total score on the Australian Sheep-Goat Scale | Numerical | Ranging from 0 to 36 |
| *GENDER* | The participant's gender | Binary | 1 = male<br>0 = female |

Two models are constructed based on the presented research questions as follows. The conceptualization follows the principle of parsimonious model construction for Bayesian analytics, which helps increase predictability (Nguyen et al., 2022a). To test whether these parsimonious models are well-specified, Pareto smoothed importance-sampling leave-one-out cross-validation (PSIS-LOO) test was carried out (Vehtari et al., 2017). Watanabe-Akaike, or widely available information criterion (WAIC), was also used to compare the goodness-of-fit between models (Watanabe, 2010).

$$HIT \sim ASGS + GENDER \quad (1)$$

$$HIT \sim ASGS + GENDER + ASGS * GENDER \quad (2)$$

In Model 2, the interaction between $ASGS$ and $GENDER$ is added to examine the empirical probabilities of $HIT$ across different scenarios of belief-gender interactions.

### *2.3. Statistical analysis*

Besides the high compatibility with the mindsponge information processing mechanism, Bayesian statistics have other crucial advantages, as argued below. BMF Analytics follows the parsimonious model construction principle, which argues that while designing research, complexity should be avoided if not necessary (Nguyen et al., 2022b). Parsimonious models have higher predictive power. But with few variables, there often is a higher number of unknown parameters and uncertainties. Bayesian inference can fill this shortcoming, which treats all properties, including unknown parameters and uncertainties (Gill, 2014).

Moreover, the aided Markov Chain Monte Carlo (MCMC) algorithms can iteratively generate a large number of samples from the joint posterior distribution of the model's parameters (Cowles, 2013; Dunson, 2001; Wagenmakers et al., 2018). This makes fitting models with interaction terms (non-linear relationships) more accurate. It is worth noting that in parapsychology, experiments can be costly due to their complexity and may require participants from special populations. Thus, small sample sizes are a big issue for the frequentist approach. Bayesian analytics aided by the MCMC technique can provide relatively more accurate statistical predictions when working with small samples.

Over-reliance on *p*-value is another major problem in modern parapsychology as well as other scientific fields. This greatly contributes to the current replication crisis and may even lead to exploitative frauds such as "*p*-hacking" practices. Besides parapsychology, studies argue that the recent reproducibility crisis in social sciences and psychology is partly due to the problematic use of *p*-value. (Camerer et al., 2018; Open Science Collaboration, 2015). The *p*-value is being treated as a dichotomous threshold in modern science for rejecting null hypotheses. Halsey et al. (2015) suggest that rather than using binary judgments based on *p*-values to evaluate statistical results, scientists should instead use other reliable methods, such as visual representations of estimated coefficients. Using Bayesian analysis as an alternative to the *p*-value approach can be advantageous because estimation and visualization of credible intervals are fundamental components of Bayesian statistics.

Another major issue in parapsychological research is confirmatory and replication studies in which findings are often inconsistent due to the unspecified conditions of inducing paranormal phenomena. Incorporating prior knowledge to aid estimation is a fundamental function of Bayesian analysis that can help with this issue. If a study wants to exclude such subjectivity, they can employ uninformative priors which specify flat prior distributions to uninformative priors that specify flat prior distributions to provide the least amount of prior information possible to the model estimation (Diaconis & Ylvisaker, 1985) (Diaconis & Ylvisaker, 1985). When informative priors are used, the "prior-tweaking" technique can be employed to test the robustness of the posterior results (Nguyen et al., 2022a). If there is little difference in the posterior results of a model using different priors, the estimated model is considered robust. With prior incorporation and other presented Bayesian properties, researchers in parapsychology can use new evidence to update the posterior estimation (empirical probability) of certain research targets without worrying too much about statistical integrity issues due to samples' differences compared to the frequentist approach.

Both models were fitted with the following setups of MCMC: 5,000 iterations, 2,000 warm-up iterations, and four Markov chains. To validate the simulated posteriors, we used the following techniques. We use diagnostic statistics of effective sample size (*n_eff*) and Gelman shrink factor to check the convergence of Markov's chains (*Rhat*). Generally, the model's Markov chains are said to be convergent if the *n_eff* value is higher than 1,000 and the *Rhat* value is equal to 1. Graphical representations such as trace plots, Gelman-Rubin-Brooks plots, and autocorrelation plots were also used to diagnose the convergence. The Bayesian analysis in the present study is conducted using the **bayesvl** R package due to several advantages (Vuong et al., 2020). The package has good visualization functions, which aid in result presentation and interpretation. The package is free, publicly available, and easy to use, which supports replication or related further studies.

For the sake of transparency and possible reproduction (Vuong, 2020), all of the study's data files and code snippets have been deposited at the Open Science Framework (OSF) server (DOI: 10.17605/OSF.IO/XBA2H).

## 3. Results

### *3.1. Model 1*

The *k* values of the PSIS diagnostic plot are less than 0.5. Thus, Model 1 can be deemed to fit well with the data (see Figure 1), and the model is not oversimplified.

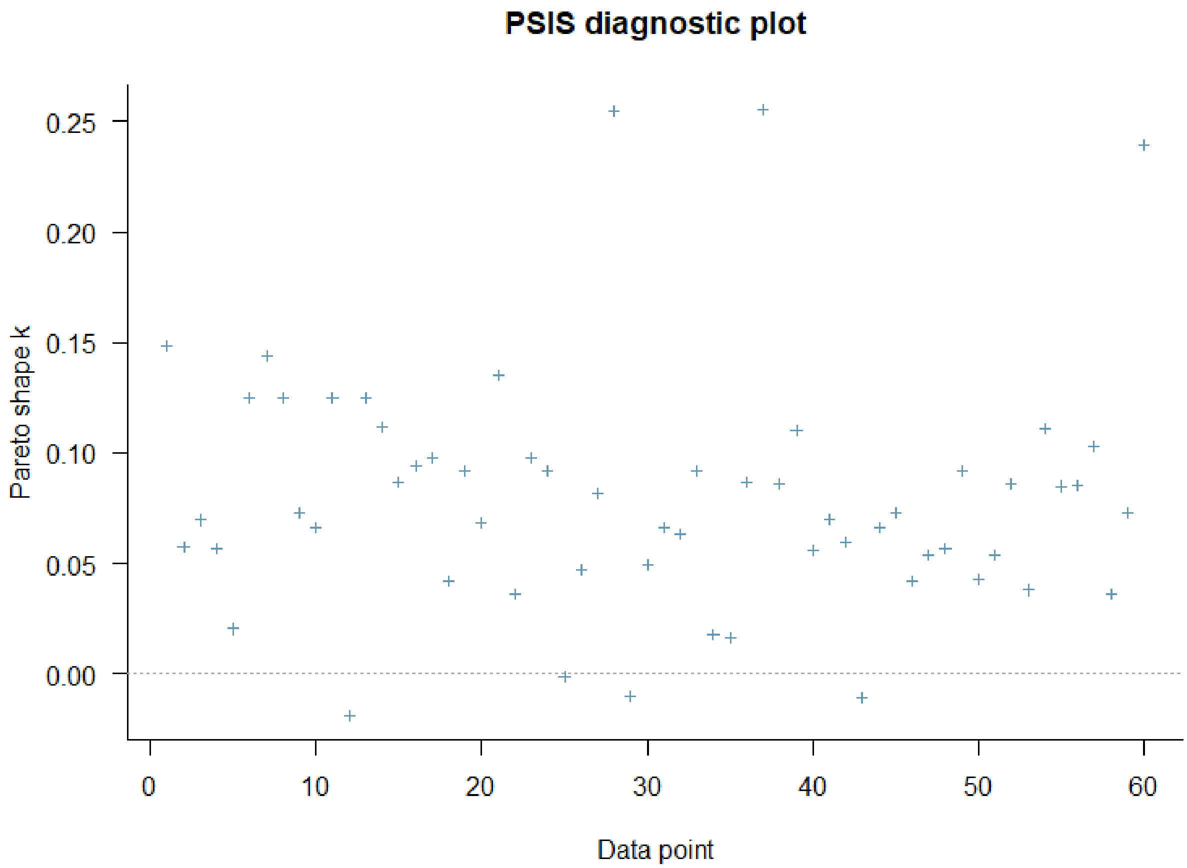


**Figure 1**: Model 1's PSIS diagnostic plot

**Table 2:** Model 1's simulated posterior coefficients

| Parameters | Mean | SD | *n_eff* | *Rhat* |
|---|---|---|---|---|
| *Constant* | 0.10 | 0.62 | 5203 | 1 |
| *ASGS* | -0.07 | 0.04 | 5316 | 1 |
| *GENDER* | 0.65 | 0.57 | 6652 | 1 |

The *n_eff* values of all coefficients are greater than 1,000, and *Rhat* values are equal to 1, indicating good convergence (see Table 2). The trace plots show the fluctuations around a central equilibrium, meaning that the chains converge to the same posteriors (see Figure 2).

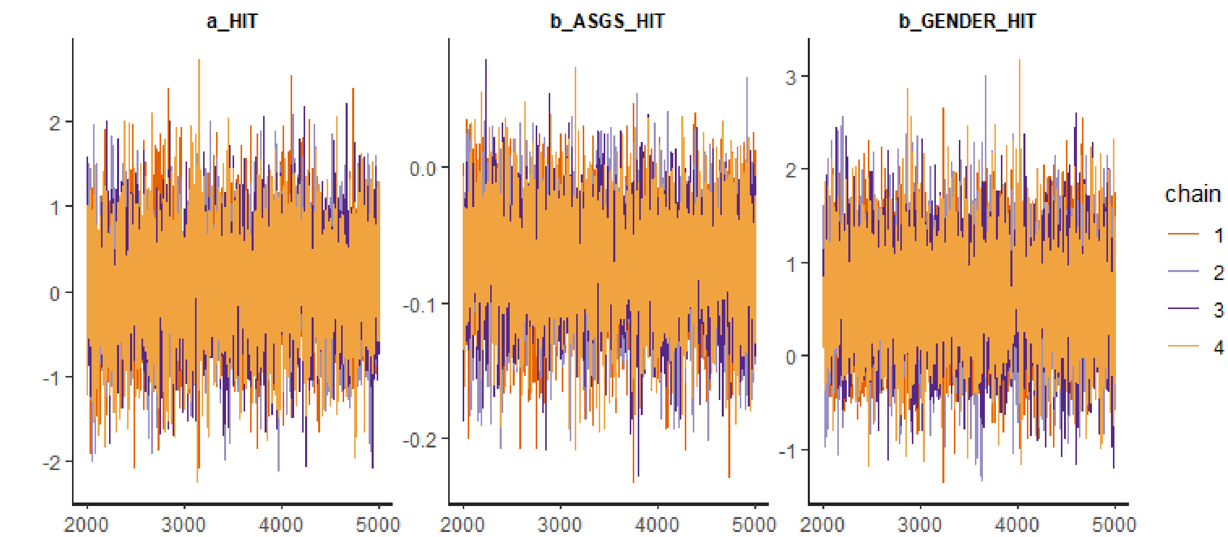


**Figure 2:** Model 1’s trace plots

The Gelman-Rubin shrink factors dropping rapidly to 1 (see Figure 3) and the decline of autocorrelation levels (see Figure 4) also confirm the convergence of Model 1.

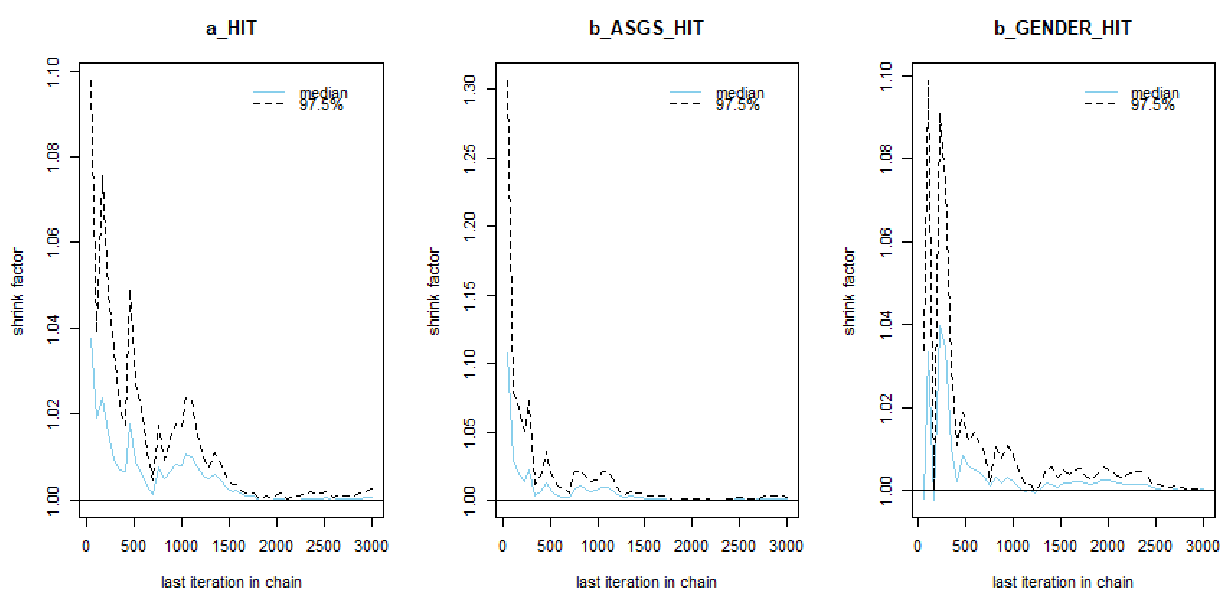


**Figure 3:** Model 1’s Gelman plots

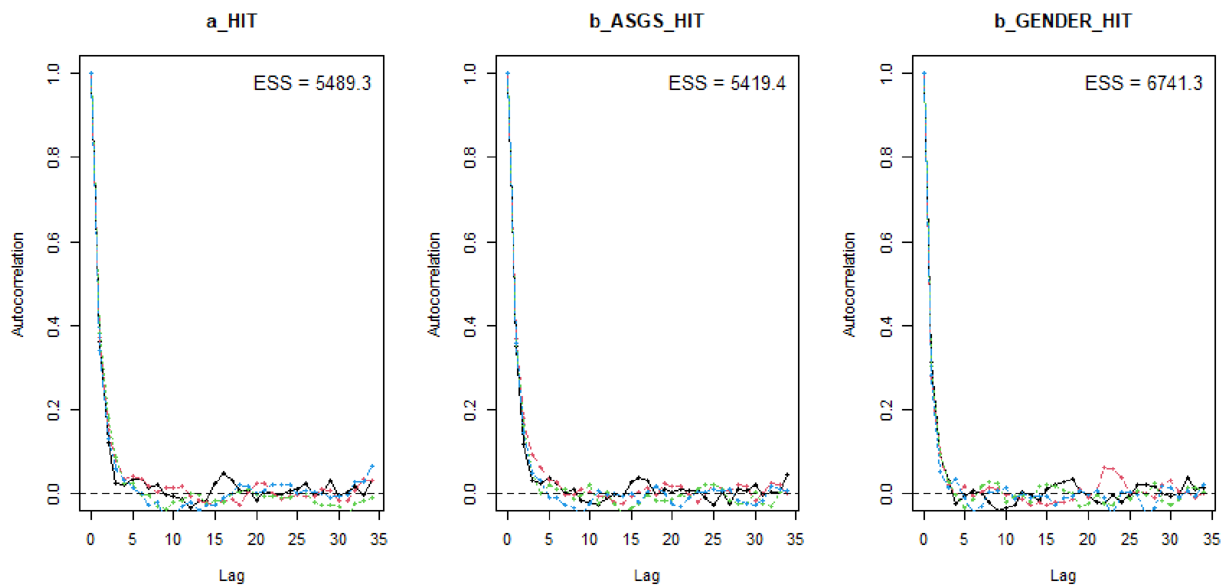


**Figure 4:** Model 1’s autocorrelation plots

The analysis shows that paranormal belief strength is negatively associated with a successful hit in the precognition task ($\mu_{ASGS}$= -0.07 and $\sigma_{ASGS}$= 0.04); males are more likely to have successful hits compared to females ($\mu_{GENDER}$= 0.65 and $\sigma_{GENDER}$= 0.57). This is visualized in Figure 5, as most distributions of *ASGS* lie on the negative side, and most distributions of *GENDER* lie on the positive side.

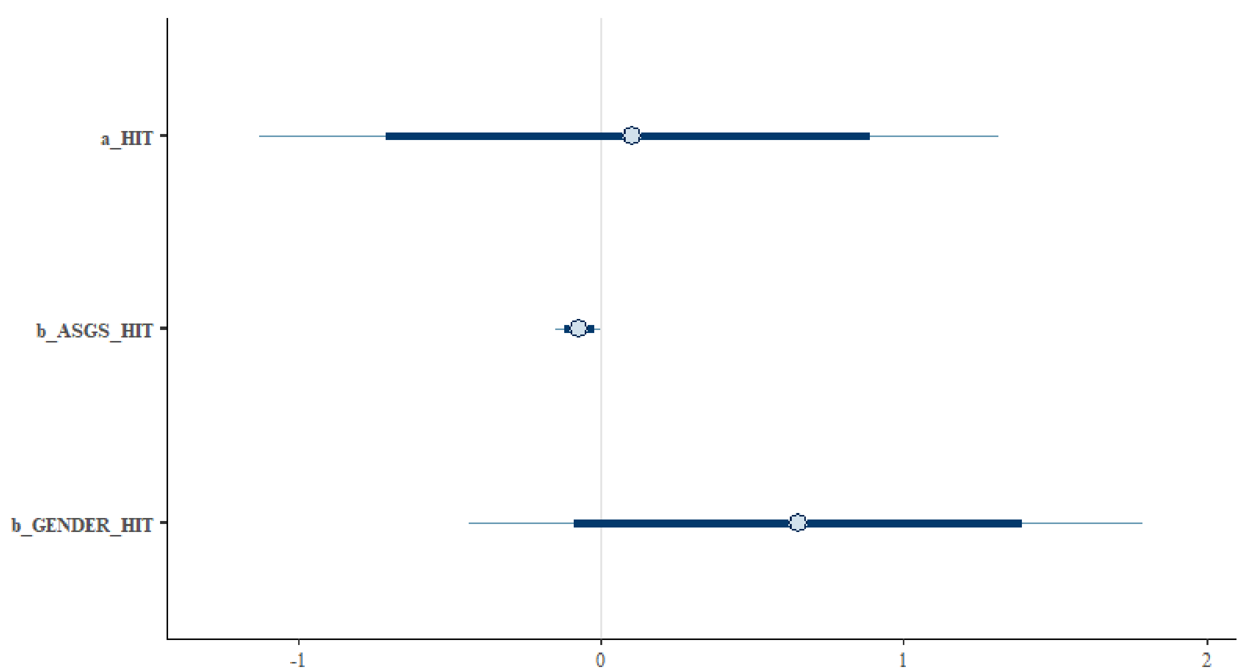

**Figure 5:** Posterior distributions of Model 1's parameters

### *3.2. Model 2*

The *k* values of the PSIS diagnostic plot for Model 2 are also less than 0.5, indicating acceptable goodness-of-fit (see Figure 6).

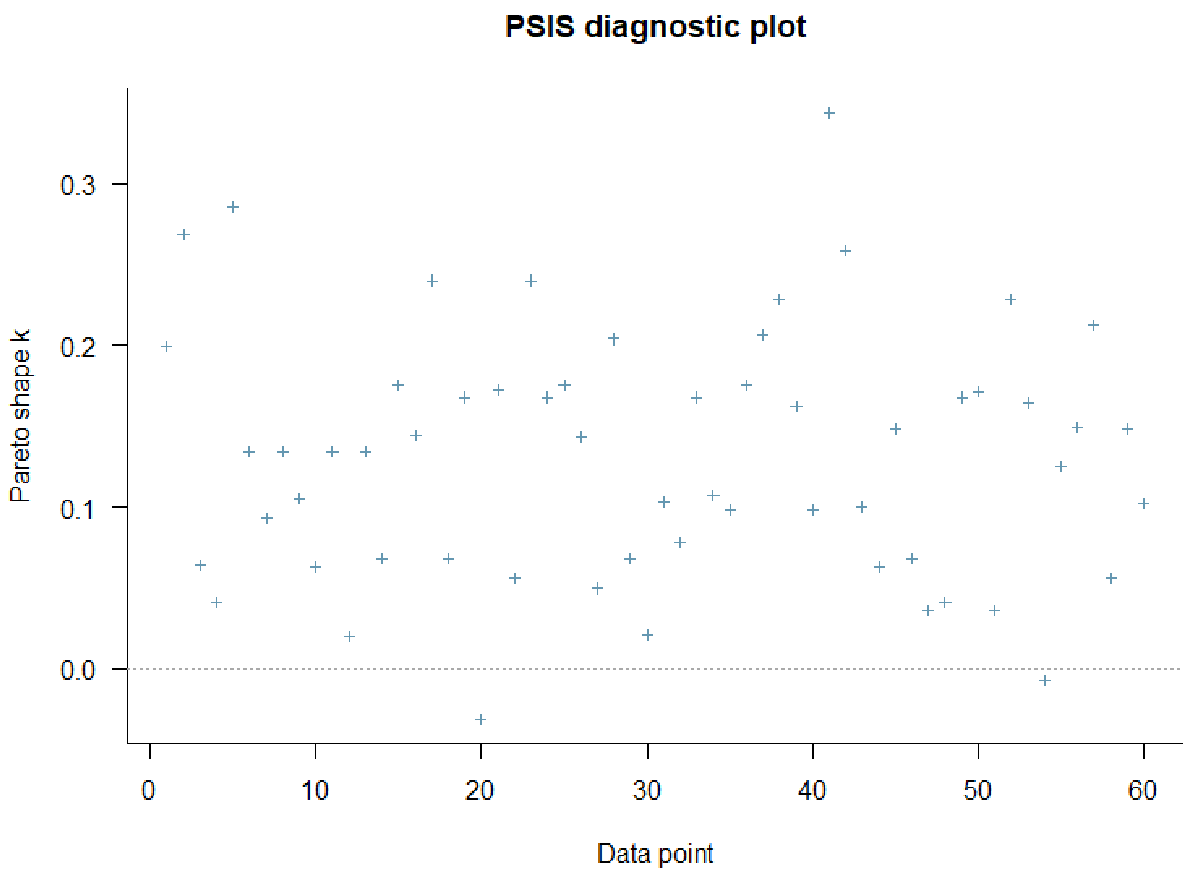


**Figure 6**: Model 2's PSIS diagnostic plot

**Table 3:** Model 2's simulated posterior coefficients

| Parameters | Mean | SD | *n_eff* | *Rhat* |
|---|---|---|---|---|
| *Constant* | -0.72 | 0.81 | 2971 | 1 |
| *ASGS* | -0.01 | 0.05 | 3085 | 1 |
| *GENDER* | 2.71 | 1.35 | 3008 | 1 |

| | | | | |
|---|---|---|---|---|
| *ASGS*GENDER* | -0.15 | 0.09 | 2998 | 1 |

The WAIC value of Model 1 (81.3) is slightly higher than Model 2 (80.8). Although the model with smaller WAIC fits the actual data better, here, the expected log predictive density difference is small (elpd_diff = 0.3), indicating that there is an insignificant difference between the goodness-of-fit of the two models.

Similar to the explanation for Model 1, Model 2 also shows good convergence, as seen through the n_eff and Rhat values (see Table 3) as well as the trace plots (Figure 7), the Gelman plots (Figure 8), and the autocorrelation plots (Figure 9).

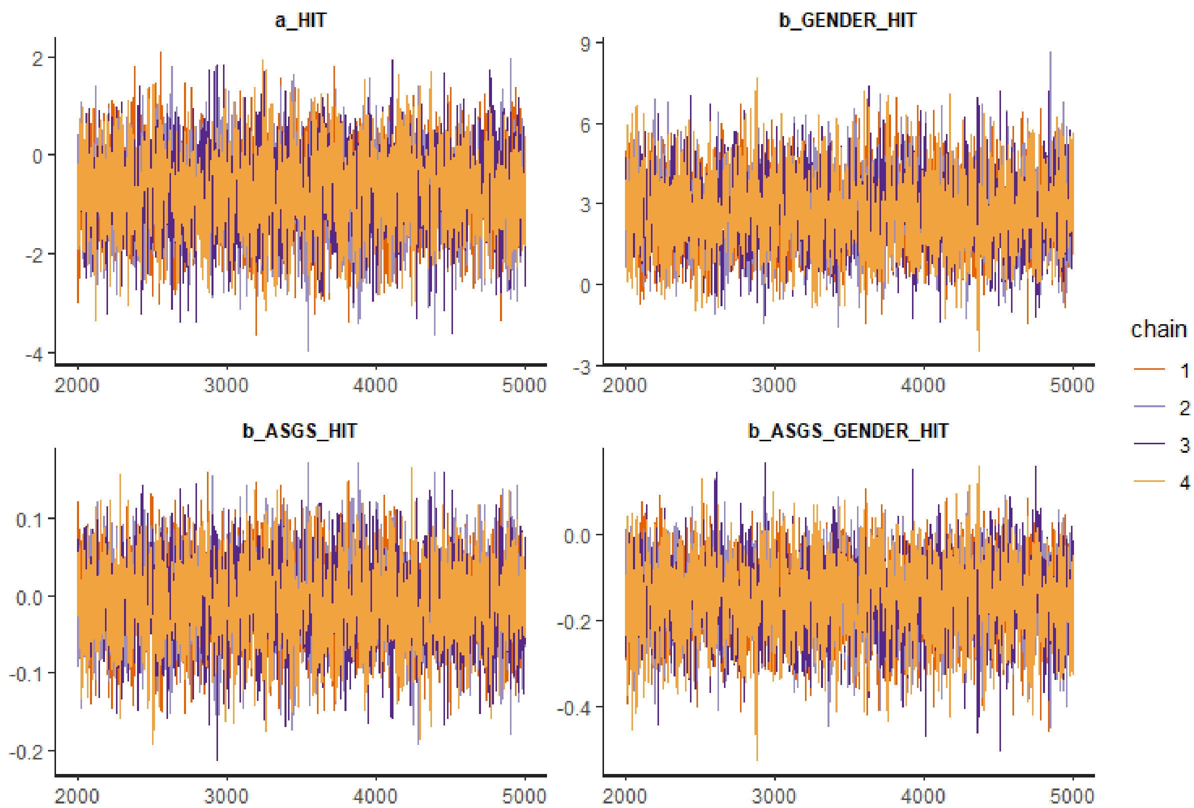


**Figure 7:** Model 2’s trace plots

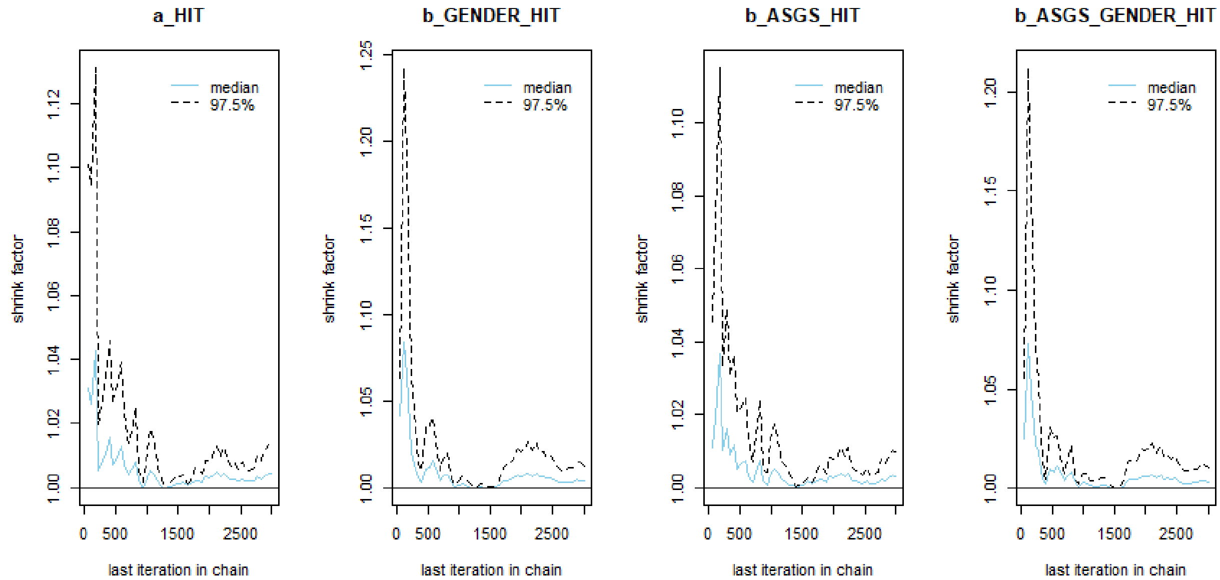


**Figure 8:** Model 2's Gelman plots

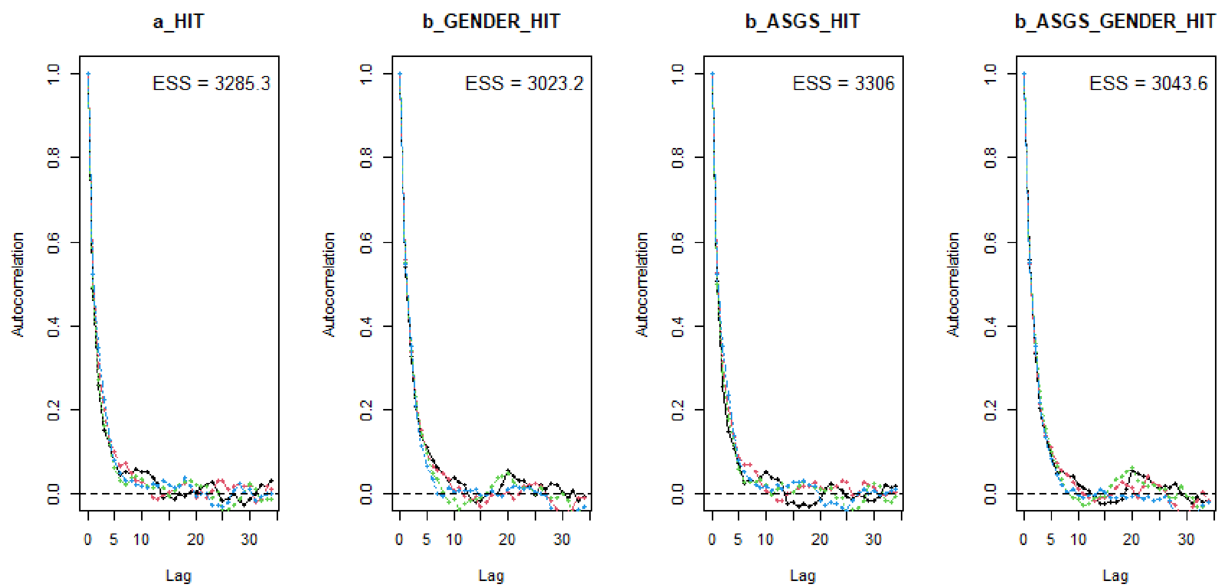


**Figure 9:** Model 2's autocorrelation plots

The results in Model 2 also confirm the association between *HIT* and *GENDER,* similar to Model 1, but the linear relationship between *HIT* and *ASGS* is not clear ($\mu_{ASGS}$= -0.01 and $\sigma_{ASGS}$= 0.05). However, the interaction between *ASGS* and *GENDER* has significant effects on *HIT* ($\mu_{ASGS*GENDER}$= -0.15 and $\sigma_{ASGS*GENDER}$= 0.09). The distributions of *GENDER* and *ASGS*GENDER* are visualized on a 2D density plot in Figure 10.

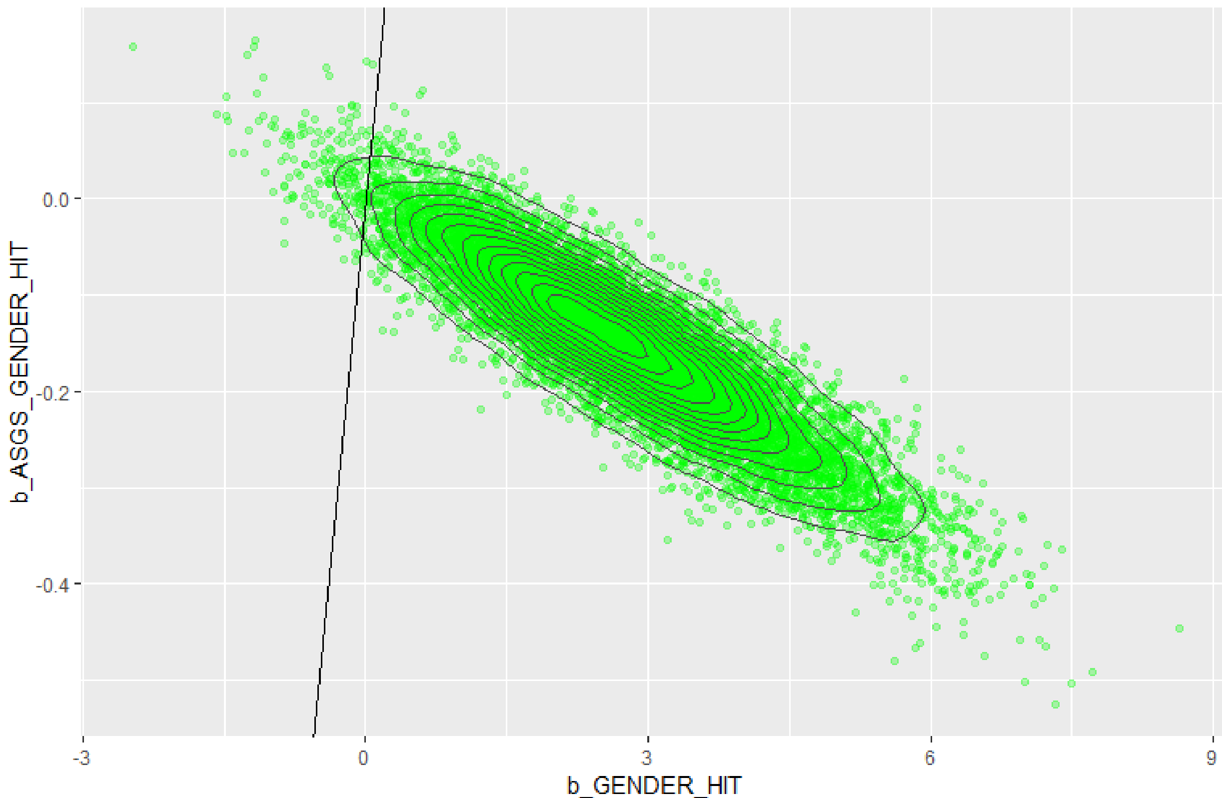


**Figure 10:** Model 2's two-dimensional density plot of *GENDER* and *ASGS*GENDER*

The visualization of hit probabilities below can aid interpretation. Because the outcome variable *HIT* is binary, the probabilities of successfully landing a hit in the precognition task based on different genders and degrees of paranormal beliefs can be calculated using the probability calculation method for binary logit models. We chose the distribution's mean value because it has the highest likelihood of occurring since Bayesian analysis treats all parameters probabilistically.

$$\ln\left(\frac{\pi_{Yes}}{\pi_{No}}\right) = -0.72 - 0.01 * ASGS + 2.71 * GENDER - 0.15 * ASGS * GENDER$$

For example, the hit probability of a female having a total ASGS score of 15 can be calculated as follows.

$$\pi_{Yes} = \frac{e^{(-0.72-0.01*ASGS+2.71*GENDER-0.15*ASGS*GENDER)}}{1 + e^{(-0.72-0.01*ASGS+2.71*GENDER-0.15*ASGS*GENDER)}}$$

$$= \frac{e^{(-0.72-0.01*15+2.71*0-0.15*15*0)}}{1 + e^{(-0.72-0.01*15+2.71*0-0.15*15*0)}} = 0.2953 = 29.53\%$$

The estimation of hit probabilities (*y*-axis) based on different genders (line colors) and degrees of paranormal beliefs (*x*-axis) is visualized in Figure 11.

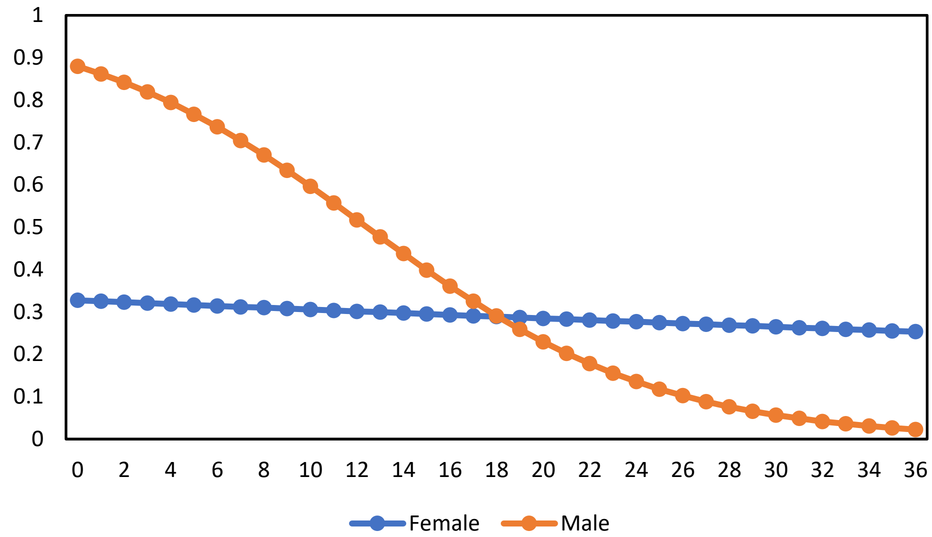


**Figure 11:** Empirical probabilities of successfully landing a hit in the precognition task based on different genders and degrees of paranormal beliefs

## 4. Discussion

Using BMF analytics on the dataset from Watt et al. (2020), we found that men may have higher chances to score a hit in a precognition task compared to women. Interestingly, we found that stronger beliefs in the paranormal may decrease the success probability in performing precognition tasks. However, besides looking only at these linear relationships, examining the interaction between gender and paranormal beliefs show clearer patterns for each scenario involving the two factors. Specifically, while paranormal belief strength is negatively associated with hit probability in both men and women, men show a greater shift along that tendency. In other words, the effect of paranormal beliefs on precognition task performance is stronger in men than women. Men with low degrees of paranormal belief likely perform better than men with strong beliefs, while such changes are slight in women.

So far, direct research on the effects of gender on precognition has been extremely limited. One earlier study shows that men may have a larger precognition effect than women, but with an insignificant difference (Hitchman et al., 2012). A study on retrocausal influence through measuring electroencephalographic signals in anticipation of possible future outcomes shows that there exist physiological differences between males and females in hypothetical unconscious presentiment effects (Radin & Lobach, 2007). Both factors of gender and paranormal beliefs seem to influence precognition performance, but in complex and unclear pathways, often resulting in inconsistency across studies (Mossbridge & Radin, 2021). Our findings point to the influence produced by the interactions between these two factors.

From the perspective of information processing with mindsponge-based reasoning, beliefs are reinforced trusted values in one's mindset being used as references for evaluating related information. The filtering system of the mind connects and compares new information with existing ones stored in memory and thus is heavily subjected to biases. In normal physiological and mental conditions, a significant part of the received information is auto-filtered and auto-interpreted (e.g. think about blind spots in vision or listening to human languages). Precognitive information (if existing) is transmitted through unknown and unfamiliar hypothetical channels, which makes its values easily overridden or interfered with by imagination – the much more well-used cognitive processes. Thus, the act of guessing (which occurs in most precognition experiments) can inhibit the reception and interpretation of hypothetical precognitive information. This notion shares similarities with the proposed idea about latent inhibition affecting sensitivity to paranormal stimulus in precognition tasks by Hitchman et al. (2015). Women's paranormal beliefs are strongly related to their intuitiveness (Aarnio & Lindeman, 2005; Ward & King, 2020), so they may be more likely to rely on intuition (unknown information mechanisms) in precognition tasks. Men are more likely to be affected by the interference of imagination (internal information generation) when guessing and therefore are less sensitive to hypothetical precognitive information (external inputs). This is in alignment with the explanation by Blagrove et al. (2006) that paranormal beliefs can cause the illusion of having influence over one's luck. In terms of information interaction (Nguyen & Le, 2022), the subjective sphere of influence (perceived interactions) deviates from the objective sphere of influence (actual interactions) caused by "incorrect" beliefs.

Our study has some implications for parapsychological research. While the suggestion for using special populations (people more likely having psi abilities) for experiments (Watt et al., 2020) is reasonable, researchers should be careful when assessing participants' characteristics. Due to the unclear, complex pathways of how beliefs influence hypothetical psi reception, self-reported beliefs in the paranormal may not be a reliable way to assess actual psi potential (if existing). Instead of items such as creative activity levels or beliefs in paranormal notions, researchers may want to focus on more distinct items such as significant personal paranormal experiences or objectively measurable qualities (e.g. the case of Wim Hof). Studying paranormal phenomena can benefit from information processing approaches, which help reduce the unpredictability in theoretical conceptualization. For example, the frame-content duality view of information as a hypothetical particle for transmitting impacts may have potential (Nguyen & Le, 2021), particularly when both notions of time and conscious processing may share the same unknown fundamental information mechanism (Mossbridge, 2017). Additionally, this study also shows the advantages of employing Bayesian analytics in parapsychological research, especially when the cost of science is a real and major issue in this relatively low-funded field (Vuong, 2018).

Our study has some limitations. Firstly, the sample size is quite small. However, we also demonstrated that Bayesian analysis aided by the MCMC technique is advantageous when working with small samples compared to the frequentist approach. Secondly, the existence of precognition is still highly debatable and best treated as hypothetical. Here we strongly suggest that if researchers continue to gather evidence, the endeavors should follow a united yet flexible theoretical framework. The information processing Bayesian Mindsponge Framework was demonstrated for that purpose.

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