Can Sequential Persuasion Strategies Referencing Specific Purposes Enhance the Persuasiveness of Online Requests? A Case Study

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Abstract

How to improve the persuasiveness of online requests is crucial to achieve acceptance and foster positive social relationships. The effectiveness of persuasion strategies and the influence of the sequence in which these strategies are applied have been demonstrated in the literature. However, existing research has largely overlooked the importance of linking the sequential persuasion strategies to the specific purpose. In this study, we first employ a few-shot Iterative Collaboration Method (ICM) to identify the purpose of the online requests, referencing human needs as well as the persuasion strategies used. Then, the sequential patterns of persuasion strategies supporting respective purposes are mined. Finally, Large Language Models (LLMs), incorporated the identified effective sequential strategies are used to rewrite the original requests. The results indicate that the sequence of strategies used for different purposes, can significantly increase the level of persuasion. The code and dataset can be found at https://github.com/phillip2f/Seq-Strategies-and-Purpose.

Keywords: sequential persuasion strategy; purpose; online request; few-shot learning; pattern mining;

Introduction

Persuasion plays an important role in changing people's attitudes and behaviors. It has been shown to be successful in increasing the effectiveness of advertising (Yuichi, Akihiro, & Daisuke, 2021), helping people adopt healthier lifestyles (Chatterjee & Price, 2009) and promoting beneficial social and political changes (Coppock, 2023). Much of the research on persuasion emphasizes that aligning messages along specific strategies enhances their effectiveness (Mishra, Samad, Totala, & Ekbal, 2022; Robert et al., 2024; Wang et al., 2019). Aristotle's three modes of persuasion (*ethos, pathos, and logos*) and the seven principles of influence (*reciprocity, scarcity, authority, social proof, liking, unity, consistency*) by Cialdini (2016) laid the foundation for formulating persuasion strategies. For instance, the sentence, *"I would like to borrow $50 and will pay back $60 on May 1st."*, employs the Reciprocity strategy, indicating that people are more likely to return favors or provide concessions to those who have treated them well.

Furthermore, real-world requests often draw on multiple persuasion strategies. Especially, the sequence in which persuasion strategies are presented can significantly impact how the others perceive the message and to what extent to they are willing to take action (Baff, Wachsmuth, Khatib, & Stein, 2020; Boella, Hulstijn, & Torre, 2004; Dibble et al., 2011). However, studies on the sequences of persuasion strategies for online requests (Shaikh et al., 2020) have not sufficiently explored the critical connection between the specific purpose driving the request and the resulting persuasion rate.

Human behavior is fundamentally driven by human needs (Baran, 2000; Max-Neef, 1992). Maslow (1987) categorized human needs into a hierarchy, placing physiological needs, such as food and shelter, at the bottom, followed by safety, social connection, esteem, cognitive, aesthetics needs, and self-actualization at the top. In online communities, requests for help often have specific purposes tied to these needs. For instance, a request for food aligns with the primary purpose of fulfilling physiological needs, while a request for business help may serve higher-order goals, such as esteem or self-actualization. Aligning purpose with persuasion strategies can make the request more persuasive (Braca & Dondio, 2023). Therefore, designing the optimal sequence of persuasion strategies, particularly in relation to the purpose of request, could offer valuable guidance for improving their fulfillment, while also identifying strategies that might unintentionally undermine persuasion.

This study examines the effectiveness of sequential persuasion strategies in relation to the purpose of online requests. Specifically, we develop a few-shot Iterative Collaboration Method (ICM) to classify the purpose of requests according to Maslow's Hierarchy of Needs (see Table 1) and identify the persuasion strategies (outlined in Table 2) for each of the sentences in requests. Subsequently, sequential strategy patterns are mined based on their persuasion rate. Finally, Large Language Models (LLMs) considering target persuasion strategy sequences are utilized to rewrite the original request. Two types of evaluations have been conducted (human-based and machine-based) to determine the effectiveness of the sequential persuasion strategies. The results indicate that the persuasiveness of requests can be enhanced by employing top effective sequential persuasion strategies tailored for the identified purpose.

Our main contributions are summarized as: (1) A framework to identify the effective sequential strategy patterns reflecting the specific purpose in online requests, and to rewrite the requests with effective sequential strategy patterns. (2) A few-shot Iterative Collaboration Method to classify persuasion strategies of discourses and purpose of the requests based on a limited human labeled dataset. (3) Extensive experiments to verify whether the sequential persuasion strat-

In D. Barner, N.R. Bramley, A. Ruggeri and C.M. Walker (Eds.), *Proceedings of the 47th Annual Conference of the Cognitive Science Society*

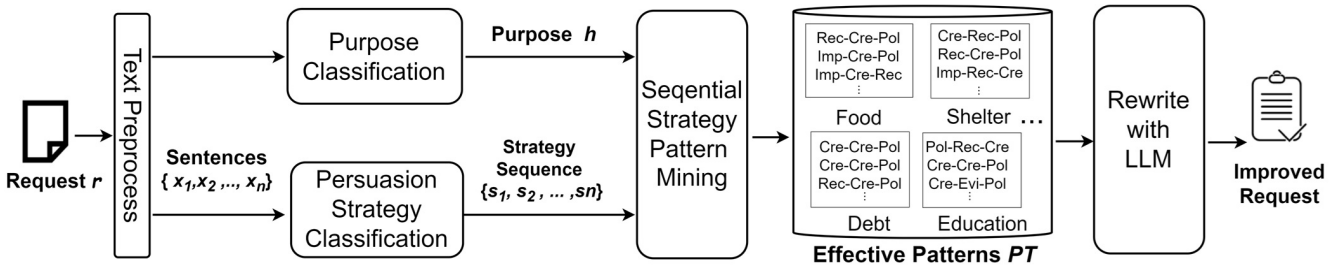

Figure 1: Our framework of rewriting online requests with sequential persuasion strategies.

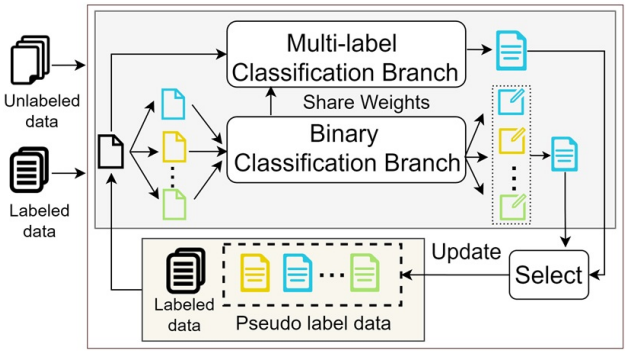

Figure 2: Our few-shot Iterative Collaboration Method (ICM)

egy patterns can enhance request, through the evaluation of the rewritten requests.

Sequential Persuasion Strategy Framework

The framework illustrated in Figure 1 consists of three key components. First, the classification of purposes and persuasion strategies for online request. Second, a mining process extracts effective sequential strategy patterns based on the classification results. Finally, a rewriting method leverages these sequential patterns to guide LLMs in generating improved persuasive requests.

Iterative Collaboration Method

Accurate classification of persuasion strategies and purposes in requests requires a robust method. However, traditional supervised approaches, which demand large-scale labeled datasets, face limitations in online request analysis due to annotation scarcity. To overcome this, we propose a few-shot Iterative Collaborative Method (ICM) with two branches (Figure 2). The first one is a binary classification branch, which classifies input text into individual categories based on their corresponding descriptions. The second one is a multi-label classification branch, which classifies input text based on category names. The collaboration of these two branches can enhance model performance by generating high-quality pseudo-labels.

Each branch represents a text classification task, trained by prompt-based tuning (Ding et al., 2021), which applies cloze-style tasks to tune LLMs, such as predicting the missing word or phrase in a format like "The strategy of the sentence is [MASK]". The set of candidate words for the [MASK] is defined as the label words set V. Essentially, a prompt is composed of a template $\mathcal{T}(.)$ with input data x.

During prompt engineering, a verbalizer, i.e., an injective mapping function $\phi : C \to V$, links the categories C to the label words V. The likelihood for classifying input data x to each label via word probability distributions at the masked position is:

$$P(c|x) = P([\text{MASK}] = \phi(c)|\mathcal{T}(x)) \tag{1}$$

In general, the prediction labels y with max probability p are calculated as follows:

$$y = \underset{c \in C}{argmax}(P([\text{MASK}] = \phi(c)|\mathcal{T}(x))) \tag{2}$$

For the binary branch, each input text is independently queried against every category $c \in C$, where C denotes the predefined category set. The output $\tilde{y}_c^b$ for each query being either 'yes' or 'no', indicating whether the input text belongs to category c.

For each category, its description $\mathcal{D}_c$ is provided, and the template $\mathcal{T}_c^b(.)$ for classifying input text x on category c is:

$$\mathcal{T}_c^b(x) : \text{'}x\text{'}.\ \text{Does it } \mathcal{D}_c\text{? [MASK]} \tag{3}$$

For example, when c represents 'Politeness' strategy and use 'use polite language' as its description, the prompt of query whether the input sentence is belong to 'Politeness' is: 'Thank you so much! Does it **use polite language**? [MASK]'.

Then the prediction process for input text x in binary branch is as follows: 1. For each category c, record the probability p_c^b of it being labeled as '*yes*'. 2. Among all categories predicted as '*yes*', select the one with the highest probability p_c^b as the final prediction. 3. If no category is predicted as '*yes*', assign '*Others*' as the default prediction.

$$\tilde{y}_c^b = \underset{c^b \in [yes,no]}{argmax}\,(P^b([\text{MASK}] = \phi(c^b)|\mathcal{T}_c^b(x))) \tag{4}$$

$$y^b = \begin{cases} argmax(\{p_c^b\}), & \exists c \mid \tilde{y}_c^b = yes, \\ Others, & \forall c \mid \tilde{y}_c^b = no. \end{cases} \tag{5}$$

In multi-label branch, the label word set is equal to the category set, for example, 'Politeness' is used both as a category and as the label word of the category as well. The template $\mathcal{T}^m(.)$ of multi-label classification branch for input text x is:

$$\mathcal{T}^m(x) : \text{`}x\text{'}.\ \text{It is [MASK]}. \tag{6}$$

Then we use Equation 2 to calculate the prediction label and its probability for the input text x.

During each iteration in ICM, the binary branch is trained first. And then its weights will be used to initialize the weights of multi-label branch. Subsequently, multi-label branch is trained with the same dataset as for binary branch which is updated by the pseudo labels from previous iteration. The prediction results from the two branches are calculated and the consistent results with higher probability are selected as pseudo labels for the next iteration of training.

ICM is used to identify both the purpose of a request and the persuasion strategy of each sentence. This approach helps us link the purpose of the request with the specific strategies used in each part of the text.

Sequential Strategy Pattern Mining

Once the purposes and the persuasion strategies prediction labels are calculated by trained models, the PrefixSpan algorithm (Pei et al., 2001) is adopted for frequent sequence pattern mining.

To mine the frequent and persuasive patterns, we divide the request set R_h into success set R_h^w and failure set R_h^f for each purpose h from the purposes set H. Subsequently, the frequent sequence patterns PT_h^* for purpose h from each R_h^* with a support threshold sr and the l length of elements can be obtained:

$$PT_h^* = \text{Length-}l\{PrefixSpan(R_h^*, sr)\} \tag{7}$$

where $*$ can indicate either success w or failure f.

To discover the effective or none-effective patterns from these candidate frequent patterns, the persuasion rate PR for each pattern is calculated as follows:

$$PR(pt_{h,i}^*) = \sum_{r \in R_h^w} I(r, pt_{h,i}^*) / \sum_{r \in R_h} I(r, pt_{h,i}^*) \tag{8}$$

where the $pt_{h,i}^*$ is the i-th pattern of the pattern set PT_h^*. The $I(r, pt)$ is an indicator function expressing whether pt is contained in the request of r,

$$I(r, pt) = \begin{cases} 1, pt \subseteq r, \\ 0, pt \not\subseteq r. \end{cases} \tag{9}$$

Finally, for purpose h, we select the positive persuasive sequential patterns PT_h^w from the mined results of success set with the top persuasion rate values and negative patterns PT_h^f from the mined results of the failure set with the top failure persuasion rate values.

Rewriting Requests with Sequential Strategy Patterns

LLM is utilized to rewrite the request with effective strategy patterns by applying template $\mathcal{T}^r(.)$ to generate rewritten request r^r:

$$r^r = LLM(\mathcal{T}^r(\mathcal{D}, E, pt_h^w, r, Y)) \tag{10}$$

And the rewrite template $\mathcal{T}^r(.)$ is:

> Here are descriptions of persuasion strategy: $\{D\}$.
> The examples of text with the corresponding strategy are: $\{E\}$. Input a request post: $\{r\}$.
> The strategies used in each sentence are: $\{Y\}$
> The process of rewriting shall follow these requirements:
> 1. Use the sequence of strategies: $\{pt_h^w\}$.
> 2. Generation of rhetorical devices is allowed for aligning with the specific persuasion strategy.
> 3. Keep as much of the original request's information as possible.

Where E represents for the example sentences of each persuasion strategies in the format {Example_Text, Strategy_Name}, r represents the input original request, followed by the identified strategies Y of each sentence in r, and pt_h^w denotes the positive sequential patterns for the purpose h.

Experiments

Dataset

Our framework is evaluated by using requests from users of the r/borrow[1] subreddit on the Reddit platform. These requests primarily involve borrowing money from others.

Original Request Dataset This dataset was collected by Jiaao and Diyi (2021), which contains 49,855 requests and there of 24174 requests were fulfilled. We furthermore follow the similar settings of persuasion strategies according to Table 2. There are 1,500 requests, each annotated at the sentence level with its corresponding persuasion strategy. Among these labeled data, five primary strategies and their distributions are as follows: *reciprocity* (18%), *credibility* (8%), *politeness* (16%), *evidence* (39%), and *impact* (12%). The remaining sentences are categorized under *others*.

Purpose Dataset To analyze the relationship between the purpose of a request and the sequential persuasion strategies, a subset of 1,057 requests was manually labeled. Based on the content of the requests, 17 categories of purposes were identified, corresponding to the six levels of human needs (Table 1). And 'No Purpose' was created for requests that lacked an explicitly stated purpose. Five annotators participated in the manual annotation process after completing a basic training and a trail annotation on 40 sample requests to familiarize themselves with the labeling guidelines. The inter-annotator agreement, as measured by Cohen's Kappa, was 0.518, indicating a moderate agreement.

[1] https://www.reddit.com/r/borrow/

Table 1: Purposes and their related needs. The category of No Purpose is not listed.

Human Needs	Purposes
Physiology	food, shelter, clothing, transportation
Safety	physical security, health security, stability, immediate expense, debt, buffer money
Love and belonging	social connections, affection, family
Esteem	esteem
Cognitive	education
Self-Actualization	enjoyment, fulfillment

Table 2: Persuasion strategies, and their descriptions for online loan requests.

Strategy	Description
Reciprocity	Offer interests or benefit to who lend the money.
Credibility	Use credentials or proof to establish trust.
Politeness	Use polite language.
Evidence	Use concrete details in expression.
Impact	Emphasize the importance or impact

Rewritten Dataset To evaluate the effectiveness of the sequential strategy patterns, two types of rewritten datasets were generated using LLMs: a free rewrite dataset and a constrained rewrite dataset guided by positive sequential strategy patterns. Initially, top 3 positive patterns and top 3 negative patterns are collected based on their persuasion rates. Additionally, requests that contain one or more patterns of top 3 negative patterns and contain none of the top 3 positive patterns are gathered as the candidate inputs for the rewriting process. Then, for the free rewrite, the input requests, the description of the strategy and the strategies identified from input requests are provided. For the pattern constrained rewrite, in addition to above information, one positive sequential pattern, randomly selected from top 3, is provided. There are 3131 unique requests were collected as input for both free rewrite and pattern constrained rewrite task. Five state-of-the-art LLMs: Gemini-1.5 (Gemini Team, 2024), GPT-4o (OpenAI, 2024), Doubao-pro (Doubao Team, 2024), Claude-3.5 (Anthropic, 2024), and Llama3.1 (Meta AI, 2024) were employed to independently generate both types of rewritten requests. In total, there are 15655 requests are collected for each type of rewrite by the 5 LLMs.

Classification of Purposes and Persuasion Strategies

To classify the purpose of the request and the persuasion strategy of each sentence with the request, we conducted the ICM training process to fine-tuning Flan-T5 model (Chung et al., 2024) by adopting 10-shot (180 labeled requests) and 20-shot (120 labeled sentences) configurations for these two tasks respectively. We evaluated the performance of our model on a separate hold-out test set from the original request dataset and purpose dataset, and compared our ICM model with Setfit (Tunstall et al., 2022) which is an efficient few-shot fine-tuning of Sentence Transformers, T5 the same with the backbone model of ICM and Setfit, GPT-4o one of the state of art commercial LLMs, and RoBERTa (Liu et al., 2021). The Flan-T5 with 250M parameters are used as the backbone models for ICM, T5 and Setfit, and RoBERTa-large with 355M parameters is applied here.

Table 3: Macro F1 scores for purpose and persuasion strategy prediction. Best scores are in **bold**, * Not fine-tuned.

Task	ICM	RoBERTa	GPT-4o*	T5	Setfit
Purpose	**59.3**	49.1	55.1	55.7	45.6
Strategy	**74.4**	48.5	66.8	69.0	71.2

Among Macro-F1 averaged performance results in Table 3, our ICM models achieve the highest performance for two classification tasks, laying a solid foundation for subsequent analysis, which provides a reliable basis of labeled data for the subsequent sequential strategy patterns mining.

Sequential Persuasion Strategy Patterns

To discover sequential strategy patterns, a filter is applied to limit the pattern with three elements, according to the "rule of three" in persuasion settings that three is the most efficient number of arguments to make an effective and compelling case (Shu & Carlson, 2014). The mining results from our dataset are analyzed and the most effective and least effective patterns are selected for comparative analysis and the results are presented in Table 4. All positive sequential patterns have higher persuasion rates than average, indicating their persuasive effectiveness for certain purposes. The results show varying effectiveness of persuasion strategy patterns based on request purposes. The top successful patterns have significantly higher persuasion rates than unsuccessful ones, especially for clothing, social connections, family, and education purposes.

The Effectiveness of Strategy Patterns

To verify whether the rewrite is effective and to distinguish whether the persuasion enhancement of the request is indeed originating from the persuasion strategies sequence rather than from the writing ability of the LLM itself, automatic machine based evaluation and human based evaluation are conducted on the original and rewritten datasets.

Machine Evaluation Two evaluation approaches are designed to reflect different perspectives: the acceptance predictions of the requests by the traditional machine learning model (AE1), and the preference test of pairwise requests by LLMs (AE2).

For the AE1 test, a fine tuned BERT[2] model with a similar training process of Wolf et al. (2020) is employed to predict

[2]https://huggingface.co/bert-base-uncased/tree/main

Table 4: The comparison of results of the most successful and unsuccessful patterns for different purposes of requests in r/borrow. In each pattern, we use colon to separate strategies. The persuasion rate (PR), the increasing value towards average persuasion rate (INC) and the support value (SUP) are also indicated. We also list average persuasion rates (AVG) for each purpose. All the numbers except support values are in percentage format and the categories of strategies we used are: Evidence (Evi), Impact (Imp), Reciprocity (Rec), Politeness (Pol), Credibility (Cre) and Others (Oth). The Politeness, Credibility and Reciprocity are the most commonly used strategies within the effective patterns, while Evidence and Impact are more commonly applied in negative patterns. The length of pattern l is 3 and the support threshold sr is 0.05 here.

Purpose	**AVG**	**Positive Pattern**	**PR**	**INC**	**SUP**	**Negative Pattern**	**PR**	**INC**	**SUP**
Food	47.2	Rec:Cre:Pol	**53.6**	13.5	0.16	Evi:Evi:Evi	35.9	-23.9	0.37
Shelter	29.7	Cre:Rec:Pol	**33.4**	12.5	0.10	Evi:Imp:Imp	19.8	-34.5	0.10
Clothing	37.8	Oth:Evi:Imp	**60.0**	58.7	0.13	Imp:Cre:Evi	27.3	-27.8	0.13
Transportation	39.5	Pol:Rec:Pol	**44.6**	12.9	0.11	Evi:Imp:Imp	26.7	-32.4	0.15
Physical safety	40.1	Pol:Evi:Rec	**48.9**	21.9	0.09	Evi:Imp:Cre	25.0	-37.7	0.15
Health security	41.2	Rec:Cre:Cre	**50.0**	21.4	0.07	Oth:Evi:Evi	29.1	-29.4	0.11
Stability	42.1	Imp:Cre:Cre	**44.7**	6.2	0.07	Evi:Evi:Imp	29.8	-29.2	0.25
Debt	40.9	Cre:Pol:Pol	**49.1**	20.0	0.09	Evi:Pol:Evi	30.0	-26.7	0.10
Buffer money	47.1	Cre:Cre:Pol	**50.0**	6.2	0.09	Imp:Imp:Pol	34.5	-26.8	0.09
Immediate expense	48.2	Cre:Pol:Pol	**52.9**	9.8	0.10	Oth:Evi:Pol	27.3	-43.4	0.14
Social connections	39.8	Rec:Cre:Evi	**57.7**	45.0	0.11	Imp:Imp:Evi	24.3	-39.0	0.13
Affection	40.2	Imp:Cre:Rec	**50.9**	26.7	0.09	Cre:Evi:Evi	30.0	-25.4	0.09
Family	33.0	Pol:Rec:Pol	**40.0**	21.2	0.13	Rec:Rec:Evi	19.8	-40.0	0.12
Esteem	41.6	Evi:Cre:Oth	**41.7**	0.2	0.07	Cre:Rec:Pol	23.8	-42.8	0.15
Education	35.0	Pol:Rec:Cre	**41.4**	18.3	0.07	Evi:Pol:Evi	20.8	-40.6	0.11
Enjoyment	46.6	Cre:Evi:Evi	**56.0**	20.2	0.08	Pol:Imp:Pol	28.6	-38.6	0.12
Fulfillment	34.9	Pol:Imp:Rec	**41.0**	17.5	0.09	Cre:Cre:Pol	22.1	-36.7	0.13

Table 5: Predicted persuasion rates of the original requests and the rewritten requests by five distinct LLMs for each specific purpose. All outcomes are in the form of percentages. Pat represents the results of using effective strategy pattern in the rewriting process, and noPat refers to the rewriting without incorporating pattern information. The temperature setting for all LLMs to generate rewritten requests is set to 0.6. The LLama3.1 model with 8B parameters is used here.

Purpose	**Original**	**Gemini-1.5**		**GPT-4o**		**Doubao-pro**		**Claude-3.5**		**Llama3.1**	
		Pat	**noPat**	**Pat**	**noPat**	**Pat**	**noPat**	**Pat**	**noPat**	**Pat**	**noPat**
Food	31.8	**48.1**	31.0	**44.1**	24.1	**42.1**	24.9	30.6	14.3	**48.7**	18.3
Shelter	7.9	**14.5**	6.6	**17.9**	3.8	**30.7**	6.2	**13.8**	2.4	**22.8**	3.4
Clothing	23.3	**40.0**	**30.0**	**26.7**	20.0	**46.7**	20.0	20.0	13.3	**43.3**	20.0
Transportation	13.7	**15.8**	**17.0**	10.3	9.8	**13.9**	11.8	8.2	5.3	**19.7**	8.6
Physical safety	32.8	**45.3**	23.4	32.8	21.9	32.8	21.9	**34.4**	12.5	**37.5**	12.5
Health security	24.5	**41.7**	23.9	**38.0**	15.3	**52.8**	17.8	**44.8**	7.4	**50.9**	11.7
Stability	24.5	**36.0**	21.6	**24.8**	16.1	**33.7**	18.7	**27.4**	7.5	**36.6**	14.4
Debt	23.8	**41.0**	23.1	**36.8**	17.3	**42.3**	19.5	**36.5**	11.7	**45.0**	15.6
Buffer money	31.4	**49.3**	31.4	**34.8**	24.0	**51.7**	25.3	**39.9**	15.9	**50.0**	18.2
Immediate expense	40.2	**52.9**	**46.0**	36.8	35.6	**43.7**	32.2	**44.8**	27.6	**59.8**	34.5
Social connections	27.3	**36.4**	21.2	**30.3**	21.2	**39.4**	21.2	**30.3**	12.1	**39.4**	15.2
Affection	10.9	**24.8**	**16.8**	**18.8**	6.9	**26.7**	**18.8**	**12.9**	3.0	**17.8**	7.9
Family	16.1	**22.0**	**17.3**	**16.7**	11.9	**23.2**	13.1	13.7	5.4	**20.2**	11.9
Esteem	24.2	24.2	22.6	21.0	12.9	17.7	19.4	16.1	12.9	**25.8**	11.3
Education	15.3	**24.5**	10.2	14.3	9.2	**29.6**	11.2	**16.3**	5.1	**25.5**	10.2
Enjoyment	36.4	**45.5**	36.4	27.3	18.2	18.2	36.4	27.3	9.1	**54.5**	9.1
Fulfillment	19.5	**21.4**	**22.1**	14.9	16.9	15.6	13.6	12.3	11.0	**23.4**	14.3

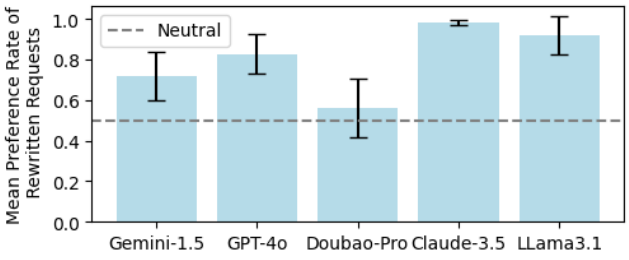

Figure 3: Proportion and STD value of persuasive preference on rewritten requests by different LLMs.

the persuasiveness of requests, achieving a Macro-F1 score of 0.65 for binary persuasion prediction, thereby demonstrating competitive performance.(Shaikh et al., 2020). The persuasion predictions were performed on both the original and rewritten datasets. To facilitate comparison of the overall persuasive effect of the rewrites, successful persuasion rates of the three types of requests (original, rewritten with the patterns, and rewritten without the patterns) are presented in Table 5. The results indicate that, across all the five LLMs, the persuasion rates of requests rewritten with sequential persuasion strategy patterns are higher than those rewritten without patterns. When comparing the rewritten requests with the original ones, all LLMs proved effective in enhancing the persuasiveness of requests for most of purposes. This finding further suggests that leveraging LLMs to rewrite requests with optimized sequential strategy patterns can significantly enhance their persuasiveness.

For the AE2 test, to ensure the reliability of the judgment, multiple LLMs (Gwenyth, DeLucia, & Dredze, 2023) were used to compare the persuasiveness of the original and the rewritten dataset. A total of six LLMs were employed for this evaluation, Gemini-1.5, GPT-4o, Doubao-pro, Claude-3.5, Llama3.1 and Qwen-2.5 (Qwen Team, 2024). For each pair of original request and rewritten request, five LLMs were used to determine persuasion preference, and the results with a majority of agreement were selected as the final answers. Among the rewritten dataset, 78.96% of the requests are found to be more persuasive than the original ones, and the mean score for each model's results is shown in Figure 3.

Human Evaluation Fifteen participants (6 women, 9 men) with age range 22-35 were recruited and none of whom were the authors of the original requests. Each participant rated persuasiveness for the same set of 18 request-pairs on a 7-point Likert scale (1 = strong preference for the first showed request; 4 = neutral; 7 = strong preference for the second showed request). Each pair consists of an original request and its pattern constrained rewrite generated by the Gemini-1.5 model. To avoid length-induced bias, we excluded any pair where the difference in word count exceeded 10%. Within each pair, the presentation order of requests was randomized, participants were not informed of the position of the original and the rewritten requests. After the evaluation, ratings were rescaled to fit the setting so that the rate of first showed request was the original one and the second was its rewrite.

The results show that 14 out of 18 pairs received mean scores above the neutral midpoint (4.0). Statistical analysis revealed an overall mean preference score ($\mu = 4.89$, SD = 0.88, $p < 0.001$). This indicates that rewriting requests with sequential persuasion strategy patterns are more persuasive than the original versions, confirming optimized sequential strategies can enhance the persuasiveness of requests.

Discussion and Conclusion

In this paper, we demonstrate that the effectiveness of sequential persuasion strategies varies based on the purpose of the request. For example, the "*Credibility-Reciprocity-Politeness*" pattern is the most effective for purposes like shelter, yet it ranks among the least persuasive for the purpose of esteem. Conversely, the "*Evidence-Credibility-Others*" pattern is more effective for esteem purpose, as it combines verifiable, concrete information with *Evidence* and *Credibility* strategies. Our findings align with the Self-Determination Theory (Deci & Ryan, 2013), which posited that competence and autonomy can enhance individual values, and the lack of concrete information can undermine rationality and trust. When we compare strategies used in certain sequential patterns, we find that using the same strategies in different sequences has significantly different impacts on the persuasion appeal. For instance, the pattern "*Reciprocity-Credibility-Politeness*" aligns most effectively with food (Physiology Needs), while the reversed order "*Politeness-Reciprocity-Credibility*" is more effective for the purpose of education (Cognitive Needs).

In addition, we find three strategies (*Reciprocity*, *Credibility* and *Politeness*) are commonly employed in most of the effective patterns. This aligns with the investigations that trust and reciprocity play a significant role in economic activities (Berg, John, & Kevin, 1995; Ortmann, Fitzgerald, & Boeing, 2020), and their effectiveness can be enhanced when using politeness in requests (Brown & Levinson, 1987).

The Sequential Persuasion Strategy Framework not only advances the theoretical understanding of persuasion in online requests, but also offers practical guidelines for optimizing requests with sequential persuasion strategies towards different purposes. These insights have the potential to improve real-world applications, enabling more effective textual requests by selecting appropriate sequential strategy patterns.

It is important to note possible limitations of our experiments which will be addressed in future work. The patterns observed in our current study are based on predefined persuasion strategies, purposes of requests, and experienced lengths. The effectiveness of a pattern is highly dependent on the collected data, which may limit its applicability in generating more persuasive textual rewrites across different lending scenarios or other contexts.

Acknowledgments

This work was supported by the National Key R&D Program of China (2024YFC3308500), the National Natural Science Foundation of China (62332015), the Beijing Natural Science Foundation (L247008), and the Project of ISCAS (ISCASJCMS-202401).

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