Graph-based Multilingual Language Model: Leveraging Product Relations for Search Relevance

Nurendra Choudhary Virginia Tech, Arlington, USA nurendra@vt.edu Nikhil Rao Amazon, Palo Alto, USA nikhilsr@amazon.com

ABSTRACT

The large-scale nature of product catalog and the changing demands of customer queries makes product search a challenging problem. The customer queries are ambiguous and implicit. They may be looking for an exact match of their query, or a functional equivalent (i.e., substitute), or an accessory to go with it (i.e., complement). It is important to distinguish these three categories from merely classifying an item for a customer query as relevant or not. This information can help direct the customer and improve search applications to understand the customer mission. In this paper, we formulate search relevance as a multi-class classification problem and propose a graph-based solution to classify a given query-item pair as exact, substitute, complement, or irrelevant (ESCI). The customer engagement (clicks, add-to-cart, and purchases) between query and items serve as a crucial information for this problem. However, existing approaches rely purely on the textual information (such as BERT) and do not sufficiently focus on the structural relationships. Another challenge in including the structural information is the sparsity of such data in some regions. We propose Structure-Aware multilingual LAnguage Model (SALAM), that utilizes a language model along with a graph neural network, to extract region-specific semantics as well as relational information for the classification of query-product pairs. Our model is first pre-trained on a large region-agnostic dataset and behavioral graph data and then fine-tuned on region-specific versions to address the sparsity. We show in our experiments that SALAM significantly outperforms the current matching frameworks on the ESCI classification task in several regions. We also demonstrate the effectiveness of using a two-phased training setup (i.e., pre-training and fine-tuning) in capturing region-specific information. Also, we provide various challenges and solutions for using the model in an industrial setting and outline its contribution to the e-commerce engine.

CCS CONCEPTS

• Information systems → Retrieval models and ranking; *Query* representation; • Applied computing → Online shopping.

KEYWORDS

Graphs, language models, search relevance, e-commerce

*Also with Amazon, Palo Alto, USA.

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1 INTRODUCTION

The goal of an e-commerce search engine is to show a ranked list of items that best match a shopper's query intent. Unlike standard search engines [13, 17], e-commerce engines cannot solely rely on the textual and semantic content of a query. This is because shoppers' queries are often ambiguous, broad, lack specific intent or have an implicit intent. A simple one-size-fits-all approach to ecommerce product retrieval seldom works for all types of customer queries. Practitioners often mitigate this using additional human labeled data to re-rank items or aptly message the shoppers as to why an item was surfaced. The shopper may be looking for an exact match for their query, or a functional equivalent (i.e., substitute), or an accessory to go with it (i.e., complement). It is important to distinguish these three categories from merely classifying an item as relevant or not for a given query. Specifically, annotated data is used to classify query and item pairs into Exact (E), Substitute (S), Complement (C), and Irrelevant (I) (ESCI) classes.

Obtaining human annotated data is time consuming and costly. The size of datasets available to train ESCI classification models is orders of magnitude smaller than those used to train relevance models [4] (which typically rely on anonymized aggregated customer shopping behavior). In addition, the labeled data available per-region to train these models is even smaller. However, there is additional information that is present in e-commerce datasets, in the form of query-item graphs capturing interactions between these pairs, and co-purchase behavior across products in the catalog. We hypothesize that one can train better ESCI classifiers by aggregating information along nodes and edges of this graph to extract queries and items that are similar to the ones in the labeled dataset.

Models that use graph information have shown to be competitive in e-commerce search applications. These models typically tend to outperform their pointwise or pairwise counterparts such as C-DSSM [21, 28] and MV-LSTM [32], and their adversarial [20] or multilingual [1] extensions. This is because the aforementioned methods only focus on the textual information in the query-product pairs, and ignore any relational information across queries and products. However, existing approaches work with very small graphs, and are not built to scale to the sizes of graphs typically seen in the real-world applications. In this paper, we propose **Structure-Aware** **multilingual LAnguage Model (SALAM)**, illustrated in Figure 2, that combines text and graph information in a scalable manner, overcoming the drawbacks of the aforementioned methods.



Figure 1: Sample of a query-product pair with (a) only text and (b) text and graph structure. Note that classifying the relation in (a) based only on text is difficult because both the products have a single token match with the query. However, with the aid of graph structure in (b), the classification becomes easier with more semantic token matches and additional information about the relations.

Academic research in this topic has explored certain solutions to the problem of integrating text and graph using hybrid techniques such as TextGNN [40], TextGCN [35], and Graphormer [37]. However, these approaches are not scalable to industrial applications which typically need to handle hundreds of millions of queries everyday and require low processing latency.

SALAM is first pretrained on a corpus of labeled data across multiple regions as well as the query-product graph. This allows for a model that can be initialized using *all* the labeled data available. Next, SALAM is fine-tuned on region-specific labeled datasets. We show via extensive experiments that the use of auxiliary graph structured information and the proposed two-stage training approach vastly outperforms baseline methods by 10%-65% across multiple regions. The specific architectural choices in SALAM also allow it to be deployed in web-scale systems. SALAM utilizes a mul-



Figure 2: An overview of the proposed SALAM. Given the input query-product pair with their corresponding local neighborhoods, SALAM combines the power of textual and graph representations for ESCI classification.

tilingual language model (MLM) [5] in congruence with a Graph Convolution Network (GCN) [15], to capture the textual and graph features of query-product pairs, respectively. These features are combined in the latent space with an attention layer [30] to capture the inter-dependency between the textual and graph-based features, which are further utilized for the final ESCI classification. To summarize, the major contributions of this paper are as follows:

- (1) We present Structure-Aware multilingual LAnguage Model (SALAM) that combines a MLM and GCNs within an attentionbased framework to aggregate features from both the text and graph attributes of query-product pairs, respectively. We show that the proposed unique aggregation mechanism is able to outperform the current state-of-the-art models on the task of ESCI classification with similar computational resources and model latency limits.
- (2) We demonstrate the benefits of utilizing the graph features and attention aggregation through an ablation study.
- (3) We illustrate the performance gains in multi-region/multilingual classification produced by using a two-phase (pre-training and fine-tuning) approach over one that trains a single model.
- (4) We detail the challenges that affect the practical viability of SALAM in industrial settings, and provide solutions for the same. We also outline the primary benefits of our approach to an e-commerce search engine.

The rest of the paper is organized as follows; Section 2 presents the related literature in this topic. Section 3 defines our problem statement and the model architecture. Section 4 describes our experimental results in a comparative evaluation and Section 5 presents our deployment strategy along with the contributions of the model to the e-commerce engine. Section 6 concludes the paper.

2 RELATED WORK

In this section, we describe the earlier works relevant to our current problem. We present three broad areas of representation learning: graph, text, and hybrid (graph+text) methods.

Graph Representation Learning. Earlier research into graph embeddings relied on two broad methods: matrix factorization and random walks. Matrix factorization methods [22, 26] attempt to factorize the adjacency matrix A to a low-dimensional representational matrix L by minimizing $||L^T L - A||$. Random walk techniques [10, 19, 25, 29, 33] utilize a traversal along the edge connections of a node to retrieve its neighborhood and learn the representation. These approaches form a vector space model based on the node's neighborhood and have shown the importance of learning graph representations. However, these methods depend on the methodology of the random walk traversal technique and do not handle the entirety of a node's neighborhood. Hence, we utilize the power of deep networks to aggregate features from the nodes' neighborhood. Some of the popular deep architectures include Graph Neural Network (GNN) [27], GraphSage [11], Graph Convolution Network (GCN) [15], and Graph Attention Network (GAT) [31]. In our proposed SALAM model, we utilize the scalable GCN architecture for learning features from the graph structure of query-product pairs.

Text Representation Learning. Early research in text embeddings relied on capturing the context of individual words (or tokens). These approaches [18, 24] show the effectiveness of distributional representations in extracting semantic features. However, most of the problems that involve text need sentence embeddings and not word-level representations. Towards this, text representations evolved to utilize sequential word information using recurrent networks [32], convolution networks [28], and attention networks [2]. Graph-based Multilingual Language Model

Recently, newer techniques are based on learning a pre-trained language model [6, 8] that can be fine-tuned on specific tasks. Such approaches have shown improved performance over the other representational techniques. Thus, in our model, we utilize this twostep approach, i.e., pre-training and fine-tuning steps, to capture region-agnostic and region-specific information, respectively.

Hybrid (Graph + Text) Representation Learning. Recently, we see an increasing research effort focused on extracting hybrid graph and text information from structured datasets. TextGNN [40] and TextGCN [35] utilize text embeddings to initialize node features in a graph network framework. Graphormers [38] utilize manual graph features (such as spatial encoding and centrality measures) within a text-based transformer architecture to capture hybrid features. These methods, while effective, are not scalable to a practical application that receives millions of queries per day and hence, we developed SALAM as an effective architecture with low latency. Another line of approaches [9, 36] focus on the problem of structured reasoning for question answering. However, these approaches require specific relational knowledge graphs which are, generally, not readily available and require significant investment for construction. Our model uses the platform generated purchase information for knowledge and hence, does not need any additional investment.

3 MODEL ARCHITECTURE

In this section, we first discuss the problem statement and then explain the different components of our architecture and detail its training and inference pipeline.

3.1 Problem Statement

Let us say that the input query-product pair is (Q, P). From a global graph \mathcal{G} , we pre-compute their neighborhood based on historical purchase information as $Q_{\mathcal{G}}$ and $P_{\mathcal{G}}$, respectively. The goal of this work is to build a prediction model P_{θ} with parameters θ such that

$$\hat{y} = \underset{y' \in \{E, S, C, I\}}{\operatorname{arg\,max}} P_{\theta}(y'|x, \theta); \quad \theta = \underset{\theta}{\operatorname{arg\,max}} P_{\theta}(\hat{y} = y|x, \theta)$$
(1)

where \hat{y} is the predicted output of model P_{θ} for a corresponding input sample $x = (Q, P, Q_{\mathcal{G}}, P_{\mathcal{G}})$ and $y \in \{E, S, C, I\}$ is the ground truth label for the sample x.

3.2 Model Components

In this section, we describe the function of different components of SALAM and show their hybrid graph-text feature extraction and aggregation methods. As shown in Figure 3a, we begin the pipeline with an input query-product pair either received from a user or a collection of historical queries, x = (Q, P). Using x, we compute the corresponding graph neighborhoods $x_{\mathcal{G}} = (Q_{\mathcal{G}}, P_{\mathcal{G}})$ using the Graph Construction module. The textual features of the input pair are then encoded using a language model and the neighborhood $x_{\mathcal{G}}$ is aggregated using a Neighborhood aggregation network to produce two complementary representations $t_{Q,P}$ (based on text) and $g_{Q,P}$ (based on graph). These representations are then pooled together using attention to finally produce the probabilities $P_{\theta}(y'|x, \theta)$ using a normalizing function (i.e., softmax). We will now provide more specific details of these components used in our model.

Graph Construction. In this module, we pre-compute a local neighborhood of connections between queries and products. Several such query-product graphs are, generally, available in the context of e-commerce engines such as purchase information, retrieval history, and click-through rates. For simplicity, in our problem, we utilize the purchase information, i.e., a query node and product node have an edge between them if the product has been purchased for a given query, else no edge exists. To construct the neighborhood, we perform a breadth-first traversal over the root node till a depth threshold of n^1 . Additionally, we also store the corresponding nodes' features as semantic encoding of its text, obtained from a pre-trained XLM model [6]. The graph $x_{\mathcal{G}} = (Q_{\mathcal{G}}, P_{\mathcal{G}})$ for query-product pair x = (Q, P) is stored in a hash map for constant time retrieval during the training and inference phase.

Language Model. To encode the text attributes (Q, P), we adopt the multilingual XLM [6] model². For a pair of text sequences, the language model provides a sequence of encoding of $e \in \mathbb{R}^{F}$, which is further reduced to $t \in \mathbb{R}^{f}$, (where $f \ll F$) through a dense linear layer, $\phi_{F}^{f} : \mathbb{R}^{F} \to \mathbb{R}^{f}$ for computational efficiency in the attention pooling and final classification layer.

$$t_{Q,P} = \left\{ \phi_F^f(XLM(Q,P)) \right\}^f \tag{2}$$

where $\{X\}^f$ implies that X is a feature vector of f dimensions.

Neighborhood Aggregation. In SALAM, we use a Graph Convolution (GCN) encoder [15] to encode the graph neighborhood of the query-product pair. The choice of the graph neicoder is dependent on the trade-off between its performance and scalability on the huge e-commerce purchase information. From our experiments, described in Section 4.4, we chose GCN due to its performance advantage over other graph encoders with similar parameters. Let us say the input to a GCN for a neighborhood of N nodes with feature dimensions F is given by $h_0 \in \mathbb{R}^{N \times F}$. An L-layer GCN aggregates the node neighborhood into features as:

$$h_{l+1} = \sigma \left(D^{-\frac{1}{2}} A D^{-\frac{1}{2}} h_l W_l \right)$$
(3)

Thus,
$$GCN(h_0) = \{h_L\}^f$$
 (4)

where h_l and h_{l+1} are the input and output to the l^{th} GCN layer. W_l is the learnable feature map for the layer and σ is a non-linear activation function. $D \in \mathbb{R}^{N \times N}$ and $A \in \mathbb{R}^{N \times N}$ are the diagonal degree and adjacency matrices of the graph, respectively. h_L is the output of the final GCN layer and consequently the encoding of the nodes' neighborhood.

Applying this to the given input graph of query-product pair $x_{\mathcal{G}} = (Q_{\mathcal{G}} \in \mathbb{R}^{N \times F}, P_{\mathcal{G}} \in \mathbb{R}^{N \times F})$ with node features $Q, P \in \mathbb{R}^{F}$, we independently encode the neighborhood graphs of both the query and product using GCNs and then concatenate (\circ) the resultant features for the final output, $g_{Q,P}$ as given below:

$$\{g_{Q,P}\}^{2f} = \{GCN(Q_{\mathcal{G}})\}^f \circ \{GCN(P_{\mathcal{G}})\}^f$$
(5)

¹Due to computational constraints, we empirically set n to be 2.

²XLM is chosen due to its popularity and multilingual nature, any other trainable multilingual text encoder can be used as an alternative.

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Figure 3: An overview of SALAM's architecture (a) and its training (b) and inference (c) pipelines. (a) The inputs to the architecture are a query-product text pair with a pre-computed graph neighborhood which is obtained from the purchase information. The textual and graph features are encoded using a language model and GCN, respectively. Subsequently, the concatenation of the features are pooled with an attention mechanism to finally predict the probability of the classes. (b) The training pipeline uses the query database and product catalogue with a ground truth label for back-propagation and saves a model checkpoint on convergence. (c) The inference pipeline employs the checkpoint to classify search relevance on a user query and products from the catalogue to generate the final label, which is stored in the database for relevance computation in the e-commerce engine.

Attention Pooling. The graph and text features, while encoded independently, are derivatives of the same e-commerce dataset. Hence, our current encoding misses the inter-relations between the features. To capture these dependencies, we rely on an attentive pooling mechanism [30] that calculates attention weights to higher order interactions between the nodes' text and graph features to subsequently combine them into a single feature set. The final output of the attentive pooling between the graph and text features, $o_{O,P}$, is computed as:

$$\{e_{Q,P}\}^{3f} = \{t_{Q,P}\}^{f} \circ \{g_{Q,P}\}^{2f}$$

$$\{q_{Q,P}\}^{h} = \phi_{3f}^{h} (e_{Q,P}); \ \{k_{Q,P}\}^{h} = \phi_{3f}^{h} (e_{Q,P}); \ \{v_{Q,P}\}^{h} = \phi_{3f}^{h} (e_{Q,P})$$

$$(7)$$

$$\{a_{Q,P}\}^{h} = \left\{\frac{\exp(\alpha_{ij})}{\sum_{j=0}^{h} \exp(\alpha_{ij})} v_{i}\right\}_{i=0}^{h}; \quad \{\alpha_{ij}\}^{1} = \frac{q_{i}k_{j}}{\sqrt{2h}}$$
(8)

$$\left\{o_{Q,P}\right\}^{|y|} = Softmax\left(\phi_h^{|y|}(a_{Q,P})\right) \tag{9}$$

where *h* is the number of hidden units in the attention layers and, $q_{Q,P}$, $k_{Q,P}$ and $v_{Q,P}$ are the query, key and value vectors, respectively, obtained using independent linear transformation layers

 $\phi_{3f}^h : \mathbb{R}^{3f} \to \mathbb{R}^h$ for the attention layer. α_{ij} is the attention weight assigned to the interaction between i^{th} query and j^{th} key feature. $\phi_h^{|y|} : \mathbb{R}^h \to \mathbb{R}^{|y|}$ is a dense layer for feature compression to the final number of classes and $Softmax(\cdot)$ is used to map the final set of features to the probability space for loss computation as:

$$L(o_{Q,P}, y_k) = -\sum_{k=1}^{|y|} y_k \log(o_{Q,P}); y_k = \begin{cases} 1, \text{ if class is } k\\ 0, \text{ otherwise} \end{cases}$$
(10)

Handling Multi-Regionality. SALAM uses a two-phase approach of pre-training on the all the regions together and further fine-tuning on particular regions to utilize the entire volume of training data and add regional specificity, respectively. This approach shows significant improvement in performance (as shown in Section 4.3) compared to the single phase training framework.

3.3 Implementation Details

SALAM is implemented using Pytorch framework [23] on a single Nvidia V100 GPU with 4GB VRAM. The model is optimized using AdamW [16] with standard beta parameters of 0.9 and 0.999 and a weight decay rate of 0.01. The language model adopted for text encoding is XLM-Roberta-base with the standard parameter setting given in [5]. We limit our node neighborhood to a depth of n = 2with a maximum neighborhood size of N = 100. For the graph encoding, we utilize a 2-layer GCN model (L = 2) with 16 hidden units. The raw feature set of the nodes and text encoding of the language model is of F = 768 dimensions which is scaled down to f = 16 (empirically determined) for computational efficiency. The pooling is done on a single head attention network with h = 8hidden units in the linear transformations. The loss function used for gradient descent is binary cross entropy weighted by the class distribution of the samples in the training dataset. SALAM is trained and evaluated on three classification variants of the ESCI search relevance with following unique downstream applications: (i) E vs S vs C vs I, (ii) E vs S vs CI, and (iii) E vs SCI. The code and evaluation of our method is already made publicly available at https://github. com/amazon-research/structure-aware-language-models/.

3.4 Training and Inference Pipeline

In an industrial setting, the training and inference phases have their unique set of requirements both in terms of model latency and complexity. In this section, we explain our pipelines that were designed to meet the general industry requirements.

During the training phase, depicted in Figure 3b, the model can have access to a significant amount of both memory (RAM/disk) and compute power (GPUs). More importantly, we also observe that a significant portion (70%-80%) of queries received by e-commerce search engines remain constant over the days of a month, and thus, we consider a monthly update cycle for our model checkpoints. Hence, the training phase also gets a significant amount of time due to the monthly entropy of the underlying dataset (i.e., update frequency). Thus, SALAM's dependence on graph pre-computation (a time intensive operation) and query-product pairing (a memory intensive operation) can be managed in practice. However, one limitation remains that the model checkpoints need to be industrycompliant, and hence, the number of model parameters are resourcedependent (generally a single GPU). For this, we choose our hyperparameters (as given in Section 3.3) to limit model size to 2.5 GB (remaining GPU memory post overhead allocation). The training pipeline receives the query-product pair from the query database and product catalogue, with a manually assigned ESCI label. This information is used to pre-compute the node neighborhoods from purchase information and to train the SALAM architecture, whose parameters are further stored as a checkpoint upon convergence. The checkpoint is further finetuned to region-specific checkpoints using the same procedure, but with only region-specific datasets.

For the **inference phase**, presented in Figure 3c, the model's requirement is to handle a large number of query-product pairs. Due to this, the model's scalability and latency become the primary concerns. Hence, we only use the pre-computed node neighborhood (no computation during inference) and limit our compute power to a single GPU. The inference pipeline initiates an instance of the SALAM model and loads the parameters from the latest checkpoint. Subsequently, it processes the query-product pairs and their node neighborhoods (computed during training) received as input to predict the relevance labels and stores them in a database for utilization in the e-commerce engine's relevance computation pipeline. Note that, the inference pipelines for different regions is

unique and accordingly utilize the corresponding region-specific model checkpoints.

Further experiments on the evaluation of training and inference pipelines are presented in Sections 4.2 and 4.5, respectively. The training and inference algorithms are detailed in Appendix A.

4 EXPERIMENTAL STUDY

In this section, we describe our experimental setup that analyzes SALAM's performance on the ESCI classification tasks compared to its current alternatives. The experiments intend to answer the following research questions:

- **RQ1.** Does SALAM outperform the current alternatives on the task of search relevance classification?
- **RQ2.** Is the two-phase training with pre-training and fine-tuning better than the alternative training frameworks?
- RQ3. What are the considerations in the choice of graph encoders?
- **RQ4.** How does SALAM compare to its alternatives in suitability for an industrial application?

4.1 Datasets and Baselines

The datasets used in our experiments contain $\approx 12M$ manually annotated query-product ESCI pairs collected from the real-world queries of an e-commerce search engine. The pairs are collected from 16 different e-commerce site regions³ with queries in various languages. No customer information or personally identifiable information were used in collecting this data. We evaluate the performance of our model on the following three different downstream tasks of the e-commerce search engine: (i) Four class (E vs S vs C vs I): applied in complementary item recommendation [12], (ii) Three class (E vs S vs CI): applied in alternate product suggestion [3] and (iii) Two class (E vs SCI): for better precision in product recommendation [4]. Each one of these three variants leads to different class distributions which is adjusted in our model using class weights of the binary cross entropy loss. 20% of each region's dataset is held-out for testing and the other 80% is divided into a training and validation ratio of 4:1 for 5-fold cross validation in our experiments. More details on the various e-commerce regions and the class distributions are given in Appendix B.

For the baselines, we consider the publicly available mBERT [8] and XLM [6] models as well as the multilingual proprietary framework, hereinafter, referred to as *proprietary e-commerce baseline (or) PEBL*. The reason for the baseline choice is the multilingual nature of our experiments. The models are all first trained on a combined training dataset of all the regions for a small number of epochs (4 in our case), and then fine-tuned on the region-specific datasets for a larger number of epochs (20 in our case) to finally get the region-specific checkpoints used in our experimental studies.

4.2 RQ1: Model Performance

In this experiment, we compare SALAM's performance against the baselines on the task of search relevance classification. The candidate models return a single class for each input query-product pair and the performance is evaluated on the metrics of precision,

³Australia (AU), Canada (CA), India (IN), Singapore (SG), United Kingdom (UK), United States (US), Japan (JP), Germany (DE), France (FR), Italy (IT), Spain (ES), Netherlands (NL), Turkey (TR), United Arab Emirates (AE), Mexico (MX), and Brazil (BR).

Table 1: Performance comparison of SALAM against the baselines on the task of search relevance classification in different e-commerce regions on four class E-S-C-I classification. The metrics used for evaluation are Precision (P), Recall (R), and F1. The metrics are presented for each class to avoid bias from class distribution and a macro-average over the classes is provided in column M. Due to the proprietary nature of the models, the results shown are relative to the public mBERT model, i.e., a cell value of x implies that the model performs $(1 + x) \times$ mBERT. The best results in each segment are highlighted in bold. All the F1-improvements of SALAM over PEBL and mBERT are statistically significant with a p-value threshold of 0.05.

	Region	n Australia (AU)					Canada (CA)						I	ndia (IN	1)		Singapore (SG)				
	Class	Ε	S	C	Í	Μ	E	S	C	Í	Μ	Е	S	C Ì	Í	М	Е	S	° îc	Í	Μ
Р	mBERT	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	XLM	.107	.085	.119	02	.072	.074	.092	.147	06	.060	.065	06	02	19	05	.111	.454	.086	06	.097
	PEBL	.213	.170	.238	04	.143	.147	.183	.293	11	.119	.130	13	04	37	10	.222	.908	.172	11	.193
	SALAM	.261	.097	.256	.009	.155	.163	.153	.183	02	.116	.116	.021	00	04	.025	.354	.555	.029	08	.150
R	mBERT	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	XLM	01	.788	.817	.774	.332	01	.601	1.654	1.416	.382	04	.277	.948	.723	.235	01	.520	.490	1.417	.289
	PEBL	02	1.58	1.63	1.55	.664	02	1.20	3.31	2.83	.764	07	.553	1.90	1.45	.470	02	1.04	.979	2.83	.578
E1	MEEDT	04	2.00	2.05	1.77	.801	05	1.30	4.47	2.78	.8/2	02	.505	2.12	1.00	.333	08	1.//	1.51	3.32	./91
1.1	VIM	.000	.000	510	400	.000	.000	367	1.047	702	328	.000	101	510	246	140	.000	.000	320	.000	206
	PEBL	102	952	1.02	800	563	065	733	2.09	1 40	656	029	202	1.02	491	298	111	984	639	1 53	591
	SALAM	.111	1.05	1.20	.923	.644	.067	.775	2.40	1.50	.716	.049	.276	1.14	.912	.408	.138	1.10	.752	1.74	.680
	-		United	Kingdo	m (UK)			Unit	ed State	s (US)			Ja	apan (J	P)			Ge	rmany (DE)	
		Е	S	c	Ι	Μ	E	S	С	I	Μ	Е	S	C	I	Μ	Е	S	c	I	Μ
Р	mBERT	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	XLM	.043	02	01	28	07	.055	07	00	28	07	.075	.394	.121	06	.105	.089	.065	.034	02	.043
	PEBL	.085	05	01	57	13	.110	14	00	57	14	.149	.788	.242	12	.210	.177	.129	.067	04	.086
	SALAM	.086	.138	01	10	.028	.134	03	04	08	.005	.193	1.15	.633	.517	.517	.190	.103	.303	.119	.177
R	mBERT	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	XLM DEDI	04	.205	2.497	3.466	.300	04	.354	1.114	.906	.220	01	.537	.941	2.512	.335	02	.721	1.196	1.090	.358
	SALAM	07	.409	4.99 8.40	6.93 5.50	.599	08	./08	2.23	1.81	.440	02	1.07	1.88	5.02	.009	05	1.44	2.39	2.18	./15
E1	mBEDT	03	.010	0.49	000	.780	03	000	000	000	./01	.033	000	000	0.20	000	04	000	2.04	2.07	./49
1.1	XIM	.000	.000	1 554	962	210	007	150	725	130	125	031	469	598	1.070	295	.000	405	611	598	288
	PEBL	005	196	3 11	1.92	419	013	300	1 45	260	249	062	937	1 20	2.14	590	068	809	1.22	1 20	575
	SALAM	.028	487	4 34	3.02	.685	.040	.570	2.58	.784	.514	.115	1.43	2.22	3.57	.996	.077	.843	1.30	1.55	.650
	011011111			1.51	0.01												,				
	0111111	.020	F	rance (F	R)				Italy (IT)			S	pain (E	S)	.,,,,		Neth	erlands	(NL)	
	01121111	E	Fi S	rance (F C	R) I	м	Е	S	Italy (IT C) I	м	E	s s	pain (E C	S) I	М	E	Neth S	erlands C	i (NL) I	м
P	mBERT	E .000	Fi S .000	rance (F C .000	R) I.000	M .000	E .000	S .000	Italy (IT C .000	() I .000	M .000	E .000	S .000	pain (E C .000	S) I .000	M .000	E .000	Neth S .000	erlands C .000	(NL) I .000	M .000
P	mBERT XLM	E .000 .036	Fi S 03	rance (F C .000 .014	R) I .000 16	M .000 03	E .000 .088	S .000 .007	Italy (IT C .000 08	() () () () () () () () () () () () () (M .000 02	E .000 .069	S .000 .116	pain (E C .000 .103	S) I .000 .000	M .000 .069	E .000 .100	Neth S .000 .127	erlands C .000 .100	I .000 08	M .000 .051
P	mBERT XLM PEBL	E .000 .036 .072	Final S .000 03 07	.000 .014 .03	R) I .000 16 32	M .000 03 06	E .000 .088 .176	S .000 .007 .014	Italy (IT C .000 08 17	I .000 11 21	M .000 02 04	E .000 .069 .137	\$.000 .116 .231	pain (E C .000 .103 .205	S) I .000 .000 .000	M .000 .069 .138	E .000 .100 .200	Neth S .000 .127 .254	erlands C .000 .100 .200	I .000 08 16	M .000 .051 .101
P	mBERT XLM PEBL SALAM	E .000 .036 .072 .114	Final	rance (F C .000 .014 .03 08	I .000 16 32 .076	M .000 03 06 .023	E .000 .088 .176 .218	S .000 .007 .014 .080	Litaly (IT C .000 08 17 .036) I .000 11 21 .149	M .000 02 04 .123	E .000 .069 .137 .138	\$.000 .116 .231 .230	pain (E C .000 .103 .205 .149	I I .000 .000 .000 .000 .033	M .000 .069 .138 .134	E .000 .100 .200 .285	Neth S .000 .127 .254 .238	erlands C .000 .100 .200 .246	• (NL) I •.000 •.08 •.16 •.02	M .000 .051 .101 .175
P	mBERT XLM PEBL SALAM mBERT	E .000 .036 .072 .114 .000	F: S .000 03 07 03 .000 .000 .252	rance (F C .000 .014 .03 08 .000	I .000 16 32 .076 .000	M .000 03 06 .023 .000	E .000 .088 .176 .218 .000	S .000 .007 .014 .080 .000	Italy (IT C .000 08 17 .036 .000	I .000 11 21 .149 .000 1.112	M .000 02 04 .123 .000 214	E .000 .069 .137 .138 .000	S .000 .116 .231 .230 .000	pain (E C .000 .103 .205 .149 .000	I .000 .000 .000 .000 .000 .0033 .000 .000 .000	M .000 .069 .138 .134 .000 .210	E .000 .100 .200 .285 .000	Neth S .000 .127 .254 .238 .000 .285	erlands C .000 .100 .200 .246 .000 702	(NL) I .000 08 16 02 .000 1 225	M .000 .051 .101 .175 .000 .256
P	mBERT XLM PEBL SALAM mBERT XLM PEBI	E .000 .036 .072 .114 .000 02	F: S .000 03 07 03 .000 .253 505	rance (F C .000 .014 .03 08 .000 1.101 2 20	R) I .000 16 32 .076 .000 .739 1.48	M .000 03 06 .023 .000 .197 393	E .000 .088 .176 .218 .000 04	S .000 .007 .014 .080 .000 .703 1.41	Italy (IT C .000 08 17 .036 .000 1.291 2.58	I .000 11 21 .149 .000 1.113 2 23	M .000 02 04 .123 .000 .314 627	E .000 .069 .137 .138 .000 01	S .000 .116 .231 .230 .000 .466 931	pain (E C .000 .103 .205 .149 .000 .959 1.92	I I .000 .000 .000 .033 .000 .856 1.71	M .000 .069 .138 .134 .000 .319 .637	E .000 .100 .200 .285 .000 03 03	Neth S .000 .127 .254 .238 .000 .285 569	erlands C .000 .100 .200 .246 .000 .702 1.40	(NL) I .000 08 16 02 .000 1.235 2.47	M .000 .051 .101 .175 .000 .256 512
P	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM	E .000 .036 .072 .114 .000 02 04 - 04	Final S S S S S S S S S S S S S S S S S S S	rance (F C .000 .014 .03 08 .000 1.101 2.20 3.92	R) I .000 16 32 .076 .000 .739 1.48 1.92	M .000 03 06 .023 .000 .197 .393 .678	E .000 .088 .176 .218 .000 04 08 - 06	S .000 .007 .014 .080 .000 .703 1.41 1.93	Italy (IT C .000 08 17 .036 .000 1.291 2.58 3.77) I .000 11 21 .149 .000 1.113 2.23 2.65	M .000 02 04 .123 .000 .314 .627 875	E .000 .069 .137 .138 .000 01 02 03	S .000 .116 .231 .230 .000 .466 .931 .913	pain (E C .000 .103 .205 .149 .000 .959 1.92 2.01	I .000 .000 .000 .000 .000 .033 .000 .856 1.71 1.89	M .000 .069 .138 .134 .000 .319 .637 .663	E .000 .100 .200 .285 .000 03 07 07	Neth S .000 .127 .254 .238 .000 .285 .569 1.24	erlands C .000 .100 .200 .246 .000 .702 1.40 1.89	(NL) I .000 08 16 02 .000 1.235 2.47 3.01	M .000 .051 .101 .175 .000 .256 .512 .753
P R F1	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT	E .000 .036 .072 .114 .000 02 04 04 .000	Final Stress Str	rance (F C .000 .014 .03 08 .000 1.101 2.20 3.92 .000	I .000 16 32 .076 .000 .739 1.48 1.92 .000	M .000 03 06 .023 .000 .197 .393 .678 .000	E .000 .088 .176 .218 .000 04 08 06 .000	S .000 .007 .014 .080 .000 .703 1.41 1.93 .000	Italy (IT C .000 08 17 .036 .000 1.291 2.58 3.77 .000	I .000 11 21 .149 .000 1.113 2.23 2.65 .000	M .000 02 04 .123 .000 .314 .627 .875 .000	E .000 .069 .137 .138 .000 01 02 03 .000	S .000 .116 .231 .230 .000 .466 .931 .913 .000	pain (E C .000 .103 .205 .149 .000 .959 1.92 2.01 .000	I .000 .000 .000 .000 .000 .000 .033 .000 .856 1.71 1.89 .000	M .000 .069 .138 .134 .000 .319 .637 .663 .000	E .000 .100 .200 .285 .000 03 07 07	Neth S .000 .127 .254 .238 .000 .285 .569 1.24 .000	C .000 .100 .200 .246 .000 .702 1.40 1.89 .000	(NL) I .000 08 16 02 .000 1.235 2.47 3.01 .000	M .000 .051 .101 .175 .000 .256 .512 .753 .000
P R F1	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM	E .000 .036 .072 .114 .000 02 04 04 .000 .010	Final States of the second sec	I.01 rance (F C .000 .014 .03 08 .000 1.101 2.20 3.92 .000 .748	I .000 16 32 .076 .000 .739 1.48 1.92 .000 .288	M .000 03 06 .023 .000 .197 .393 .678 .000 .163	E .000 .088 .176 .218 .000 04 08 06 .000 .026	S .000 .007 .014 .080 .000 .703 1.41 1.93 .000 .384	Italy (IT C .000 08 17 .036 .000 1.291 2.58 3.77 .000 .641	I .000 11 21 .149 .000 1.113 2.23 2.65 .000 .491	M .000 02 04 .123 .000 .314 .627 .875 .000 .252	E .000 .069 .137 .138 .000 01 02 03 .000 .030	S .000 .116 .231 .230 .000 .466 .931 .913 .000 .296	pain (E C .000 .103 .205 .149 .000 .959 1.92 2.01 .000 .534	I .000 .000 .000 .000 .000 .033 .000 .856 1.71 1.89 .000 .000	M .000 .069 .138 .134 .000 .319 .637 .663 .000 .245	E .000 .100 .200 .285 .000 03 07 07 .000 .037	Neth S .000 .127 .254 .238 .000 .285 .569 1.24 .000 .213	erlands C .000 .100 .200 .246 .000 .702 1.40 1.89 .000 .430	(NL) I .000 08 16 02 .000 1.235 2.47 3.01 .000 .609	M .000 .051 .101 .175 .000 .256 .512 .753 .000 .236
P R F1	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL	E .000 .036 .072 .114 .000 02 04 04 .000 .010 .020	Fig. .000 03 .000 .253 .505 1.11 .000 .138 .275	1.01 c .000 .014 .03 .000 1.101 2.20 3.92 .000 .748 1.50	.000 .000 16 32 .076 .000 .739 1.48 1.92 .000 .288 .576	M .000 03 06 .023 .000 .197 .393 .678 .000 .163 .326	E .000 .088 .176 .218 .000 04 08 06 .000 .026 .051	S .000 .007 .014 .080 .000 .703 1.41 1.93 .000 .384 .767	Italy (IT C .000 08 .17 .036 .000 1.291 2.58 3.77 .000 .641 1.28) I .000 11 21 .149 .000 1.113 2.23 2.65 .000 .491 .981	M .000 02 04 .123 .000 .314 .627 .875 .000 .252 .504	E .000 .069 .137 .138 .000 01 02 03 .000 .030 .030 .059	S .000 .116 .231 .230 .000 .466 .931 .913 .000 .296 .591	pain (E C .000 .103 .205 .149 .000 .959 1.92 2.01 .000 .534 1.07	S) I .000 .000 .000 .033 .000 .856 1.71 1.89 .000 .460 .919 .919	M .000 .069 .138 .134 .000 .319 .637 .663 .000 .245 .489	E .000 .100 .200 .285 .000 03 07 .070 .000 .037 .073	Neth S .000 .127 .254 .238 .000 .285 .569 1.24 .000 .213 .425	eerlands C .000 .200 .246 .000 .702 1.40 1.89 .000 .430 .860	i (NL) I .000 08 16 02 .000 1.235 2.47 3.01 .000 .000 1.225 .000	M .000 .051 .101 .175 .000 .256 .512 .753 .000 .236 .471
P R F1	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM MERT XLM PEBL SALAM	E .000 .036 .072 .114 .000 02 04 04 .000 .010 .020 .040	Fig. .000 03 .007 .03 .000 .253 .505 1.11 .000 .138 .275 .573	1.01 c .000 .014 .03 .000 1.101 2.20 3.92 .000 .748 1.50 2.11	I .000 16 .32 .076 .000 .739 1.48 1.92 .000 .288 .576 1.13 .576	M .000 03 06 .023 .000 .197 .393 .678 .000 .163 .326 .558	E .000 .088 .176 .218 .000 04 08 06 .000 .026 .051 .083	S .000 .007 .014 .080 .000 .703 1.41 1.93 .000 .384 .767 1.02	Italy (IT C .000 08 .17 .036 .000 1.291 2.58 3.77 .000 .641 1.28 1.94) I .000 11 .21 .149 .000 1.113 2.23 2.65 .000 .491 .981 1.53	M .000 02 04 .123 .000 .314 .627 .875 .000 .252 .504 .743	E .000 .069 .137 .138 .000 01 02 03 .000 .030 .030 .059 .056	S .000 .116 .231 .230 .000 .466 .931 .913 .000 .296 .591 .583	pain (E C .000 .103 .205 .149 .000 .959 1.92 2.01 .000 .534 1.07 1.05	S) I .000 .000 .000 .000 .033 .000 .856 1.71 1.89 .000 .000 .460 .919 1.01	M .000 .069 .138 .134 .000 .319 .637 .663 .000 .245 .489 .499	E .000 .100 .200 .285 .000 .03 .07 .07 .000 .037 .073 .110	Neth S .000 .127 .254 .238 .000 .285 .569 1.24 .000 .213 .425 .688	eerlands C .000 .200 .246 .000 .702 1.40 1.89 .000 .430 .860 1.09	 (NL) I .000 08 16 02 .000 1.235 2.47 3.01 .609 1.22 1.58 	M .000 .051 .101 .175 .000 .256 .512 .753 .000 .236 .471 .639
P	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM	E .000 .036 .072 .114 .000 02 04 04 .000 .010 .020 .040	F: S .000 03 07 03 .000 .253 .505 1.11 .000 .138 .275 .573		I .000 16 32 .076 .000 .739 1.48 1.92 .000 .288 .576 1.13 .TR)	M .000 03 06 .023 .000 .197 .393 .678 .000 .163 .326 .558	E .000 .088 .176 .218 .000 04 04 06 .000 .026 .051 .083	S .000 .007 .014 .080 .000 .703 1.41 1.93 .000 .384 .767 1.02 mited A	Italy (IT C .000 08 17 .036 .000 1.291 2.58 3.77 .000 .641 1.28 1.94 rab Emi) I .000 11 21 .149 .000 1.113 2.23 2.65 .000 .491 .981 1.53 rates (A	M .000 02 04 .123 .000 .314 .627 .875 .000 .252 .504 .743 E)	E .000 .069 .137 .138 .000 01 03 .000 .030 .030 .059 .056	S .000 .116 .231 .230 .000 .466 .931 .913 .000 .296 .591 .583 Matexantic Matexantic States Sta	pain (E C .000 .103 .205 .149 .000 .959 1.92 2.01 .000 .534 1.05 exico (M	I .000 .000 .000 .000 .000 .000 .033 .000 .856 1.71 1.89 .000 .460 .919 1.01 IX) IX	M .000 .069 .138 .134 .000 .319 .637 .663 .000 .245 .489 .499	E .000 .100 .200 .285 .000 03 07 07 .000 .037 .073 .110	Neth S .000 .127 .254 .238 .000 .285 .569 1.24 .000 .213 .425 .688 B	erlands C .000 .100 .200 .246 .000 .702 1.40 1.89 .000 .430 .860 1.09 razil (B	<pre>: (NL) I .000 08 16 02 .000 1.235 2.47 3.01 .000 .609 1.22 1.58 R)</pre>	M .000 .051 .101 .175 .000 .256 .512 .753 .000 .236 .471 .639
P	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM PEBL SALAM	E .000 .036 .072 .114 .000 02 04 04 .000 .010 .020 .040 E	F S .000 03 07 03 .000 .253 .505 1.11 .000 .138 .275 .573 Tr S		I .000 16 32 .076 .000 .739 1.48 1.92 .000 .288 .576 1.13 TR) I	M .000 03 06 .023 .000 .197 .393 .678 .000 .163 .326 .558 M	E .000 .088 .176 .218 .000 04 06 .000 .026 .051 .083 Un E	S .000 .007 .014 .080 .000 .703 1.41 1.93 .000 .384 .767 1.02 mited A S	Italy (IT C .000 08 17 .036 .000 1.291 2.58 3.77 .000 .641 1.28 1.94 rab Emit C) I .000 11 21 .149 .000 1.113 2.23 2.65 .000 .491 .981 1.53 rates (A I	M .000 02 04 .123 .000 .314 .627 .875 .000 .252 .504 .743 E) M	E .000 .069 .137 .138 .000 01 02 03 .000 .030 .030 .059 .056 E	S .000 .116 .231 .230 .000 .466 .913 .000 .296 .591 .583 Mathematical S	pain (E C .000 .103 .205 .149 .000 .959 2.01 .000 .534 1.05 exico (M	I .000 .000 .000 .000 .000 .000 .000 .000 .856 1.71 1.89 .000 .460 .919 1.01 IX) I	M .000 .069 .138 .134 .000 .319 .663 .000 .245 .489 .499 M	E .000 .100 .200 .285 .000 03 07 .070 .000 .037 .073 .110 E	Neth S .000 .127 .254 .238 .000 .285 .569 1.24 .000 .213 .425 .688 B S	erlands C .000 .100 .200 .246 .000 .702 1.40 1.89 .000 .430 .860 1.09 rrazil (B C	<pre>F(NL) I F(NL) F(NL)</pre>	M .000 .051 .101 .175 .000 .256 .512 .753 .000 .236 .471 .639 M
P	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM	E .000 .036 .072 .114 .000 02 04 .000 .010 .020 .040 E .000 .020	F S .000 03 .07 .000 .253 .505 1.11 .000 .138 .275 .573 The S .000	1.00 C .000 .014 .03 .000 1.101 2.20 3.92 .000 .748 1.50 2.11 urkey (I C .000	I .000 16 32 .076 .000 .739 1.48 1.92 .000 .288 .576 1.13 TR) I	M .000 03 06 .023 .000 .197 .393 .678 .000 .163 .326 .558 M .000	E .000 .088 .176 .218 .000 .04 08 06 .000 .026 .051 .083 Un E .000	S .000 .007 .014 .080 .000 .703 1.41 1.93 .000 .384 .767 1.02 mited A S .000	Italy (IT C .000 08 17 .030 .000 1.291 2.58 3.77 .000 .641 1.294 1.94 rab Emi C .000 .000	I .000 11 21 .000 1.113 2.23 2.65 .000 .49 .981 1.53 rates (A I	M .000 02 04 .123 .000 .314 .627 .875 .000 .252 .504 .743 E) M .000 .252	E .000 .069 .137 .138 .000 .01 .02 .03 .000 .030 .059 .056 E .000	S S .000 .116 .231 .230 .000 .466 .913 .000 .296 .591 .583 Mathia S .000 .000 .000	pain (E C .000 .103 .205 .149 .000 .959 2.01 .000 .534 1.05 exico (M C .000	S) I .000 .000 .0033 .000 .033 .000 .856 1.71 1.89 .000 .460 .919 1.01 IX I .000	M .000 .069 .138 .134 .000 .319 .663 .000 .245 .489 .499 M .000	E .000 .100 .200 .285 .000 03 07 .070 .000 .037 .073 .110 E .000	Neth S .000 .127 .254 .238 .000 .285 .569 1.24 .000 .213 .425 .688 B S .000	erlands C .000 .100 .200 .200 .246 .000 .702 1.40 1.89 .000 .430 .860 1.09 razil (B C .000	I .000 08 16 02 .000 1.235 2.47 3.01 .000 .609 1.22 1.58 R) I .000 .02	M .000 .051 .101 .175 .000 .256 .512 .753 .000 .236 .471 .639 M .000
P	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM PEBL SALAM mBERT XLM mBERT XLM	E .000 .036 .072 .114 .000 .02 .04 .04 .000 .010 .020 .040 .010 .020 .040 .020 .040 .020 .040	File S .000 03 .07 03 .000 .253 .505 1.11 .000 .138 .275 .573 Tr S .000 .043 .000 .043 .055 .555 .573 .000 .000 .03 .07 .03 .07 .03 .07 .03 .07 .03 .07 .03 .07 .03 .07 .03 .07 .03 .07 .03 .000 .253 .505 1.11 .000 .138 .275 .575	1.50 F c 000 .014 .03 .03 .000 1.101 2.20 .000 .748 1.50 2.11 urrkey (T C .000 .012	I .000 16 .32 .076 .000 .739 1.48 1.92 .000 .288 .576 1.13 TR) I .000 .03 .000 .03 .000 .03	M .000 03 06 .020 .197 .393 .678 .000 .163 .326 .558 M .000 .030 .030	E .000 .088 .176 .218 .000 .04 08 06 .000 .026 .051 .083 U1 E .000 .106	S .000 .007 .014 .080 .703 1.41 1.93 .000 .384 .767 1.02 nited A S .000 .115	Italy (IT C .000 08 17 .036 .000 1.291 2.58 3.77 .000 .641 1.28 1.94 rab Emi C .000 .093	I .000 11 21 .149 .000 1.113 2.23 2.65 .000 .491 .981 1.53 rates (A I .000 10	M .000 02 .012 .000 .314 .627 .875 .000 .552 .502 .743 E) M .000 .056 .112	E .000 .069 .137 .138 .000 .01 .02 .03 .000 .030 .056 E .000 .105	S S .000 .116 .231 .230 .000 .466 .931 .913 .000 .296 .591 .583 Matexan S .000 .042 .982	pain (E C .000 .103 .205 .149 .000 .959 1.92 2.01 .000 .534 1.07 1.05 exico (M C .000 .307 .149	S) I .000 .000 .000 .000 .000 .033 .000 .856 1.71 1.89 .000 .460 .919 1.01 IX) I .000 11	M .000 .069 .138 .134 .000 .319 .637 .663 .000 .245 .489 .499 M .000 .053	E .000 .100 .200 .285 .000 .03 .07 .07 .07 .070 .000 .037 .073 .110 E .000 .147	Neth S .000 .127 .254 .000 .285 .569 1.24 .000 .213 .425 .688 B S .000 .025 5	erlands C .000 .100 .200 .246 .000 .702 1.40 1.89 .000 .430 .860 1.09 razil (B C .000 .360	i (NL) I .000 08 16 02 .000 1.235 2.47 3.01 .000 .609 1.22 1.58 R) I .000 05 11	M .000 .051 .101 .175 .000 .256 .512 .753 .000 .236 .471 .639 M .000 .090
P	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM	E .000 .036 .072 .114 .000 .02 .04 .04 .000 .010 .020 .040 E .000 .087 .173 .220	F S .000 03 .000 .253 .505 1.11 .000 .138 .275 .573 Tr S .000 .043 .083 .085 .018		I .000 16 .32 .076 .000 .739 1.48 1.92 .000 .288 .576 1.13 TR) I .000 03 .000	M .000 03 06 .023 .000 .197 .393 .678 .000 .163 .326 .558 M .000 .030 .030 .059 .091	E .000 .088 .176 .218 .000 04 08 06 .000 .026 .051 .083 UI E .000 .106 .212 .209	S .000 .007 .014 .080 .000 .703 1.41 1.93 .000 .384 .767 1.02 nited A S .000 .115 .230 .208	Italy (IT C .000 08 17 .036 .000 1.291 2.58 3.77 .000 .641 1.28 1.94 rab Emit C .000 .098 .193	I .000 11 .21 .149 .000 1.113 2.23 2.65 .000 .491 .981 1.53 rates (A I .000 10 .202	M .000 02 04 .123 .000 .314 .627 .875 .000 .252 .504 .743 E) M .000 .056 .1127	E .000 .069 .137 .138 .000 .01 .02 .03 .000 .030 .059 .056 E .000 .105 .210 .258	S S .000 .116 .231 .230 .000 .466 .931 .913 .000 .296 .591 .583 Material S S .000 .042 .083 .059	pain (E C .000 .103 .205 .149 .000 .959 1.92 2.01 .000 .534 1.07 1.05 exico (M C .000 .307 .614 .686	S) I .000 .000 .000 .000 .0033 .000 .856 1.71 1.89 .000 .460 .919 1.01 IX) I .000 11 22 .015 .015	M .000 .069 .138 .134 .000 .319 .637 .663 .000 .245 .489 .499 .499 M .000 .053 .106	E .000 .100 .200 .285 .000 .037 .077 .070 .000 .037 .073 .110 E .0000 .147 .291	Neth S .000 .127 .254 .238 .000 .285 .569 1.24 .000 .213 .425 .688 B S .000 .028 .055 .055 .055	erlands C .000 .200 .200 .200 .200 .702 1.40 1.89 .000 .430 .860 1.09 rrazil (B C .000 .360 .716	i (NL) I .000 08 16 12 .000 1.235 2.47 3.01 .000 .609 1.22 1.58 R) I .000 05 05 16 00	M .000 .051 .101 .175 .000 .256 .512 .753 .000 .236 .471 .639 M .000 .090 .179 .214
P R P P	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM PEBL SALAM PEBL SALAM	E .000 .036 .072 .114 .000 02 04 04 .000 .010 .020 .040 E .000 .087 .173 .220	F S 03 03 03 03 03 03 00 253 505 1.11 000 138 275 573 Tr S 000 043 085 010 03 03 03 03 03 03 03 0		I .000 16 .076 .000 .739 1.48 1.92 .000 .288 .576 1.13 TR) I .000 03 05 .075	M .000 -03 -06 .023 .000 .197 .393 .678 .000 .163 .326 .558 M .000 .030 .030 .059 .090	E .000 .088 .176 .218 .000 04 08 06 .000 .026 .051 .083 U1 E .000 .106 .212 .209	S .000 .007 .014 .080 .000 .703 1.41 1.93 .000 .384 .767 1.02 nited A S .000 .115 .230 .200	Italy (IT C .000 08 17 .036 .000 1.291 2.58 3.77 .000 .641 1.28 1.94 rab Emit C .000 .098 .196 .000	I .000 11 .149 .000 1.113 2.23 2.65 .000 .491 .981 1.53 rates (A I .000 10 .20 .000	M .000 02 04 .123 .000 .314 .627 .875 .000 .252 .504 .743 E) M .000 .056 .112 .127 .000	E .000 .069 .137 .138 .000 .01 .02 .030 .000 .030 .059 .056 E .000 .105 .210 .220	S .000 .116 .231 .230 .000 .466 .931 .913 .000 .296 .591 .583 Ma S .000 .042 .083 .059 .000	pain (E C .000 .103 .205 .149 .000 .959 1.92 2.01 .000 .534 1.07 1.05 exico (M C .000 .307 .614 .000	S) I .000 .000 .000 .000 .033 .000 .856 1.71 1.89 .000 .460 .919 1.01 IX) I .000 .11 .22 .000 .11 .22 .000	M .000 .069 .138 .134 .000 .319 .637 .663 .000 .245 .489 .499 .499 M .000 .053 .106 .195 .000	E .000 .100 .200 .285 .000 .03 .07 .07 .07 .000 .037 .073 .110 E .000 .147 .294 .291	Neth S .000 .127 .254 .238 .000 .285 .569 1.24 .000 .213 .425 .688 B S .000 .028 .055 .056	erlands C .000 .200 .200 .200 .702 1.40 1.89 .000 .430 .860 1.09 razil (B C .000 .360 .719 .749	i (NL) I .000 08 .16 102 .000 1.235 2.47 3.01 .000 .609 1.22 1.58 R) I .000 05 11 .000 .005	M .000 .051 .101 .175 .000 .256 .512 .753 .000 .236 .471 .639 M .000 .090 .179 .214
P P R	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM	E .000 .036 .072 .114 .000 02 04 04 .000 .010 .020 .040 E E .000 .087 .173 .220 .002	F S .000 03 07 03 .000 .253 .505 5.1.11 .000 .138 .275 .573 To S .000 .043 .085 .018 .004		I .000 16 32 .076 .000 .732 .076 .000 .732 .076 .000 .288 .576 .000 .288 .576 .113 .000 .03 .05 .074 .000	M .000 03 .06 .023 .000 .193 .393 .678 .000 .163 .326 .558 M .000 .030 .030 .059 .091 .000 190	E .000 .088 .176 .218 .000 .04 .08 .06 .000 .026 .051 .083 Un E .000 .106 .212 .209 .000 .02	S .000 .007 .014 .080 .000 .703 1.41 1.93 .000 .384 .767 1.02 nited A S .000 .115 .230 .208 .000 .376	Italy (IT C .000 08 .17 .036 .000 1.291 2.58 3.77 .000 .641 1.248 1.94 rab Emi C .000 .098 .196 .103 .0044	I .000 11 21 .149 .000 1.113 2.23 2.65 .000 .491 .981 1.53 rates (A I .000 10 20 .000 1.870	M .000 04 .123 .000 .314 .627 .875 .000 .252 .504 .743 E) M .0056 .112 .127 .000 .352	E .000 .069 .137 .138 .000 -01 -02 -03 .000 .030 .030 .059 .056 E E .000 .105 .210 .258 .000	S .000 .116 .231 .230 .000 .466 .931 .913 .000 .296 .591 .583 Me S .000 .042 .083 .059 .000 .488	pain (E C .000 .103 .205 .149 .000 .959 2.01 .000 .534 1.07 1.05 exico (N C .000 .307 .614 .686 .000	S) I .000 .000 .000 .000 .033 .000 .856 1.71 1.89 .000 .460 .919 1.01 IX) I .000 .111 22 .015 .000	M .000 .069 .138 .134 .000 .637 .663 .000 .245 .489 .499 .499 M .000 .053 .106 .195 .000	E .000 .200 .285 .000 .03 .07 .07 .000 .037 .073 .110 E .000 .147 .294 .291 .000	Neth S .000 .127 .254 .238 .000 .285 .569 1.24 .000 .213 .425 .688 B S .000 .028 .055 .056 .000 .025 .055 .056	erlands C .000 .100 .200 .246 .000 .702 1.40 1.89 .000 .430 .860 1.09 razil (B C .000 .360 .719 .746 .000 1.155	i (NL) I .000 08 16 02 .000 1.235 2.47 3.01 .000 .609 1.22 1.58 R) I .000 05 11 00 .000 .605 11	M .000 .051 .101 .175 .000 .256 .512 .753 .000 .236 .471 .639 M .000 .090 .179 .214 .000 .330
P	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM	E .000 .036 .072 .114 .000 .02 .04 .000 .010 .020 .040 .040 .087 .173 .220 .000 .027 .04	F S .000 .03 .07 .03 .000 .253 .505 .111 .000 .138 .275 .573 .000 .043 .085 .018 .000 .168 .327		I .000 16 32 .076 .000 .739 1.48 .92 .000 .288 .576 .000 .288 .576 .000 .033 .055 .074 .000 .376	M .000 -03 .06 .023 .000 .197 .393 .678 .000 .163 .326 .558 M .000 .030 .059 .059 .091 .000 .380	E .000 .088 .176 .218 .000 .04 .08 .000 .026 .051 .083 U1 E .000 .106 .212 .209 .000 .026 .010 .026 .212 .209	S .000 .014 .080 .014 .000 .014 .000 .014 .000 .001 .000 .384 .767 1.02 nited A S .000 .115 .230 .208 .000 .376 .752	Italy (IT C .000 .08 .17 .036 .000 1.291 2.58 3.77 .000 .641 1.294 rab Emi C .000 .098 .103 .000 1.034	I .000 11 21 .149 .000 1.113 2.23 2.65 .000 .491 .981 1.53 rates (A I .000 10 .000 .000 .000 .02 .000 .02 .000 .870 .974	M .000 04 .123 .000 .314 .627 .875 .000 .252 .504 .743 E) M .000 .554 .122 .000 .564 .112 .127 .000 .352 .703	E .000 .069 .137 .138 .000 -01 -02 .03 .030 .030 .030 .056 .056 .000 .105 .210 .258 .000 -03 .06	S .000 .116 .231 .230 .000 .466 .931 .913 .000 .296 .593 .583 Ma S .000 .042 .083 .059 .000 .483 .059	pain (E C .000 .103 .205 .149 .000 .959 1.92 2.01 .000 .534 1.05 exico (M C .000 .307 .614 .686 .000 .952	S) I .000 .000 .000 .000 .000 .033 .000 .856 1.71 1.89 .000 .460 .919 1.01 IX) I .000 .11 .22 .015 .0000 1.345 2.69 .69	M .000 .063 .138 .134 .000 .319 .663 .000 .245 .489 .489 .000 .053 .106 .195 .000 .314	E .000 .200 .285 .000 .285 .000 .037 .077 .077 .077 .070 .037 .073 .110 E E .000 .147 .294 .291 .000 .035	Neth S .000 .127 .254 .238 .000 .285 .569 1.24 .000 .213 .425 .688 B S .000 .028 .055 .056 .000 .710 .142	Internation 000 .000 .200 .246 .000 .702 1.40 .89 .000 .430 .800 .000 .000 .430 .600 .000 .360 .719 .746 .000 1.155 2.31	I .000 08 16 02 .000 1.235 2.47 3.01 .000 .609 1.258 R) I .000 .005 11 .000 .000 .000	M .000 .051 .101 .175 .000 .256 .512 .753 .000 .236 .471 .639 M .000 .090 .179 .214 .000 .300 .659
P P R	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM	E .000 .036 .072 .114 .000 02 04 .000 .010 .020 .040 E .000 .087 .173 .220 .000 02 02 02 03	F S -000 -03 -07 -03 .000 .253 .505 1.11 .000 .138 .275 .575 .575 .575 .575 .000 .043 .085 .018 .000 .164 .327 .468		I .000 16 .076 .076 .076 .000 .739 1.48 .092 .000 .288 .576 .000 .288 .576 .000 .088 .076 .000 .0376 .000 .376 .000 .376 .000 .376 .000 .376 .752 .864	M .000 .03 .06 .023 .000 .197 .393 .678 .000 .163 .326 .558 M .000 .030 .030 .059 .091 .000 .190 .380 .474	E .000 .088 .176 .218 .000 .04 .04 .000 .026 .051 .083 U1 E .000 .106 .212 .209 .000 .02 .02 .02 .02 .03	S .000 .007 .014 .080 .000 .703 1.41 .93 .000 .384 .767 1.02 nited A S .000 .115 .230 .208 .000 .376 .238 .000 .376 .752 .836	Italy (IT C .000 08 .17 .036 .000 1.291 2.58 3.77 .000 .641 1.28 1.94 rab Emi C .000 .098 .196 .103 .000 1.074 2.15 2.88	I .000 11 .21 .149 .000 1.113 2.265 .000 .491 .981 1.53 rates (A I .000 .010 .020 .020 .020 .020 .020 .020 .020 .020 .020 .020 .020 .020 .020 .021	M .000 02 .04 .123 .000 .314 .627 .875 .000 .252 .504 .743 E) M .000 .552 .000 .564 .743 E) M .000 .552 .703 .739	E .000 .069 .137 .138 .000 .01 .03 .030 .030 .030 .059 .056 E .000 .105 .210 .258 .000 .03 .210 .258	S .000 .116 .231 .230 .000 .466 .913 .000 .296 .591 .583 .000 .048 .000 .0483 .059 .000 .488 .975 .000	pain (E C .000 .103 .205 .149 .000 .959 1.92 2.01 .000 .534 1.05 exico (M C .000 .307 .614 .686 .000 .959 1.92 2.61	S) I .000 .000 .000 .000 .000 .033 .000 .856 1.71 1.89 .000 .460 .919 1.01 LX) I .000 .1345 2.69 2.88	M .000 .069 .138 .134 .000 .319 .637 .663 .000 .245 .489 .499 .499 M .000 .053 .106 .195 .000 .314 .628 .832	E .000 .200 .285 .000 .285 .000 .03 .07 .07 .07 .07 .07 .07 .07 .07 .07 .07	Neth S .000 .127 .254 .238 .000 .285 .569 1.24 .000 .213 .425 .688 B S .000 .028 B S .000 .028 .055 .056 .000 .710 1.42 1.51	erlands C .000 .200 .246 .000 .702 1.40 1.89 .000 .430 .860 1.09 razil (B C .000 .360 .719 .746 .000 1.155 2.31 2.42	i (NL) I .000 08 01 02 .000 1.235 .02 .000 1.235 .000 .609 1.221 .000 .609 1.228 .000 .000 .609 .022 1.58 R I .000 .005 .011 .000 .618 1.13 .13 .13	M .000 .051 .101 .175 .000 .256 .512 .753 .000 .236 .471 .639 M .000 .090 .090 .179 .214 .000 .330 .678
P R P R F1	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT	E .000 .036 .072 .114 .000 .02 .04 .04 .000 .010 .020 .040 E .000 .087 .173 .220 .000 .02 .02 .03 .000	F S 03 03 03 03 03 03 03 03	Initial condition rance (F C .000 .014 .03 .000 1.101 2.20 .000 .748 1.50 2.11 urkey (I C .000 .012 .020 .021 .000 .012 .020 .000 .652 1.300 .157 .000	I .000 16 .32 .076 .000 .739 1.48 .92 .000 .288 .576 1.13 .000 .033 .003 .0374 .000 .376 .752 .000	M .000 03 06 .023 .000 .197 .393 .678 .000 .163 .326 .558 .000 .163 .326 .558 .000 .030 .030 .030 .030 .0591 .000 .380 .474 .000	E .000 .088 .176 .218 .000 .04 .04 .000 .026 .051 .000 .026 .051 .080 .000 .106 .212 .209 .000 .02 .02 .02 .03 .000	S .000 .007 .014 .080 .000 .703 1.41 1.93 .000 .384 .767 1.02 nited A S .000 .115 .208 .000 .376 .752 .836 .000	Italy (IT C .000 08 .17 .036 .000 1.291 2.58 3.77 .000 .641 1.28 1.94 1.94 C .000 .098 .103 .000 1.074 2.15 2.88 .000	I .000 11 .21 .149 .000 1.113 2.23 .000 .1113 2.65 .000 .491 .981 1.53 rates (A I .000 .10 .02 .000 1.870 3.74 2.94 .000	M .000 02 .04 .123 .000 .314 .627 .000 .252 .504 .743 E) M .000 .056 .112 .127 .000 .352 .703 .739 .000	E .000 .069 .137 .138 .000 .01 .030 .030 .030 .059 .056 E .000 .105 .210 .258 .000 .258 .000 .03 .06 .06 .06	S .000 .116 .231 .230 .000 .466 .931 .913 .000 .296 .591 .581 .581 .000 .042 .083 .059 .000 .488 .976 1.61 .000	pain (E C .000 .103 .205 .149 .000 .959 1.92 2.01 .000 .534 1.07 1.06 .000 .334 1.07 1.05 .000 .307 .614 .686 .000 .959 1.92 2.61 .000	I .000 .000 .000 .000 .000 .033 .000 .856 1.71 1.89 .000 .460 .919 1.01 IX) I .000 .111 .000 .112 .000 1.345 2.69 2.88 .000	M .000 .069 .134 .000 .319 .663 .000 .245 .489 .499 M .000 .053 .106 .195 .000 .314 .632 .000 .314 .628 .000	E .000 .100 .200 .285 .000 .03 .07 .07 .07 .07 .07 .07 .07 .07 .07 .07	Neth S .000 .127 .254 .238 .000 .285 .569 .242 .000 .213 .425 .688 S .000 .028 .056 .000 .710 1.42 1.51 .000	Internation 000 .000 .200 .246 .000 .702 1.40 .000 .430 .889 .000 .430 .860 1.09 razil (B C .000 .360 .719 .746 .000 1.155 2.31 2.42 .000	i (NL) I 000 -08 16 02 .000 1.235 2.47 2.000 1.235 2.47 3.01 .000 .609 1.22 1.58 R) I .000 05 11 00 .000 .618 1.24 1.13 .000 .011	M .000 .051 .101 .175 .000 .256 .512 .753 .000 .236 .471 .639 M .000 .090 .179 .214 .000 .330 .658 .000
P F1 P R	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM MBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM	E .000 .036 .072 .114 .000 .02 .04 .04 .040 .020 .040 .020 .040 .020 .040 .020 .040 .020 .040 .020 .02	F S 03 03 03 03 03 03 000 253 505 1.11 000 138 275 573 573 573 573 000 043 000 043 000 03 03 03 03 03 03 	Instance (F C .000 .014 .03 .000 .1101 2.20 .000 .120 .000 .748 1.50 2.11 urkey (T C .000 .012 .000 .652 1.30 1.50 .000 .652 1.30 1.507	I .000 16 .32 .076 .000 .739 1.48 1.92 .000 .288 .576 1.13 TR) I .000 .03 .05 .074 .000 .376 .752 .864 .000 .185	M .000 03 .000 .197 .933 .678 .000 .163 .326 .558 M .000 .030 .030 .030 .030 .0591 .000 .380 .474 .000 .142	E .000 .088 .176 .218 .000 .04 .06 .000 .026 .051 .000 .026 .051 .083 UI E .000 .106 .212 .000 .026 .02 .02 .02 .02 .04 .03 .000 .026 .02 .02 .02 .04 .02 .02 .02 .02 .02 .02 .02 .04 .05 .000 .04 .05 .000 .026 .051 .000 .026 .051 .000 .026 .051 .000 .026 .051 .000 .026 .051 .000 .026 .051 .000 .026 .051 .000 .026 .051 .000 .026 .051 .000 .026 .051 .000 .026 .051 .000 .026 .051 .000 .026 .051 .000 .026 .020 .026 .000 .026 .020 .026 .000 .026 .026	S .000 .007 .014 .080 .000 .703 1.41 1.93 .000 .384 .767 1.02 mited A S .000 .115 .230 .208 .000 .376 .752 .836 .000 .254	Italy (IT C .000 08 17 .036 .000 1.291 2.58 3.77 .000 .641 1.28 1.94 1.98 1.98 1.90 .000 .098 .103 .000 1.074 2.15 2.88 .000 .660	I .000 11 .21 .149 .000 1.113 2.23 .000 .491 .981 1.53 rates (A I .000 .10 .02 .000 1.870 3.74 2.94 .000 .773	M .000 02 .04 .123 .000 .314 .627 .875 .000 .252 .504 .743 E) M .000 .056 .1127 .000 .352 .703 .703 .000 .288	E .000 .069 .137 .138 .000 .01 .030 .030 .030 .056 E E .000 .105 .210 .056 .200 .258 .000 .258 .000 .258 .000 .03 .06 .06 .060 .000	S .000 .116 .231 .230 .000 .466 .913 .000 .296 .591 .591 .591 .591 .000 .042 .033 .059 .000 .488 .976 1.61 .000 .293	pain (E C .000 .149 .000 .959 1.92 2.01 .000 .534 1.07 1.05 .000 .307 .646 .000 .959 1.92 2.61 .000	S) I .000 .000 .000 .000 .033 .000 .856 1.71 1.89 .000 .460 .919 1.01 IX) I .000 .111 .22 .015 .000 1.345 2.69 2.88 .000 .598 .598	M .000 .069 .134 .000 .319 .637 .663 .000 .245 .489 .499 M .000 .053 .000 .314 .628 .832 .0000 .271	E .000 .100 .200 .285 .000 .03 .07 .07 .07 .07 .07 .07 .07 .07 .07 .07	Neth S .000 .127 .254 .238 .000 .285 .569 1.24 .000 .213 .425 .688 B S .000 .028 .055 .056 .000 .710 1.42 1.51 .000 .368	Internation 000 .000 .200 .246 .000 .702 1.40 .000 .430 .860 1.09 .000 .430 .600 .000 .430 .600 .000 .360 .746 .000 .155 2.31 2.422 .000 .795	I .000 08 16 02 .000 1.235 2.47 3.01 .000 .609 1.22 1.58 R) I .000 .055 11 .000 .000 .000 .000 .000 .000 .000 .000 .220	M .000 .051 .101 .175 .000 .256 .512 .753 .000 .236 .471 .639 M .000 .090 .179 .214 .000 .330 .659 .678 .000
P F1 P R	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM	E .000 .036 .072 .114 .000 .02 .04 .000 .010 .020 .040 E .000 .087 .173 .200 .087 .173 .200 .000 .087 .173 .200 .000 .02 .04 .04 .02 .04 .02 .04 .04 .02 .04 .04 .02 .04 .04 .02 .04 .04 .04 .020 .04 .04 .020 .04 .04 .04 .04 .020 .04 .04 .04 .04 .04 .04 .04 .04 .04 .0	F S 03 03 03 03 03 03 03 03	Image Image rance (F C .000 .014 .03 .000 1.101 2.20 .000 .014 .03 .000 .748 1.50 2.11 .000 .012 .023 .000 .652 1.30 1.57 .000 .342 .683 .683	I .000 16 .32 .076 .000 .739 1.48 1.92 .000 .288 .576 1.13 TR) I .000 .03 .055 .074 .000 .376 .752 .864 .000 .185 .369	M .000 03 06 .023 .000 .197 .393 .678 .000 .163 .326 .558 M .000 .030 .030 .030 .059 .091 .000 .190 .380 .474 .000 .142 .283	E .000 .088 .176 .218 .000 04 08 06 .000 .026 .051 .083 U1 E .000 .106 .212 .000 .026 .02 04 03 .000 .045 .090	S .000 .007 .014 .080 .000 .703 1.41 1.93 .000 .384 .767 1.02 nited A S .000 .115 .230 .000 .376 .752 .836 .000 .254 .508	Italy (IT C .000 08 17 .036 .000 1.291 2.58 3.77 .000 .641 1.28 1.94 rab Emit C .000 .098 .196 .000 .000 .001 .002 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .660 .022	I .000 11 .21 .149 .000 1.113 2.23 2.65 .000 .491 .981 1.53 rates (A I .000 .10 .20 .000 1.870 3.74 2.94 .000 .773 1.55	M .000 04 .123 .000 .314 .627 .875 .000 .252 .504 .743 E) M .0056 .112 .127 .000 .352 .703 .739 .000 .288 .575	E .000 .069 .137 .138 .000 -01 -02 -03 .000 .030 .059 .056 E E .000 .105 .210 .258 .000 -03 -06 06 .000 .040	S .000 .116 .231 .230 .000 .466 .931 .913 .000 .296 .591 .583 Ma S .000 .042 .083 .059 .000 .488 .976 1.61 .000 .295 .585	pain (E C .000 .103 .205 .149 .000 .959 2.01 .000 .534 1.05 exico (N C .000 .307 .614 .686 .000 .959 1.92 2.61 .000	S) I .000 .000 .000 .000 .000 .033 .000 .856 1.71 1.89 .000 .460 .919 1.01 IX) I .000 .111 .222 .015 .000 1.345 2.69 2.88 .000 .598 1.20 .598	M .000 .069 .138 .134 .000 .319 .637 .663 .000 .245 .489 .499 M .000 .053 .106 .195 .000 .314 .628 .832 .0000 .271 .542	E .000 .100 .200 .285 .000 .03 .07 .07 .07 .07 .000 .037 .073 .110 E .000 .147 .294 .294 .294 .294 .294 .294 .000 .03 03 05 04 .000 .000	Neth S .000 .127 .254 .238 .000 .285 .569 1.24 .000 .213 .425 .688 B S .000 .028 .055 .056 .055 .056 .000 .710 1.42 1.51 .000 .368 .736	C .000 .100 .200 .246 .000 .721 .40 1.89 .000 .430 .860 1.09 razil (B C .000 .360 .719 .746 .000 .1155 2.31 2.42 .000 .795 1.59	I .000 08 16 02 .000 1.235 2.47 3.01 .000 09 1.22 1.58 R) I .000 05 11 .000 .618 1.24 .13 .000 .290 .579	M .000 .051 .101 .175 .000 .256 .512 .753 .000 .236 .471 .639 M .000 .090 .179 .214 .000 .330 .659 .678 .000 .276 .551

recall, and F-score. The results of our experiments on the four class variant of the problem are given in Table 1. Results on other variants follow a similar trend and are provided in Appendix C.

From our results, we observe that SALAM consistently outperforms both the baselines on F1-score across all regions and classes upto 65% (on an average by 15%). While SALAM is able to provide higher precision than the previous baselines for the 'E' class in several regions such as AU, CA, IN, and others, the major boost in overall performance is driven by improvement in performance on the classes of S, C, and I. This demonstrates SALAM's ability to leverage the graph information to learn better discriminative features unaffected by the innate class imbalance of the datasets. Also, we note that the performance improvement for the regions with highest number of data samples, i.e., IN, UK, and US is also the highest at 11%, 23%, and 24%, respectively. This implies that SALAM is able to learn better discriminative features with higher number of training samples. Furthermore, we note that the average performance improvement on majority English language e-commerce regions is 13.5% and non-English language e-commerce regions is 7.9%. However, comparing the regions of English CA and non-English TR with similar number of data samples, we observe that the performance improvement is comparable at $\approx 6\%$. Hence, we conclude that, while the stand-alone performance is high, the reason for lower performance boost in non-English language regions is caused by a lower number of data samples and not due to the model architecture. Another point to note is that the SALAM's performance is 30% – 80% higher than XLM. Given that XLM is the language model used in SALAM, this performance gain demonstrates the main advantage of including graph information in the task of search relevance classification.

4.3 RQ2: Two-phase Learning Framework

To confirm the effectiveness of the two-phase learning framework with region-agnostic pre-training and region-specific fine-tuning, we compare it against a single phase training and validation approach. To get the single phase model (SALAM-S), we train the model on the combined training datasets of all the models but for a larger number of epochs (24 in this experiment)⁴. The comparison metrics are precision, recall, and F1. The results of this experiment are presented in Table 2.

Table 2: Loss in performance by using a single phase training framework (SALAM-S) in comparison to the two phase training model. The metrics are relative to the performance of SALAM, i.e., a cell value of x implies that SALAM-S performs $(1 + x) \times$ SALAM.

Region	Р	R	F1	Region	Р	R	F1
AU	154	110	150	FR	054	265	207
CA	080	197	153	IT	129	153	148
IN	107	089	117	ES	085	117	106
SG	097	062	080	NL	070	134	107
UK	030	175	124	TR	040	097	071
US	055	155	121	AE	038	072	061
JP	159	182	174	MX	069	114	102
DE	103	212	171	BR	076	070	073

From our results, we observe that two-phase learning improves the performance on test set by 3%-27% when compared to a singlephase framework trained on the same number of epochs. This exhibits the unique nature of each region's e-commerce queries and promotes the case for region-specific fine-tuning even in the case of multilingual models.

4.4 RQ3: Graph Encoders

For this experiment, we select the popular graph representation frameworks of DeepWalk, Chebyshev, Simple Graph Neural Network (GNN), Graph Recurrent Network (GRN), Graph Convolution Networks (GCN), and Graph Attention Network (GAT) as our candidates. We replace the neighborhood aggregation module with the candidate graph networks in our comparative analysis. To select the graph encoder, we primarily consider the performance metrics of precision, recall, and F1, but in a computationally restrained (to 4GB of VRAM) setting to simulate industry setup. The results of our study are presented in Table 3.

Table 3: Comparison between variants of SALAM with different graph encoders. The results are shown relative to the performance of the DeepWalk variant, i.e., a cell value of ximplies that the variant performs $(1 + x) \times$ DeepWalk.

Model Variant	Р	R	F1
SALAM-DeepWalk [25]	.000	.000	.000
SALAM-GNN [34]	.126	.498	.327
SALAM-GRN [39]	.167	.557	.377
SALAM-GAT [31]	.208	.616	.427
SALAM-Chebyshev [7]	.213	.627	.435
SALAM-GCN [15]	.235	.678	.472

In our analysis, we observe that given the industry-level memory constraints, the GCN network performs the best in the classification task and hence, we select it as the graph encoder in SALAM.

4.5 RQ4: Practical Environment

In this section, we analyze the memory requirements and processing speed of the model's training and inference pipeline and compare it against the baselines for its suitability to an industrial application⁵.

Table 4: Memory and processing requirements of different models in the training and inference pipeline. The columns present the number of parameters (Param), pre-training time (PTT), fine-tuning time (FTT), inference time (IT), VRAM requirement (Mem), and disk space requirement (Disk). PTT and FTT are provided in seconds per epoch and IT is given in milliseconds per sample. Mem and Disk requirements are given in Gigabytes.

Model	Param	PTT	FTT	IT	Mem	Disk
mBERT	110M	128K	215	10.67	1.01	16.2
XLM	270M	133K	229	10.87	2.49	39.8
PEBL	150M	130K	217	10.83	1.38	22.1
SALAM	279M	135K	231	11.05	2.57	169.1

From Table 4, we note that our model and the baselines have similar memory requirements to the XLM model and conforms to the constraints of a general industrial application environment. Additionally, we note that the increase in training and inference times of SALAM when compared to PEBL is within $\approx 3\%$ and $\approx 2\%$, respectively. Given the monthly build timelines, the difference is negligible even for a larger scale of data. However, a significant challenge is the graph pre-computation module. Given, the large scale of product catalogues and the frequency of queries, it is computationally challenging to retrieve the local neighborhood during inference. Hence, we utilize the training set and purchase information to pre-compute the local neighborhoods and store it as a hash-table for O(1) retrieval during inference. The inductive nature of SALAM ensures language model-level results are available for the non-covered infrequent queries. However, when compared to PEBL, the graph adds to a huge disk requirement (128GB) and additional maintenance in practice.

⁴Note that the two phase approach uses 4 epochs for pre-training and 20 for finetuning, so to maintain a fair comparison we train the single phase with 24 epochs.

⁵generally 4GB of VRAM, 16 GB RAM, and 1TB of disk space.



Figure 4: SALAM Workflow. The existing annotation module can seamlessly be integrated with the training and inference module of our model. The additional disk requirement for the pre-computed graph database is trivial and within limits of general industrial settings.

5 DISCUSSION

In this section, we describe the strategy to deploy SALAM in an industrial application and discuss its impact to e-commerce search.

5.1 Deployment Strategy

As illustrated in Figure 4, SALAM can be trained offline using manually annotated datasets and region-specific checkpoints can be stored for inference. One can load these checkpoints to unique SALAM instances for the different e-commerce regions and deploy the model in a industrial setting using the LuaJIT⁶ platform. LuaJIT loads the model in-memory for real-time inference, removing the additional overhead of weight transfer from disk to GPU memory. In accordance with the inference pipeline, query-product pairs can be processed in batches on multiple processing units and the labels saved for further utilization in downstream modules. For any workflow that already uses query-product pair as an input for classification, integration of SALAM with such workflows is trivial with minor changes. The graph preprocessing operation is also cached and looked up in real-time. Specifically, given the long tailed nature of product search queries, one can precompute query and product neighborhoods for the samples that correspond to the majority of traffic. Efficient online inference methods can also be used to compute the representations in real-time for the tail. Given the performance gains from the graph information and negligible difference in inference time, deploying SALAM makes it a viable investment in practice.

5.2 Contribution to the search engine

In this section, we describe the impact of having an ESCI classifier in a product search engine. E-commerce product search ranking depends on lexical, behavioral, and semantic matching. Behavioral data can sometimes be noisy, and this leads to biases in the data used to train these models (see for e.g., [20]). Having a classifier perform an ESCI-based classification at the final stage, or use these as inputs to other downstream models can help reduce these issues. Results from these models can also be used for customer messaging as to why a certain item was shown in response to a query; for example, why a charger was shown for a phone query. Improving the performance of ESCI classifiers can thus help improve both product search quality and the trust customers place in these systems, helping practitioners better serve their customers in turn.

6 CONCLUSION

In this paper, we presented Structure-Aware multilingual LAnguage Model (SALAM), a hybrid text and graph based model, that uses a language model in congruence with a GCN network to respectively capture both semantic and relational information for the task of ESCI classification. We have shown the effectiveness of our model in comparison to the currently used alternatives on multiple ESCI classification problem variants. Additionally, we have also demonstrated the effectiveness of a two-phase training setup in handling multiple e-commerce regions, as well as empirically demonstrated our choice of the graph encoder. Moreover, we have also compared SALAM with its alternatives in terms of memory and processing requirements during inference and also detailed its case for deployment in existing industrial pipelines.

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⁶https://luajit.org/

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A SALAM ALGORITHMS

Algorithms 1 and 2 are the training and inference process flows of the SALAM model, respectively.

Algorithm 1: SALAM training flow.

Input: Query-product pairs $x = \{(Q, P)\}$, Pre-computed neighborhoods $x_G = \{(Q_G, P_G)\}$, Ground truth *y*; **Output:** Predictor P_{θ}, θ ; 1 Initialize model parameters θ ; ² for number of epochs; until convergence do Initialize loss l = 0; 3 for $(Q, P) \in x, (Q_G, P_G) \in x_G$ do 4 # Process through language model 5 $t_{O,P} = \phi_F^f(XLM(Q, P));$ using Eq. (2) 6 # Aggregate node neighborhoods 7 $g_{O,P} = GCN(Q_G) \circ GCN(P_G)$; using Eq. (5) 8 # Attention Pooling C $e_{O,P} = t_{O,P} \circ g_{O,P}$; using Eq. (6) 10 $q_{Q,P} = \phi_{3f}^{h} (e_{Q,P}); \text{ using Eq. (7)}$ 11 $k_{Q,P} = \phi_{3f}^{\vec{h}} (e_{Q,P}); \text{ using Eq. (7)}$ 12 $v_{Q,P} = \phi_{3f}^{h} (e_{Q,P}); \text{ using Eq. (7)}$ 13 $a_{Q,P} = \left\{ \frac{exp(\alpha_{ij})}{\sum_{i=0}^{h} exp(\alpha_{ij})} v_i \right\}_{i=0}^{h}; \text{ using Eq. (8)}$ 14 $o_{Q,P} = Softmax\left(\phi_h^{|y|}(a_{Q,P})\right); \text{ using Eq. (9)}$ 15 # Loss Calculation 16 $l = l + L(o_{Q,P}, y_k)$; using Eq. (10) 17 end 18 $\theta \leftarrow \theta - \nabla_{\theta} l;$ # Update parameters 19 end 20 21 return P_{θ}, θ

Algorithm 2: SALAM inference flow.

Input: {(Q, P)}, {(Q_G, P_G)}, Region-specific Model Parameters θ_r ; Output: Label y_k ; $t_{Q,P} = \phi_{F,\theta_r}^f (XLM_{\theta_r}(Q, P))$; using Eq. (2) $g_{Q,P} = GCN_{\theta_r}(Q_G) \circ GCN_{\theta_r}(P_G)$; using Eq. (5) 3 # Attention Pooling $e_{Q,P} = t_{Q,P} \circ g_{Q,P}$; using Eq. (6) $q_{Q,P} = \phi_{3f,\theta_r}^h (e_{Q,P})$; using Eq. (7) $k_{Q,P} = \phi_{3f,\theta_r}^h (e_{Q,P})$; using Eq. (7) $v_{Q,P} = \phi_{3f,\theta_r}^h (e_{Q,P})$; using Eq. (7) $a_{Q,P} = \left\{ \frac{exp(\alpha_{ij})}{\sum_{j=0}^h exp(\alpha_{ij})} v_i \right\}_{i=0}^h$; $\alpha_{ij} = \frac{q_i k_j}{\sqrt{2h}}$; using Eq. (8) $o_{Q,P} = Softmax \left(\phi_{h,\theta_r}^{|y|} (a_{Q,P}) \right)$; using Eq. (9) $y_k = \arg \max(o_{Q,P})$

B DATASET DETAILS

In this section, we study the different details of our dataset which contains a total of $\approx 12M$ annotated samples with E-S-C-I labels. The dataset is subsampled for annotation and does not, in any way, represent the exact query volumes received by e-commerce engines. On an average, 71.8%, 15.1%, 8.1%, and 4.9% of the overall dataset are E, S, C, and I classes. We notice that the *Exact* class is a significantly dominant part of the dataset and there is an apparent class imbalance. Hence, to handle the imbalance we use cross entropy with class weights computed as given in [14].

Figure 5 depicts the distribution of our dataset across the different e-commerce regions. We observe that the regions of US and IN constitute $\approx 37\%$ of the total number of samples and consequently, also show higher performance improvements in our experiments (given in Section 4). The rest of regions are similarly distributed of the remaining 63% and hence show comparable performance gains.



Figure 5: Regional distribution of our dataset. The areas of the chart present the size of different e-commerce regions in the overall composition of our dataset⁷.

C FURTHER RESULTS

Table 5 presents results on the three class (E vs S vs CI) and two class (E vs SCI) classification variants of the search relevance problem that are applied to various downstream applications in the e-commerce engine. An example application of the three class problem is alternate product suggestion and that of the two class problem is high precision product search.

 $^{^7\}mathrm{The}$ sample distribution of the datasets is given in (%) due to its proprietary nature.

Table 5: Performance comparison of SALAM against the baselines on the task of search relevance classification in different e-commerce regions for three class E-S-CI and two class E-SCI classification. The evaluation metrics are Precision (P), Recall (R), and F1. The metrics are presented for each class to avoid bias from class distribution. Due to the proprietary nature of the models, the results shown are relative to the public mBERT model, i.e., a cell value of x implies that the model performs $(1 + x) \times$ mBERT. The best results in each segment are highlighted in bold. All the F1-improvements of SALAM over PEBL and mBERT are statistically significant with a p-value threshold of 0.05.

	Region	n Australia (AU)					Canada (CA)					India (IN)					Singapore (SG)				
	Class	Е	S	CI	E	SCI	E	S	CI	E	SCI	E	S	CI	E	SCI	E	S	CI	Е	SCI
Р	mBERT	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	XLM	.020	12	00	.044	03	.022	12	02	.048	03	00	10	04	00	01	.014	27	02	.035	07
	PEBL	.028	05	.020	.054	.028	.027	05	.005	.056	.040	00	08	02	.001	.025	.013	15	01	.043	00
	SALAM	.029	06	.044	.035	.025	.018	07	.062	.046	.029	00	.089	.171	00	.137	.100	08	03	.091	02
R	mBERT	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	XLM	03	.102	.014	03	.120	04	.105	.077	03	.198	03	00	04	01	01	05	.064	01	05	.093
	PEBL	01	.118	.042	.005	.136	02	.109	.096	.000	.216	02	01	07	.012	.000	02	.077	01	01	.093
	SALAM	02	.150	.055	.007	.089	02	.127	.041	00	.179	.033	.040	00	.063	02	04	.318	.168	03	.189
F1	mBERT	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	XLM	01	01	.007	.009	.046	01	01	.031	.010	.081	02	06	04	00	01	02	10	01	01	.018
	PEBL	03	.153	.086	.030	.084	02	.119	.112	.028	.128	00	06	06	.007	.013	08	.146	.089	.020	.050
	SALAM	03	.164	.105	.021	.058	03	.116	.112	.022	.105	.024	.044	.059	.031	.058	05	.325	.179	.034	.089
			United	Kingdo	om (UK))		Unite	d State	s (US)			Ja	ıpan (Jl	P)			Ger	many (DE)	
		Е	S	CI	E	SCI	E	S	CI	E	SCI	E	S	CI	E	SCI	E	S	CI	Е	SCI
Р	mBERT	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	XLM	01	12	06	01	03	.010	10	02	.009	04	.018	06	.038	.035	.004	.020	10	.006	.060	00
	PEBL	01	01	01	01	.048	.012	04	.021	.023	01	.021	03	.049	.038	.031	.027	.005	.033	.069	.071
	SALAM	.011	.090	.491	01	.233	.011	.154	.552	.006	.194	.046	.199	.613	.049	.228	.026	.007	.034	.052	.067
R	mBERT	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	XLM	01	10	08	00	06	03	.083	.005	03	.043	02	.099	.064	02	.141	03	.093	.040	02	.204
	PEBL	.016	13	08	.021	06	01	.100	01	02	.095	01	.105	.074	01	.146	01	.089	.116	.013	.221
	SALAM	.036	.396	12	.068	09	.050	.285	08	.068	.000	.066	.422	.202	.072	.159	01	.072	.155	.015	.168
F1	MBERI	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
	DEDI	01	11	06	01	04	01	01	01	01	00	.000	.022	.050	.006	.068	01	01	.024	.019	.099
	PEDL	.018	01	25	.000	00	.008	.089	10	.002	.058	.008	.122	05	.014	.085	01	.098	.15/	.041	.14/
_	SALAM	.030	.547	07	.027	.000	.040	.292	.000	.037	.095	.037	.412	.273	.001	.195	02	.090	.136	.034	.119
											Spain (ES)						B ot b	owlow do			
		F	e Fr	CI	F F	SCI	F	<u> </u>	taly (11	.) F	SCI	F	<u> </u>	pain (E	S) F	SCI	F	Neth	erlands	(NL) F	SCI
	mPEDT	E	5 000	CI	E 000	SCI	E	S	CI) E	SCI	E	<u>S</u>	CI	S) E	SCI	E	S	CI	E	SCI
P	mBERT XI M	E .000 013	S .000	CI .000	E .000	SCI .000	E .000 013	S .000 - 08	CI .000 .057) E .000 024	SCI .000	E .000	S .000 - 09	CI .000 016	S) E .000 029	SCI .000 019	E .000	Neth S .000	erlands CI .000	(NL) E .000 016	SCI .000
P	mBERT XLM PFBL	E .000 .013 011	S .000 17 - 11	CI .000 03 - 03	E .000 .009 017	SCI .000 07 001	E .000 .013 .021	S .000 08 - 01	taly (11 CI .000 .057 089) E .000 .024 033	SCI .000 02 031	E .000 .006 014	S .000 09 - 04	CI .000 .016 038	S) E .000 .029 040	SCI .000 .019 073	E .000 01 026	Neth S .000 20 - 11	CI .000 04 - 01	E .000 .016 .058	SCI .000 06 008
P	mBERT XLM PEBL SALAM	E .000 .013 .011	S .000 17 11 02	CI .000 03 03 .270	E .000 .009 .017 .049	SCI .000 07 .001	E .000 .013 .021 .043	S .000 08 01 .055	taly (11 CI .000 .057 .089 .394	E .000 .024 .033 .046	SCI .000 02 .031	E .000 .006 .014 - 00	S .000 09 04 .021	CI .000 .016 .038 023	5) E .000 .029 .040 022	SCI .000 .019 .073	E .000 01 .026 .050	Neth S .000 20 11 .085	CI .000 04 01	(NL) E .000 .016 .058 .059	SCI .000 06 .008
P	mBERT XLM PEBL SALAM mBERT	E .000 .013 .011 .052	S .000 17 11 02 000	CI .000 03 03 .270	E .000 .009 .017 .049	SCI .000 07 .001 .026	E .000 .013 .021 .043	S .000 08 01 .055	CI .000 .057 .089 .394 000) E .000 .024 .033 .046 000	SCI .000 02 .031 .099	E .000 .006 .014 00	S .000 09 04 .021	CI .000 .016 .038 .023	5) E .000 .029 .040 .022 000	SCI .000 .019 .073 .099	E .000 01 .026 .050	Neth S .000 20 11 .085 000	CI .000 04 01 .090	E .000 .016 .058 .059 000	SCI .000 06 .008 .080
P	mBERT XLM PEBL SALAM mBERT XLM	E .000 .013 .011 .052 .000 03	S .000 17 11 02 .000 .100	CI .000 03 03 .270 .000 .052	E .000 .009 .017 .049 .000 03	SCI .000 07 .001 .026 .000 .068	E .000 .013 .021 .043 .000 02	S .000 08 01 .055 .000 .080	CI .000 .057 .089 .394 .000 .012) E .000 .024 .033 .046 .000 03	SCI .000 02 .031 .099 .000 .079	E .000 .006 .014 00 .000 02	S .000 09 04 .021 .000 .041	CI .000 .016 .038 .023 .000 .009	E .000 .029 .040 .022 .000 00	SCI .000 .019 .073 .099 .000 .099	E .000 01 .026 .050 .000 05	S .000 20 11 .085 .000 .000	CI .000 04 01 .090 .000 01	E .000 .016 .058 .059 .000 05	SCI .000 06 .008 .080 .000 .051
P R	mBERT XLM PEBL SALAM mBERT XLM PEBL	E .000 .013 .011 .052 .000 03 01	S .000 17 11 02 .000 .100 .046	Ance (F CI .000 03 03 .270 .000 .052 .004	E .000 .009 .017 .049 .000 03 01	SCI .000 07 .001 .026 .000 .068 .102	E .000 .013 .021 .043 .000 02 .004	S .000 08 01 .055 .000 .080 .094	CI .000 .057 .089 .394 .000 .012 .032) E .000 .024 .033 .046 .000 03 .004	SCI .000 02 .031 .099 .000 .079 .093	E .000 .006 .014 00 .000 02 01	S .000 09 04 .021 .000 .041 .058	CI .000 .016 .038 .023 .000 .009 .041	E .000 .029 .040 .022 .000 00 .019	SCI .000 .019 .073 .099 .000 .099 .129	E .000 01 .026 .050 .000 05 02	S .000 20 11 .085 .000 .000 .000	CI .000 04 01 .090 .000 01 .058	E .000 .016 .058 .059 .000 05 01	SCI .000 06 .008 .080 .000 .051 .120
P R	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM	E .000 .013 .011 .052 .000 03 01 01	S .000 17 11 02 .000 .100 .046 .486	Ance (F CI .000 03 03 03 .270 .000 .052 .004 .314	E .000 .009 .017 .049 .000 03 01	SCI .000 07 .001 .026 .000 .068 .102 .276	E .000 .013 .021 .043 .000 02 .004 .033	S .000 08 01 .055 .000 .080 .094 .288	taly (11 CI .000 .057 .089 .394 .000 .012 .032 .087) E .000 .024 .033 .046 .000 03 .004 .038	SCI .000 02 .031 .099 .000 .079 .093 .117	E .000 .006 .014 00 02 01 .000	S .000 09 04 .021 .000 .041 .058 01	ci .000 .016 .038 .023 .000 .009 .041 .039	5) E .000 .029 .040 .022 .000 00 .019 .034	SCI .000 .019 .073 .099 .000 .099 .129 .067	E .000 01 .026 .050 .000 05 02 .019	S .000 20 11 .085 .000 .000 .000 .021 .319	CI .000 04 01 .090 .000 01 .058 .113	E .000 .016 .058 .059 .000 05 01 .042	SCI .000 06 .008 .080 .000 .051 .120 .109
P R F1	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT	E .000 .013 .011 .052 .000 03 01 01 .000	S .000 17 11 02 .000 .100 .046 .486 .000	CI .000 03 .270 .000 .052 .004 .314	E .000 .009 .017 .049 .000 03 01 .000	SCI .000 07 .001 .026 .000 .068 .102 .276 .000	E .000 .013 .021 .043 .000 02 .004 .033 .000	S .000 08 01 .055 .000 .080 .094 .288 .000	CI .000 .057 .089 .394 .000 .012 .032 .087) E .000 .024 .033 .046 .000 03 .004 .038 .000	SCI .000 02 .031 .099 .000 .079 .093 .117 .000	E .000 .006 .014 00 .000 02 01 .000 .000	S .000 09 04 .021 .000 .041 .058 01 .000	ci .000 .016 .038 .023 .000 .009 .041 .039	E .000 .029 .040 .022 .000 00 .019 .034	SCI .000 .019 .073 .099 .000 .099 .129 .067 .000	E .000 01 .026 .050 .000 05 02 .019 .000	S .000 20 11 .085 .000 .000 .000 .021 .319 .000	erlands CI .000 04 01 .090 .000 01 .058 .113 .000	E .000 .016 .058 .059 .000 05 01 .042 .000	SCI .000 06 .008 .080 .000 .051 .120 .109 .000
P R F1	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM	E .000 .013 .011 .052 .000 03 01 01	S .000 17 11 02 .000 .100 .046 .486 .000 02	CI .000 03 03 .000 .052 .004 .314 .000 .010	E .000 .009 .017 .049 .000 03 01 .000	SCI .000 07 .001 .026 .000 .068 .102 .276 .000 .003	E .000 .013 .021 .043 .000 02 .004 .033 .000 00	S .000 08 01 .055 .000 .080 .094 .288 .000 .000	ci .000 .057 .089 .394 .000 .012 .032 .087 .000 .035) E .000 .024 .033 .046 .000 03 .004 .038 .000 00	SCI .000 02 .031 .099 .000 .079 .093 .117 .000 .027	E .000 .006 .014 00 02 01 .000 .000 01	S .000 09 04 .021 .000 .041 .058 01 .000 03	pain (E) CI .000 .016 .038 .023 .000 .009 .041 .039 .000 .012	E .000 .029 .040 .022 .000 .019 .034 .000 .013	SCI .000 .019 .073 .099 .000 .099 .129 .067 .000 .058	E .000 01 .026 .050 .000 05 02 .019 .000 03	S .000 20 11 .085 .000 .000 .021 .319 .000 10	erlands CI .000 04 01 .090 .000 01 .058 .113 .000 03	E .000 .016 .058 .059 .000 05 .011 .042 .000 .005	SCI .000 06 .008 .080 .000 .051 .120 .109 .000 04
P R F1	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL	E .000 .013 .011 .052 .000 03 01 01 01 04	S .000 17 11 02 .000 .100 .046 .486 .000 .02 .195	ance (F CI .000 03 .000 .03 .000 .052 .004 .314 .000 .057	E .000 .009 .017 .049 .000 03 01 .000 01 .000	SCI .000 07 .001 .026 .000 .068 .102 .276 .000 .003 .055	E .000 .013 .021 .043 .000 02 .004 .033 .000 00 01	S .000 08 .01 .055 .000 .080 .094 .288 .000 .002 .140	ci .000 .057 .089 .394 .000 .012 .032 .087 .000 .035) E .000 .024 .033 .046 .000 03 .004 .038 .000 00 .018	SCI .000 02 .031 .099 .000 .079 .093 .117 .000 .027 .062	E .000 .006 .014 00 02 01 .000 01 01	S .000 09 04 .021 .000 .041 .058 01 .000 03 .049	pain (E) CI .000 .016 .038 .023 .000 .009 .041 .039 .000 .012 .061	5) E .000 .029 .040 .022 .000 00 .019 .034 .000 .013 .029	SCI .000 .019 .073 .099 .000 .099 .129 .067 .000 .058 .101	E .000 01 .026 .050 .000 05 02 .019 .000 03 03	S .000 20 11 .085 .000 .000 .021 .319 .000 .048	erlands CI .000 04 01 .090 .000 01 .058 .113 .000 03 .074	E .000 .016 .058 .059 .000 05 .011 .042 .000 .005 .046	SCI .000 06 .008 .080 .000 .051 .120 .109 .000 04 .023
P R F1	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM PEBL SALAM	E .000 .013 .011 .052 .000 03 01 01 01 04 02	S .000 17 11 02 .000 .100 .046 .486 .000 .02 .195 .507	ance (F CI .000 03 .03 .03 .03 .03 .03 .03 .03 .03 .000 .052 .004 .314 .000 .057 .380	E .000 .009 .017 .049 .000 03 01 .000 01 .000 .011 .000	SCI .000 07 .001 .026 .000 .068 .102 .276 .000 .003 .055 .152	E .000 .013 .021 .043 .000 02 .004 .033 .000 00 01 .020	S .000 08 .01 .055 .000 .080 .094 .288 .000 .002 .140 .280	taly (11 CI .000 .057 .089 .394 .000 .012 .032 .032 .000 .035 .018 .178) E .000 .024 .033 .046 .000 03 .004 .038 .000 00 .018 .042	SCI .000 02 .031 .099 .000 .079 .093 .117 .000 .027 .062 .108	E .000 .006 .014 00 02 01 .000 01 01 01	S .000 09 04 .021 .000 .041 .058 01 .000 .03 .049 .046	pain (E) CI .000 .016 .038 .023 .000 .009 .041 .039 .000 .012 .061 .052	5) E .000 .029 .040 .022 .000 00 .019 .034 .000 .013 .029 .028	SCI .000 .019 .073 .099 .000 .099 .129 .067 .000 .058 .101 .083	E .000 01 .026 .050 .000 05 02 .019 .000 03 03 00	S .000 20 11 .085 .000 .021 .319 .000 .048 .319	erlands CI .000 04 01 .090 .000 01 .058 .113 .000 03 .074 .153	E .000 .016 .058 .059 .000 05 .011 .042 .000 .005 .046 .075	SCI .000 06 .008 .080 .000 .051 .120 .109 .000 04 .023 .053
P R F1	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM PEBL SALAM	E .000 .013 .011 .052 .000 03 01 01 01 04 02	S .000 17 11 02 .000 .100 .046 .486 .000 .02 .195 .507	ance (F CI .000 03 .000 .052 .000 .052 .000 .010 .057 .380 mrkey (T	E .000 .009 .017 .049 .000 03 01 .000 01 .000 .017	SCI .000 07 .001 .006 .000 .068 .102 .276 .000 .003 .055 .152	E .000 .013 .021 .043 .000 02 .004 .003 .000 00 01 .020 Un	S .000 08 .01 .055 .000 .080 .094 .288 .000 .002 .140 .280	taly (11 CI .000 .057 .089 .394 .000 .012 .032 .087 .000 .035 .018 .178 rab Emi) E .000 .024 .033 .046 .000 03 .004 .008 .000 00 .018 .042 rates (A	SCI .000 02 .031 .099 .093 .117 .000 .027 .062 .108 E)	E .000 .006 .014 00 02 01 .000 01 01 01	S .000 09 .021 .000 .041 .058 .01 .000 .03 .049 .046	pain (E: CI .000 .016 .023 .009 .041 .039 .000 .012 .061 .052 exico (N	5) E .000 .029 .040 .022 .000 .019 .034 .000 .013 .029 .028 IX)	SCI .000 .019 .073 .099 .000 .099 .129 .067 .000 .058 .101 .083	E .000 01 .026 .050 05 02 .019 .000 03 03 00	S .000 20 11 .085 .000 .021 .319 .000 .048 .319	erlands CI .000 04 01 .090 01 .058 .113 .000 03 .074 .153 razil (B	E .000 .016 .058 .059 .001 .005 .001 .002 .000 .000 .000 .000 .000 .005 .046 .075 R)	SCI .000 06 .008 .080 .000 .051 .120 .109 .000 04 .023 .053
 	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM PEBL SALAM	E .000 .013 .011 .052 .000 03 01 01 01 04 02 E	S .000 17 11 02 .000 .100 .046 .486 .000 .02 .195 .507 Tu S	ance (F CI .000 03 .000 .052 .000 .052 .000 .010 .057 .380 mrkey (T	E .000 .009 .017 .049 .000 03 01 .000 01 .000 .017 .017 .000 .017 .018 .019 TR)	SCI .000 07 .001 .0260 .000 .068 .102 .276 .000 .003 .055 .152 SCI	E .000 .013 .021 .043 .000 02 .004 .003 .000 00 01 .020 Un E	S .000 08 .01 .055 .000 .080 .094 .288 .000 .002 .140 .280 .0140	taly (11 CI .000 .057 .089 .394 .000 .012 .032 .087 .000 .035 .018 .178 rab Emit CI) E .000 .024 .033 .046 .000 03 .004 .004 .008 .000 00 .018 .042 rates (A E	SCI .000 02 .031 .099 .000 .079 .093 .117 .000 .027 .062 .108 E) SCI	E .000 .006 .014 00 02 01 .000 01 01 01 01 01 E	S .000 09 .021 .000 .041 .058 01 .000 .03 .049 .046 Met	pain (E) CI .000 .016 .023 .000 .023 .000 .039 .000 .012 .052 exico (N CI	S) E .000 .029 .040 .022 .000 00 .019 .034 .000 .013 .029 .028 IX) E	SCI .000 .019 .073 .099 .000 .099 .129 .067 .000 .058 .101 .083 .083	E .000 01 .026 .050 05 02 .019 .000 03 03 00 00 E	S .000 20 11 .085 .000 .021 .319 .000 .048 .319 Bi S	erlands CI .000 04 01 .090 01 .058 .113 .000 03 .074 .153 razil (B)	E .000 .016 .058 .059 .001 .005 .001 .002 .000 .000 .001 .001 .002 .000 .005 .046 .075 R) E	SCI .000 06 .008 .080 .051 .120 .000 .04 .023 .053 SCI
P	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM PEBL SALAM mBERT	E .000 .013 .011 .052 .03 .01 .01 .01 .01 .04 .02 E .000	Fr S .000 17 .02 .000 .100 .046 .486 .000 .02 .195 .507 Tu S .000	ance (F CI .000 03 .270 .000 .052 .004 .314 .000 .057 .380 rrkey (I CI .000	E .000 .017 .049 .000 03 01 .000 01 .000 01 .000 01 .000 01 .000 01 .000 01 .000 01 .000	SCI .000 .07 .001 .026 .000 .068 .102 .276 .000 .003 .055 .152 SCI .000	E .000 .013 .021 .043 .000 02 .004 .033 .000 01 .020 Un E .000	S .000 08 .001 .055 .000 .080 .094 .288 .000 .002 .140 .280 sitted An S .000	taly (11 CI .000 .057 .089 .394 .000 .012 .032 .032 .032 .087 .000 .035 .018 .178 tab Emi CI .000) E .000 .024 .033 .046 .000 03 .004 .000 .008 .042 rates (A E .000	SCI .000 02 .031 .099 .093 .117 .000 .027 .062 .108 E) SCI .000	E .000 .006 .014 00 02 01 .000 01 01 01 E .000	S .000 09 .021 .000 .041 .058 01 .000 .03 .046 Me S .000	pain (E: CI .000 .016 .038 .023 .000 .009 .041 .039 .000 .012 .000 .012 .052 xico (M CI .000	E .000 .029 .040 .022 .000 .019 .034 .000 .013 .028 .028 LX) E .000 .000	SCI .000 .019 .073 .099 .000 .099 .129 .067 .000 .058 .101 .083 SCI .000	E .000 01 .026 .050 .000 05 02 .019 .000 03 03 00 E E .000	Neth S .000 20 .11 .085 .000 .021 .319 .000 .148 .319 .000 .108 .319 .000 .018 .319 .000	erlands CI .000 04 .090 .000 01 .058 .113 .000 03 .074 .153 razil (B CI .000	E .000 .016 .058 .059 .000 .05 .011 .042 .000 .005 .042 .000 .045 .046 .075 .04 .075 .04 .075 .04 .075	SCI .000 06 .008 .080 .000 .051 .120 .109 .000 04 .023 .053 SCI .000
P	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM PEBL SALAM mBERT XLM	E .000 .013 .011 .052 .000 03 01 01 01 02 E E .000 .003	Fr S .000 17 .01 .02 .000 .100 .046 .486 .000 .02 .195 .507 Tu S .000 17	ance (F CI .000 03 .270 .000 .052 .004 .314 .000 .057 .380 irkey (I CI .000 01	E .000 .017 .049 .000 03 01 .000 01 .000 01 .000 01 .000 01 .000 .015 .019 R E .000 .032	SCI .000 07 .001 .026 .000 .068 .102 .276 .000 .003 .055 .152 SCI .000 04	E .000 .013 .021 .043 .000 02 .004 .0033 .000 01 .020 Un E E .000 .001	S .000 08 .001 .055 .000 .080 .094 .288 .000 .002 .140 .280 s .000 16	taly (11 CI .000 .057 .089 .394 .000 .012 .032 .087 .000 .035 .018 ab Emi CI .000 04) E .000 .024 .033 .046 .000 03 .004 .038 .000 08 .042 rates (A E .000 .014	SCI .000 02 .031 .099 .093 .117 .000 .027 .062 .108 KE) SCI .000 05	E .000 .006 .014 00 .000 01 .000 01 01 01 01	S .000 09 .021 .000 .041 .058 01 .000 .03 .046 Me S .000 10	pain (E: CI .000 .016 .038 .023 .000 .009 .041 .039 .000 .012 .061 .052 xico (M CI .000 .033	E .000 .029 .040 .022 .000 .019 .034 .000 .013 .028 .028 LX) E .000 .034	SCI .000 .019 .073 .099 .000 .099 .129 .067 .000 .058 .101 .083 SCI .000 03	E .000 01 .026 .050 .000 05 02 .019 .000 03 03 03 00 03 00 03 00 03 00 01	Neth S .000 20 .11 .085 .000 .001 .0021 .319 .000 .010 .10 .319 .000 .001 .002 .319 .319 .319 .000 .000 .000 .000	erlands CI .000 04 .090 .000 01 .058 .113 .000 03 .074 .153 razil (B CI .000 02	E .000 .016 .058 .059 .000 05 .011 .042 .000 .005 .042 .000 .042 .000 .045 .046 .075 R) E .000 .018	SCI .000 06 .008 .000 .051 .120 .109 .000 04 .023 .053 SCI .000 .011
P	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM PEBL SALAM mBERT XLM PEBL	E .000 .013 .011 .052 .000 03 01 01 01 04 02 E E .000 .003 .028	Fr .000 17 11 02 .000 .046 .486 .000 .02 .195 .507 Tu S .000 17 04	ance (F CI .000 03 03 .000 .052 .000 .052 .000 .054 .000 .057 .380 rrkey (I CI .000 .01 .025	E .000 .009 .017 .049 .03 .01 .000 .01 .000 .01 .000 .019 R) E .000 .032 .058	SCI .000 07 .001 .026 .000 .068 .102 .276 .000 .003 .055 .152 SCI .000 04 .037	E .000 .013 .021 .043 .000 02 .004 .033 .000 01 .020 Un E E .000 .001 .002	S .000 08 01 .055 .000 .080 .094 .288 .000 .002 .140 .280 .000 .000 .000 .000 .140 .200 .140 .200 .140 .200 .140 .200 .140 .200 .12	clip CI .000 .057 .089 .394 .000 .012 .035 .018 .178 clip .000 .035 .018 .178 .000 .035 .018 .178 .000 .035) E .000 .024 .033 .046 .000 03 .000 03 .000 03 .000 00 .018 .042 F E C .000 .014 .000 .014 .000 .014 .000 .024 .033 .046 .000 .038 .000 .034 .000 .034 .000 .014 .000 .014 .019	SCI .000 02 .031 .099 .093 .099 .093 .117 .000 .027 .062 .108 E) SCI .000 05 .011	E .000 .006 .014 00 02 01 01 01 01 01 01 01 01	S .000 09 04 .000 .041 .058 .01 .000 .049 .049 .046 Mc S .000 10 .055	pain (E) CI .000 .016 .038 .023 .000 .009 .041 .039 .000 .012 .061 .052 exico (N CI .000 .033 .047	S) E .000 .029 .040 .022 .000 00 .013 .029 .028 IX) E .000 .034 .000 .034 .000	SCI .000 .019 .073 .099 .000 .099 .129 .067 .000 .058 .101 .083 .083 .000 .03 .024	E .000 01 .026 .050 05 .000 03 03 00 03 00 03 00 03 00 03 00 03 00 01 02 00 01 02 02 01 02 02 02 01 02 02 02 02 02 02 02 02	Neth S .000 20 11 .085 .000 .001 .001 .021 .319 .048 .319 Bi S .000 09 03	erlands <u>CI</u> .000 04 01 .090 .000 01 .058 .113 .000 03 .074 .153 razil (B) <u>CI</u> .000 02 .010	E .000 .016 .058 .059 .000 05 .000 .046 .075 R) E .0000 .015 .046 .075 R) .000 .018 .034	SCI .000 06 .008 .080 .000 .051 .120 .000 04 .023 .053 SCI .000 01 .048
P	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL XLM PEBL SALAM	E .000 .013 .011 .052 .000 03 01 01 04 02 E E .000 .003 .028 .053	Fr .000 17 11 02 .000 .100 .046 .486 .000 .02 .95 .507 Tut S .000 17 04 04	ance (r CI .000 03 03 .000 .052 .000 .052 .000 .052 .000 .010 .057 .380 trkey (I Ci00 01 .025 .058	E .000 .009 .017 .049 .001 .001 .001 .001 .001 .001 .001 .001 .001 .001 .001 .005 .019 TR) E .0032 .058 .057	SCI .000 07 .001 .026 .008 .102 .276 .000 .003 .055 .152 SCI .000 04 .037 .068	E .000 .013 .021 .043 .000 02 .004 .033 .000 01 .020 Un E .000 .001 .001 .002 .000	Image: style="text-align: center;">Image: style="text-align: style="text-align: center;">Image: style="text-align: style="text-align: center;"/>Image: style="text-align: center;"////////////////////////////////////	clip CI .000 .057 .089 .394 .000 .012 .035 .087 .000 .035 .018 .178 ab Emi .000 .024 .033 .04 .034 .004) E .000 .024 .033 .046 .000 03 .000 03 .000 03 .000 00 .018 .042 F E .000 .014 .019 .001	SCI .000 02 .031 .099 .090 .079 .093 .117 .000 .027 .062 .108 E) SCI .000 .027 .062 .108 E) SCI .000	E .000 .006 .014 00 02 01 .000 01 01 01 01 01 01	S S .000 .09 .04 .021 .000 .041 .021 .000 .041 .000 .03 .049 .046 M€ S .000 .10 .05 .015	pain (E) CI .000 .016 .038 .023 .000 .009 .041 .039 .000 .012 .061 .052 exico (N CI .000 .033 .047 .192	5) E .000 .029 .040 .022 .000 00 .019 .034 .000 .013 .029 .028 IX) E .000 .034 .049 .033	SCI .000 .019 .073 .099 .099 .129 .067 .000 .058 .101 .083 SCI .000 -03 .024 .079	E .000 01 .026 .050 05 02 .019 .000 03 03 00 E E .000 .002 .012 01	Neth S .000 20 11 .085 .000 .021 .319 .000 .010 .048 .319 .000 .000 .018 S .000 .03 .014	erlands CI .000 04 01 .090 .000 01 .090 .01 .000 03 .074 .153 razil (B CI .000 02 .010 .093	E .000 .016 .058 .059 .000 05 .000 .005 .046 .075 R) E .000 .018 .034	SCI .000 -06 .008 .080 .000 .051 .120 .000 -04 .023 .053 SCI .000 .01 .048 .044
P P	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM MBERT XLM PEBL SALAM mBERT XLM mBERT	E .000 .013 .011 .052 .000 .03 .01 .01 .01 .000 .03 .028 .028 .028 .053 .000	Fr .000 17 11 02 .000 .100 .046 .486 .000 .02 .192 .507 Tru S .000 17 04 .04 .000	ance (r CI .000 03 03 .000 .052 .004 .314 .000 .057 .380 arkey (I CI .000 .01 .025 .058	E .000 .009 .017 .049 .003 01 .000 .015 .019 TR) E .0002 .032 .049	SCI .000 07 .001 .026 .000 .068 .102 .276 .000 .003 .055 .152 SCI .000 04 .037 .068 .000	E .000 .013 .021 .043 .000 02 .004 .033 .000 01 .020 Un E .000 .001 .000 .000	Image: style="text-align: center;">Image: style="text-align: center;"/>Image: style="text-align: style="text-align: center;"/>Image: style="text-align: center;"/>Image: style="text-align: style="text-align: style="text-align: style="text-align	city (I) CI .000 .057 .089 .394 .000 .012 .032 .087 .000 .035 .018 .178 cold .000 .035 .044 .03 .064) E .000 .024 .033 .046 .000 03 .004 .038 .000 00 .018 .042 rates (A E .000 .019 .001 .000	SCI .000 02 .031 .099 .093 .117 .000 .027 .062 .108 E) SCI .000 05 .011 .056 .000	E .000 .006 .014 00 02 01 .000 01 01 01 E E .000 .013 .023 .017 .000	s s .000 09 04 .021 .000 .041 .058 01 .000 03 .049 .046 Mc s .000 05 .015 .000	pain (E) CI .000 .016 .038 .023 .000 .041 .039 .000 .011 .052 .061 .052 exico (N CI .000 .033 .041	5) E .000 .029 .040 .022 .000 -00 .019 .034 .000 .019 .028 IX) E .000 .033 .000	SCI .000 .019 .073 .099 .009 .129 .067 .000 .058 .101 .083 SCI .000 03 .024 .079 .000	E .000 01 .026 .050 .000 02 .019 .000 03 03 00 E E .000 .002 .012 01	Neth S .000 20 11 .085 .000 .021 .319 .000 10	erlands CI .000 04 01 .090 .010 .058 .113 .000 03 .074 .153 razil (B CI .000 02 .010 .093 .000	(NL) E .000 .016 .058 .059 .000 .05 .011 .046 .075 R) E .000 .018 .025 .000	SCI .000 .06 .008 .080 .000 .051 .120 .000 04 .023 .053 SCI .000 01 .048 .044
P P R	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM mBERT XLM	E .000 .013 .011 .052 .000 03 .01 01 01 01 02 E E .000 .003 .028 .053 .000 04	Fr .000 17 11 000 .100 .046 .486 .000 .02 .195 .507 Tu S .000 17 .000 .107 .04 .000 .035	ance (r CI .000 03 03 .000 .052 .004 .314 .000 .057 .380 urkey (I CI .000 .01 .025 .058 .000 .000	R) E .000 .009 .017 .09 .017 .000 .03 01 .005 .019 R .000 .032 .057 .000 04	SCI .000 07 .001 .020 .000 .068 .102 .276 .000 .003 .055 .152 SCI .000 04 .037 .068 .000 .005	E .000 .013 .021 .043 .000 02 .004 .033 .000 01 .020 Un E E .000 .001 .002 .000 .000 .000 .000 .000	Image: style="text-align: center;">Image: style="text-align: center;"/>Image: style="text-align: center;"////////////////////////////////////	city city CI .000 .007 .089 .090 .012 .032 .087 .0087 .008 .018 .178 cab Emit CI .000 03 .064 .000 .033 .064) E .000 .024 .033 .046 .000 .03 .004 .038 .000 .018 .042 .018 .042 .018 .042 .018 .000 .014 .014 .019 .001 .000 .024 .033 .046 .000 .03 .004 .03 .000 .03 .004 .03 .000 .03 .000 .03 .000 .03 .000 .03 .000 .000 .03 .0000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .00	SCI .000 02 .031 .090 .079 .093 .117 .000 .027 .062 .108 VE) SCI .000 05 .011 .056 .000 .038	E .000 .006 .014 -00 .000 02 01 .000 01 01 01 01 01 01	S .000 .09 .04 .021 .000 .041 .058 .01 .000 .03 .046 Me .000 .10 .000 .015 .000	pain (E: CI .000 .016 .038 .023 .000 .041 .039 .000 .012 .061 .052 exico (N CI .000 .033 .047 .000 .033 .047 .000 .033	5) E .000 .029 .040 .020 .000 .019 .034 .000 .028 E .000 .034 .000 .033 .000 .033 .000	SCI .000 .019 .073 .099 .000 .099 .129 .067 .000 .058 .101 .083 SCI .000 -03 .024 .079 .000 .090	E .000 01 .026 .050 02 .019 .000 03 03 03 00 .000 .002 .010 .000 .011 .000 04	Neth S .000 20 11 .080 .000 .021 .319 .048 .319 Bi S .000 09 .03 .014 .000	erlands CI .000 04 01 .058 .113 .000 03 .074 .153 razil (B) CI .000 02 .010 .000 .02 .010 .000 .02 .010 .000 .000 .03 .074 .058 .000 .03 .074 .058 .000 .03 .074 .058 .000 .03 .074 .058 .000 .03 .074 .058 .000 .03 .074 .058 .000 .03 .074 .058 .000 .000 .03 .074 .058 .000 .003 .074 .058 .000 .003 .074 .058 .000 .003 .074 .058 .000 .000 .003 .074 .058 .000 .000 .003 .074 .058 .000 .000 .003 .074 .000 .000 .000 .003 .007 .000 .003 .000 .000 .003 .000 .000 .003 .000 .000 .000 .003 .000	(NL) E .000 .016 .058 .059 .000 .05 .011 .042 .005 .046 .075 .046 .005 .046 .005 .046 .005 .046 .000 .018 .0325 .000 .025	SCI .000 .06 .008 .080 .000 .051 .120 .000 04 .023 .053 SCI .000 01 .044 .044 .000 .031
P F1 P R	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM	E .000 .013 .011 .052 .000 .03 .01 .01 .04 .02 E E .000 .003 .028 .053 .000 .04 .04 .04 .02	Fr .000 17 11 02 .000 .046 .486 .000 .02 .195 .507 Tu S .000 17 .044 .000 .035 .025	ance (r CI .000 .003 .03 .03 .03 .03 .000 .052 .004 .314 .000 .010 .057 .380 rrkey (1 CI .000 .01 .025 .058 .000 .022 .053	E .000 .009 .017 .049 .000 .017 .040 01 .005 .019 R) E .000 .032 .058 .057 .000 .021	SCI .000 07 .001 .026 .000 .068 .102 .276 .000 .003 .055 .152 SCI .000 04 .037 .068 .000 .065 .100	E .000 .013 .021 .043 .000 02 .004 .003 .000 01 .020 Un E E .000 .001 .002 .000 .001 .002 .000 .000	s s .000 08 01 .055 .000 .094 .288 .000 .002 .140 .280 .000 .140 .280 .000 16 12 .000 .140 .12 .000 .000 .000 .16 .000 .000 .000 .000 .16 .000 .000 .000 .000 .000 .16 .000	taly (11 C1 .000 .057 .089 .394 .000 .012 .032 .087 .000 .035 .018 .178 .018 .178 .000 04 .03 .04 .03 .04 .03 .04 .03 .04 .03 .04 .03 .04 .03 .04 .03 .04 .03 .04 .03 .04 .05 .04 .05 .05 .04 .05 .05 .05 .05 .05 .05 .05 .05) E .000 .024 .033 .046 .000 .004 .004 .000 .018 .042 rates (2 F .000 .014 .000 .014 .000 .014 .000 .014 .000 .000 .004 .000 .004 .000 .004 .000 .004 .000 .004 .000 .004 .000 .000 .004 .000 .000 .004 .000 .000 .000 .004 .0000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000	SCI .000 02 .031 .099 .000 .079 .093 .117 .000 .027 .062 .108 KE) SCI .000 05 .011 .050 .000 .038 .042	E .000 .006 .014 -00 .000 02 01 01 01 01 01 01 01 01	s s 000 09 04 .021 .000 .041 .058 01 .000 03 .049 .046 Mc s .000 10 05 .000 .054 .086	pain (E: CI .000 .016 .038 .023 .000 .009 .041 .039 .000 .012 .061 .052 .061 .052 .000 .033 .047 .192 .000 .030 .047 .192 .000 .030 .047 .192	5) E .000 .029 .040 .022 .000 .019 .034 .009 .028 IX) E .000 .034 .049 .030 .030 .030 .030 .030 .030 .030 .000 .029 .040 .029 .040 .029 .040 .029 .040 .029 .040 .029 .040 .029 .040 .029 .040 .029 .040 .029 .040 .029 .040 .029 .040 .029 .040 .029 .040 .029 .040 .029 .040 .029 .040 .019 .028 .028 .028 .028 .028 .028 .028 .028 .028 .034 .000 .036 .030 .036 .030 .035 .030 .030 .030 .035 .030 .035 .03	SCI .000 .019 .073 .099 .009 .129 .067 .000 .058 .101 .083 .011 .083 .024 .000 03 .024 .079 .000 .090 .117	E .000 01 .026 .050 02 .019 .000 03 03 03 00 .002 .002 .012 01 .000 .002 .012 01	Neth S .000 20 11 .085 .000 .000 .021 .319 .004 .048 .319 .000 .048 .319 Bi S .000 .003 .004 .000 .005 .005	erlands CI .000 04 01 .058 .113 .000 03 .074 .153 razil (B CI .000 02 .010 .093 .000 .003 .074 .058 .000 .000 .000 .003 .007 .000 .000 .003 .000 .000 .003 .000 .000 .002 .010 .000 .000 .000 .003 .000 .000 .000 .000 .003 .000 .00	(NL) E .000 .016 .058 .059 .000 .05 .01 .042 .005 .046 .075 .046 .005 .046 .005 .046 .005 .046 .005 .046 .005 .046 .075 .046 .075 .034 .025 .020 .022 .032	SCI .000 06 .008 000 .051 .120 .000 04 .023 .053 SCI .000 01 .048 .044 .000 .031 .054
P 	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM PEBL SALAM mBERT XLM PEBL SALAM PEBL SALAM	E .000 .013 .011 .052 .000 .01 .01 .01 .04 .02 E E .000 .003 .028 .003 .028 .003 .028 .004 .04 .004 .004 .002	Fr S .000 17 11 02 .000 .100 .046 .486 .000 02 .195 .507 Tu S .000 17 04 .04 .04 .04 .04 .04 .000 .15 .05 .05 .05 .05 .05 .05 .05 .0	ance (r CI .000 .000 03 .03 .03 .03 .03 .03 .03 .03 .03 .03 .03 .03 .03 .03 .03 .03 .04 .052 .000 .010 .001 .0025 .058 .000 .025 .058 .000 .025	E .000 .009 .017 .049 .001 .001 .001 .001 .001 .001 .001 .001 .001 .001 .001 .001 .001 .001 .001 .001 .001 .001 .002 .0032 .057 .000 .004 .017 .004	SCI .000 07 .001 .026 .000 .068 .102 .276 .000 .003 .055 .152 SCI .000 .04 .037 .068 .000 .065 .100 .095	E .000 .013 .021 .043 .000 02 .004 .000 01 .020 Un E .000 .001 .001 .002 .000 .001 .002 .000 .000	Image: style="text-align: center;">Image: style="text-align: center;"/>Image: style="text-align: style="text-align: center;"/>Image: style	taly (11 CI .000 .057 .089 .394 .000 .012 .032 .087 .000 .035 .018 .178 .018 .018 .018 .018 .018 .035 .018 .018 .035 .018 .035 .018 .035 .018 .035 .018 .035 .018 .035 .04 .04 .04 .04 .04 .04 .04 .04) E .000 .024 .033 .046 .000 .03 .004 .038 .000 .000 .008 .042 rates (A E .000 .014 .019 .001 .002 .002 .002 .033	SCI .000 02 .031 .099 .000 .079 .093 .117 .000 .027 .062 .108 KE) SCI .000 .05 .011 .056 .001 .038 .042 00	E .000 .006 .014 00 02 01 .000 01 01 01 01 01 01	S S .000 .09 .04 .021 .000 .041 .058 .01 .000 .03 .049 .046 M€ S .000 .10 .055 .015 .000 .054 .086 .237	pain (E: CI .000 .016 .038 .023 .009 .041 .039 .000 .012 .061 .052 .061 .052 .061 .052 .000 .033 .047 .192 .000 .029 .011 .023	5) E .000 .029 .040 .022 .000 .019 .034 .003 .029 .028 IX) E .000 .034 .049 .033 .000 .034 .049 .033 .000 .034 .049 .033 .000 .029 .029 .000 .029 .000 .029 .000 .029 .000 .029 .000 .029 .000 .029 .000 .029 .000 .003 .029 .000 .029 .000 .019 .028 .029 .028 .000 .034 .003 .029 .028 .000 .034 .003 .005 .003 .003 .003 .003 .003 .003 .003 .003 .003 .003 .00	SCI .000 .019 .073 .099 .129 .067 .000 .058 .101 .083 .000 .03 .024 .079 .000 .090 .117 .069	E .000 01 .026 .050 02 .019 .000 03 03 00 E E .000 .002 .012 01 .000 04 00 .014	Neth S .000 20 11 .085 .000 .011 .021 .319 .000 .10 .048 .319 .000 .048 .319 .000 .009 .03 .014 .000 .005 .012 .025	erlands CI .000 04 01 .090 .000 01 .058 .113 .000 03 .074 .153 razil (B CI .000 .02 .010 .093 .000 .000 .000 .000 .000 .02 .010 .02 .010 .02 .010 .02 .010 .020 .000 .020 .000 .020 .000 .020 .000 .020 .000 .020 .000 .020 .000 .020 .0	(NL) E .000 .016 .058 .059 .001 .042 .000 .046 .075 .046 .075 .046 .075 .046 .075 .046 .075 .034 .025 .002 .032 .032 .032	SCI .000 .06 .008 .000 .051 .120 .000 .049 .023 .053 SCI .000 .01 .048 .044 .000 .031 .050 .031
P R P R R	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM	E .000 .013 .011 .052 .000 .01 .01 .01 .04 .02 E E .000 .028 .028 .053 .000 .028 .000 .028 .053	Fr 3 .000 .17 .11 .02 .000 .046 .486 .000 .025 .007 Tu S .007 .17 .04 .04 .04 .04 .04 .025 .091 .000	ance (r CI .000 .003 .03 .03 .03 .03 .03 .03 .03 .03 .000 .052 .004 .314 .000 .057 .380 mrkey (1 CI .001 .025 .058 .000 .025 .053 .115	E .000 .009 .017 .049 .001 .001 .001 .001 .001 .001 .001 .001 .001 .001 .001 .001 .001 .001 .001 .001 .001 .001 .005 .019 TR) E .000 .032 .057 .000 .017 .040	SCI .000 07 .001 .026 .000 .003 .005 .152 SCI .000 .04 .037 .068 .000 .065 .100 .095 .000	E .000 .013 .021 .043 .000 02 .004 .033 .000 01 .020 Urr E .000 .001 .001 .002 .000 .000 .000 .000	S .000 .08 .01 .055 .000 .094 .288 .000 .094 .288 .000 .010 .021 .002 .140 .16 .12 .055 .000 .080 .094 .000 .000 .000 .000 .000 .000 .000 .000 .000	taly (11 CI .000 .057 .089 .394 .000 .032 .087 .000 .035 .018 .178 .000 .035 .018 .178 .000 .04 .03 .04 .04 .04 .05 .04 .05 .04 .05 .04 .05 .05 .04 .05 .05 .05 .04 .05 .05 .05 .05 .05 .05 .05 .05) E .000 .024 .033 .046 .004 .038 .004 .003 .004 .000 .008 .042 rates (A E .000 .018 .042 rates (A .000 .019 .001 .000 .003 .002 .031 .000 .038 .000 .000 .000 .000 .000 .000 .000 .001 .000 .001 .000 .001 .002 .001 .000 .000 .001 .000 .001 .000 .001 .001 .000 .001 .001 .000 .001 .002 .001 .002 .001 .002 .001 .002 .002 .001 .002 .002 .002 .002 .002	SCI .000 02 .031 .099 .003 .117 .000 .027 .001 .027 .002 .003 .011 .005 .011 .056 .000 .038 .042 .000	E .000 .006 .014 00 02 01 .000 01 01 01 01 01 01	S .000 09 04 .021 .000 .041 .058 01 .000 .038 .049 .046 Me .000 .10 .055 .015 .000 .054 .086 .237 .000	pain (E: CI .000 .016 .038 .023 .009 .041 .039 .000 .012 .061 .052 .000 .033 .047 .192 .000 .030 .029 .011 .000	5) E .000 .029 .040 .022 .000 .019 .034 .000 .019 .029 .028 IX) E .000 .034 .049 .033 .000 .034 .049 .033 .000 .034 .049 .033 .000 .034 .029 .028 .033 .000 .034 .000 .034 .000 .034 .000 .034 .000 .034 .000 .034 .000 .034 .000 .034 .000 .034 .000 .034 .000 .034 .000 .034 .000 .034 .000 .034 .000 .034 .000 .033 .000 .032 .000 .034 .000 .003 .000 .034 .000 .003 .000 .034 .000 .003 .000 .003 .000 .003 .000 .003 .000 .003 .000 .003 .000 .003 .000 .003 .000 .003 .000 .003 .000 .003 .000 .003 .000 .003 .000 .003 .000 .003 .000 .002 .00	SCI .000 .019 .073 .099 .029 .029 .067 .000 .058 .101 .083 SCI .000 .03 .024 .079 .000 .099 .000 .099 .000 .099 .000 .024 .000 .099 .000 .000 .019 .000 .019 .000 .019 .099 .000 .099 .000 .099 .000 .099 .000 .099 .000 .099 .000 .099 .000 .099 .000 .099 .000 .099 .000 .099 .000 .099 .000 .099 .000 .099 .000 .000 .059 .000 .058 .000 .058 .000 .058 .000 .058 .000 .058 .000 .058 .000 .058 .001 .003 .003 .003 .003 .003 .003 .003	E .000 01 .026 .050 02 .019 .000 03 03 03 00 E E .000 .002 .012 01 .000 00 .000 00 .000	S .000 20 11 .085 .000 .021 .319 .000 .01 .000 .000 .000 .014 .000 .0012 .003 .012 .003	erlands CI .000 04 01 .090 .001 .058 .113 .000 03 .074 .153 razil (B CI .000 .02 .010 .093 .000 02 .000 .000 .000 .000 .000 .02 .000 .000 .000 .000 .02 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .001 .058 .011 .058 .013 .000 .000 .000 .001 .058 .013 .000 .003 .074 .053 .002 .000 .002 .000 .002 .000 .002 .000 .002 .000 .002 .000 .002 .000 .002 .000 .002 .000 .002 .000 .000 .002 .000 .002 .000 .000 .002 .000 .000 .002 .000 .000 .002 .000 .000 .002 .000 .000 .002 .000 .000 .002 .000 .000 .002 .000 .000 .002 .000 .000 .000 .002 .000 .000 .000 .002 .000 .000 .000 .002 .000 .000 .000 .000 .002 .000 .000 .000 .000 .000 .002 .000	E .000 .016 .058 .059 .001 .002 .001 .002 .000 .000 .000 .000 .000 .000 .0046 .075 .046 .075 .034 .025 .000 .025 .000 .025 .0018 .034 .025 .0032 .031	SCI .000 .06 .008 .080 .000 .051 .120 .000 .04 .023 .053 SCI .000 .01 .048 .044 .044 .044 .000 .036 .036
P F1 P R F1	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM	E .000 .013 .011 .052 .003 .01 .01 .01 .01 .02 E E .000 .003 .028 .053 .028 .053 .000 .042 .000 .000 .000 .000 .000	Fr .000 17 11 02 .000 .100 .046 .486 .000 .02 .195 .507 Tu S .000 17 04 .000 .035 .025 .091 .000 .025	ance (r CI .000 .03 03 .000 .052 .004 .314 .000 .057 .380 mrkey (1 CI .000 .01 .025 .058 .000 .021 .023 .115 .000 .021	E .000 .009 .017 .049 .001 .001 .001 .001 .001 .001 .001 .001 .001 .001 .001 .005 .019 TR) E .000 .032 .057 .000 .040 .000 .017 .040	SCI .000 07 .001 .026 .000 .068 .102 .276 .000 .035 .152 SCI .000 04 .037 .068 .000 .065 .100 .095 .000 .023 .000	E .000 .013 .021 .043 .004 .02 .004 .033 .000 01 .020 Un E .000 .001 .001 .002 .000 .000 .000 .02 .000 .02 .000 .02 .000	Image: style="text-align: center;">Image: style="text-align: center;"/>Image: style="text-align: style="text-align: style="text-align: style="text-align: style="text-align: s	taly (11 CI .000 .057 .089 .394 .000 .012 .032 .087 .000 .035 .018 .178 CI .000 .03 .04 .000 .03 .064 .000 .03 .04 .000 .03 .04 .000 .03 .04 .000 .03 .04 .000 .05 .04 .000 .05 .05 .000 .05 .04 .05 .05 .000 .05 .05 .05 .000 .05 .05) E .000 .024 .033 .046 .000 03 .004 .038 .000 00 .018 .042 rates (<i>F</i> E .000 .014 .019 .001 .000 03 .000 .031 .000 .031 .000 .031 .000 .032 .033 .000 .038 .046 .000 .038 .046 .000 .038 .046 .000 .038 .046 .000 .038 .046 .000 .038 .046 .000 .046 .000 .048 .000 .048 .000 .048 .000 .048 .000 .048 .000 .048 .000 .048 .000 .048 .048 .000 .048 .048 .048 .048 .048 .048 .048 .048 .048 .048 .048 .048 .048 .048 .049 .048 .049 .048 .049 .048 .049 .049 .000 .048 .049 .040 .049 .040 .049 .040 .049 .040 .049 .040 .04	SCI .000 02 .031 .099 .093 .117 .000 .027 .062 .108 SCI .000 05 .011 .056 .010 .036 .042 00 .050 .042 .000 05	E .000 .006 .014 00 02 01 .000 01 01 01 E E .000 .013 .023 .017 .000 02 .003 .024 .000 00	S .000 09 04 .000 .041 .058 01 .000 .043 .040 .058 .01 .000 .033 .049 .046 Met S .0000 .10 .055 .015 .000 .054 .237 .000 .024	pain (E: CI .000 .016 .038 .023 .000 .041 .039 .000 .012 .000 .052 .000 .052 .000 .033 .047 .192 .000 .030 .029 .011 .000 .029 .011 .000	5) E .000 .029 .040 .022 .000 -00 .019 .034 .000 .019 .029 .028 IX) E .000 .034 .029 .029 .029 .029 .034 .029 .029 .034 .029 .033 .000 .033 .000 .038 .000 .003 .002 .038 .000 .003 .000 .003 .000 .003 .000 .003 .000 .003 .000 .003 .000 .003 .000 .003 .000 .003 .0000 .000 .000 .000 .000 .000 .000 .000 .000 .000 .00	SCI .000 .019 .073 .099 .029 .029 .029 .029 .029 .029 .038 .000 .038 .024 .079 .000 .024 .079 .000 .090 .117 .069 .000 .07 .07	E .000 01 .026 .050 .000 03 03 03 00 03 00 03 00 03 00 03 00 01 01 .000 04 01 01 01 01 02 01 02 02 02 02 02 02 02 02	Neth S .000 20 11 .085 .000 .021 .319 .000 .048 .319 .000 .048 .319 .000 .03 .0014 .000 .0012 .039 .000 .024	erlands CI .000 04 01 .090 .001 .058 .113 .000 03 .074 .153 razil (B) CI .000 02 .000 00 .000 .000 .000 .000 .000 .010 .000 .000 .000 .010 .000 .010 .020 .000 .000 .000 .010 .020 .000 .000 .010 .020 .000 .020 .000 .000 .010 .058 .000 .013 .000 .013 .000 .013 .000 .013 .000 .013 .000 .013 .000 .014 .058 .000 .015 .000 .015 .000 .015 .000 .015 .000 .015 .000 .015 .000 .015 .000 .000 .015 .000 .000 .015 .000 .000 .014 .000 .020 .000 .0	E .000 .016 .058 .059 .000 .05 .01 .046 .075 R) E .000 .018 .034 .025 .030 .034 .025 .031 .000 .032 .031	SCI .000 .068 .008 .000 .051 .120 .000 04 .023 .053 SCI .000 01 .048 .044 .044 .044 .044 .044 .044 .044
P F1 P R F1	mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM mBERT XLM PEBL SALAM	E .000 .013 .011 .052 .000 03 01 01 04 02 E .000 .003 .028 .000 .000 04 .000 .000 .000 .020 .000	Fr .000 17 11 02 .195 .507 Tu S .000 .110 .02 .195 .507 Tu S .000 .17 .04 .000 .035 .025 .091 .001 .07 .053	ance (r ance (r cI .000 03 03 .000 .052 .004 .314 .000 .010 .057 .380 rkey (1 cI .000 01 .025 .058 .000 02 .053 .115 .000 01 .055	E .000 .009 .017 .040 .009 .017 .049 .000 .03 .01 .011 .005 .019 R E .000 .032 .058 .057 .000 .04 .017 .040 .033 .000	SCI .000 07 .001 .020 .000 .068 .102 .276 .000 .003 .055 .152 SCI .000 04 .037 .068 .000 .065 .100 .095 .005 .023 .080	E .000 .013 .021 .043 .000 02 .004 .033 .000 01 .020 Un E E .000 .001 .002 .000 .000 04 02 .000 02 .020 .020	S .000 08 01 .055 .000 .080 .094 .288 .000 .022 .140 .280 .000 .140 .280 .000 .12 .000 .008 .014 .090 .08 .014 .090	taly (11 C1 .000 .057 .089 .090 .012 .032 .087 .000 .035 .018 .178 c1 .000 .04 .03 .064 .03 .04 .03 .04 .03 .04 .03 .04 .03 .05 .000 .03 .04 .03 .05 .000 .03 .04 .05 .000 .03 .05 .000 .03 .04 .05 .000 .03 .04 .05 .03 .05 .000 .05 .05 .000 .05 .000 .035 .018 .000 .025 .018 .000 .025 .018 .025 .018 .000 .035 .018 .000 .035 .018 .000 .035 .018 .000 .035 .018 .000 .035 .018 .000 .035 .018 .000 .035 .018 .000 .035 .018 .000 .035 .033 .045 .033 .045 .033 .045 .033 .045 .033 .045 .033 .045 .033 .045 .033 .045 .033 .045 .033 .045 .033 .045 .033 .045 .033 .045 .033 .045 .033 .045 .035 .045 .033 .045 .035 .045 .035 .045 .035 .045 .035 .045 .035 .045 .035 .045 .035 .045 .035 .055) E .000 .024 .033 .046 .000 .03 .004 .038 .000 .018 .042 .000 .018 .042 .000 .014 .019 .000 .001 .000 .03 .000 .03 .000 .03 .004 .000	SCI .000 02 .031 .093 .079 .093 .117 .000 .027 .062 .108 E) SCI .000 .038 .042 .000 .038 .042 .000 .038 .042 .000	E .000 .006 .014 -00 .000 02 01 01 01 01 01 01 01 01	s s 000 09 04 .021 .000 .041 .058 01 .000 03 .049 .046 Me s .000 10 05 .000 .054 .086 .237 .000 .02 .174 .000	pain (E: CI .000 .016 .038 .023 .000 .009 .041 .039 .000 .012 .061 .052 .000 .033 .047 .192 .000 .030 .047 .047 .047 .000 .030 .047 .047 .047 .047 .000 .030 .047	S) E .000 .029 .040 .022 .000 .019 .034 .000 .013 .029 .028 IX) E .000 .034 .049 .033 .000 .034 .049 .033 .000 .038 .000 .036 .000 .038	SCI .000 .019 .073 .099 .009 .129 .067 .000 .058 .101 .083 .000 .03 .024 .000 .024 .000 .024 .000 .090 .117 .000 .000 .073 .024 .000 .000 .000 .024 .000 .000 .000 .024 .000 .000 .000 .000 .024 .000 .000 .000 .000 .000 .000 .000 .000 .005 .001 .005 .005 .005 .005 .005 .005 .005 .005 .005 .005 .005 .005 .005 .005 .005 .005 .005 .000 .005 .000 .005 .000 .005 .000 .005 .000 .000 .003 .024 .000 .007 .004 .000	E .000 01 .026 .050 02 .019 .000 03 03 03 00 .002 .000 .002 .012 01 .000 04 00 .014 .000 02 00	Neth S .000 20 11 .085 .000 .021 .319 .004 .048 .319 .000 .048 .319 Bit S .000 .003 .001 .003 .012 .000 .044 .000	erlands CI .000 04 01 .058 .113 .000 03 .074 .153 razil (B) CI .000 02 .010 .000 .02 .010 .000 .02 .010 .000 .02 .010 .000 .02 .010 .003 .007 .003 .000 .000 .003 .000 .000 .003 .000 .000 .003 .000 .000 .000 .003 .000 .000 .000 .000 .000 .003 .000	(NL) E .000 .016 .058 .059 .000 .05 .011 .042 .000 .005 .042 .005 .046 .075 .046 .075 .046 .0075 .046 .0075 .046 .0075 .046 .0075 .046 .0075 .046 .0075 .046 .0075 .031 .030 .030 .030	SCI .000 06 .008 .000 .051 .120 .000 04 .023 .053 .053 .053 .000 01 .048 .044 .048 .044 .040 .031 .050 .031 .050 .030 .020 .023 .023