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Can Machine Translate Dialogue Acts: Evidence from Translating Dialogues from English to Arabic

MUTAHAR QASSEM
Najran University, Saudi Arabia
mutaharnahari@gmail.com

MIAAD MOHAMMAD ALDAHERI
University of Jeddah, Saudi Arabia

ABSTRACT

Machine translation advances translation quality at morphological, syntactic, and semantic levels. The pragmatic level of machine translation is also evolving, but challenges remain due to cultural and contextual issues on the one hand and machine translation deficiencies on the other. While computational studies have made strides in automating translation tasks, linguistic-oriented research in this area remains sparse. In response to this gap, this study seeks to assess the effectiveness of Neural Machine Translation, as exemplified by Google Translate, in translating dialogue acts inherent in natural English conversations into Arabic, drawing upon Austin's theory of speech acts and leveraging a corpus of authentic sources[1]. Our findings highlight certain challenges in the machine's identification of the performative functions of the utterances in conversations, viz. directives, expressives and representatives. Such challenges emanate from specific linguistic features of English conversations (e.g., idiomatic expressions, polysemous words, and deixis) and the lack of contextual information in everyday discourse. These challenges ultimately impede the faithful representation of speakers' intentions in the translated output.

Keywords: Neural Machine Translation; dialogue acts; English; Arabic translation quality

INTRODUCTION

Machine translation has made significant advances at various levels of language (morphological, syntactic, semantic, and pragmatic) in its various stages of model development, namely Rule-based Machine Translation, Statistical Machine Translation, and, most recently, Neural Machine Translation (NMT). Many models, including Rule-based Machine Translation, Statistical Machine Translation, and, more recently, Neural Machine Translation, have been proposed to deal with speech or dialogue acts. Natural Language Processing (NLP) approaches to pragmatic features include speech recognition, natural language reasoning and inference, sentiment analysis, and word sense disambiguation (Thomas, et al., 2020). NMT utilizes attention mechanisms, which improve the performance of 'speech recognition, 'image caption generation, and machine translation (Shen and Lee, 2016).

There is little integration of semantics and pragmatics theories in enhancing NLP task performance in the account of NLP research with pragmatic-centered research (Li et al., 2020). In addition to sentence level and textual analysis, very few have included in-depth communicative narrative analysis. Although pragmatic level NLP studies can be used to decode the process of comprehending, producing, modifying, and realizing contextually relevant social discourses,

[1] https://www.eslfast.com/robot/ and https://helenadailyenglish.com/english-conversations-in-real-life-with-common-phrases-meaning-example

syntactic and semantic level techniques remain the first step in practical NLP (Cambria & White, 2014).

Through syntactic and semantic processing, NLP has advanced pragmatic research from simple lexical comprehension to pragmatic analysis of natural language. Recent research aims to present solutions for linguistic problems (semantic focus). The major strength of NLP lies in its ability to recognize a statement's implicit context and intention (Cambria & White, 2014). If NLP could detect the speaker's intention and convey the ideas conveyed in linguistic symbols, it would overcome the pragmatic and lexical aspects of natural languages.

The pragmatic-NLP field has started looking into how utterances are socially organized. A pragmatic-focused NLP methodology is necessary to produce knowledge to a system which is based on the communication processes connected to language forms and language patterns that support or restrict action (Agerfalk, 2010; Li et al., 2020). Within the context of this research, the authors intend to investigate the effectiveness of Neural Machine Translation in translating dialogue acts in determining the extent to which neural machine translation is successful in rendering dialogue acts from English into Arabic. In other words, can neural machine translation render the speakers' intentions inherent in daily English dialogues into Arabic?

FEATURES OF DIALOGUE AND DIALOGUE ACTS

Language is a means of communication, connecting people from around the world to collaborate, share information and build relationships. Speakers utilize dialogues to express opinion, agreement, disagreement, request, invitations, etc. Dialogue Act originated from John Austin's `illocutionary act theory (Austin, 1962), which was developed by John Searle later as a method of defining the semantic content and communicative function of a single utterance of dialogue (Searle, 1969). One may ask if speech act and dialogue act are the same. Dialogue is a specialized speech act in that the former is general and the latter is specific; hence, dialog acts differ in different dialog systems (Elmadany, et al. 2015). Dialogue act is approximately the equivalent of Searle's speech act (1969). The term dialogue act is linked to the development and deployment of spoken language dialogue systems, viz. Dialogue Act (DA) recognition.

Dialogue acts manifest speakers' intentions, using language behaviors, which differs from one language to another. Among the difficulties in understanding the speakers' intentions in a dialogue is that daily conversations include looser structure, insufficient syntactic ordering of the speaker's ideas, loose coordination, and occurrence of irregular and non-sentences (Martinková, 2013). These dialogue features constitute a problem for a machine translation system to understand the speaker's intentions and the movement from one idea to another. Besides, daily conversations display parallelism in the development of ‘constructions, elliptical structures, idiomatic expressions, deictic means, and indeterminate expressions, which complicate the machine's task in predicting dialogue acts. (Müllerová, 2011).

The detection of the dialogue act identifies the speaker's intention in the movement of conversations and recognizes the speaker's intention, which may assist in reasoning the entire dialogue (Kumar, 2011). This prediction task remains difficult because there are numerous ways to formulate an intention. It is difficult for machines to detect speakers' intentions across languages (Kumar, 2011). Dialogue Acts represent the function of an utterance (or its part) in a dialogue. More specifically, a statement's function can be to greet, request, agree, or disagree. As a result, dialogue acts are delivered via phrase-level labels such as statements, yes-no questions, open questions, acknowledgments, and so on (Cerisara et al., 2017). Various machine learning models have been proposed over the past 20 years to detect speakers' intentions inherent in dialogues across various languages (Kim & Kim, 2018). However, much less attention was directed to this task in Arabic due to the lack of resources for training an Arabic speech-act classifier (Elmadany et al., 2017).

Studies on the translation of dialogue acts that have utilized dialogue acts to set labels for a semantic interpretation of a given utterance have led to their use in many applications requiring Natural Language Understanding (NLU) (Clay et al., 2016). For Duran and Battle (2018), identifying dialogue acts is crucial in predicting the meaning of an utterance for many applications that require natural language understanding. The essential factors in recognizing dialogue act include the semantic and pragmatic information of the speakers' utterances. Kumar (2011) utilized contextual information of dialogue acts to improve accuracy in phrase-based statistical speech translation. Recently, Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) have considered the classification of dialogue acts on both sentential and discourse levels (Ji et al., 2016; Kalchbrenner & Blunsom, 2013; Lee & Dernoncourt, 2016). The sentence level is concerned with how the order and meaning of words are composed to form the meaning of a sentence (Li, 2012). On a discourse level, the order and meaning of sentences are composed to form the meaning of sequences in a dialogue (Schegloff, 2007).

Among the problems that hinder the detection of dialogue acts is that dialogue structure exhibits briefness and formulaic expressions and lacks contextual information (Kumar, 2011). These features may negatively influence the understanding of the machine speakers' intentions. The dialogue acts in an utterance are often directly influenced by the preceding utterances and the current context of the dialogue. For example, `okay' may differ (to acknowledge understanding or agree to a request) depending on the utterance it responds to (Wang et al., 2010). Therefore, neural network based research seeks to model the semantic content and contextual information of an utterance (i.e., previous utterance or dialogue sequences, or a change in speaker turn to predict the DA of an utterance (Kalchbrenner & Blunsom, 2013; Lee & Dernoncourt, 2016).

NEURAL MACHINE TRANSLATION

Machine translation significantly develops translation industry by providing tools that offer translation between languages, saving time and effort. The issue of speed of machine translation is a significant breakthrough as it offers translation in a record time. However, the quality issue has been a challenge for machine translation in all its stages of development, which are Rule-Based Machine translation, Corpus-Based Machine Translation, Statistical Machine Translation (SMT), and Neural Machine Translation (NMT). Brown & Levinson (1987) show the drawback of statistical machine translation, drawing on his study on English-French language pairs, saying that it lacks accuracy when working with languages of different word order. The latest approach in the development of machine translation is Neural Machine Translation (NMT), which utilizes artificial neural networks with large amounts of data, thus achieving better accuracy than traditional SMT models (Tiwari et al., 2020). Unlike the traditional SMT (which used three models) NMT utilizes a single neural network that can maximize the translation performance. The encoder-decoder encodes a source sentence into a fixed-length vector from which a decoder generates a translation (Bahdanau et al. 2014). Despite its high performance, it falls into the problem of low-resource language pairs or for specific domains (Popescu-Belis (2019). However, in some languages with extensive resources, such as English-French or German-English news translation, NMT achieved a high level of accuracy, similar to human performance (Popescu-Belis (2019). Besides, the major challenge for NMT lies in its ability to utilize contextual features when translating the whole text, which entails modeling between Source Text (ST) and Target Text (TT) words, phrases, or sentences.

The second significant shift from pragmatic-based SMT is that the NMT systems use one model based on an encoder-decoder neural network, performing all the necessary operations.

PREVIOUS STUDIES

Several studies have dealt with the neural machine translation of dialogues, though most of these studies deal with the topic from a computational perspective (Colombo et al., 2020; Joukhadar et al., 2019; Popescu-Belis, 2019; Kim & Kim, 2018; Elmadany, et, al, 2017; Sennrich, et al.2016; Shen and Lee, 2016). At a national level (English-Arabic translation), a few studies assessed the performance of machine translation (Almahasees & Mustafa, 2017; Soori & Awab, 2015). The novelty of this study is the analysis of neural machine translation from a pragmatic perspective, viz., translation of dialogue acts. The concern of this section is to shed light on these studies.

Colombo et al. (2020) have utilized the seq2seq approach to improve the modeling of tag sequentiality, which includes: encoder and decoder. The encoder handles input sequences and creates a context vector. Meanwhile, the decoder produces output sequences, like part-of-speech tags, by using the context vector and considering the tags it has generated previously. In other words, it reads a sequence, understands the context, and then rearranges it properly (Cheng et al 2021). They have utilized such an approach to predict DA. They have found that the seq2seq model achieved an accuracy of 85%, concluding that the seq2seq approach presented a novel approach to the DA classification problem. Joukhadar et al. (2019) conducted a study on the recension of the Levantine Arabic dialect dialogue acts, using various machine learning algorithms to detect the speech act inherent in the conversations (greeting, goodbye, thanks, etc.). They have utilized Logistic Regression, Support Vector Machine (SVM), Multinomial NB, Extra Trees Classifier, and Random Forest Classifier, comparing the results of the proposed models on a hand-crafted corpus in restaurants' orders and airline ticketing domain. They found SVM model achieved the best results with 86% accuracy. Kim and Kim (2018) proposed a convolutional neural network model to identify speech acts, predictors, and sentiments, proposing a model for embedding appropriate informative abstractions for speech act identification, predicator identification, and sentiment identification. They found that the proposed model achieved better performance than independent models: 6.8% higher in speech act identification, 6.2% higher in predictor identification, and 4.9% higher in sentiment identification. Elmadany, Mubarak, and Magdy (2017) presented Arabic Speech, Acts, and Sentiment (ArSAS), an Arabic corpus of tweets annotated for recognition of speech act, and sentiment analysis of a large set of twenty thousand Arabic tweets. They classified the topics of the corpus into six different classes of speech-act labels, such as expression, assertion, and question, aiming to make this corpus promote the research in both speech-act recognition and sentiment analysis tasks for Arabic language.

Shen and Lee (2016) studied the neural attention model of dialogue act detection and key term extraction. They found that the attention mechanism improved the sequence labeling task. One of their exciting findings is that when the input sequence is long, it can include many noisy or irrelevant parts. They recommend applying the attention mechanism, which assists in the sequence classification task because it can highlight important parts of the entire sequence for the classification task.

As for studies that assess machine translation from a linguistic perspective, Almahasees (2020) investigated the capacity of the three systems to translate various texts taken from the United Nations (UN), the World Health Organization (WHO), the Arab League, News, and literary texts, using holistic analysis and error analysis. It was found that Google has the best performance regarding both adequacy and fluency of the selected domain texts for this language pair over the two years (2016 and 2017). Soori and Awab (2015) assessed MT systems' capacity in translating verb-noun collocations, Google Translate and Microsoft Translator. They found that Google Translate generates better results than Microsoft Translator. Yusof et al. (2017) evaluated intelligibility in human and machine translation, using mixed-methods approach, which involves both quantitative and qualitative data collection. The authors presented three criteria for evaluation of human and machine translation: comprehensibility, coherence, and wellformedness.

Scrutinizing the studies above showed that none assess the machine's performance in recognizing dialogue acts. Besides, most of the studies deal with the topic from computational perspectives. Accordingly, this study assesses the performance of machine translation in translating dialogue acts from English to Arabic. The main research questions that the study aims to answer are:

Q.1. To what extent could Google Translate render dialogue acts inherent in conversation from English to Arabic?
Q.2. What barriers hinder the rendition of dialogue acts into Arabic?

METHODOLOGY

The authors utilized a qualitative method to analyze the English- Arabic translations of dialogues offered by Google Translate. Google Translate adopts the latest approach of machine translation (i.e., Neural Machine Translation), which notices changes in the quality of the translation of written and spoken discourses. The study's corpus was authentic dialogues taken from websites specialized in English conversations[2]. These dialogues are authentic that occur in real-life situations. The dialogues exhibit pragmatic features (dialogue acts), including idiomatic expressions. The aim behind selecting these conversations is to assess Google Translate's effectiveness in rendering pragmatic features of English dialogues into Arabic, following Austin's Speech Acts. The authors utilized a convenient sample in achieving the objectives of the investigation, meaning the dialogues selected utterances that exhibited dialogue acts using idiomatic expressions, which are standard features of native speakers' daily communication. The authors chose a small sample (two dialogues) to conduct a detailed investigation of a specific aspect—namely, dialogue acts within a text corpus. In such instances, a thoughtfully curated, smaller sample can sufficiently address research questions without the necessity of a large-scale dataset. Utilizing a larger text sample may not yield novel insights but rather replicate existing patterns of dialogue acts.

This study was confined in its assessment of the translation of dialogue acts, aiming to assess the effectiveness of Google Translate in rendering the dialogue acts inherent in English

[2] https://www.eslfast.com/robot/ and https://helenadailyenglish.com/english-conversations-in-real-life-with-common-phrases-meaning-example .

conversation into Arabic. Based on Austin's theory of speech act (1962), the authors analyzed the conversations translated by Google Translate. Dialogue Acts were operationalized in this study as utterance functions such as greeting, requesting, agreeing or disagreeing, and suggesting. Austin (1962) concentrated on how to do things with words, implying that detecting the speaker's intent throughout the conversational movement is one of the main functions of the dialogue, which may aid in overall dialogue reasoning (Kumar, 2011). Because there are so many different ways to form an intention, this prediction task remains difficult. Machine translation encounters challenges in understanding speech intentions in different languages (Kumar, 2011). Illocutionary acts were classified by Austin (1962) into verdictives, exercitives, commisives, behabitives, and expositives. He refers to verdictives as "the delivery of an official or unofficial finding based on evidence or reasons as to value or fact insofar as these are distinguishable" (e. g. acquit, hold, calculate, describe, analyze, estimate, date, rank, etc.). Exercitives are an illocutionary class that involves deciding to favor or against a particular course of action or advocating for it. (For example, order, command, direct, plead, beg, recommend, request, and so on.) The purpose of the commissive act is to commit the speaker to a specific course of action. Examples of the verbs of this class are a promise, vow, pledge, covenant, contract, guarantee, embrace, swear, etc. The fourth class is expositives, which are used in acts of exposition that involve expounding ideas (e.g., affirm, deny, emphasize, illustrate the answer, report, accept, etc.). The last class is behabitives, which includes the notion of reaction to other people's behavior and fortunes and attitudes and expressions of attitudes (apologize, thank, deplore, commiserate, etc.).

Austin's classification is further developed by Searle (1976), who provides an obvious classification. He classified illocutionary acts as representatives, directives, commisives, expressives, and declarations. Representatives for Searle (1976) is a speech act that seeks to commit the speaker to the truth or falsity of the expressed proposition. In directives class, the speaker involves the hearers to do something such as modest attempts (invitation or suggestion) or fierce attempts such as insisting on hearers to do something (e.g., command, order, beg, etc.). The commisive class is an illocutionary act for getting the speaker (i.e., the one performing the speech act) to do something (promising, threatening, intending, etc.). The expressive class aims to express the psychological state specified in the sincerity condition about a state of affairs such as 'thank,' 'congratulate,' 'apologize,' 'condole,' 'deplore,' and 'welcome.' The last class for Searle is declarations which includes performing the act of appointing, the act of nominating you as a candidate, performing the act of declaring a state of war, performing the act of marrying you, then you are married, etc. (Searle, 1975, 15). According to the classifications of illocutionary acts, the authors assessed Google's automated translation of the dialogues acts inherent in the dialogues.

CODING AND CATEGORIZATION OF DATA

We aimed to analyse the dialogue acts in the two authentic conversations based on the taxonomy of speech acts developed by Searle (1969), which is proposed by Austin (1962). First, we read the model of performatives developed by Searle and his teacher Austin. Then, we applied the design of Searle's taxonomy on speech acts (1976). Subsequently, we applied the performative categories of this taxonomy to the two conversation to reveal whether the Google Translate is able to convey these acts into Arabic. We used certain codes for the performative utterances: (F) labels the functional aspect of the performative utterance and (p) indicates the propositional content of the speech act. In doing so, the code F(p) stands for the function of the proposition. The taxonomy contains five categories, which includes the following performative functions:

(Representatives(re), Directives(di), Commissives (co), Expressives(ex) and Declaratives (de). The application of (f) and (P) to the codes of the five categories results in the following codes: Fre(P), Fdi(p), Fco(P), Fex(P) and Fde(P).

During the process of categorizing dialogue acts, we extracted various lexical, grammatical, and semantic features and examined their influence on illocutionary acts. These factors can have a detrimental impact on the successful conveyance of the speaker's intentions to the listener. See Table 1.

TABLE 1. Classification of dialogue acts in the data

Dialogue acts	Code	Verbs
Representatives(re)	Fre(P)	tell , describe , deny, agree, state time, negate, suppose
Directives(di)	Fdi(P)	ask , check , request , invite , encourage advice, suggest
Commissives (co)	Fco(P)	promise, assure
Expressives(ex)	Fex(P)	greet , praise , thank, complain, see off , enquire about one's well-being, empathize,
Declaratives (de)	Fde(P)	

RESULTS

The presentation of data is organized according to the flow of the conversation to ensure that all pragmatic features of the conversations are analyzed, noting that the data were analyzed according to the Searle's classifications of performative functions of verbs.

DIALOGUE 1

Dialogue 1 is about one of the friends' daily casual phone conversation, which starts as usual with a greeting, which is grouped under 'expressives' according to the classification of Searle's of performative utterances. The two dominant dialogue topics are a school assignment and planning to meet. Below is a translation analysis of the interlocutors' turn-taking as shown in Table 2.

TABLE 2. Machine vs. Suggested Translations

ST	TT	Suggested translation[3]
A: Hey, What's up! Just checking in. What are you doing?	مرحبًا ما الأمر! مجرد تسجيل الوصول. ماذا تفعل؟	مرحبا! كيف حالك؟ أردت أن أطمأن عليك. ما أخبارك؟

Generally, Google Translate is successful in the translation of some utterances and failing in others. The first dialogue act in the dialogue is greeting 'Hey,' which is translated as ''مرحبًا.' The translation was successful despite the multiple meanings of the lexis 'hey.' Despite a good start of Google Translate, it fails in translating the act of the second and third utterances of the opening of the dialogue 'What *is up?' and 'And just check in'*. These utterances have multiple meanings, depending on the context and intention of the speaker. The utterance 'What *is up'* has three meanings according to Online Cambridge Dictionary (1. used to ask someone what the problem is, 2. used as a friendly greeting and to ask someone how they are and what is happening, or 3. used for asking how someone is or what someone has been doing (Online

[3]While the source text is informal, our suggested translations are standard Arabic since all speakers have consensus on its use.

[4]Cambridge Dictionary). Here, the machine fails to select the appropriate translations from these options. The machine translated 'what's the matter?' as 'ما الأمر', which in Arabic means, 'what is the problem' or 'what is the matter.' Such translation could not identify the performative function of the utterance (i.e., greeting). At the same time, the context of the conversation shows that the speaker uses 'what is up' to greet his friend since it is preceded by 'hey' and followed by ' what are you doing' Similarly, the machine makes the error in the translation of 'checking in,' which is translated as 'تسجيل الوصول,' which results in a deviation from the SL meaning while in this context the phrase 'check in' means 'to contact someone by making a phone call, short visit, etc. The machine could not render the performative function of the phrase 'checking in' (i.e., enquire about someone's well-being), which is classified according to Searle as Expressives which might be due to the failure to identify the context. The Longman definition of 'check in' in the third entry is that the idiom is used in American English to call someone to tell them that you are safe or where you are.

In translating the reply to the opening of the conversation, the machine succeeds to some extent in delivering performative function of the utterances (i.e. telling and describing), which is classified under 'representatives' according to Searle. See Table 3.

TABLE 3. Machine vs. Suggested Translations

ST	TT	Suggested translations
Just finishing up things at school. I've got a paper due tomorrow, but it's almost done. Maybe another hour	مجرد الانتهاء من الأمور في المدرسة. لدي ورقة مستحقة الدفع غدًا، لكنها على وشك الانتهاء. ربما ساعة أخرى	أعمل على الانتهاء من مهامي الدراسية. أعمل على ورقة بحثية ينبغي تسليمها في الغد، لكني أوشكت على الانتهاء منها. ربما احتاج ساعة أخرى.

The ambiguity occurs in the translation of the utterances: 'finishing *up things at school'* ('مجرد إنهاء الأمور في المدرسة'), 'paper due' ('لدي ورقة مستحقة غدًا') and 'another hour' (ربما ساعة أخرى). The machine' translations exhibited ambiguous renditions of such phrases and utterances. The correct translation requires to add in the TT to ensure clarification of meanings of the utterances. See Table 3 for suggested translations above.

The utterances 'that sounds brutal' and 'don't' mind' are idiomatic utterances whose meanings differ according to the context and the speakers' intention. The machine' translations of such utterances exhibited the machine' inability to identify the functions of such utterances. See Table 4.

TABLE 4. Machine vs. Suggested Translations

ST	TT	Suggested translations
A: Ohhhh. That sounds brutal. Haha.	.. أوهه. هذا يبدو وحشيًا. هاها	أوه. يبدو ذلك بالغ الصعوبة. ههه
B. Brutal but interesting. I don't mind it.	وحشية، ولكنها مثيرة للاهتمام. أنا لا أمانع ذلك.	صعبا، لكنه ممتعا. لا يصعب علي القيام به.

The machine's inappropriate translations of the utterances above are due to the literal rendering of the utterances. The utterance 'that sounds brutal' and 'I don't mind' are used to empathize with a friend regarding the difficulties of school tasks and his friend's reply to his ability to deal with such tasks respectively. In the context of empathizing a friend for having a challenging school task, saying "it sounds brutal", his friend replies' I don't' mind', meaning that the speaker is willing to accommodate the school tasks without complaint. The machine's literal translation

[4] https://dictionary.cambridge.org/dictionary/english/what-s-up

misses this context and the speaker's intention, leading to convey implicit performative functions of the utterances.

The statement, "So, what are you doing?" serves as the initiation of the second interlocutor's turn to inquire about their friend's updates. Despite the presence of a question mark, the machine incorrectly interprets it as a declarative statement "That is, what are you doing." Refer to Table 5 for further details.

TABLE 5. Machine vs. Suggested Translations

ST	TT	Suggested translations
So, what you doing?	وذلك ما تفعلون؟	وماذا عنك؟

This machine's translation of the interrogative question into a declarative statement changes the function of the utterance from asking to telling.

In replying to the question 'so, what are you doing', the machine made lexical and syntactic errors as stated in Table 6.

TABLE 6. Machine vs. Suggested Translations

ST	TT	Suggested translations
A. Well. Just finished work hitting up a dance class and then maybe dinner. Want to meet up?	بئر. انتهيت للتو من العمل في فصل رقص ومن ثم ربما تناول العشاء. يريد الاجتماع؟	حسنا! انتهيت من العمل للتو، وسأذهب إلى درس في الرقص ثم ربما أتناول العشاء. أترغب أن نلتقي؟
B: Let's play it by ear	دعونا نلعبها بالأذن	لنلتقي بحسب الظروف.

The firs error is the translation of 'well' as ' بئر ', which refers to the water source while the word 'well' here is a discourse marker that prefaces a topic. The second error occurs in the translating the utterance 'wants to meet up'. The machine fails to deliver the performative function of the utterance (i.e. appointing a meeting) due to failure in the identification of the second person deixis. Instead of translating the deixis as a second person, the machine translates it as a third person, which has a negative effect in delivering performative function of the question (i.e., directives). In translating the phrase 'hitting up and then dinner", the tense was mistranslated due to the inability of the machine to identify the intended temporal meaning of the verb 'hitting up,' which indicates future tense, while the machine translates the verb into the past tense. The idiomatic utterance 'let's play it by ear' is translated by the machine literally, which results in failing to deliver the act of the utterance (agree on convenient time). In translating the idiomatic expression 'let's play it with the ear,' the machine fails to translate the act of the expression due to the literal translation of the expression. Such inappropriate translation also violates the maxim of relevance, which concerns clarity in what is said.

In replying to the above utterance 'Let's play it by ear!', the machine makes many errors that have negative on delivering the performative functions oh the verbs as shown in Table 7.

TABLE 7. Machine vs. Suggested Translations

ST	TT	Suggested translations
Sure. I probably won't go until later—8 or 9ish.	.بالتأكيد. ربما لن أذهب إلا في وقت لاحق. 8 أو 9 العش.	بالتأكيد. ربما لن أذهب إلا في وقت متأخر. حوالي الثامنة أو التاسعة.
B. Sweet. That's great. Pizza and a pint?	.حلو. ذلك رائع. بيتزا ونصف لتر؟	جميل. ذلك وقت مناسب. ما رأيك ببيتزا وشراب؟

A. Perfect. We can meet downtown.	في أحسن حال. يمكننا أن نلتقي في وسط المدينة	أتفق. يمكننا اللقاء في مركز المدينة.
B. Okay. See you soon.	حسنًا. اراك قريبا.	حسنا. أراك قريبا
Ciao	تشاو	وداعا

In translating '8-9ish (about from 8-9), the machine could not identify the meaning of the of 'ish', which results in the ambiguous meaning, failing to identify the performative function of representatives, i.e., describing. Besides, the machine could not translate the acts of the utterance '*Sweet',* which is used to show agreement while the machine translates' sweet' into Arabic as 'حلو' that describes good tasting. On the contrary, 'sweet 'in the conversation is used to show agreement with the time of appointment.

The performative function of the utterance "Pizza and a pint?" is directive, specifically suggesting an action or making a proposal. The speaker is essentially offering the idea of having pizza and a drink, which occurs likely in a casual and social context. The challenge with machine translation, especially with short and context-dependent phrases like this, is that it could not fully capture the speaker's intention or the cultural nuances associated with the suggestion. The machine provides a literal translation of the words without grasping the broader context or the social aspects of the offer. Understanding the speaker's intention often relies on not just the words used but also the tone, context, and cultural norms. In this case, the suggestion of "Pizza and a pint?" is a common and informal way of proposing a casual meal, but a machine could not pick up on the informality or the social aspect without a deeper understanding of the context.

The machine translates 'perfect' as 'في أحسن حال' (back-translated as 'fine'), while the intention behind 'perfect' here is to express agreement with his friends' suggestion of 'pizza and a pint?'. In so doing, the machine could not identify the implicit performative function of the verb 'perfect'. Additionally, Google Translate transliterates the Italian exclamation 'Ciao,' which might affect the conveyance of the farewell expression, despite its equivalence in Arabic."

DIALOGUE 2

The casual conversation occurs at a party between two friends, which is about one of the interlocutor's difficulties in making a relationship with a woman. One of the friends noticed that his friend was worried and so he asked him about the reason for his worry. Below is a translation analysis of their turn-taking.

The machine made many errors in delivering the implicit performative functions of the verbs in dialogues as shown in Table 8.

TABLE 8. Machine vs. Suggested Translations

ST	TT	Suggested translation
A: What is eating you?	ما يأكل لك '	ما الذي يقلقك ؟
B: What do you mean? A: I'm fine	ماذا تقصد؟ : ج: أنا بخير	ماذا تعني؟ أنا بخير.
No, you aren't. Come on, whatever it is. Get it off your chest well	: لا أنت لست كذلك. تعال مهما كان. أخرجه من صدرك جيدًا	لا. لست كذلك. أخبرني مهما يكن الأمر. أخرج ما في جعبتك.

The first utterance aims to query a friend about the reason for his worry 'What is eating you?' It was translated by Google Translate 'ما يأكل لك,' which can be back-translated as 'what is eating for you'. The error lies in the failure to identify the function of the utterance (i.e. asking about worrying him). The error made by the machine is due to the literal translation of the metaphorical idiom and adding a preposition 'for', which results in a deviation from the SL meaning. The intended meaning of the English utterance is 'what's bothering or annoying you? Or 'what's on your mind?'. In all cases, the idiom predicts a bad mood that a person is going through, and this is one of the slang English idiomatic expressions, and it is an expression that we can find in Arabic (e.g., I ate myself), which means I annoy myself. If the translation is 'what is eating you?', it would have been close to the intended meaning, but the separation between the verb and the pronoun with a preposition has a negative effect on the understanding of the intended meaning. The addition of the 'preposition 'for' results in a deviant meaning. Clearly, the syntactic features of the translated utterance passively affect the understanding of the lexical meaning, resulting in ambiguous meanings.

In the utterances: 'No, you aren't', 'Come on, whatever it is!' and 'Get it off your chest well', the machine fails to translate 'come on' in this context. The idiom 'come on' has different meanings, but here the machine chooses the option that does match the context, which fails to show the idiom's illocutionary act. The speaker says 'come on whatever it is' to encourage his friend to tell the matter whatever it is[5](Cambridge Dictionary).

The second issue is the translation of the idiom 'get it off your chest', which means 'If you get something off your chest, you talk about something that has been worrying you' (Collins Dictionary6). The literal translation of 'اخرجه من صدرك 'results in ambiguous and inappropriate translation which fails to communicate the performative function of the verb (i.e. requesting his friend to show what is worrying him). Such translation shows that Google Translate has a problem delivering the meaning of idiomatic expression.

In the following moves of the conversations, there are many idioms the machine could not translate properly, failing to identify their performative functions as shown in Table 9.

TABLE 9. Machine vs. Suggested Translations

ST	TT	Suggested translations
B: ……….. I don't have the guts to walk over there.	B :ليس لدي الشجاعة للسير هناك. A	لا أجروْ على الذهاب إليها.
A: Come on, Bill. This is your chance; just give it a shot. What do you have to lose?	: تعال إلى بيل. هذه فرصتك فقط أعطها رصة. ماذا لديك لتخسر؟ ل	هيا بيل. هذه فرصتك.ما عليك سوى المحاولة. لن تخسر شيئا.
B: She wouldn't be caught dead with me.	لن يتم القبض عليها ميتة معي.	لن توافق أن تظهر معي أثناء الحفلة.
A: Why do you say that?	لماذا تقول هذا؟	لماذا تقول ذلك.

[5] said to encourage someone to do something, especially to hurry or try harder, or to tell you something,
[6] https://www.collinsdictionary.com/dictionary/english/get-something-off-your-chest

B: Well, I think you should just bite the bullet, go over there and start a conversation. A: maybe later	حسنًا، أعتقد أنه يجب عليك فقط أن تأخذ الرصاصة وتذهب إلى هناك وتبدأ محادثة	حسنا. اعتقد انه بنبغي عليك أن تتخذ القرار وتذهب هناك، وتبدأ الحديث معها.
A: why put it off? Who knows, you two might hit it off.		لماذا تؤجل؟ من يعلم، قد تتوافقان.
B: That'll be the day.		هذا هو اليوم الموعود!

The idiom ‘she wouldn't be caught dead’ means that woman hates to be talked to by the man. The man thinks that the woman does not like to appear with him in the party and that is what he is hesitant to talk to her. The literal translation distorts the SL meaning and breaks the coherence, violating the maxim of relevance. The performative function of the idiomatic utterance is to show fear to talk to her, but the machine ‘s translation of the utterance fails to identify the function of the utterance due to the literal translation of the utterance.

In translating the idiom 'you should just bite the bullet[7],' it is rendered literally, which may not resonate with the general readership of the target language (TL). This idiom conveys the notion of 'forcing oneself to undertake a challenging or unpleasant task' or 'demonstrating courage in a difficult situation.' Its primary function is to encourage his friend to engage in conversation with a woman. However, the literal translation results in ambiguity and fails to capture the intended meaning. Similarly, when translating the idiom 'might hit it off',[8] the machine fails to convey meaning of the idiom, which signifies an immediate and positive rapport between individuals, aiming to reassure his friend about the possibility of forming a friendly connection with a woman. Nevertheless, the machine provides a literal translation, which contradicts the original meaning in the ST (i.e., conflict)

In the case of 'that will be the day[9], it is translated literally, thus missing the nuanced meaning of the phrase. This idiom has two contrasting interpretations: one suggesting skepticism (referring to something unlikely to occur) and the other expressing optimism (indicating an exceptionally wonderful event). In this context, it serves to encourage the speaker's friend to initiate a conversation with a woman, conveying the idea that it would be a remarkable development if he succeeds in establishing a relationship. Unfortunately, the machine fails to recognize the expressive function of this utterance.

DISCUSSION

Data analysis has revealed that the performative functions of verbs in the targeted conversations are classified into directives, representatives, and expressive forms. Importantly, the data does not indicate the presence of declarative functions, primarily due to the formal nature of declarations, which typically occur in formal settings. The machine's limitations in identifying the performative functions of utterances within dialogues can be attributed to various factors, including the use of

[7] https://dictionary.cambridge.org/dictionary/english/bite-the-bullet
[8] https://dictionary.cambridge.org/dictionary/english/hit-it-off-with?q=hit+off
[9] https://idioms.thefreedictionary.com/that%27ll+be+the+day

idiomatic expressions, polysemous words, and deixis. Additionally, the machine's failure to grasp the context results in an inability to effectively convey the speakers' intentions. It was noticed that some of the machine's translations were constrained to the most common meanings of the words and phrases the machine has been provided with, which resulted in uncontextualized translations. Furthermore, the machine tends to make errors in short brief dialogues, making it less effective in handling straightforward inputs that require cognitive compensation to achieve the intended meaning. It is found that the grammatical errors produced by Google Translate further exacerbate the issue, leading to a failure to convey the pragmatic content from the SL to the Tl.

The data analysis conducted on targeted conversations has provided valuable insights into the performative functions of verbs. These functions have been categorized into four primary types: directives, representatives, commissives, and expressive forms. Examples of directives in the targeted conversations include the use of the following verbs (ask, check, request, invite, encourage, advise, suggest), which influence the actions or responses of participants in the conversation. In contrast, representatives are employed to convey information, present factual details, or provide descriptions, serving to disseminate knowledge and make informative statements (e.g., tell, describe, deny, agree, state, time, negate, suppose). Additionally, commissives constitute another significant category in the analysis. Verbs in this group are deployed to express commitments and promises (e.g., promise, assure). They function as linguistic tools for individuals to convey their intentions, obligations, or vows, thereby underscoring their commitment to future actions or behaviors. Finally, expressive forms encompass verbs that enable individuals to convey their emotions, feelings, attitudes, or opinions, allowing them to express their inner thoughts and reactions effectively (e.g., greet, praise, thank, complain, see off, etc.). Significantly, our analysis did not reveal the presence of declarative functions in the examined conversations, which can primarily be attributed to the formal nature typically associated with declarative statements. Declarative functions are commonly employed in formal contexts, where individuals make authoritative statements or assert definitive facts. In everyday conversations and less formal settings, people tend to rely on the identified performative functions, such as directives, representatives, and expressive forms, to convey their intentions, emotions, and information.

Idiomatic expressions play a significant role in everyday conversations in English, making them a prominent feature of the language (Martinková, 2013). However, these expressions pose a unique challenge when it comes to machine translation, as they often cannot be directly translated word-for-word. The findings indicate that idiomatic expressions are among the factors that impede machine translation's ability to accurately identify the performative functions of utterances in the dialogues. Idiomatic expressions are deeply rooted in the culture and language they originate from, and they may not have direct equivalents in other languages. In this case, English and Arabic differ significantly in how they use these formulaic expressions.

We can solve the problem of formulaic expressions by identifying their context. For example, the commonly used phrases in greetings like "Hey, what's up! mere check-in.'', should be a treated as a sequence in the context of greeting. The problem of identifying such expression arises in informal conversations because people often use short phrases and loose structures, which is called "Understatement", which contradicts the Quantity principle. In a casual talk, speakers tend to say less than expected, but the context, facial expression and gestures help identify the speakers' intention. For example, they might use words like "good" or "nice" without elaborating. These understatements pose a challenge for machines to identify their performative functions (Brown and Levinson, 1987).

Deixis is one of the problematic areas that impede the machine from adequate translation of the dialogues, which stems from differences in the use of deixis in English and Arabic. These differences can lead to inaccuracies in translation, as the machine may not fully grasp the context-dependent nature of deixis, affecting the quality of the translated dialogues. Besides, Arabic is morphologically richer than English, which hinders the machine in selecting the appropriate deixis in English (Al-Haj & Lavie, 2012).

The issue of unclear signals in phrases like "wants to meet up," timing shifts in "hitting up and then dinner," and the lack of straightforward meanings in expressions like "what you doing?," "perfect," and "Ciao" has several reasons, including:

a. Automated translation errors are more common in longer conversations.
b. Google Translate may struggle with interactive texts because they have specific lengths and interconnections, causing some sentences to be misinterpreted. Additionally, breaking text into parts for each participant's dialogue makes the machine treat them separately.
c. The texts used to train Google Translate may be formal, while real oral dialogues often involve informal expression, slang, and understatements, especially in opening and closing expressions

Despite the development of Neural Machine Translation, it still faces difficulties in conveying dialogue acts. The Seq2seq model leveraging NMT techniques is reported beneficial in many studies (Colombo et al., 2020; Tiwari et al., 2020.). However, in translation, the dialogue acts from English to Arabic; Google Translate failed to deliver the speaker's intention, in addition to ambiguity in the translation product. The problem lies in the idea that some idiomatic expressions have different meanings in different contexts, which constitutes a hindrance for the Google Translate in selecting the appropriate translation. A clear example of this case is manifested in translating 'what is up.' Here, the limitation is not only in the seq2seq model or attention model (a kind of hidden alignment) but also in the lack of digital Arabic content. Searching engines revealed the most common translation of 'what is up' is 'ما الأمر,' which is not common among Arabic speakers in daily conversation. It is a formal Arabic expression that is used in formal contexts. In this regard, Elmadany et al. (2017) found a lack of resources for training an Arabic speech-act classifier. Popescu-Belis (2019) argues that NMT faces the problem of low-resource language pairs or for specific domains. He found that in certain languages like English-French or German-English news translation, NMT has reached unprecedented levels, leading to claims that it achieves human parity. However, for the English-Arabic pair, the machine is not fed with data that assists the machine in providing the proper translation.

Google Translate has proven its significant development in the field of translation, where errors have become less for the correct output. However, in the light of the texts applied by this study, we found that the automation of SL construction and inference in representing the pragmatic level of the source language, which affected the differences between the two languages, the depth of meaning of linguistic expressions denote two translations, one literal and the other contextual, and its influence by separating structure from the dialogue. Besides, dialogue structure exhibits elliptical structures, briefness, and formulaic expressions, irregular and non-sentences, which lack contextual information (Martinková, 2013). The machine faces a challenge in predicting the speaker's intention because there are various ways of formulating an intention. Wang et al. (2010) argue that the expression `okay' could be interpreted differently in different contexts (an acknowledgment of understanding or an agreement to a request), and the intention is dependent on the utterance it is responding to (Wang et al., 2010). Despite much work of NMT to settle these problems through neural network-based research to model the semantic content of a sentence, in conjunction with some other contextual information, such as previous utterance or dialogue sequences, or a change in speaker turn, to predict the appropriate discourse analysis for the current utterance, NMT still faces hindrances in the prediction of utterance intention (Kalchbrenner & Blunsom, 2013; Lee & Dernoncourt, 2016),

The pragmatic level was the most complex linguistic level facing the machine because the machine depends on understanding language through linguistic signs. These linguistic signs are embedded in culture and context, complicating the prediction of the speaker's intention. Undoubtedly, we cannot ask the machine to fulfill these human capabilities that distinguish the human being. Therefore, this study recommends continuous feeding of the machine in various fields since the semantic and pragmatic level is increasing in living languages, and their uses are evolving over time.

CONCLUSION

This study stands out as an investigation of the effectiveness of Google Translate in rendering dialogue acts within the English-Arabic language pair, which has not received attention in linguistic-based research. The findings illuminate the machine's limitations in effectively conveying speaker's intentions and its struggles in distinguishing words and expressions with multiple meanings, including the complexities of idiomatic expressions. These challenges are rooted in both the machine's inherent constraints and the scarcity of linguistic resources tailored to the English-Arabic context. Crucially, the study emphasizes the enduring significance of human intervention, such as the review and analysis of machine-generated outputs, and advocates for enhancing Google Translate's capabilities through the incorporation of comprehensive libraries encompassing a spectrum of linguistic expressions at both semantic and pragmatic levels. This enrichment would empower the machine to perform more accurate translations of expressions and utterances with multifaceted interpretations in the target language. The study contributes to the assessment of machine's translation of dialogues acts in English-Arabic pair, which lacks coverage in research, using qualitative data. The authors suggest further studies, using both quantitative and qualitative data and large sample to texts to offer more rigorous investigation of the topic.

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APPENDIX 1

DIALOGUE 1

Phone conversation[10]

A: Hey, What's up! Just checking in. What are you doing?
B. Just finishing up things at school. I've got a paper due tomorrow, but it's almost done. Maybe another hour.
A. Ah, Cool. What's it about? I miss school.
B. Actually, it's an economics paper about democracy.
A. Ohhhh. That sounds brutal. haha.
B. Brutal but interesting. I don't mind it. So.. what are you doing?
A. Well. Just finished work, hitting up a dance class, and then maybe dinner. Want to meet up?
B. Let's play it by ear.
A. Sure. I probably won't go until later. 8 or 9-ish.
B. Sweet. That's great. Pizza and a pint?
A. Perfect. We can meet downtown.
B. Okay. See you soon.
A. Ciao.

APPENDIX 2

[10] https://helenadailyenglish.com/real-english-conversation-phone-conversation.html

DIALOGUE 2

At a party[11]

AL: What's eating you
BILL: What do you mean? I'm fine.
AL: NO, you aren't. Come on, whatever it is, get it off your chest.
BILL: Well . . . see that woman over there? Her name's Elizabeth. I've been trying to find a way to meet her for months, and now, here she is. But I don't have the guts to walk over there.
AL: Come on, Bill! This is your chance. Just give it a shot. What do you have to lose?
BILL: She wouldn't be caught dead with me.
AL: Why do you say that?
BILL: Oh, let's just skip it, OK? I don't know why I even told you.
AL: HOW do you know her, anyway?
BILL: We work in the same building.
AL: Well, I think you should just bite the bullet, go over there, and start a conversation.
BILL: Maybe later.
AL: Why put it off? Who knows? You two might hit it off.
BILL: That'll be the day.
AL: Why are you so negative all of a sudden? I've never seen you like this.
BILL: Maybe you're right. I should just take the initiative and walk over there. But what should I say?
AL: NOW you're talking. Just introduce yourself and start talking about the party or mention that you've seen her at work. She's bound to recognize you, too.
BILL: Well, maybe. Oh . . . you're probably right. If I pass up this chance, I'll never forgive myself. Well, here I go. Wish me luck!

[11] https://helenadailyenglish.com/real-english-conversation-at-a-party.html