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# A MODEL FOR CUSTOMIZING AI ASSISTANTS FOR SPECIALIZED TRANSLATION FOR EDUCATIONAL PURPOSES

***Abstract:*** *This study proposes a model for personalising AI assistants for specialised translation through prompt engineering, context adaptation, and the integration of terminological resources. The resulting model incorporates an agent profile, an educational context modelling layer, a contextual framework, and a structured workflow. This model was validated using Agent Builder in Microsoft Copilot Studio, as well as proto-agents in ChatGPT and Claude, to translate Bulgarian educational texts related to computer science and educational technology. The results suggest that personalised AI assistants can facilitate the creation of terminologically consistent and pedagogically appropriate translations, even under constraints of limited time and technical resources.*

***Keywords:*** *generative artificial intelligence, AI assistants, specialized translation, prompt engineering, customization, educational texts.*

## 1. INTRODUCTION

In recent years, generative language models such as ChatGPT, Claude, Gemini, Grok, and Microsoft 365 Copilot have emerged as some of the fastest-evolving technologies in the field of natural language processing. In addition to producing high-quality text, these platforms provide mechanisms for adapting their outputs to specific user tasks through system instructions, contextual materials, terminological resources, and example texts (Avramenko, 2025).

Alongside the advancement of generative models, there has been growing interest in developing personalized AI assistants for specialized professional tasks. Contemporary platforms enable such assistants to be configured through prompt engineering and contextual adaptation techniques, eliminating the need for additional fine-tuning of the underlying language models (Ekin, 2023). This creates new opportunities for building translation assistants tailored to specific professional and educational needs.

This study examines the opportunities and limitations of developing personalized AI translation assistants through prompt engineering and contextual customization. The analysis covers two approaches to their implementation: the use of Microsoft Copilot Studio and the direct customization of models such as ChatGPT and Claude through specialized instructions. The study focuses on the translation of Bulgarian-language educational materials in computer science disciplines intended for international students.

This research aims to analyze the capabilities of contemporary generative AI platforms for developing personalized translation assistants and to propose a practical model for their construction. To achieve this objective, the study examines the principal personalization mechanisms, develops a framework for creating a specialized translation assistant, and evaluates translation quality according to three key criteria: terminological accuracy and consistency, semantic and functional adequacy, and the extent of post-editing required.

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## 2. METHODOLOGY

### *2.1 Literature Review*

The first stage of the study consisted of a review of publications from the past five years addressing the application of generative language models in translation practice, as well as methods for the development, customization, and personalization of AI assistants and AI agents. The pedagogical dimension of personalising AI agents for working with educational content and context was also examined, as discussed in Section 2.3 below.

It should be noted that the concepts of *AI translation assistants* or *AI translation agents* are interpreted differently in the contemporary literature, encompassing both autonomous agentic environments (Qi, 2026) and configurations implemented through prompt engineering (Davlatova et al., 2026; Yamada, 2023). The present study focuses on both agent-based configurations implemented through specialized platforms and proto-agent systems created via prompt engineering, in which role behavior, terminological control, and the logic of the translation process are defined through a structured set of instructions, or a *master prompt*.

The selection of sources was based on criteria including recency, scientific rigor, and practical applicability in educational and professional contexts. Particular attention was given to studies addressing prompt engineering techniques, contextual adaptation, the use of terminological resources, and personalized instruction frameworks.

### *2.2. Main Approaches to the Personalization of AI Translation Agents*

Most of the approaches examined do not require additional fine-tuning of the underlying language model but instead rely on various mechanisms for managing context and instructions.

One of the most advanced approaches involves the use of multi-agent systems. Briva-Iglesias (2025) proposes a model in which the translation process is distributed among several virtual agents with distinct roles, including translator, editor, terminology consultant, and quality evaluator. Their interaction is implemented through *prompt chaining*, where the output of one stage serves as the input for the next (Briva-Iglesias, 2025). This approach enables more precise control over the individual stages of the translation process. Nevertheless, such a model is more appropriate for enterprise-level solutions. For individual instructors who need to produce translations of acceptable quality, multi-agent systems are generally impractical due to the high licensing costs of suitable software or large language models, the requirement for basic programming skills, and the considerable setup time compared with single-agent or proto-agent systems.

A second group of methods focuses on terminological personalization. Ghazvininejad, Gonen, and Zettlemoyer (2023) developed the DIPMT (Dictionary-based Prompting for Machine Translation) method, in which predefined translation equivalents extracted from bilingual dictionaries are integrated directly into the prompt instructions. In this way, the model receives terminological guidance during translation generation without requiring additional training.

Another widely adopted approach is the use of example translations (*few-shot prompting*). Research by Merx et al. (2024) demonstrates that translation quality depends less on the number of examples provided than on their thematic and semantic similarity to the target task. Particularly strong results are achieved when example translations are combined with terminological resources, an approach that is especially valuable when working with low-resource languages.

Recent studies have also devoted considerable attention to contextual personalization. Zhang et al. (2025) proposed the MAPS (Maps, Audience, Purpose, Style) framework, which structures information about the target audience, communicative purpose, genre characteristics, and stylistic requirements of the text. Such an approach enables translations to be better adapted to specific communicative situations and can serve as a foundation for the development of specialized AI translation assistants.

Another line of research focuses on instruction structure and prompt design. Pourkamali and Sharifi (2024) demonstrate that carefully designed prompt frameworks produce more stable and predictable outputs than conventional user prompts. Similar conclusions were reached by Bawden and Yvon (2023), who showed that incorporating additional context and preceding sentences improves translation coherence and facilitates the correct handling of references, pronouns, and grammatical categories.

The review of the existing literature indicates that contemporary approaches to personalization can be grouped into several major categories:

• role-based distribution of tasks among multiple agents;
• integration of terminological resources;
• provision of example translations;
• explicit description of the communicative context; and
• optimization of prompt instructions.

Together, these mechanisms constitute the general methodological foundation for the development and personalization of AI translation assistants.

The present study does not propose a fundamentally new personalization technique. Instead, it develops an integrated model that combines the most effective mechanisms identified in the reviewed literature into a unified framework.

### *2.3. Methodology of the Educational Context Modelling Layer*

Recent studies in AI-supported education suggest that effective personalisation should go beyond linguistic adaptation and domain-specific terminology (AWEJ, 2024). Educational applications of generative AI are increasingly integrating pedagogical goals, instructional roles, learner characteristics, and learning design principles into prompt architectures and agent configurations (Park & Choo, 2024; Choi et al., 2024; Lin et al., 2026). Similarly, international policy documents emphasise that the integration of generative AI into education should preserve the pedagogical purpose of learning resources, supporting meaningful learning processes rather than merely automating content generation (UNESCO, 2026).

Based on these findings, the present study adopts an integrative methodology combining established personalisation mechanisms with pedagogical contextualisation. This multidisciplinary personalisation enables the AI assistant to preserve the instructional logic and educational accessibility of translated learning materials, as well as semantic and terminological accuracy.

## 3. DEVELOPMENT OF AN AI TRANSLATION ASSISTANT

### *3.1. Selection of the LLM Core and the Type of AI Assistant*

The first stage in developing a personalized AI translation assistant is the selection of the underlying large language model (LLM core) and the appropriate personalization mechanism. This choice determines the quality of the generated translations, the available agent configuration options, access to external resources, and the level of control over the translation workflow.

In the present study, Microsoft Copilot, ChatGPT, and Claude were selected because they represent some of the most widely used consumer platforms based on generative language models and provide personalization mechanisms through system instructions, contextual settings, external knowledge sources, and specialized agent configurations without requiring additional fine-tuning of the underlying model. Furthermore, these platforms support different approaches to the development of specialized AI assistants, including both visual agent configuration environments and prompt engineering techniques.

Table 1 presents a comparative overview of the selected generative AI platforms.

*Table 1. Comparative Characteristics of the Generative AI Platforms Used in the Study*

| Criterion | Microsoft Copilot | ChatGPT | Claude |
|---|---|---|---|
| Base model | GPT-4o / GPT-4.1 (within the Microsoft ecosystem) | GPT-4o, GPT-4.1 | Claude Sonnet 4, Claude Opus 4 |
| Access type | Microsoft 365, Copilot Studio | Web interface, GPTs, OpenAI Studio, API | Web interface, Projects, API |
| Support for custom agents | Yes (Copilot Studio, Build Agent) | Yes (GPTs, OpenAI Studio) | Partial (Projects, system instructions) |
| System instructions | Yes | Yes | Yes |

| Criterion | Microsoft Copilot | ChatGPT | Claude |
|---|---|---|---|
| Knowledge base / external documents | Yes | Yes | Yes |
| API integration | Yes | Yes | Yes |
| Support for multi-step workflows | High | Medium to high | Medium |
| Long-document processing | Good | Good | Excellent |
| Compliance with complex instructions | High | Very high | Very high |
| Terminological consistency | High | High | Very high |
| Suitable for technical translation | Yes | Yes | Yes |
| Suitable for academic texts | Yes | Yes | Particularly suitable |
| Integration with office documents | Excellent | Limited | Limited |
| Usable without programming skills | Yes | Yes | Yes |
| Suitable for enterprise deployment | Excellent | Good | Good |
| Suitable for individual translators | Moderate | Excellent | Excellent |

The selection of these three platforms enables a comparison between two principal approaches to the development of AI translation assistants. The first approach involves the use of specialized agent development environments, while the second relies on the direct personalization of existing generative language models through instructions and contextual configuration.

Within the Microsoft ecosystem, a specialized agent can be developed using Microsoft Copilot Studio. After obtaining the appropriate license, the platform provides the Build Agent functionality, through which the agent's role, instructions, knowledge sources, and user interaction scenarios can be defined. In addition, internal documents, terminology databases, and workflows from the Microsoft 365 ecosystem can be integrated into the agent configuration.

An alternative approach is the direct personalization of a language model through a specialized master prompt. In this method, the behavior of the AI assistant is specified through a comprehensive set of instructions that, similarly to the Build Agent approach, define the agent's role, objectives, translation strategy, terminological requirements, characteristics of the target audience, and example translations. However, in this case, the instructions are provided directly within the interaction with the language model rather than through a dedicated agent development environment. Such a configuration can be implemented in both ChatGPT and Claude without the need for specialized agent-building platforms.

### *3.2. Conceptual Model of the Personalized AI Translation Assistant*

The proposed model is based on the assumption that translation quality depends not only on the characteristics of the underlying large language model but also on the organization of the knowledge, instructions, and processes that govern its behavior. In this context, the translation agent is conceptualized as an integrated system composed of four principal components: Autonomy, Tool Use and External Knowledge Integration, Memory, and Workflow Customization.

The practical implementation of these components is embodied in the developed master prompt, which defines the agent's professional identity, the context of its application, the rules governing terminology management, the sequence of translation operations, and the format of the final output.

A further key aspect is that the proposed model treats the pedagogical framework as an integral component of personalisation rather than an additional workflow condition or supplementary role to the agent identity. The agent is configured to adapt not only terminology and style, but also the translation process, while considering the pedagogical purpose of the source material. This involves being aware of instructional objectives, the expected level of learner expertise, the role of the teacher in the learning process, and the methodological principles underlying the educational content. Consequently, personalisation operates at the linguistic, domain-specific, and pedagogical levels simultaneously.

In this way, the conceptual model is transformed into an operational configuration that can be employed both in specialized agent development environments and through direct interaction with generative language models.

#### 3.2.1. Components of AI Agent Personalization

Analysing existing approaches made it possible to identify six main components of personalisation that, together, constitute the overall architecture of the personalised AI translation assistant for educational texts. These components view personalisation as a comprehensive process of configuring the agent's professional role, contextual framework, knowledge resources, example-based guidance, operational procedures, and pedagogical context awareness, rather than as a single model adjustment.

In contrast to conventional translation personalization approaches, the proposed model treats educational context as an integral component of personalization. The agent is configured not only to adapt terminology, style, and translation workflow, but also to consider the pedagogical purpose of the source material. This includes awareness of instructional objectives, the expected level of learner expertise, the role of the teacher within the learning process, and the methodological principles underlying the educational content. Consequently, personalization operates simultaneously at linguistic, domain-specific, and pedagogical levels.

##### 3.2.1.1. Agent Profile

The first component defines the professional identity and specialization of the agent. Through system instructions, the agent's role, competencies, limitations, and priorities in performing translation tasks are specified. In the proposed model, the agent is defined as a professional translator of academic texts in the fields of education, computer science, educational technologies, and AI literacy. In addition, a hierarchy of priorities is established, emphasizing terminological accuracy, preservation of meaning, academic writing style, and pedagogical clarity.

##### 3.2.1.2. Context Personalization

The second component defines the communicative environment in which the agent operates. For this purpose, an adapted version of the MAPS framework is employed to describe the subject domain, target audience, communicative purpose, and stylistic characteristics of the target text. Context personalization enables translation decisions to be tailored to a specific academic and educational setting rather than being generated according to a universal model.

##### 3.2.1.3. Knowledge Integration

The third component provides access to specialized knowledge beyond the parameters of the underlying language model. In accordance with the principles of Dictionary-based Prompting for Machine Translation (DIPMT), the agent can incorporate terminological dictionaries, bilingual glossaries, predefined translation equivalents, institutional terminology standards, and corpus-based resources. This mechanism improves terminological consistency and reduces the risk of generating inappropriate translation equivalents.

##### 3.2.1.4. Few-Shot Personalization

The fourth component is based on the provision of example translations that demonstrate the desired terminological, stylistic, and structural behavior of the system. Rather than determining translation decisions autonomously, the model is supplied with exemplars that function as implicit instructions. This approach is particularly effective for the translation of specialized texts characterized by established terminological and genre-specific conventions.

#### 3.2.1.5. Educational Context Modelling Layer

The fifth component provides information about the educational purpose of the translated material, the characteristics of the intended learners, the instructional role of the teacher, and the methodological requirements of the course. By modelling these factors explicitly, the agent is instructed to preserve the explanatory structures, conceptual progression, pedagogical scaffolding, and learner-oriented communication strategies present in the source text. Consequently, the translation process becomes sensitive not only to linguistic meaning but also to the educational function of the material.

#### 3.2.1.6. Workflow Customization

The final component defines the organization of the translation workflow. Beyond generating translations, the agent may execute a sequence of interconnected operations, including terminology verification, linguistic revision, quality assurance, and final validation of the output. The practical implementation of this component is achieved through internal instructions that specify the agent's operational logic and the sequence in which individual tasks are performed.

### *3.3. Master Prompt for the Personalization of an AI Translation Agent*

In the context of generative language models, a master prompt can be regarded as a configuration layer positioned between the underlying language model and the specific user request (Sahoo et al., 2024). Its primary function is to define the agent's professional role, operational context, knowledge resources, and task execution logic (Sahoo et al., 2024).

Unlike conventional user prompts, which describe a single task, a master prompt establishes a persistent operational environment that can be repeatedly applied to the translation of multiple texts within the same subject domain. A similar approach has been widely adopted in educational applications of generative AI, where personalization is achieved through system prompts and a predefined set of parameters that determine the characteristics of the final output (Zaslavskiy & Zaslavskaya, 2025). Consequently, personalization through the careful design of the instructional environment can be achieved without additional fine-tuning of the underlying language model.

The master prompt template developed in the present study incorporates the six principal personalization components described above.

*Table 2. Six Principal Components of the Master Prompt for an AI Translation Agent*

| Component | Function | Master Prompt Elements |
|---|---|---|
| **Identity** | Defines the agent's professional role and expertise | *You are a [Language pair] translation agent. You specialize in translating texts within a defined domain and communicative context. You act as a professional translator and subject matter expert rather than a general-purpose chatbot.* |
| **Priorities** | Establishes the hierarchy of translation objectives and quality criteria | *Follow these priorities in order: (1) Terminological accuracy and consistency; (2) Preservation of meaning and factual correctness; (3) Stylistic appropriateness; (4) Audience suitability; (5) Readability and linguistic naturalness.* |
| **Context (MAPS)** | Describes the subject domain, target audience, communicative purpose, and stylistic requirements | *Domain: [Subject field] Audience: [Target audience] Purpose: [Communicative goal] Style: [Genre and stylistic requirements].* |

| Component | Function | Master Prompt Elements |
|---|---|---|
| **Knowledge & Terminology** | Integrates terminology resources, glossaries, translation examples, terminology rules, and preferred domain-specific equivalents | *Use the provided terminology resources as authoritative references. Apply terminology consistently throughout the document. Preserve domain-specific concepts, definitions, references, and document structure. When multiple translation equivalents exist, select the variant that best matches the domain, audience, and communicative purpose.* |
| **Educational Context Modelling** | Incorporates the pedagogical function of educational materials into the translation process by modelling instructional goals, learner characteristics, and teaching methodology | *The source text is an educational resource intended for learning. Preserve its instructional purpose, conceptual progression, explanatory structure, and pedagogical scaffolding. Consider the intended learning outcomes, learner characteristics, the teacher's instructional role, and methodological recommendations of the course. Produce a translation that remains educationally accessible while maintaining linguistic and terminological accuracy.* |
| **Workflow & Output Modes** | Defines the translation workflow and the format of the final output | *Internally perform the following steps: (1) Analyze the source text; (2) Identify key terminology; (3) Interpret the pedagogical context; (4) Produce a draft translation; (5) Verify terminology consistency; (6) Review style, readability, and educational accessibility; (7) Produce the final version. Do not display intermediate reasoning unless explicitly requested. Output Modes: Mode 1 – Translation only; Mode 2 – Translation with terminology table; Mode 3 – Translation review and correction; Mode 4 – Style polishing and post-editing. Output only the result corresponding to the selected mode.* |

This structure enables the conceptual model of the personalized AI translation agent to be implemented consistently across different generative AI platforms, including Microsoft Copilot, ChatGPT, and Claude. Regardless of the platform employed, the fundamental personalization mechanisms remain the same and are based on a combination of role definition, contextual adaptation, external knowledge integration, and a predefined translation workflow.

## 4. PRACTICAL IMPLEMENTATION

### *4.1. Validation of the Proposed Method for Developing and Personalizing an AI Translation Agent in Microsoft Copilot Studio*

Within the Microsoft Copilot Studio environment, the agent configuration was implemented using the Build Agent functionality, with the master prompt developed in the present study serving as its foundation. The prompt incorporated the agent profile, contextual personalization, terminology management rules, workflow organization, and quality control mechanisms.

A baseline agent configuration was established, including the definition of the agent's role, subject domain, target audience, and translation priorities.

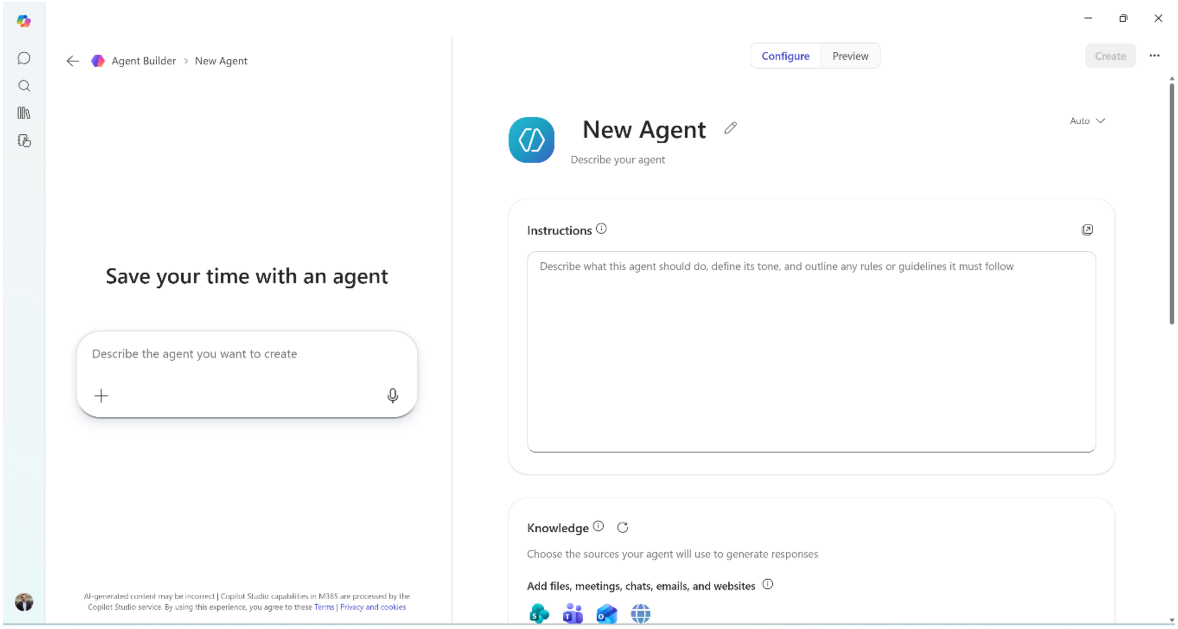


*Fig. 1. Interface for Creating an Agent in Microsoft Copilot Studio*

After defining the agent profile, the master prompt was integrated into the system, incorporating instructions for terminological consistency, the use of an academic writing style, adaptation to the target audience, and an internal workflow for translation self-verification.

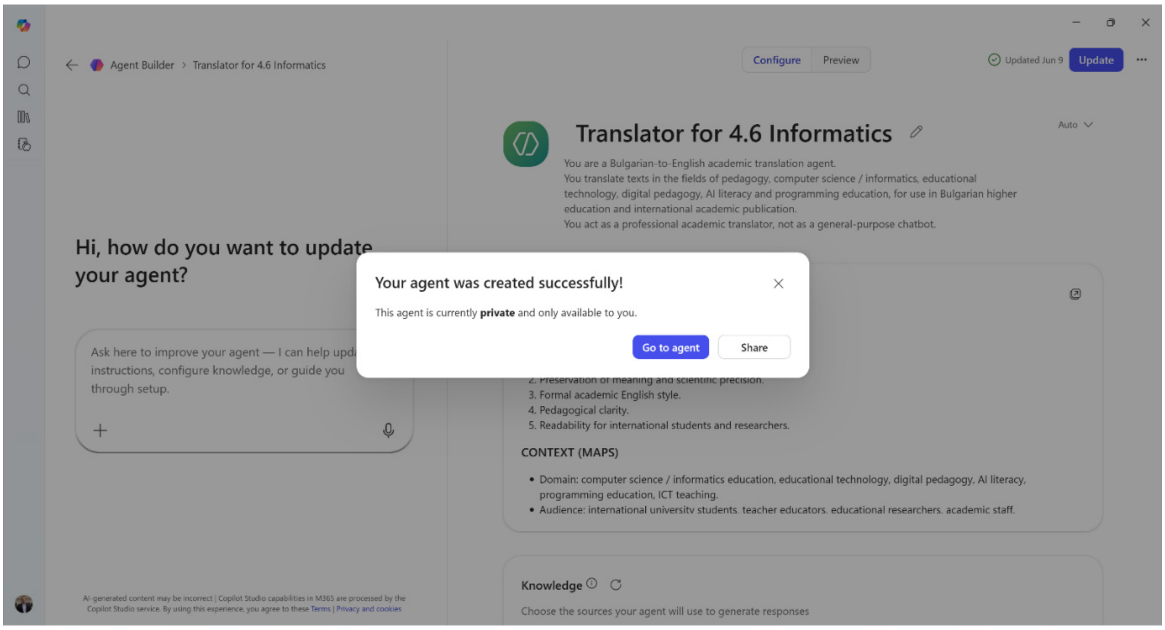


*Fig. 2. Configuration of the Agent's System Instructions in Microsoft Copilot Studio*

A 14-page lecturer's paper on computer science and educational technology was used for the experimental validation in translation from Bulgarian to English. The initial translation was generated in 1 minute and 14 seconds. Analysis of the result shows that, despite the high level of linguistic accuracy, the agent interpreted part of the task as requiring the content to be condensed and summarized. This necessitates further refinement of the instructions, aimed at preserving the document's full structure, including examples, exercises, test questions, and bibliographic descriptions.

After adjusting the configuration, a second iteration of the translation process was conducted. The total time for analyzing the results, revising the instructions, and re-executing the task amounted to approximately 19 minutes.

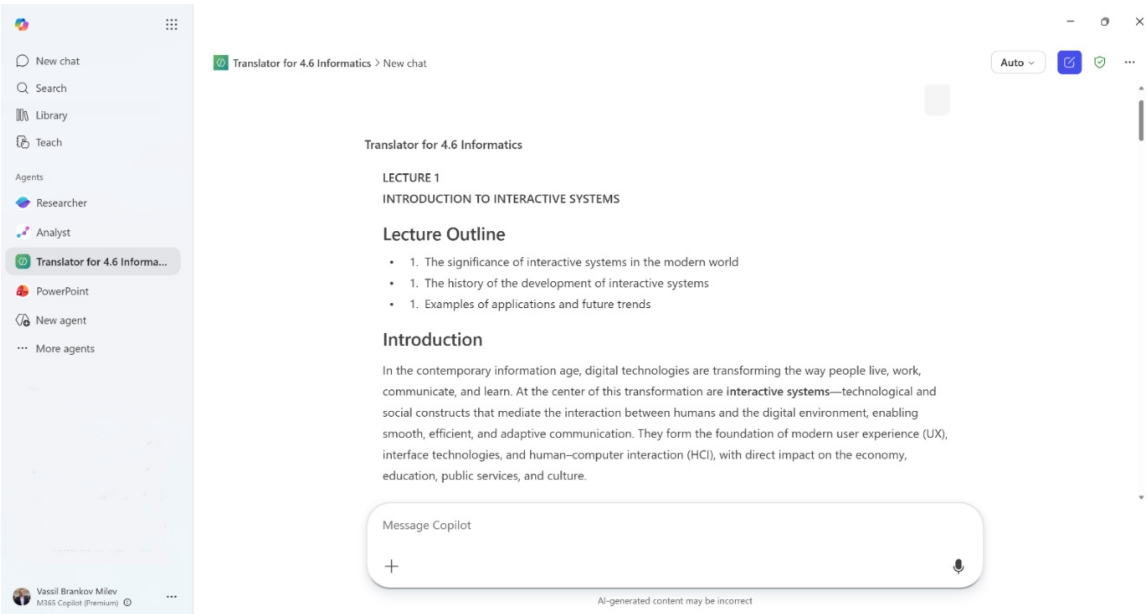


*Fig. 3. Example of a Translation Ready for Subsequent Revision of the Instructions*

The results show that the main time investment in building a personalized translation agent is not related to the actual generation of the translation, but rather to the design and configuration of the working environment. Once the configuration is finalized, the agent can be used repeatedly to process similar texts without the need for reconfiguration.

Translation quality was assessed using the translation productivity evaluation system developed in a previous study, which measures indicators of adequacy, terminological consistency, linguistic correctness, and functional suitability of the final text.

***4.2. Validation of a Method for Creating and Personalizing Translation Proto-agent Systems Using ChatGPT and Claude.***

To further validate the proposed model, a validation was conducted through direct personalization of ChatGPT and Claude using prompt engineering techniques. Unlike Microsoft Copilot Studio and OpenAI Studio, this approach does not require the use of specialized agent development environments and is based solely on a structured master prompt.

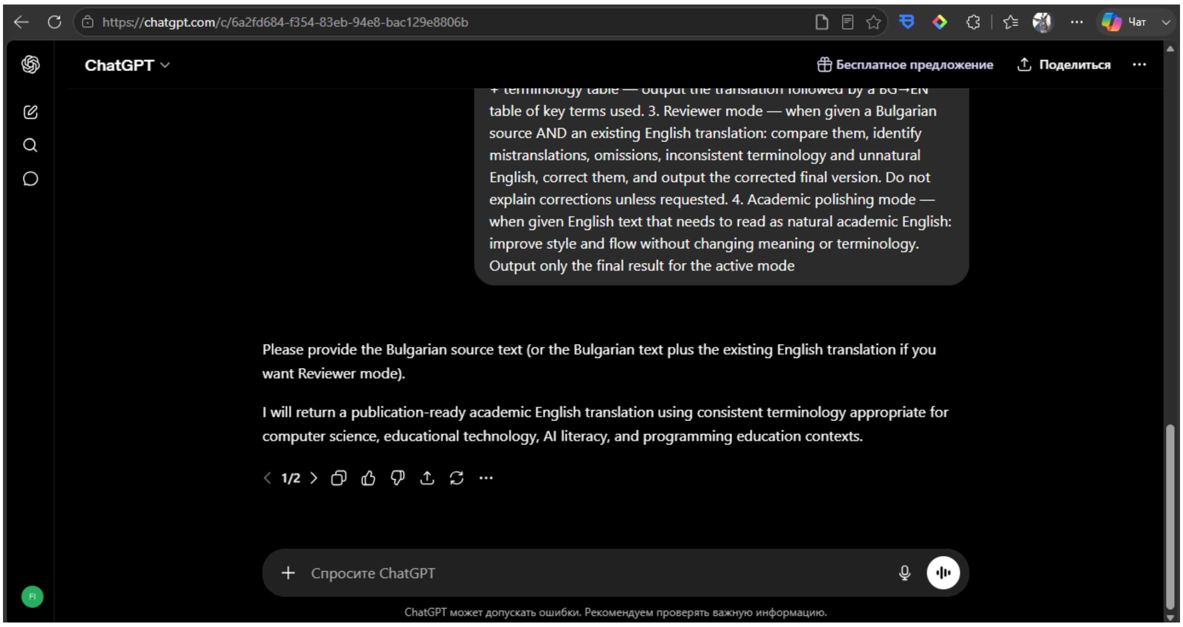


*Fig. 4. Implementation of the Translation Proto-agent in ChatGPT*

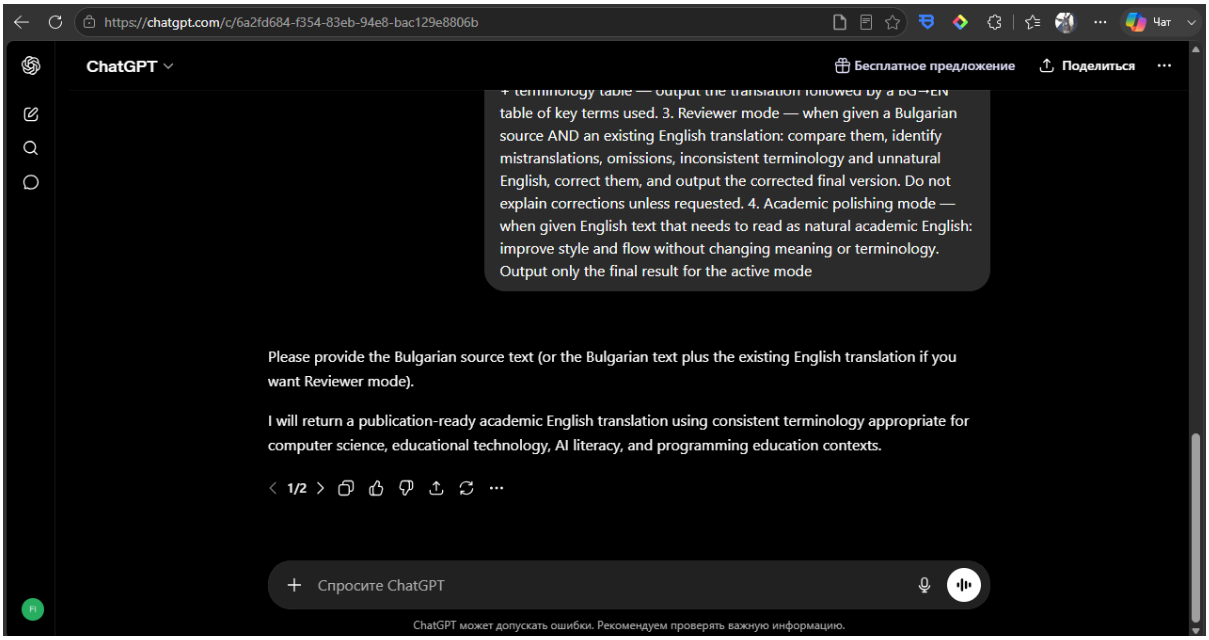


*Fig. 5. Operation of the Proto-agent System in Claude*

## 5. DISCUSSION

The evaluation was based on three indicators:

Terminological accuracy and consistency (T) were calculated as the ratio between the number of correctly used terminological units (Tc) and the total number of terminological units in the source text (Tt).

Semantic and functional adequacy (A) was determined through expert assessment of the translation's communicative purpose (Skopos), register, genre, and suitability for the target audience, using a scale from 1 to 10.

Post-editing effort (H) was measured as the ratio between the number of editorial corrections (Ec) and the total number of words in the translated text (W). Lower values of H indicate a reduced need for subsequent human intervention. This approach makes it possible to evaluate not only translation quality but also its practical applicability in real educational settings.

The results demonstrate that the proposed methodology enables the development of functional AI translation assistants both through the specialized agent development environment of Microsoft Copilot Studio and through proto-agent configurations implemented via a master prompt in ChatGPT and Claude. The findings support the observations of numerous researchers that, in contemporary LLM-based systems, overall effectiveness depends not only on the quality of the underlying language model but also on the organization of instructions, knowledge resources, and workflow design.

The evaluation results are presented in Table 3.

*Table 3. Evaluation Results*

| System | T | A | H |
|---|---|---|---|
| Copilot Studio Agent | 93,3% | 9 | 1,2% |
| ChatGPT Proto-Agent | 90,2% | 9 | 2,3% |
| Claude Proto-Agent | 91,1% | 8 | 2,0% |

From a pedagogical perspective, the obtained results support the view that such systems can be used not only to accelerate the translation process but also to improve the quality of educational content. In his research on the application of artificial intelligence in education, Miroslav Dechev notes the potential of AI systems to assist educators in identifying weaknesses in curricula, courses, and instructional materials that are often difficult to detect through routine teaching practice (Dechev, 2024). A personalised AI translation agent can identify terminological inconsistencies, stylistic irregularities, organisational weaknesses, and potential barriers to comprehension for the target audience. This supports educators in preparing pedagogically accessible learning materials.

Unlike conventional translation assistants, which focus on optimising linguistic quality and terminological consistency, the proposed model recognises educational texts as a distinct category of translation task. Translation decisions are therefore aligned with learning outcomes, conceptual progression, and pedagogical accessibility, thereby preserving the educational value of the original material for learners from diverse linguistic and cultural backgrounds. This approach aligns with recent studies indicating that AI-assisted translation becomes educationally effective when integrated with explicit pedagogical objectives and instructional guidance (IJLTER, 2024).

The proposed model extends the role of AI beyond that of a purely linguistic tool to include that of a translation assistant informed by pedagogy. Rather than functioning as a ‘dictionary on steroids’, as described by one of the participants in Kohout-Diaz’s study on AI in education (2026), the AI agent acts as a pedagogical and ethical mediator whose recommendations remain subordinate to the professional judgement of the teacher. This design reflects recent research emphasising that AI literacy in education encompasses the capacity to critically evaluate AI-generated outputs, recognise translation biases and hallucinations, and make informed pedagogical decisions (Chekalina, 2025).

The effectiveness of such an approach ultimately hinges on its integration into the socio-technical environment of educational institutions. Kohout-Diaz highlights the increasing discrepancy between the widespread, informal use of generative AI and the limited number of structured institutional guidelines that govern its pedagogical application (Kohout-Diaz, 2026). At the same time, concerns remain that excessive automation may diminish the human element of education. Therefore, AI systems designed for educational purposes should support empathy, teacher–student interaction, and meaningful learning experiences, rather than replacing them with technically accurate, yet decontextualised, solutions (Yüce et al., 2026; Ortí-Martínez et al., 2026).

## 6. CONCLUSION

This study explored the possibilities for creating and customizing AI translation assistants through prompt engineering and contextual adaptation without additional retraining of language models. A conceptual model was proposed, incorporating an agent profile, a contextual framework, terminological resources, and a structured workflow. Thanks to the proposed Educational Context Modelling Layer, the personalisation model significantly optimises the translation of pedagogical texts. This layer improves translation quality and facilitates the responsible, pedagogically sound integration of AI into multilingual higher education.

The validation conducted in Microsoft Copilot Studio, ChatGPT, and Claude demonstrated that modern generative platforms enable the development of specialized translation solutions tailored to specific educational and professional tasks. The results confirm that the effectiveness of such systems depends not only on the model used but also on the quality of the instructions, the context, and the workflow organization.

Of particular importance for educational practice is the ability to create translation proto-agent systems using the standard interfaces of ChatGPT and Claude. This approach allows teachers to build their own AI translation tools with minimal technical and financial resources.

Regardless of the high degree of automation, the final decision regarding the quality and suitability of the translation remains in the hands of the human expert. Prospects for future research are linked to the development of multi-agent systems in which individual agents perform functions related to text preparation, translation, editing, and quality control.

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