Using Mind Maps to Investigate the Typology of Students' Use of Large Language Models: A Preliminary Study

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Abstract. *This preliminary qualitative study examines how hand-drawn mind maps can investigate higher education students' educational and private uses of large language models (LLMs). Of 74 participants in a convenience sample of Croatian undergraduate students enrolled in IT- and economics-related study programs, 59 readable, hierarchically structured mind maps were selected, transcribed, translated from Croatian into English, and analyzed using a hybrid approach combining LLM-based analysis with expert interpretation. Specific educational and private use categories were identified and supported. LLM-generated typologies of students' generative AI use converged around integration into everyday life, STEM/technical problem-solving, and reflective or skeptical evaluation of LLMs.*

Keywords. large language models, generative AI, student behavior, higher education, mind maps, qualitative analysis, typology, educational use, private use

1 Introduction

LLMs such as ChatGPT and Gemini are used for a multitude of purposes, and numerous empirical studies, such as those discussed below, have revealed that most of their use falls into two broad categories: (1) *private* and (2) *professional and/or educational* purposes. For instance, a study of messages exchanged with ChatGPT in July 2025 (Chatterji et al. 2025) revealed that the *predominant* conversation topics were related to practical guidance (28.8%), seeking information (24.4%), writing (23.9%; e.g., text editing or correction, translation, personal communication, etc.), multimedia generation (7.3%), self-expression (5.3%), and technical help (5.1%). Another large consumer-oriented study (Carloan et al., 2025), conducted among *U.S. adults*, uncovered that typical everyday usage is related to writing emails (18%), researching topics of interest (18%), managing to-do lists (18%), writing support (18%), meal planning (16%), managing expenses (15%), taking and organizing notes (15%), creating images (15%), researching purchases (15%), and researching health questions (14%). The *Deloitte 2025 Connected Survey* (Fineberg et al., 2025) showed that users have mostly conversed with generative AI tools (chatbots) regarding work assistance (67%, only employed respondents), product recommendations (53%), personal advice (44%), physical health or medical assistance (38%), travel planning (36%), nutritional assistance (35%), financial assistance (35%), and fitness coaching (33%). A survey presented on the *Statista* portal (Statista Research Department, 2025) found that in 2025, *adults in the U.S.* predominantly used AI for activities like tasks at work (28%), to learn something new (26%), and for entertainment (22%).

The most recent *Pew Research Centre* survey (Gotfried et al., 2026), conducted in February 2026, reported the following most frequent uses of AI chatbots by *adults in the U.S.*: search for information (42%), tasks at work - among employed adults (38%), fun or entertainment (25%), creation or editing of images or videos (24%), getting medical advice (20%), for diet and fitness information (20%), obtaining news (13%), emotional support or advice (10%). A similar survey performed in March 2026 among *adults* (18+) in the U.S. by *Epoch AI* and *Ipsos* (2026) showed that the most frequent uses for AI services (by LLMs like ChatGPT, Gemini, etc.) were looking up information or getting recommendations (80%), writing or editing text - emails, documents, summaries (59%), advice or learning - including "how-to" guidance, tutoring (55%), brainstorming or generating ideas (53%), creating or editing images (44%), summarizing or analyzing a long document or webpage (41%), technical work - math, data analysis, programming, etc. (37%), and personal reflection or chatting for fun (26%). Interestingly, the *AP-NORC* poll (AP-NORC Center for Public Affairs Research, 2025), conducted in July 2025, indicated that *younger adults* (aged 18-29) report much higher frequencies of AI use, in comparison to *all adults* in their sample, for various tasks like search for information (74%), coming up with ideas (62%), work tasks (52%), helping write emails (50%), creating or editing images (47%), entertainment (44%), shopping (40%), and companionship (25%).

When the research focus was on the *student population* and educational use of ChatGPT and other chatbots, one of the earliest global surveys (Ravšelj et al., 2025), conducted from November 2023 to February 2024 with 23,218 *higher education students* from 109 different countries and territories, revealed the following most frequent uses: brainstorming, summarizing long texts, finding articles for research, and writing texts. A similar large-scale study (Chung et al., 2026), conducted on *higher education students* in Australia in the August–October 2024 period, uncovered the following most

frequent uses of generative AI: editing or improving writing (67%), generating ideas and examples (64%), summarizing notes, readings or other materials (54%), teaching me how to do something (51%), getting feedback from generative AI (50%), finding information or conducting research (47%), generating or error-checking code, formula, mathematical calculations or data analysis (36%). A more recent survey (Chatzopoulos et al., 2025), conducted at *one university in Greece* from April to November 2025, showed that the most frequent uses of generative AI tools were: information search (85%), explaining and understanding difficult concepts in simple terms (59%), help with academic work - writing papers, generating ideas and inspiration, gathering study material (48%), exam preparation (43%), programming - code assistance, algorithm explanation, code debugging (36%), text writing (30%), creating or editing images (27%), and language assistance - conversation practice, translation, grammar (24%).

One of the most recent surveys (Stephenson and Armstrong, 2026), conducted by the professional organization *Savanta* in the United Kingdom in December 2025, detected an almost universal use of various types of AI tools (up to 95%) by *higher education students*, with the following activities being most frequently reported: generating text, e.g. ChatGPT (56%), summarizing, note-taking or quizzing university textbooks, e.g. Kortext (38%), enhancing and editing personal writing, e.g. Grammarly (37%), translation or language support, e.g. Google Translate (31%), generating images, videos or audio, e.g. DALL-E (22%), speech-to-text transcription, e.g. automatic captions on YouTube (18%), writing computer code, e.g. GitHub Copilot (17%), data analysis and presentation, e.g. Julius AI (17%), for friendship, company, advice or tackling loneliness (15%), another use related to my studies, e.g. medical software (13%), for counselling or therapy provided solely by AI (8%). The authors of this study also noted that AI tools are increasingly being used by students to prepare assessed work, for instance to explain concepts, summarize relevant articles, suggest ideas for research, structure their "thoughts", search the internet, generate text that is later edited by the student before it is, more or less, directly incorporated in the assessed work.

Finally, in a *review study* of 26 related academic papers by Naznin et al. (2025), the following categories/domains of types of AI uses by higher education students were identified: (1) *personalized learning* (real time feedback, adaptive learning, collaborative learning, student engagement, and self-regulatory learning); (2) *academic writing* (academic writing process, content generation, writing tools, over-reliance, and critical thinking); (3) *coding* (code generation, code debugging, and code explanation).

However, it must be noted that a *taxonomy or categorization* of students' use of large language models (LLMs) and generative AI (GenAI) based on analyses of data collected from the students themselves was rarely studied. Most research articles list the students' frequent activities with LLMs and GenAI. Still, the study by Zhang et al. (2026) investigated how the Latent Class Analysis (LCA) would identify *subgroups of students* based on their preference for the use of LLMs/GenAI for general purposes labelled "Fun," "Homework," "Research," "Study," across several tool types ("Code," "Data," "LLM," "Write," and "Other"). This analysis indicated five subgroups of higher education students: (1) study/assignment–focused users; (2) research-oriented power users; (3) routine mainstream/regular learners; (4) light users, whose use is more selective, bounded to fewer contexts, and narrower in tool coverage; (5) all-purpose, multi-tool, cross-context users who move across learning, assignments, research, and leisure and draw on a wider set of tools.

In the study that is presented in this paper, the *educational use* of LLMs and GenAI in itself is not the main focus, but instead the *main objective* is to investigate a potential *typology of students' LLM/GenAI-related behaviors* in their daily activities, using our *small convenience sample* as an *exploratory starting point*. Therefore, in this study, we will observe the students in our study as a *non-representative subsample* of LLM and GenAI student-users of different age groups and other sociodemographic characteristics. The *second objective* is to test an approach to qualitative analysis that is based on using a less conventional method in which students create mind maps of their LLM/GenAI use. Also, in this *hybrid approach*, following the coding of the students' mind maps into hierarchical verbal descriptions, several LLMs will be employed for *initial qualitative analyses* to examine the frequency of various activities and identify potential typologies of LLM/GenAI use.

2 Mind Maps and Mental Models

Mind maps can be used in qualitative research for various purposes like planning a project, data collection, analysis of visual and narrative data, as well as presentation of findings (Wheeldon and Åhlberg, 2019). In data collection, participants may only need a blank sheet of paper and a pen(cil) to begin drawing from a central main topic or 'core,' thereby creating a visual representation of how they perceive and experience the phenomenon under investigation. Both mind maps and concept maps can be used by visually oriented social science researchers since they are a form of a participant-centric means of associating user-collected data with theory (Wheeldon and Faubert, 2009). One means to apply mind maps as a data collection method is to start by demonstrating to the subjects in research at least one visual model or example of what a mind or conceptual map is, with some additional explanation of what is required by the participants. In fact, mind maps can be used not only to effectively collect personalized visualization data from research subjects who draw them, but also to organize complex transcripts or recordings of data collected with interviews (Fearnley, 2022). In addition, mind maps can be effectively used in STEM *(Science, Technology, Engineering, and Mathematics)* education since they have the potential to reduce cognitive load and enhance learning outcomes, including improvement of theoretical comprehension and critical thinking (Kefalis et al., 2025). In fact, one meta-analysis confirmed the effectiveness of their use on students' achievements in science and technology from primary to higher education (Wang et al., 2025, June).

Contrary to the relatively simple, basic, mostly hierarchical structure of mind maps, *mental models* are "internal representations that individuals construct to explain and predict the behavior of complex systems, including their expectations of the system's capabilities and limitations" that can be effectively used, for instance, to investigate *human–AI interaction* (Bodamer et al., 2026).

While there are many definitions of mental models, basically, in human-computer interaction (HCI) research, they are founded on *eliciting users' cognitive and behavioral model(s) of a specific computing system and its use*, i.e., they can help in "explaining how and why people use, rely on, trust, or reject these systems", including AI (Sanchez et al., 2026). For instance, Wang et al. (2025, March) used transcripts of oral interviews and drawing data to investigate, in simulated chatbot ecosystem settings, mental models of a small sample of users regarding their use of chatbots for hotel booking and they classified these models into four categories: (1) chatbot as a key player; (2) chatbot as a medium; (3) chatbot as a representation; (4) chatbot as an agent. Mehmood et al. (2025) used qualitative research design to identify the following three primary types of users' mental models about roles and implications of LLMs: (1) *enthusiastic view* of LLMs as helpful assistants and/or personalized support systems; (2) viewing LLMs as *conditional partners*, and (3) *apathetic views* of LLMs that involve seeing them as potentially dangerous and/or suspicious actors.

In our study, the focus will be on the qualitative research method of drawing mind maps of students' use of LLMs for educational and private purposes to (a) investigate the *variety of LLM use* for such purposes and (b) develop broad *initial categorizations or typologies* based on the students' drawings. The goal of this study is not so much to inspect the educational uses of LLMs by a small convenience sample of higher education students, but rather the *initial exploration of potential typologies* of their LLM/GenAI-related user behavior. Also, less conventional *qualitative* methods will be applied and tested, consisting of (a) using an LLM to assist in creating written transcriptions of students' mind maps and (b) using multiple LLMs for frequency analysis and creation of potential categorizations or typologies of students' educational and private uses of LLMs. In addition, the resulting typologies of LLM use may provide *partial insights into users' mental models of LLMs* and could perhaps be considered indirect external representations of some of their segments.

3 Study Goals, Problems, and Research Questions

The main goal of the *qualitative pilot study* that is presented in this paper was to investigate the use of mind maps as a method to collect data for the creation of an *initial broad typology* of students' educational and private uses of large language models. Accordingly, the following research problems (objectives) are defined for this pilot study:

1) To identify the potential variety of students' educational and private uses of large language models that are represented in their mind maps.
2) To investigate specific categories of students' educational and private uses of large language models based on data collected through mind maps.
3) To examine whether large language models can generate meaningful and interpretable typologies of students' LLM use from written transcripts of their mind maps.

From the previously cited studies (i.e., Chatterji et al., 2025; Carloan et al., 2025; Fineberg et al., 2025; Statista Research Department, 2025; Gotfried et al., 2026; Epoch AI and Ipsos, 2026; AP-NORC Center for Public Affairs Research, 2025) among the most common uses of LLMs in the general *adult population* were the following: searching for information and research; writing and editing text; work and educational assistance; advice and recommendations; brainstorming and idea generation; image and multimedia creation; technical assistance; summarization and information organization; health, nutrition, and fitness support; personal life support and entertainment. Specifically, regarding recently published research focused on the *students populations* (i.e., Ravšelj et al., 2025; Chung et al., 2026; Chatzopoulos et al., 2025; Stephenson and Armstrong, 2026), the following uses and activities were most present: information search and academic research; writing, editing, and improving academic texts; brainstorming and idea generation; summarizing texts, notes, and learning materials; explaining and understanding concepts; learning support and tutoring (learning how to do something); exam preparation and studying; programming, coding, and technical problem solving; translation and language support; image and multimedia generation; feedback on writing and academic work; data analysis and presentation.

Based on the first problem of this study and having in mind a possible comparison with the previous lists of LLMs uses, this first research question was formulated:

RQ1: *What educational and private uses of large language models are represented in students' mind maps?*

As was briefly discussed in the previous chapter 2. "Mind Maps and Mental Models," as a research method, mind maps can be used for collecting qualitative data that illustrate how the participants in a study visually represent their knowledge, experiences, and perceptions (Wheeldon & Åhlberg, 2019). In fact, use of mind maps and mental models are forms of participant-centered qualitative analysis (Wheeldon & Faubert, 2009) and may provide an alternative means of identifying representations of participants' thinking and behavior. Mind maps are a simplified form of mental models that are often used in human–AI interaction research (Sanchez et al., 2026). Some qualitative studies have successfully developed typologies of users' mental models from interviews and drawings, demonstrating that qualitative visual data can support the creation of meaningful user typologies (Wang et al., 2025, March; Mehmood et al., 2025). However, although typologies of users' mental models of AI exist, broad categorizations that are specifically related to *students' educational and private uses* of LLMs are still scarce, which provides a rationale for the following second research question:

RQ2: *What specific categories of students' educational and private uses of large language models can be identified from mind maps created by students?*

Finally, since the third problem of our pilot study was to investigate if and how LLMs can generate typologies of students' LLM use from written transcripts of their mind maps, a third research question is defined:

RQ3: *What is the potential of large language models to support qualitative analysis by generating meaningful typologies of students' educational and private uses of LLMs from mind map transcripts?*

For each of the previously listed research questions (RQ1–RQ3), a separate explanation of methodology and presentation of results of this preliminary study will be presented.

4 Methodology

This preliminary study uses *survey data* for collecting demographic information about the convenience sample of respondents and a *hybrid* qualitative approach using students' drawings of mind maps that depict their use of LLMs in educational and private contexts together with LLM-assisted thematic and content analyses of transcripts of the hand-drawn mind maps. Furthermore, selected LLMs were used to identify potential typologies (or "styles") of students' educational and private use of LLMs. This is a rather novel approach that uses mind maps and LLMs for qualitative analyses of their transcripts.

4.1 Subjects in Research and Data Collection

The initial convenience sample of participants in this qualitative study consisted of 74 students at a Croatian university who were enrolled in IT- and economics-related undergraduate study programs. These students volunteered for a set of learning activities on using ChatGPT in a course on *English for Special Purposes*. For participating in these learning activities, which lasted a total of 60 minutes and were performed in the English language in a computer laboratory with the use of ChatGPT as an LLM, the students were given small course credit. After completing each of the learning activities, the students used a survey to evaluate them. Then, after all of the brief learning activities were completed and evaluated, the students were asked to draw on an A4 piece of blank paper a mind map of their educational and private LLM use.

Out of 74 mind maps created by the students, 59 were selected for further analysis based on the following criteria: (1) the mind map had a clear hierarchical structure, (2) the hand-written text of the mind map was readable, (3) the students' mind map was not a copy or too similar to the *model mind map* they were provided with as an example. In other words, the final sample in our study consisted of 59 students who had drawn a *readable* and *original* hierarchical mind map on their *educational and private LLM use*. It must be noted that all students were anonymous in the survey for evaluation of learning activities and in drawing the mind maps.

The initial convenience sample of 74 students consisted of 66.2% male and 33.8% female participants. Also, most respondents (51, or 68.9%) were aged 18–19, while other respondents were aged 20–21 (21, or 28.4%), or 22 and above (2, or 2.7%). Almost all respondents (73 out of 74) were first-year students. Due to anonymity and the fact that the students were not writing their age and gender on the paper with their mind maps, the precise demographic composition is not known for the 59 students (Case #1 to Case #59) whose mind maps were chosen for further analyses.

Regarding the amount of use of tools such as ChatGPT prior to this study, more than two-thirds (67.6%) of the students in the initial convenience sample of 74 participants reported high or very high use, while only a small fraction (6.8%) reported no or very little prior use of ChatGPT. When asked specifically to assess the *average frequency* of their use of ChatGPT or similar tools in the previous 3–4 weeks, 16% of subjects reported using ChatGPT less than once in a week, 16% of respondents declared using it 1–2 times per week, 31% stated that they used it 3-4 times per week, and 37% indicated a frequency of use of 5 or more times per week. In addition, when the participants were asked to estimate the amount of time that they had spent using ChatGPT during the previous 3–4 weeks, 49% of them reported using it 1–2 hours per week, 26% of declared using it 3–4 hours per week, 17% used it 5–6 hours per week, and 4% for 7 or more hours per week. Also, three respondents, or 4%, did not report any ChatGPT use during the previous 3–4 weeks.

The respondents were also asked to list the AI tools they had previously used. The most frequently mentioned AI tools were ChatGPT (85%), Gemini (74%), and DeepSeek (28%). Other reported tools included Claude (18%), Perplexity AI (15%), Copilot (12%), Grok (11%), Astra AI (7%), and NotebookLM (3%). Among the tools rarely mentioned by individual respondents were Comet, ThetaWise, Medley AI, MathGPT, Sora, DALL·E, and Codex. With regard to the number of AI tools used by individual students, most respondents reported having previously used three AI tools (35%), followed by two tools (27%) and four tools (15%).

It should be emphasized that the students voluntarily participated in the study, that the data collection method ensured their full anonymity, and that the research was approved by the institutional Ethics Committee. Also, since the students were in their first year of study and from a single higher education institution, the findings of data collection and analyses cannot be generalized to other students in Croatia.

4.2 Qualitative Methods

The qualitative methods and analytical procedures that were used in this study were (1) drawing mind maps regarding respondents' personal and educational use of LLMs, (2) creation of written transcriptions of student-generated mind maps into a hierarchical textual structure, (3) thematic frequency analysis of written transcripts using LLMs, (4) identification of initial categorizations of general "styles" or "typologies" of students' use of LLMs in the educational and private contexts.

4.2.1 Drawing Mind Maps

For this rather simple qualitative data collection *(elicitation)* procedure the main intention was that the respondent-generated mind maps have a similar basic structure: (a) central point or root node consisting of one or more most used LLMs; (b) two main primary branches or first-level nodes that are related to *educational* and *private* use of LLMs; (c) secondary branches (other subbranches) that are freely identified by the respondents regarding common means of their LLM use. The students were instructed to create a mind map of their choice, but to indirectly guide their design, the instructor used a whiteboard marker to draw by hand on a whiteboard how a potential model mind map for a higher education teacher's use of LLMs may look. This "model" mind map consisted of the following: (1)

"ChatGPT" and "Gemini" written in the *primary/central node*; (2) "PRIVATE" and "BUSINESS" as *two main primary branches*; (3) subbranches "ARTICLES SEARCH," "THEORY EVALUATION," "IDEAS FOR RESEARCH," "TRANSLATION AND EDITING" in the "BUSINESS" part of the mind map; (4) subbranches "INFORMATION SEARCH," "NEWS CHECKING," "COOKING RECIPES," "HEALTH COMMENTS" in the "PRIVATE" part of the mind map.

The students were specially instructed not to make a copy of the potential ("model") mind map on higher-education teachers' use of LLMs, but to freely draw their own mind maps regarding subbranches and specific content that relate to their own uses of LLMs.

It must be emphasized that, for this study, the use of mind maps was chosen because (a) it is a semi-structured visual and textual method for eliciting students' data about their uses of LLMs, (b) they usually maintain a simple tree-structure branching radially, and (c) they are most often produced without cross-links. In other words, it was expected that most respondent-produced mind maps would be represented as hierarchically organized textual content that is not difficult for content analyses. Still, the use of a "model" mind map, despite the instruction to draw their own versions, may have influenced the creation of some students' mind maps.

4.2.2 Transcriptions of Drawings and Text in Mind Maps

If a hand-made drawing of a mind map has a simple hierarchical tree-structure that branches radially and has no cross-links then creating its textual transcript is a simple task of (a) denoting the central point or root node, (b) labelling the primary branches or first-level nodes, (c) listing the elements of the subbranches of the first level nodes or primary branches, (d) if there are third-level subbranches, or even lower level, then the hierarchical top-down procedure is repeated until the lowest level of subbranches has been documented.

For this pilot study (and to accelerate the manual process of making textual transcriptions of respondents' mind maps), several LLMs were tested for their ability to transcribe PDF scans of hand-drawn mind maps containing block and/or cursive handwriting. Since *Gemini 3.1 Pro* proved to be a convenient choice for this task, this LLM was requested to make an interpretation of each uploaded PDF scan of mind maps, one by one, by repeating the following basic prompt written in English: "Interpret the [N-th] mind map in the PDF (the text is in Croatian language, written by hand)." In the case of all drawings of mind maps, the interpretation or textual transcription of a given mind map created by Gemini was checked by the researcher, and when there was a misreading or misinterpretation, Gemini was prompted to correct its interpretation of such maps. In other words, textual transcriptions of all mind maps created by Gemini were checked by the researcher and corrected when needed. The use of the Gemini LLM considerably accelerated the process compared with *fully manual transcription* of all mind maps by a human researcher. After all the transcriptions of mind maps with a clean hierarchical structure were completed and checked, one final Word document was assembled with all acceptable transcriptions labelled as Case #1 to Case #59. It must be noted that Gemini not only made transcriptions in the Croatian language, but also translated all of the text in the Croatian to English. Following is an example of a translation to English of the basic structure of a mind map for "Case #21" (the exact transcript of the Croatian text is written in *italics*):

- Central Node: Main Context
  - *CHAT GPT*: The central hub of the map.
  - Top Branch: *EDUKACIJA* (Education)
    - *pomoć oko učenja*: Help with studying.
    - *pomoć pri rješavanju zadataka*: Assistance in solving tasks or assignments.
    - *pomoć za projekte, radove i sl.*: Help with projects, papers, and similar academic work.
  - Bottom Branch: *PRIVATNO* (Private/Personal Use)
    - *saznavanje više informacija o određenim stvarima koje me zanimaju*: Finding out more information about specific topics of personal interest.
    - *rješavanje određenih pitanja s kojima se susrećemo na dnevnoj bazi*: Resolving or answering specific questions that are encountered on a daily basis.

As can be concluded from the previous example, this preparatory phase for further qualitative analyses resulted not only in transcripts regarding the basic structure and Croatian text of the mind maps, but also in translations of the Croatian text to English.

4.2.3 Frequency Count of Mind Map Elements

Before the categorization of elements of the respondents' mind maps, the elements of those mind maps were counted from their transcripts for all 59 cases (Case #1 to Case #59). To avoid doing this process manually or using specialized content-analysis software, the Word document with the 59 transcripts was uploaded to four different LLMs *(Microsoft's Copilot, ChatGPT 4.6, Gemini 3.1 Pro, and Claude Sonnet 4.6)* and, for the *first round* (initially), they were prompted to perform a frequency count with the following additional remark in the prompt: "Conduct the analysis in the spirit of qualitative thematic analysis or content analysis, allowing yourself interpretive freedom in grouping, naming, and structuring themes."

Before the *second round* of counting, the labels and groupings for the frequency count generated by the aforementioned LLMs were examined by an *expert in evaluating LLM use*, and a unified list of categorization labels was created based on semantic analysis, synthesis, and correction of the initial labels/names and groupings/categorizations made by the three LLMs. Then, for the second round of frequency count, all four LLMs *(Microsoft's Copilot, ChatGPT 4.6, Gemini 3.1 Pro, and Claude Sonnet 4.6)* were employed to test and possibly confirm this, now final for this phase of research, unified categorization ("thematic analysis"). Finally, the results of the second round of frequency count by different LLMs were presented, compared, and commented on.

Due to the limited number of pages and the pivotal, "proof-of-concept" nature of the research reported in

this paper, we do not explain in greater detail how the previously mentioned categories were consolidated or what criteria were applied when determining whether different LLM-generated categories represented the same underlying concept.

4.2.4 Investigation of the Typologies of Students' LLM Use

After brief experimentation with prompts of various complexity and methodological detail, as well as having in mind the exposed diversity in the categorization and counting of denotations of "educational" and "private" uses of LLMs regarding the content of the subbranches of two primary nodes of respondents' mind maps (see subchapter 5.1 "Educational and Private Uses of LLMs"), it was decided to explore the potential of LLMs to identify potential typologies (or broad categories in the form of "styles") of LLM use by the most simple prompts. The exact prompt that was used with all four LLMs *(Copilot, ChatGPT 5.5, Gemini 3.1 Pro, and Claude Opus 4.8),* after uploading the Word document with the transcriptions of respondents' mind maps, and their outputs is presented in Chapter 5.2 "Typologies of Students' LLM Use".

For this task, the selected latest and most advanced (best ranked) LLMs and their high "thinking level" were used at the time the analysis was conducted: ChatGPT 5.5 High, Gemini 3.1 Pro Extended, and Claude Opus 4.8 High. It is repeatedly emphasized that, since the LLMs approached the same complex categorization task quite differently in the probe trials, only the simplest and broadest prompt was used for this purpose.

4.2.5 Evaluation of Retrieved Initial Typologies of Students' LLM Use

In a *hybrid* approach, the initial typologies generated by the LLMs were evaluated and grouped by (1) a human expert in LLM use evaluation and (2) selected, most advanced LLMs available at the time the study was completed.

4.3 Instruments

Apart from the blank paper and pencil or pen that the students used for drawing mind maps, after completing the online learning activities in a computer laboratory for their *English for Special Purposes courses*, a survey was employed for the evaluation of each of these activities. At the beginning of this survey, a set of demographic questions was used to gather data on gender, age, and frequency of LLM use. This demographic data described the composition of the convenience sample.

For the investigation related to the problems of this study and research questions *(RQ1–RQ3)*, the following families of LLMs were used with a basic subscription plan: Microsoft's Copilot, OpenAI's ChatGPT, Google's Gemini, and Anthropic's Claude models. However, for the creation of written transcripts from the students' hand drawings of mind maps, only Google's Gemini was used.

4.4 Procedure

The procedure used for the study that is presented in this paper included a preliminary phase in February 2026 when the ability of an LLM to produce a transcript of a hand-drawn mind map was tested, as well as the potential to use LLMs in the analysis of textual transcript data derived from students' mind maps.

In February 2026, a group of 38 first-year student volunteers was recruited for the online learning activities, followed by a survey for the evaluation of each of these activities and their semi-directed free drawing of a mind map related to their use of LLMs for educational and private purposes. In June 2026, a different group of 36 new first-year student volunteers was recruited for the same purpose and activities.

The transcriptions of the mind maps and main data analyses with the use of LLMs were performed using the most advanced (latest) versions of LLMs also available to other researchers with a basic subscription at the time this study was completed. To avoid excessive token usage for large text processing tasks, the Claude Opus 4.8 model was not used in the first phases of analyses, but Claude Sonnet 4.6 was used instead.

5 Results and Discussion

In this section, the results of qualitative data analyses that were predominantly performed with the assistance of LLMs are presented, together with the basic prompts that were used for that purpose. The conducted analyses are broadly associated with (a) *thematic analysis* and (b) *content analysis*, which are among the most frequent qualitative methods (Chandrasekar et al., 2024). In addition, for coding the types of students' use of LLMs the *inductive method* was used, with the assistance of initial free categorizations of specific uses by several LLMs. For the inductive method, "codes and categories are not predetermined, but are instead identified and named as the researcher reads through the data," which may include "open or initial coding, and the constant comparative method of analysis" (Bingham, 2023). It is important to acknowledge that LLMs have already been applied to the analysis of qualitative data (see: Xiao et al., 2023; Zhang et al., 2025). However, the use of AI in qualitative data analyses may have insufficient transparency and generate divergent results upon repeated queries (Chen, 2025), as was the case in the study that is presented in this paper. Still, the application of a reliable research protocol for using AI tools like ChatGPT may considerably facilitate the qualitative data analysis process in the initial research stages (Goyanes et al., 2025).

5.1 Educational and Private Uses of LLMs

Having in mind the first problem of the study that is presented in this paper *("To identify the variety of students' educational and private uses of large language models that are represented in their mind maps")* and the related first research question (RQ1), the frequencies of each identified type of LLM use are presented in Table 1, Table 2, and Table 3. It must be emphasized that the row rubrics in Tables 1-3 are unified categorizations of LLM uses for which an expert combined the initial frequency count of four different LLMs, as was described in section 4.2.3 ("Frequency Count of Mind Map Elements") of this paper.

The exact prompt used with all four LLMs for generating the numerical data in Tables 1-3 was: "Using the

hierarchical transcript of students' mind maps on their use of LLMs such as ChatGPT and Gemini (provided in the Word document), perform a thematic analysis by producing separate concept counts for each of the following: A) central node categories (count each category separately); B) primary nodes (count each node separately); C) first-level branch category 1. Educational / Academic / School / College / Faculty (count each subcategory from 1a–1n separately); and D) first-level branch category 2. Private / Personal / Free Time / Everyday Life (count each subcategory separately). Use only the following fixed, predefined labels for the nodes and subbranches, and report the exact number of occurrences for each. (Do not count any concept more than once!)" *[Note: This first part of the prompt is followed by a list of predefined categories that are displayed in Tables 1-3.]*

The data presented in Table 1 indicates very high agreement among all four LLMs regarding the most frequently used LLMs mentioned in the central node of respondents' mind maps. ChatGPT was mentioned in 54–55 of the 59 processed mind maps, Gemini in 24 mind maps, and DeepSeek in 6 mind maps. A later, more detailed analysis revealed that in all 24 cases, Gemini was co-mentioned in the central node with ChatGPT. It should be recognized that the instruction was *not to include in the central node all the LLMs that the students use*, but only the one (or more) that they use most frequently.

Table 1. Frequency count of top three LLMs in the central node and top three categorizations of elements of mind maps in first-level nodes

LEVEL AND CONTENT	**LLM**†			
CENTRAL NODE *(TOP 3)*	**CO**	**CG**	**GM**	**CS**
ChatGPT	54	54	55	55
Gemini	24	24	24	24
Deep Seek	6	6	6	6
FIRST LEVEL NODES *(TOP 3)*	**CO**	**CG**	**GM**	**CS**
Educational / Academic / School / College / Faculty / As a student	50	**48***	58	49
Private / Personal / Free time / Everyday life	54	54	56	52
Business / Professional / Work	22	21	20	7

† CO – Copilot, CG – ChatGPT, GM – Gemini, CS – Claude Sonnet
* After prompting for a recount.

Regarding the first-level nodes related to broad categories of "education" (more specifically labelled for LLM prompting as "Educational / Academic / School / College / Faculty / As a student") and "private" (more extensively labelled for LLMs as "Educational / Academic / School / College / Faculty / As a student"), there was a notable disagreement (in the counting range from 48 to 58) for categorizations in the first-level node as "educational" and a much greater agreement (in the range between 52 and 56) among LLMs in categorizations in the first-level node "private." Some of the students also included the third type of primary node defined to the LLMs as "Business / Professional / Work". For brevity, the elements of this third primary node will not be analyzed, but this illustrates that the respondents chose the elements of the primary nodes rather freely, like the alternative wordings for the first two primary nodes that they have used.

The results of categorization of respondents' activities with LLMs, placed as *subbranches* in their mind maps, in the "education" category ("Educational / Academic / School / College / Faculty / As a student") in Table 2 demonstrate a rather high level of discrepancy or dissonance among the LLMs in counting the occurrences of concepts in the second-level branches (or further levels) of this category. These fixed categories of subbranches, which were used for prompting, were defined by the human expert as a unification of initial "free" categorizations performed by the four LLMs used in this study. The least diversity in categorizations was in relation to "Summarizing / shortening textual content" (18–20) and "Generating ideas for academic work / inspiration / project ideas" (13–15). In almost all cases (except one count by Claude Sonnet LLM regarding "Professional / client / business tasks linked to formal work"), the LLMs placed at least 4 and as many as 44 elements of subbranches in the predefined fixed categories, which can be interpreted as *support* ("confirmation") of those categories. Therefore, the data presented in Table 2 indirectly address the first two research problems and research questions (RQ1 and RQ2) in relation to the educational domain of students' activities with LLMs, *at least regarding the convenience sample that was used in this study*. It can also be stated that the revealed categories of educational activities in Table 2 correspond to the students' activities most frequently reported with LLMs in other recent surveys that were performed on much larger samples (for instance, see: Ravšelj et al., 2025; Chung et al., 2026; Chatzopoulos et al., 2026; Stephenson and Armstrong, 2026).

Regarding the previously presented findings, it is important to restate the possibility that some of the observed structures of students' mind maps at least partly reflected "task framing" instead of entirely spontaneous representations of students' mental models. In other words, some students may have relied on the model mind map of their professors' use of LLMs and the suggestion of two basic nodes (educational vs. private). This limitation of the presented study should be noted before interpreting its findings (see section 4.2.1 "Drawing Mind Maps").

Having in mind the discrepancies in counting the subbranches of the "education" primary node by different LLMs, it must be considered that within the same family of LLMs, for instance Claude, the versions Claude Sonnet 4.6, Claude Sonnet 5, and Claude Haiku 4.5 produced different counts for almost all fixed definitions of categories of subbranches. The same type of inconsistency was observed between Gemini 3.1 Pro and Gemini 3.5 Flash, as well as between Copilot with the "Think Deeper" and Copilot with the "Smart" option activated. In fact, the closest match, with mostly 0-2 different counts per type of subbranch, was between the ChatGPT 5.6 High and ChatGPT 5.5 High versions. However, in all the mentioned additional parallel/alternative analyses, the fixed categories for the "educational" subbranches were supported by only a few

individual counts as low as 2, while most counts were 5 or higher across all other categories.

Table 2. Frequency count of identified occurrences of *subbranches* that the LLMs placed in fixed categories for the **"education"** primary node

	LLM†			
EDUCATIONAL USES	**CO**	**CG**	**GM**	**CS**
Explanation, understanding and clarifying of study materials/concepts	33	44	33	40
Summarizing / shortening textual content	20	19	20	18
Solving tasks / problems / assignments / homework / answers	34	31	24	24
Creating study materials / study notes / scripts	28	12	11	10
Searching for sources / literature /papers / research	20	23	16	18
Exam preparation / quizzes / practice tests / knowledge checks / study review cards	18	15	12	13
Programming help	20	8	10	9
Writing support / grammar and spelling checking / proofreading / emails	22	20	20	14
Translation / foreign languages	10	8	6	6
Creating visual output, graphs, presentations, PPT / visual layout	20	13	13	13
Study planning / organization	10	7	6	5
Generating ideas for academic work / inspiration / project ideas	12	12	15	13
Analysis of data or theories	8	7	5	4
Professional/client/business tasks linked to formal work	15	10	7	1

† CO – Copilot, CG – ChatGPT, GM – Gemini, CS – Claude Sonnet

As can be concluded from the data displayed in Table 3, the respondents' most frequent activities in the category "private" (i.e., "Private / Personal / Free Time / Everyday Life") were related to information search using an LLM, cooking and nutrition, seeking advice / decision making, hobbies/skills and self-improvement, and entertainment. When the whole list of retrieved "private" uses of LLMs by the respondents in our study is taken into account, it very much corresponds to the non-work-related activities of adults that were reported in several recent studies by other authors (see, for instance: Carloan et al., 2025; Fineberg et al., 2025; Gotfried et al., 2026). In any case, regarding the first two problems of this study and research questions (RQ1 and RQ2), it can be concluded that very diverse private uses of LLMs were represented in students' mind maps and that the specific categories of students' private uses of LLMs have been successfully identified and supported. However, as was the case with the "educational" uses of LLMs, there was considerable diversity between the LLMs used, as well as, after additional checks, within versions of LLMs of the same family.

Table 3. Frequency count of identified occurrences of *subbranches* that the LLMs placed in fixed categories for the **"private"** primary node

	LLM†			
PRIVATE/PERSONAL USES	**CO**	**CG**	**GM**	**CS**
Searching for general information / trivia / general knowledge / curiosity	35	51	30	38
Cooking / recipes / nutrition / meal planning / calories	18	24	21	20
Travel and excursion planning / destinations search / restaurants and cafes	15	9	7	7
Health queries / symptoms / medical information	12	9	9	8
Decision-making / advice	20	30	14	18
Private image generation / visuals / multimedia creation or editing	22	9	10	9
Personal organization / private time management	12	9	6	6
Fitness / sports / training	14	12	10	10
Entertainment / media / games / movies / music	18	15	11	10
Language learning / translation – private context	10	7	7	6
Home repairs / practical household help / technical advice	8	9	6	7
Emotional support / stress reduction	6	4	3	2
Shopping / product comparison	8	3	4	3
Hobbies / skills / self-improvement / learning new things	20	22	5	19
News / current events	15	6	6	6
Writing private messages / emails	12	6	4	5

† CO – Copilot, CG – ChatGPT, GM – Gemini, CS – Claude Sonnet

The frequency counts by LLMs presented in Table 2 (subbranches of the "education" node) and Table 3 (subbranches of the "private" node) were not checked by a human expert, even though the counts differed across LLMs, because the intention was to find support for the categorizations and illustrate LLM inconsistencies, rather than to meticulously evaluate the diversity of outputs across various LLMs, which is a common phenomenon.

Another important issue is that the human experts were not used as coders of mind map elements (as a reference) to compare their findings with the LLM counts, as an evaluation of the LLMs' output. Even though this could be viewed as a limitation of the previously elaborated results of the study (in Section 5.1, "Educational and Private Uses of LLMs"), it was not the intention of the authors to perform such a comparison, since one of the main problems was to "examine whether large language models can generate meaningful and interpretable typologies of students' LLM use from written transcripts of their mind maps." Also, both RQ1 and RQ2 were directed only toward the potential usefulness of initial qualitative analyses performed by the LLMs and not the factually correct counting of individual students' mind map elements. Finally, because the convenience sample consists of first-year students from

IT- and economics-related study programs at a single Croatian university, the previous categorizations and consequent typologies cannot be generalized to the wider higher education student population in Croatia.

5.2 Typologies of Students' LLM Use

Bearing in mind the previously demonstrated diversity in the output of various LLMs and their versions regarding occurrence count of "educational" and "private" forms of LLMs use mentioned in the subbranches of the primary nodes of respondents' mind maps, it was decided to use only the simplest wording for the prompt for investigating the *typologies* of students' use of LLMs that could be deduced from the structure of the mind maps. Also, only the latest and most advanced (best ranked) LLMs at the time this analysis was conducted, with the highest optional "thinking" level, of the ChatGPT, Gemini, and Claude families were used for this task. After uploading the Word document with the transcriptions of 59 mind maps (Case #1 to Case #59), the following brief prompt was used in all three cases that will be briefly presented: "Read the Word document. Using an approach similar to cluster analysis, create a typology of LLM use (e.g., ChatGPT, Gemini) based on the textual representations (Cases #1 – #59) of students' mind maps visualizing their use of LLMs. The students were provided with an example containing two central nodes: (1) educational and (2) private. However, they were free to create a mind map of their own design. Create no more than 4–5 categories, with each category containing at least 5–8 student cases."

5.2.1 Typologies by ChatGPT 5.5 High

After the previously mentioned prompt, *ChatGPT 5.5 High* summarized its findings as "the dominant representation of LLMs is pragmatic and task-oriented. […] The original educational/private example clearly influenced many maps, but the actual clusters show a broader typology: LLM as tutor, producer, operator, life assistant, and tool ecosystem." Here are the descriptions of the main clusters proposed by ChatGPT 5.5 (italics are added by the authors):

1. ***"Study coach / concept scaffolder.*** […] Students in this group mainly represent ChatGPT/Gemini as a personal tutor: explaining difficult concepts, summarizing material, creating mini-tests, supporting exam preparation, and helping students understand required coursework. […] The tool is valued because it *explains, simplifies, tests, and repeats content in a personalized way.*"
2. ***"Academic producer / researcher / communicator.*** This type treats LLMs more as academic-work production infrastructure. Typical uses include finding sources, writing or editing emails, generating ideas for papers, creating presentations, checking grammar, summarizing academic texts, and producing documentation. These students use LLMs as productivity systems, not only to *help me learn*, but *help me produce, organize, polish, and communicate.*"
3. ***"STEM, code and task-solving operator.*** This group clusters around technical, computational, and problem-solving uses. The maps mention programming tasks, math tasks, code checking, bug fixing, IT support, C++, client design/communication, and task solutions. […] These students represent LLMs as operators or technical assistants: tools for getting through concrete tasks, debugging, coding, calculating, and solving."
4. ***"Whole-life personal assistant.*** This coherent type represents the LLM as a general companion for everyday life, not just a study or work tool. It includes personal interests, decisions, health, recipes, household issues, recommendations, motivation, communication advice, and practical life management. […] These students use LLMs as life-management assistants. The boundary between educational and private use becomes porous: the same tool helps with studying, health, food, organization, entertainment, and everyday decisions."
5. ***"Tool-ecology strategist / experimental or boundary-setting user.*** This type is defined not only by what students do with LLMs, but by how they differentiate, compare, or limit tools. Some cases explicitly separate tools by domain, compare prompts, use one tool as backup, or express skepticism. […] These students are more reflective about the AI ecosystem. They are not simply *using ChatGPT*; they are selecting, comparing, substituting, or resisting tools."

5.2.2 Typologies by Gemini 3.1 Pro Extended

The introductory comment by *Gemini 3.1 Pro Extended*, after the prompt to create users' typologies, was: "Based on a cluster-style qualitative analysis of the 59 student mind maps, the ways students use Large Language Models (LLMs) can be grouped into 5 distinct typologies. […] their self-designed configurations reveal unique behavioral archetypes based on their cognitive approach, technical depth, and level of life integration." The following are brief descriptions of the five typologies generated by Gemini 3.1 Pro:

1. ***"The Technical Developer & STEM Specialist.*** Core Approach: Algorithmic, functional, and highly specialized. These students primarily treat LLMs as an interactive IDE, a code-review partner, or a computational calculator. Their mind maps largely bypass standard essay writing or general brainstorming in favor of programming languages, logical debugging, and technical data manipulation. Key Use Cases: Debugging code syntax, learning C++, automating script creation, practicing mathematics, and handling server data encryption.
2. ***"The Academic Researcher & Strategic Writer.*** Core Approach: High-volume text synthesis and institutional compliance. These users deploy LLMs to navigate heavy academic workloads, process dense educational literature, and ensure strict alignment with rigid academic formatting criteria. Key Use Cases: Digesting long study scripts, generating targeted practice quizzes before exams, hunting down literature sources, and checking presentation layouts against strict styles like APA standards."
3. ***"The Holistic Lifestyle Designer & Personal Coach.*** Core Approach: Deep personal and somatic integration. For these individuals, the LLM functions as a proxy for specialized human experts—acting as a personal trainer, nutritional

scientist, therapist, or home economics consultant. Key Use Cases: Generating hyper-specific workout regimens (e.g., Ironman training), tracking daily calorie/carbohydrate counts, analyzing medical symptoms, managing burnout/stress, resolving communication dilemmas, and troubleshooting domestic malfunctions."

4. ***"The Pragmatic Generalist & Search Engine Substitute.*** Core Approach: Frictionless information retrieval and remedial academic assistance. This represents the largest group of students, who view the LLM essentially as an accelerated, conversational version of Google. Their interaction is highly reactive, broad, and conversational rather than heavily structural. Key Use Cases: Answering trivial or 'banal' daily questions, quick foreign language translations, basic homework assistance, looking up movie recommendations, and drafting initial outlines for assignments when they entirely lack personal motivation."
5. ***"The Strategic Tool-Evaluator & Skeptical Outlier.*** Core Approach: Meta-cognitive and highly evaluative. These users do not just map their tasks; they explicitly map the performance, constraints, and relationships of the AI tools themselves. They intentionally construct multi-model workflows or display strong, critical ethical boundaries regarding AI use. Key Use Cases: Setting up redundant backup tools (e.g., using DeepSeek strictly when ChatGPT fails), designing iterative prompt-chaining sequences to cross-compare results across different models, or entirely siloing the AI as a mandatory 'plagiarism machine' while rejecting it in personal life."

5.2.3 Typologies by Claude Opus 4.8 High

The response to the previously presented prompt by *Claude Opus 4.8 High* started with the following remark: "Below is a typology built by treating each mind map as a data point and clustering on the dimensions along which the maps actually vary, rather than the surface tool names (almost everyone uses ChatGPT, often plus Gemini, so the tool itself doesn't discriminate well). The clustering axes that turned out to be diagnostic: **Balance/tilt** between the academic and personal branches (one dominant vs. genuinely two-sided); **Depth of life-integration** on the private side (occasional info-lookup vs. AI woven through health, food, organization, well-being); **Tool ecosystem** (single ChatGPT vs. several tools vs. tools deliberately assigned to tasks); **Structural form** (did they follow the provided educational/private template or invent their own — function-based, role-based, workflow-based); **Relational stance** (AI as neutral utility vs. as advisor/companion vs. critically/sceptically)." The more detailed description by Claude Opus 4.8 High of these five types follows:

1. ***"Balanced Dual-Use Generalists.*** The modal pattern and largest cluster. These students adopted the provided template almost exactly: a two-sided split into educational and private, with a roughly even weighting and conventional, generic uses on each side — summarizing, explaining concepts, solving tasks and writing on the study side; information search, trivia, news, recipes and translation on the private side. One or two tools, no structural innovation, no strong tilt in any direction. They treat the LLM as a general-purpose helper for whatever comes up."
2. ***"Academic-Dominant Study Users.*** The map is heavily weighted toward studying; the private branch is thin, absent, or clearly secondary, and the framing is often about academic survival, efficiency, or shortcuts. Several explicitly foreground exam prep, summarizing course material step-by-step, or — at the sharper end — drafting work they're unmotivated to do or cheating. When a private branch exists it's minimal (one or two info-lookup items)."
3. ***"Everyday-Life Integrators.*** Here the personal side is rich and central rather than an afterthought. AI is genuinely embedded in daily life: health and symptoms, nutrition and cooking, fitness and training plans, travel, daily routines, organization (to-do lists, scheduling), home repairs, recommendations, and — at the deepest end — mental well-being. The academic branch is present and normal, but the distinctive signature is the breadth and specificity of life-management on the private side."
4. ***"Strategic Multi-Tool Power Users.*** These students relate to AI as a toolkit to be managed. The signature is one or more of: deliberately running several tools (often including specialist ones — MathGPT, DeepSeek, Grok, Copilot, NotebookLM, Comet, Sora), assigning tools to tasks or using one as a backup for another, building prompting/comparison workflows, technical/production work (coding, bug-fixing, client deliverables, dev & design), or abandoning the educational/private template entirely for a function-, process-, or role-based structure."
5. ***"Relational & Reflective Users.*** The smallest but most conceptually distinct cluster, defined by an unusual stance toward the AI. Two sub-flavors sit together here. Some personify or relationally lean on it — as an advisor, thinking-partner, source of an "objective opinion," or even explicitly a "psychologist," "musician," and stand-in "doctor." Others adopt a reflective or critical posture — using it to weigh perspectives and evaluate quality, or, at the extreme, rejecting it. What unites them is that the AI is treated as a counterpart for judgment or scrutiny rather than a neutral lookup utility."

5.2.4 Comparison and Integration of Retrieved Initial Typologies of Students' LLM Use

While, at first glance, the typologies of students' use of LLMs that were created by ChatGPT 5.5, Gemini 3.1 Pro, and Claude Opus 4.8 may seem rather diverse, a closer analysis of their content by an *expert in LLM use evaluation* revealed the following:

- Similarity between types labelled *Academic producer / researcher / communicator* (#2 ChatGPT 5.5), *The Pragmatic Generalist & Search Engine Substitute* (#4 Gemini 3.1 Pro), and *Academic-Dominant Study Users* (#2 Claude Opus 4.8).
- Strong resemblance between *Whole-life personal assistant* (#4 ChatGPT), *The Holistic Lifestyle Designer & Personal Coach* (#3 Gemini 3.1 Pro), and *Everyday-Life Integrators* (#3 Claude Opus 4.8).

- Moderate correspondence of *STEM, code and task-solving operator* (#3 ChatGPT 5.5), *The Technical Developer & STEM Specialist* (#1 Gemini 3.1 Pro), and *Strategic Multi-Tool Power Users* (#4 Claude Opus 4.8).
- Visible parallels between *Tool-ecology strategist / experimental or boundary-setting user* (#5 ChatGPT 5.5), *The Strategic Tool-Evaluator & Skeptical Outlier* (#5 Gemini 3.1 Pro), and *Relational & Reflective Users* (#5 Claude Opus 4.8).
- Some possible likeness between *Study coach / concept scaffolder* (#1 ChatGPT 5.5) and *The Academic Researcher & Strategic Writer* (#2 Gemini 3.1 Pro).
- Very little or no similarity with other categorizations for *Balanced Dual-Use Generalists* (#1 Claude Opus 4.8).

To test the correspondence between the previously listed associations performed by a human expert with similar semantic analyses of the typologies performed by some of the most advanced and best rated LLMs at the time this study was completed (ChatGPT 5.5, Gemini 3.1 Pro, Claude Opus 4.8, and Claude Fable 5), the following prompt was delivered to each of the LLMs: "Read the Word document. Having in mind the content of the Word document, answer which categories of students' use of LLMs in the three typologies proposed by A. ChatGPT, B. Gemini, and C. Claude are most similar? For example, there may be semantic overlap among the following categories: Academic Producer / Researcher / Communicator (#2, ChatGPT 5.5); The Pragmatic Generalist & Search Engine Substitute (#4, Gemini 3.1 Pro); Academic-Dominant Study Users (#2, Claude Opus 4.8). Analyze the semantic similarities among the five categories developed by each LLM, even when they are labeled differently. Identify and connect the categories across the three typologies that appear to represent the same or closely related patterns of student LLM use. Sometimes the cases that fall into specific categories are mentioned. For each set of similar categories, provide a brief explanation of the shared characteristics that justify the comparison."

Concerning the previous prompt, the LLMs were in consensus with the human expert and among themselves only with respect to (a) the *lifestyle set of categories* (i.e., Whole-life personal assistant, The Holistic Lifestyle Designer & Personal Coach, and Everyday-Life Integrators), (b) *STEM, code & power users categories* (i.e., STEM, code and task-solving operator, The Technical Developer & STEM Specialist, and Strategic Multi-Tool Power Users), and (c) *reflective tool evaluator and sceptic categories* (Tool-ecology strategist / experimental or boundary-setting user, The Strategic Tool-Evaluator & Skeptical Outlier, and Relational & Reflective Users). The other categories were distributed across various academic-use spectrums of interpretations. These may eventually be placed on a *single dimension* from (1) a simpler, task-oriented user with low specialization, and mostly reactive general-purpose use of LLMs, on the one end, to (2) the more sophisticated, "high-end" user with a higher level of specialization and structured, academic-production use of LLMs, on the other end.

Considering the third problem and research question (RQ3) of this pilot study, it can be concluded that the three most consistent and stable typologies of students' use of LLMs were identified as exhibiting (1) the *lifestyle set of attributes*, (2) *STEM and coding set of attributes*, and (3) *reflective tool evaluator and sceptic attributes.*

Finally, even though these categorizations are predominantly action-oriented rather than direct cognitive valuations, the students' types of LLM use may be broadly associated with their underlying *mental models*. The typologies indicate distinct perceptions of utility and modes of interaction, which are inherently connected to how students mentally construct and understand LLMs.

5.2.5 Important Remark on the Retrieved Initial Typologies of Students' LLM Use

The typologies of students' LLM use that were investigated and identified in the previous sections (5.2.1–5.2.4) demonstrate that similar assistance from LLMs could be useful and informative during the early phases of exploratory qualitative analysis, perhaps even shortening the initial probing phase of a study. Nevertheless, such LLM-generated groupings should be regarded as exploratory patterns or initial examples that may require further validation through (a) more scientifically established methodologies and (b) empirical data collection with greater precision than mind maps can provide, especially in the case of mental models research.

6 Conclusion

This pilot study shows that, with a sufficiently large sample, the use of student-created mind maps in combination with LLM-assisted data analysis can reveal meaningful categories of LLM use in both educational and private contexts. For ***RQ2***, students' *educational use* of LLMs was predominantly organized around learning support, academic production, problem solving, programming/STEM tasks, writing, summarization, and study organization, while *private use* centered on information search, everyday-life assistance, advice, entertainment, health, food, travel, hobbies, and personal communication. For ***RQ3***, LLMs showed clear potential to *support qualitative analysis* by generating interpretable initial ("probe") *typologies*, especially around (1) lifestyle integration, (2) STEM/coding use, and (3) reflective or skeptical tool evaluation. However, differences in categorization outputs among models for both RQ2 and RQ3 indicated that LLM-based typologies, both in this and other research areas, should be treated as exploratory and validated with expert interpretation of collected data.

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