Cognitive Strategy Prompts

Creativity Triggers for Human Centered AI Opportunity Detection

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ABSTRACT

Creative problem solving and innovation powered by Artificial Intelligence (AI) requires detection of user needs that can be reframed into data science problems. We propose a framework of 10 creativity triggers for creative human centered AI opportunity detection, based on research and categorization of information retrieval tasks and cognitive task analysis. The method aims to facilitate a dialog between data scientists and underrepresented groups such as non-technical domain experts.

Impact on problem discovery and idea generation was evaluated in co-creation workshops. Results show that the method significantly increases ideas' scores on the appropriateness to a specific problem and their AI relevancy. Participants experienced the prompts as a helpful mental framework about AI methods and felt encouraged to decompose user stories into more detailed cognitive tasks that help data scientists relate ideas to high level data science methods.

CCS CONCEPTS

• **Human-centered computing → HCI theory, concepts and models**; • **Computing methodologies → Artificial intelligence**; • **Software and its engineering → Requirements analysis**.

KEYWORDS

AI opportunity detection; cognitive task analysis; design thinking

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1 INTRODUCTION

The rise of Artificial Intelligence (AI) and Machine Learning (ML) has enabled an opportunity space for innovation. This includes applications of AI in health [37], finance [4] and legal [8]. An AI method can be defined as *"any method that receives data points from an environment and takes actions that mimic human behavior to affect that environment"* [36]. The term Human Centered AI (HCAI) has been used as an umbrella term that encompasses Human Computer Interaction (HCI) methods for AI systems [47], acknowledges human involvement in the creation and use of ML systems [15], emphasis of human benefit from AI [43], AI explainability and interactive ML [41].

While research has proposed guidelines for the exploration and design of AI-driven solutions [1] [39] [11], there appears to be a lack of frameworks for human centered problem discovery and problem definition specific to opportunities for the application of AI. Shneiderman [46] states the need to put humans, rather than algorithms, at the center of attention. We argue that a human centered approach to AI innovation starts with an in-depth understanding of human problem solving and cognitive strategies. The framework proposed in this study builds on research in participatory creative problem solving for requirements engineering [42] [48], cognitive task analysis [52] and categorization of information retrieval tasks [30][14][13].

1.1 Human AI Interaction

Research in HCI and HCAI has investigated aspects of design and evaluation of AI systems. Since AI is a "new material" for design [12], many designers struggle with uncertainty about AI capabilities, complexity of dynamically created content and other AI output [53]. Amershi et al. [1] proposed 18 generally applicable design guidelines for human-AI interaction for product professionals. The guidelines consider aspects of explanation of AI capabilities, error recovery and feedback. Similarly, "People + AI Research" [39] provides best practices for designers, including how to relate observed user needs with data features and design patterns for AI. Jin et al. [21] extracted 40 design heuristics for the ideation about AI systems from 1,755 granted AI patents and tested them as design stimuli in early conceptual design. Such design guidelines support the exploration of a solution space, but only partly facilitate initial problem discovery. Yet, innovation projects that skip problem definition can end up focusing on the wrong problem and hence produce solutions that are not valuable to end users [38] [32]. Furthermore, design guidelines and principles often target design practitioners rather than participatory co-creation with non-technical participants.

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1.2 Creative Problem Solving

This study builds on research in participatory co-creation methods for requirements elicitation, such as design thinking techniques [42][48] and design sprints [22] that are part of the repertoire of User Centered Design (UCD) [33][20]. Research on creative problem solving provides a body of knowledge to navigate uncertainty, align participants, stimulate creativity and idea generation, through the use of “diverging“ and “converging“ activities [19]. Dalsgaard [9] describes the ”designerly inquiry” as an iterative process including problem framing, hypothesis generation and evaluation, similar to other studies of creative processes [17][31][51]. “Problem discovery“ might include investigative, divergent activities such as task analysis, incubation and process mapping to discover a problem space as well as converging activities for problem framing. “Solution exploration“ might apply divergent creativity techniques for idea generation and sketching, as well as convergent techniques for evaluation and prioritization of ideas [7]. Our contribution aims to support the cognitive abilities of designers and domain experts for the perception and conceptualization of design opportunities for AI powered innovation.

“Creativity” has been defined as the ability to generate ideas that are “novel” and “appropriate” to a specific domain [50]. “Novel” ideas might involve a new combination of familiar ideas, exploration of new concepts or the transformation of the problem space altogether [3], or they might be “dissimilar to existing examples of [a] genre” [40]. Ideas that are “appropriate” are considered to be useful and supportive for a specific task, as well as adapted to task specific constraints [50]. This study aims to stimulate “inspirationalist” ideation, as well as ”structuralist” processes [45].

Application of creative problem solving methods in co-creation workshops has been shown to be effective for requirements elicitation for software development [42][48] and AI system design [49]. The use of prompts is not unusual in design workshops. Lockton et al. [25] present cards with textual, or image-based prompts and evaluates their use for idea generation of new products and services. Long et al. [27] have shown that collaboration and co-creation can increase AI literacy. Experiences involving co-creative AI are well-suited for engaging a broad range of non-technical participants [26]. However, we argue that prompts often lack specificity for problem definition and opportunity detection for AI systems. Belani et al. [2] state that there is no widely adopted process for requirements engineering for AI systems.

1.3 Cognitive Task Analysis

This study builds on research that has categorized cognitive tasks and information seeking behavior. Hackos and Redish [18] propose a structured approach to task analysis for problem definition based on user tasks and user goals. The authors differentiate between Hierarchical Task Analysis (HTA) and Cognitive Task Analysis (CTA). HTA aims to understand various levels of tasks and subtasks [18]. Similarly, Jobs-to-be-done (JTBD) [28] has been proposed as a method to capture users' job stories. Decomposition of tasks and subtasks allows for prioritization of tasks and associated pain points. CTA puts focus on decision making, problem solving and assessment of available information [18], building on a “Human Processor Model” metaphor Card [5].

This study's framework applies simplified versions of HTA and CTA with a focus on specific human cognitive information processing strategies. Vicente [52] describe the need for “cognitive work analysis” for the design of information retrieval systems. The notion of “cognitive strategies” [14][52], is relevant for the framework presented in this study, because it might help elicit more granular actions that can be reframed as data science problems. Based on the categorisation of information retrieval needs and cognitive processes [33][30][48], we structure information seeking, obtaining and handling of information into 5 categories:

- **Learn** – When someone is “starting” [13] or “initiating” [23] a new search in an unknown domain, they don't know what they are looking for and might need to “explore new unknown sources” [34][30], “browse and structure” new content [13], “select and explore relevant information” [23] in order to get an overview on a unfamiliar domain, and ultimately “learn new information”, such as terminology or concepts within the domain [30].
- **Lookup** – Provided that someone knows what they are looking for, and is able to “formulate” and express a search query of some kind [23], they might decide to “follow a plan” [34] and specifically “lookup known information” [30] in a more targeted search behavior, simply “re-find information that had been found before“ [48], or take note and “chain references” in order to keep track of learning and document relevant sources [13].
- **Investigate** – An information seeker further “investigates” and analyses a situation [30]. They “look for trends”, “compare and aggregate” information [34], “differentiate sources” [13], contrast and relate different data points.
- **Monitor & Extract** – Once an area or points of interest are more clearly defined, it might be of interest to “monitor new developments in a known domain” [34][13], “collect” [23] and “extract information from specific sources” [13]. This might be a continuous and iterative background task.
- **Decide** – Ultimately information seeking will lead to some “action“ based on newly generated insight [23]. Depending on the work context, such action could involve sensemaking, decision making [14], or generation of new information.

2 COGNITIVE STRATEGY FRAMEWORK

This study introduces and evaluates a framework for AI opportunity detection, based on creative problem solving [49][2][29] and cognitive task analysis [52][14]. Part 1 of the study evaluates the application of *“Cognitive Strategy”* prompts for problem discovery and idea generation for AI-driven solutions in participatory co-creation workshops. Part 2 investigates how the prompts are perceived by data scientists and evaluates how they map to data science methods.

A *“Cognitive Strategy”* for the purpose of this study is defined as *any human activity that involves gathering, interpretation or generation of information, as well as decision making based on information.* Building on the “model human processor“ [6], information retrieval [14][30][13] and task analysis [18][52], we categorize information seeking and information processing tasks into a set of cognitive strategy prompts. The set, illustrated in figure 1, is kept as small as possible, in order to make it accessible for workshop participants:

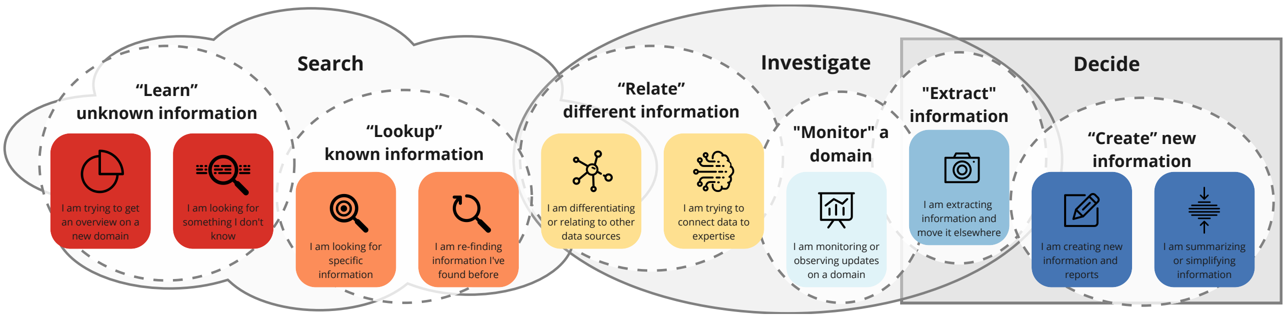

Figure 1: Cognitive strategy prompts

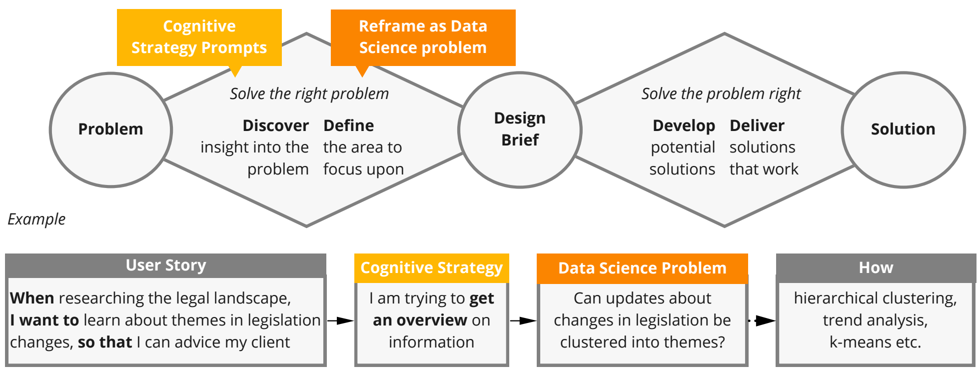

Figure 2: Application of cognitive strategy prompts

Category **Learn unknown information**

(1) **I am trying to get an overview.** When "starting" research on a new topic, "browsing and structuring information", when you "don't know what you need to know" [30][13][23]

(2) **I am looking for something I don't know.** Directed search, "exploring new unknown information", "exploratory search" with an idea what to look for, but not how to articulate it [34][30]

Category **Lookup known information**

(3) **I am looking for specific information.** "Lookup of known items" [30], well articulated search query in "semi-structured searching" [13][23]

(4) **I am re-finding information I'd found before.** "Re-finding" previously retrieved information [30], "directed search" activity [13], "follow a plan" or search strategy [34][48]

Category **Relate different information**

(5) **Differentiate, contradict, or relate to other data sources** Further "investigate and analyze" data sources [30], review and "differentiate sources" and "chain references" [13], as well as "looking for trends or correlations" [34]

(6) **Connect information to expertise.** "Investigate" [30], in relation to own knowledge and domain expertise, relate data to "matching social norms" [1], reflect on "actors resources and values" [14]

Category **Monitor changes and extract information**

(7) **I am monitoring or observing updates.** "Monitoring a known domain" [30] or "monitoring of new developments" [13][34], as well as changes and anomalies

(8) **I am finding specific information and moving it elsewhere.** "Extracting specific information" [13], "collect information" from data sources [23], specific "fact retrieval" [30], re-use in documents, reports, advice or decisions

Category **Decide based on information**

(9) **I am creating new information.** "Generation" of new data [21], reporting or documentation of informed "decision making" [14][23]

(10) **I am simplifying or summarizing.** Simplification or dimension reduction of information, such as summarization, "classification" [21] or adaptation of information to "work domain goals" [14]

On the one hand, cognitive strategy prompts are intended as an "inspirationalist" [45] technique for participatory co-design sessions. Prompts were applied after a user story writing exercise for discovery of the problem space [35]. On the other hand, we further explore the use of such prompts as a "structuralist" technique [45] to facilitate a translation from user needs into data science methods. We assume they might shift problem discovery and ideation to specific problems and ideas that are more relevant for the application of AI. We assume that each strategy can be associated with a number of specific data science methods. Figure 2 illustrates how cognitive strategy prompts fit into a user centered design process.

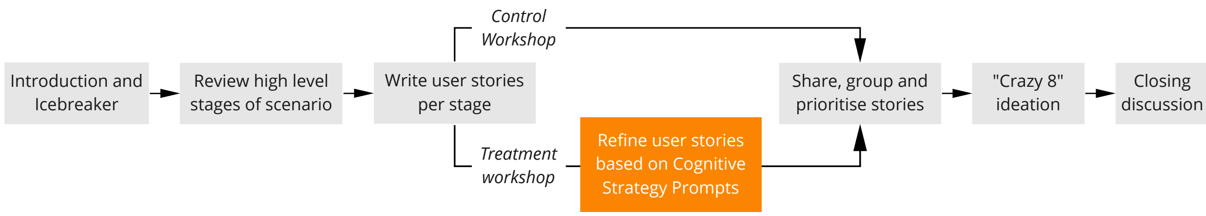

Figure 3: Workshop agendas

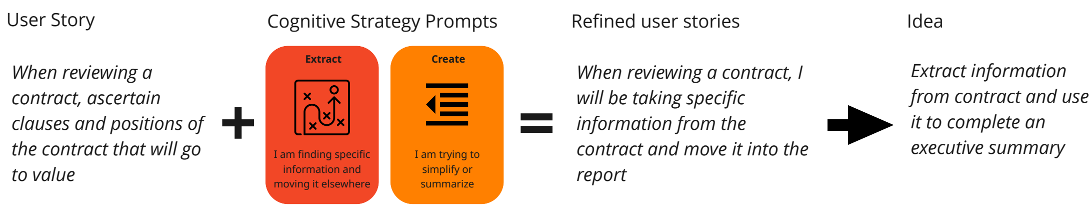

Figure 4: Illustration of application of cognitive strategy prompts

3 PART 1: COGNITIVE STRATEGY PROMPTS FOR IDEA GENERATION

Part 1 of this study evaluates the impact of cognitive strategy prompts on idea generation. Overall, 6 co-creation workshops were conducted with 10 participants. The impact was assessed based on an evaluation of the generated ideas, observations and qualitative feedback from participants.

3.1 Idea Generation Method

Three groups of 3-4 participants each were recruited from internal product teams. Mimicing a typical product innovation workshop, we selected two interdisciplinary groups (design, data science, product) and one group of legal subject matter experts. All workshops were conducted virtually using online whiteboarding software [10].

In a within-subject experiment, each group went through a facilitated *"control workshop"* as well as a *"treatment workshop"*, see figure 3. The workshops explored consumer scenarios ("phone purchase", "travel booking") as well as legal scenarios ("contract review", "contract negotiation"), in order to provide a meaningful context to participants. The order of conditions, workshops and workshop facilitators were randomly assigned, and different workshop sessions were held on separate days to reduce learning effects and bias. After an introduction, participants were asked to write user stories [28] and thereby provide domain specific detail about tasks involved in each scenario. Subsequently participants shared and prioritised the user stories. Treatment workshops introduced the cognitive strategy prompts as a set of digital cards. Participants were asked to individually pick any appropriate prompts, reflect on it, articulate how they might relate to already articulated user stories (e.g. "How do you apply this strategy?", "How does it relate to the task?"), share and prioritise with the group. Control workshops did not include this step. Finally, participants generated ideas for AI powered solutions individually in a Crazy 8 [22] exercise, based on the top voted user stories (control) or strategy prompts (treatment). Additionally, at the end of each workshop, 10 minutes were reserved for a semi-structured discussion and reflection on participants' experience in both workshop conditions.

3.2 Idea Evaluation Method

Ideas were evaluated and scored to assess the impact of the prompts onto idea generation. Previous research proposed different approaches to evaluate ideas generated through different ideation techniques. Jin et al. [21] used overall "quantity" of ideas produced as metric to evaluate whether some proposed design heuristics for AI were effective for ideation. Based on [50][3] we decided to evaluate ideas on their *"Novelty"* and *"Appropriateness"* to the scenario for which they have been generated. Ideas generated in consumer scenarios ("phone purchase", "travel booking") were scored by 2 researchers who also facilitated the workshops, while ideas generated in legal scenarios ("contract review", "contract negotiation") were evaluated by 2 legal professionals that had not taken part in any workshops. In addition, a score for *"AI Relevancy"* was introduced to assess each idea's "quality" [40] and feasibility for an AI solution. These scores were assigned by 5 AI experts (3 data scientists and 2 UX researchers, who did not participate in the workshops, with at least 2 years work experience on AI projects). Ideas were scored on each aspect on a 3-point Likert scale, according to the schema in table 1.

Table 1: Idea scoring schema

	AI Relevancy	Appropriateness	Novelty
Low	Basic data manipulation or data representation	No or poor task support	Existing concept
Med	Relation to specific data science methods	Some task support	New combination, transfer existing concept from another domain
High	Promising application of AI	Very strong task support	Radically new concept, reframe conceptual space

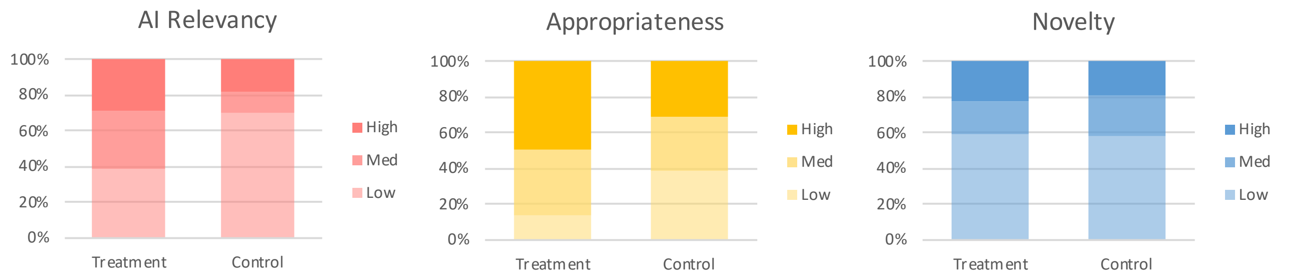

Figure 5: Idea evaluation results

Control

Appropriatness	Novelty: Low	Med	High
Low	31%	4%	4%
Med	15%	8%	8%
High	12%	12%	8%

AI Relevancy	Appropriateness: Low	Med	High
Low	27%	19%	23%
Med	4%	4%	4%
High	8%	8%	4%

AI Relevancy	Novelty: Low	Med	High
Low	38%	15%	15%
Med	12%	0%	0%
High	8%	8%	4%

Treatment

Appropriatness	Novelty: Lo	Med	Hi
Low	9%	0%	5%
Med	23%	9%	5%
High	27%	9%	14%

AI Relevancy	Appropriateness: Low	Med	High
Low	14%	14%	14%
Med	0%	14%	18%
High	0%	9%	18%

AI Relevancy	Novelty: Low	Med	High
Low	27%	5%	9%
Med	18%	5%	9%
High	14%	9%	5%

Figure 6: Idea scores distribution

Participants generated a total of 84 ideas throughout all 6 workshops (42 in 3 control workshops, 42 in 3 treatment workshops), example see figure 4. Quality of expression and specificity of the ideas, sometimes represented through a few words only, varied. Ideas that were particularly ambiguous and evoked strongly contradicting scores, i.e. "low" and "high" scores (Novelty, Appropriateness), or less than 4 out of 10 agreeing pairs of raters (AI Relevancy), were therefore excluded from the data set. This resulted in sets of 48 ideas that were scored on AI Relevancy, Appropriateness and Novelty, see table 2.

Table 2: Scoring example, original ideas for a "travel booking" scenario, workshop condition, combined scores (and individual raters' scores 0=low, 1=medium, 2=high)

Original Idea	Cond.	Scores
"Provide recommended sites that help organize any country specific requirements"	Control	AI Relev.: Low (0,1,1,0,0) Appropriate: Low (1,0) Novelty: Low (0,0)
"Create a playlist of recommended videos for me to watch"	Control	AI Relev.: Med (1,1,0,1,0) Appropriate: High (2,2) Novelty: Low (0,0)
"Suggestions of activities other travellers in the area have done"	Treatm.	AI Relev.: High (2,1,2,2,1) Appropriate: Med (1,1) Novelty: Med (1,1)
"Suggestions of new places and itineraries based on previous searches or previous vacations"	Treatm.	AI Relev.: Med (2,1,2,1,1) Appropriate: Med (1,1) Novelty: Low (1,0)

3.3 Evaluation of Generate Ideas

The results show that the application of cognitive strategy prompts in a workshop yields ideas that are significantly more appropriate for AI-driven problem solving, see fig. 5. Ideas from treatment workshops scored significantly higher on AI Relevancy ($X^2(2, N = 48) = 11.13, p < 0.01, Fleiss\ K(5) = 0.29$), compared to ideas from control workshops. Out of the ideas from treatment workshops 62% expressed a clearer relation to specific data science methods or a promising application of AI, compared to 30% from the control condition. Similarly, ideas from treatment workshops scored higher on Appropriateness ($X^2(2, N = 48) = 6.39, p < 0.05, Cohens\ K(2) = 0.42$), with about 86% of ideas from treatment workshops considered to support the task and problem at hand, compared to 62% without treatment. Neither scores for Novelty, nor the overall number of ideas varied significantly different between conditions.

This means that the prompts enabled participants to generate ideas that were perceived as more appropriate to the problem and pointing towards AI-driven solutions, while generating a similar amount of ideas at the same time, compared to the control condition. When comparing the distribution of scores for control and treatment groups, it becomes apparent how ideas' scores change between conditions. Scores for Appropriateness shift from "low" in the control condition, to "high" in the treatment condition, while remaining low on Novelty. The distribution of scores changes from low AI Relevancy and various levels of Appropriateness for the control condition to high AI Relevancy and high Appropriateness for the treatment condition overall, see fig. 6.

Table 3: Themes "Treatment Workshop"

Themes	Description	Example data	Participants
Decompose tasks	Prompts help to break down tasks	*"For some people AI is just a chatbot. With those cards, they look at a wider spectrum [and] what it could be used for"*	7/10
Structured thinking	Prompts focus and structure thinking	*"Your brain suddenly gets wired in a different way [...] it's more structured"*	7/10
AI applications	Clear AI Features and Application	*"[Prompts] helped me think about AI in a different way", "The cards made me understand more about what AI does"*	4/10
Multitasking	Prompts don't align with multitasking	*"When you're actually doing the job you're doing lots of things at one time. Whereas the cards suggests that you're only doing one thing"*	3/10
Fun	Playful, fun to use	*"It was just fun, a bit visual, playing with this interactive element"*	3/10
Challenging	Prompts cause high cognitive load	*"it's a bit like trying to pop your tummy and rub your head at the same time", "I will almost wonder if we could have had slightly fewer cards"*	2/10
Divergent thinking	Encouraged to explore more ideas	*"You're thinking, why has the team offered me 10 cards and I've only used two", "It also made wonder where I missed [using] another card"*	2/10

Table 4: Themes "Control Workshops"

Theme	Description	Example data	Participants
Unclear about AI	Uncertainty what constitutes an AI feature or an AI related idea	*"I think that some of the ideas could be relevant to AI [...] but I'm not really sure"*	7/10
Locked in the known	Ideas generation based on past projects	*"I came up with ideas, maybe I actually linked them back to some projects"*	3/10

3.4 Qualitative Evaluation of the Cognitive Strategy Framework

Overall, the participants responded positively to the prompts. Reflection on treatment sessions evoked the following themes, see table 3. Many participants felt relieved that the card exercise liberated them from the need to think about a technology. Participants described that the prompts helped them structure their thoughts in an effort to reframe problems and processes (7/10 participants) and decomposing tasks into more nuanced subtasks (7/10 participants). In contrast, the follow up to control workshops brought up different themes, see table 4. Many participants mentioned they felt unsure what constitutes an AI feature (7/10 participants). Participants felt they lacked a mental framework of AI features (2/10 participants).

Further, the prompts were perceived to help *"understand better what AI does"* (4/10 participants). Individual comments indicated that participants felt the need to explore more prompts (2/10 participants). Meanwhile in control workshops participants stated that some of their ideas were based on past projects (3/10 participants). While participants familiar with design workshops, mentioned that the prompt cards where *"fun"* to use (3/10 participants), legal domain experts experienced high cognitive load and stated that the prompts were challenging to apply (2/10 participants). Qualitative feedback shows that cognitive strategy prompts support the problem definition and idea generation for AI powered solutions.

4 PART 2: REFRAMING COGNITIVE STRATEGIES AS DATA SCIENCE PROBLEMS

Part 2 of the study explored how cognitive strategy prompts map to data science methods and what level of detail is required by data scientists, to reframe user tasks and ideas to data science problems.

4.1 Data Science Mapping Method

In order to evaluate whether cognitive strategy prompts could facilitate data science problem solving based on user needs, the experiment combined a focus group and survey.

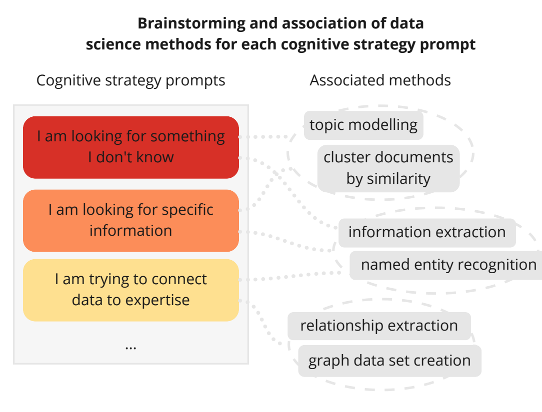

Figure 7: Illustration of brainstorming of data science methods during the focus group

First, a focus group was conducted with 3 data scientists. Reviewing one cognitive strategy prompt at a time, they brainstormed data science methods and approaches that could support each prompt, see figure 7. A total number of 62 ideas for data science methods (27 unique) were condensed into a simplified set of 20 data science methods. Participants were further asked to think aloud on the prompts' helpfulness to reframe user needs as data science problems and provide feedback on potential improvements.

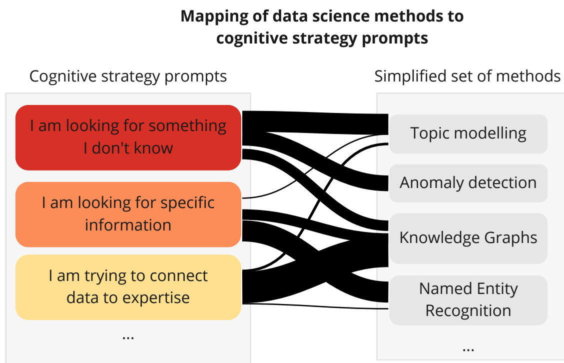

Figure 8: Illustration of data science method to cognitive strategy mapping survey

Second, in a subsequent survey, another 8 data scientists, who did not participate in the focus group, were asked to map each cognitive strategy prompt to any data science method in the simplified set, see figure 8. All participants were domain experts in data science with at least 3 years of work experience.

4.2 Evaluation of Data Science Mapping

Results from focus group and survey show that participants seemed to easily associate each cognitive strategy prompt with a distinct profile of data science methods and approaches. Some prompts were mapped to only a few methods (e.g., "I am creating new information" maps to "Text Generation" methods), while others were mapped to a broad scope of methods (e.g., "I am looking for specific information" maps to various information retrieval and search methods) by a large percentage of participants, see figure 9. Participants chose various alternative solutions and did not seem to feel unnecessarily restricted by each prompt. While the prompts seemed to facilitate the initial problem discovery with non-technical domain experts, the mapping might allow to translate each prompt into a range of data science methods and facilitate ideation with data scientists.

4.3 Qualitative Evaluation of Data Science Mapping

Qualitative feedback from the focus group brought up a number of aspects that might help data scientists to better reframe user needs into data science problems, see table 5. It appeared crucial to participants to understand detail about "user actions" (2/3 participants) and "user goals" (2/3 participants) and capture such detail in "data user stories". Prompts were perceived to "lack detail on input data" (2/3 participants) as well as "desired output data" (1/3 participant), such as the amount of data that is available and accessible, its quality, and whether it can be considered to be labelled data or not.

5 DISCUSSION

In summary, this study attempts to formalize, facilitate and inspire AI powered problem solving and data science requirements engineering.

5.1 Discussion of Cognitive Strategy Prompts

Results from part 1 show that the application of cognitive strategy prompts in co-creation workshops yields ideas that score higher on Appropriateness and AI Relevancy, while the scores on Novelty of ideas and the number of ideas remain the same compared to a control condition. We interpret that the prompts did not necessarily stimulate divergent thinking, but seemed to allow non-technical participants to reframe scenario and user stories in a way that helped them generate ideas that appeared more relevant for AI-driven solutions.

Meanwhile, qualitative feedback in part 1 indicates that the prompts and co-creation activities provided a helpful mental framework for non-technical participants, similar to results reported by Long et al. [26]. Participants felt supported to decompose user stories into more detailed cognitive tasks and structure their thinking about AI solutions. Beyond co-creation workshops, the prompts might provide a useful framework for user research, requirements engineering and conceptual design activities for AI-driven solutions.

Assessment and scoring of ideas, described in a few words only, resulted in low inter rater agreement, which is a limitation of this study. More research should assess the impact of the prompts on ideation on a larger scale. In order to fully support the "heartbeat" of divergent and convergent activities in creative problem solving [19], prompts might best be combined with divergent ideation techniques for the creative expansion of the solution space such as SCAMPER [44] or Crazy 8s [22]. Future work should take into account creative data work for problem framing and solution exploration, in particular data acquisition and data exploration, as discussed by Kun et al. [24]. The prompts might best be applied in the context of an adaptive ideation system as discussed by Girotto et al. [16]. In order not to overwhelm participants, the framework was designed with the smallest possible number of prompts. However, while some participants described the prompts as fun, others experienced high cognitive load. It might be worthwhile to explore the use of the framework for a more general introduction to AI powered problem solving prior to a workshop. The amount of prompts used in a workshop could be tailored to the topic of the workshop.

5.2 Discussion of Data Science Mapping

Results from part 2 show that cognitive strategy prompts can further facilitate reframing of user needs into data science problems. The mapping established in part 2 might serve as a starting point for ideation and AI problem solving that caters for distinct profiles of different prompts, but equally allows to explore various alternative solutions.

Further work could explore explanation cards how AI can support different prompts, or the definition and application of "data user stories". According to data science participants in part 2 of this study, user stories as defined by Patton and Economy [35] should be enhanced with further detail about specific cognitive tasks, cognitive strategy, expected input and desired output, as well as user goals, and success metrics.

Data Science Methods

Cognitive Strategy Prompt		Business Intelligence		Clustering Methods					Generative Methods		Information Retrieval							Search			
		Statistics/Business	Trend Analysis	Dimensionality Reduction	Clustering	Anomaly Detection	Topic Modelling	Summarization	Text Generation	Translation	Classification	Information Extraction	Information Retrieval	Named Entity Recognition	Question Answering	Relationship Extraction	Semantic Analysis	Knowledge Graphs	Ranking	Recommender System	Search
Learn	Overview	25%	38%	38%	50%	50%	50%	38%	13%			63%	38%		25%	13%	13%	50%		25%	50%
	Look unknown	38%	63%	25%	88%	63%	75%	25%				25%			13%	25%	13%	50%		25%	25%
Lookup	Lookup specific	25%	0%				13%		13%		38%	75%	88%	75%	75%	50%		50%	13%	25%	75%
	Re-find	50%					13%				25%	75%	63%	13%	50%	25%		38%	13%	13%	88%
Investigate	Differentiate		13%	13%	25%	13%		13%			50%	13%		25%		25%	63%	13%	25%		
	Connect	13%		13%	50%		25%	13%			50%		13%	13%		63%	38%	88%	13%	25%	25%
Monitor	Monitor	63%	100%	13%	13%	50%	13%	13%			13%	13%	13%			13%	13%	25%	13%	13%	
	Extract			13%				13%			25%	88%	63%	50%	38%	50%	38%	38%			63%
Decide	Summarise			100%	13%		13%	100%	25%	25%		50%	13%	13%	25%						
	Create	25%		38%			13%	38%	100%	38%		13%		13%		13%		13%			

Figure 9: Cognitive strategy to data science method mapping

Table 5: Themes Data Science Focus Group

Themes	Description	Example data	Participants
User actions	Precise description of user actions and cognition	*"In the software world, there is this idea of user stories [. . .] if we were to define user stories based on the type of data, the action [...], the intended outcome and how they want to measure the outcome, I think that might be a good way of capturing all of the key bits of information."*	2/3
User goals	Definition of outcomes that are desirable for the user	*"I felt like the most important part of the card was the user action and understanding, from a user perspective, what their primary goal is, and what the primary action they want to perform is"*	2/3
Input data	Detail about data handled by the user	*"We need to know about the quality of data, in order to know how much easier it is to classify, based on the data. e.g. how many classes, [...] how many dimensions?"*	2/3
Desired output	Detail about final output data	*"Sometimes we have classification with 200 classes but when we talk with SMEs, we realize that they only care about the top 10"*	1/3
Misuse of terms	Non-technical stakeholders use AI terminology in the wrong way	*"Sometimes there is a disconnect between what they think the task is and what it actually requires from us, for example, they told me [...] to attribute points [in] kind of a regression [. . .] but actually, it was more of a classification task once we really dive into the actual problem."*	1/3

5.3 Limitations

The results in this study are based on a limited sample size of participants, workshop sessions and data science domain experts. Equally low inter-rater agreement between idea raters is a limitation of this study. We acknowledge that a small set of prompts cannot possibly encompass each and every application of an ever-growing set of AI methods. Future research could explore domain specific sets of prompts (e.g., Health, Finance, Retail etc.), or prompts related to specific areas within AI (e.g., Computer Vision, Natural Language Processing, Active Learning, interactive ML etc.) and scale the research to a larger sample of participants and research sessions. In particular, informing explainable AI with an understanding of cognitive strategy and user goals could be promising.

Nevertheless, despite the limitations, our study demonstrates the benefit of using cognitive strategy prompts in design workshops, where the goal is to generate ideas for AI powered solutions to well defined problems.

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