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THE INNOVATIVE POTENTIAL OF GENERATIVE PRE-TRAINED TRANSFORMERS (GPTs) FOR QUALITY INSPECTIONS IN SWEDISH CONSTRUCTION PROJECTS

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Abstract

Approaching quality inspection plans in Swedish construction projects as mere checklists and minimizing the clients' involvement, can reduce their value. We propose improving this process through a general cloud service concept for clients, designers, and contractors, utilizing generative pre-trained transformers (GPTs). Methodologically, we synthesize literature insights on GPT uses for construction, and empirical inquiries on developing a quality self-inspection service. We posit that through such a service, project knowledge, known quality defects and lessons-learned from previous cases can be better accessed and shared – potentially leading to time savings, suggesting best practices, and improving the collaboration among clients, designers, and contractors.

Introduction and background

In the Swedish construction sector, quality errors and defects have been annually costing ca. 100 billion SEK (ca. 8.8 billion €) (Boverket, 2018). According to Koch et al. (2020), quality problems derive from a broad set of causes, incl. design failures (e.g., detail mistakes, incomplete documents, and faulty technical aspects) execution errors on site, weather disturbances, and more. Koch and Jonsson (2015) showed that the presence of such quality defects forms a recurrent reality in Swedish construction sites.

The existence and reproduction of quality defects must be understood in context. In Sweden, the responsibility of complying with the relevant regulatory framework is handed over to the contractors and designers through a series of self-inspections and reporting of inspection and testing, labelled as "self-control" (Tolstoy, 2012; Koch and Jonsson, 2015) – statutory in the Swedish Planning and Building Law (PBL 2010:900). Critically, the industry's established practice in connection to quality self-inspections reflects "a sufficiently high quality" logic that has been reported to reduce the process into more of a "check listing" rather than an actual business strategy (Koch and Jonsson, 2015). In some cases, site managers and/or craftsmen take the implementation of quality self-inspection upon themselves (Koch and Jonsson, 2015). This is a practice which, while potentially benefitting from professional experience (Koch and Jonsson, 2015), can indeed be adversely affected by complex and ingrained behaviors and a lack of communication and commitment between both the professionals enacting the self-inspections. The collaboration with the clients can also suffer (Engström and Stehn, 2016) – with the latter often experiencing a reduced understanding of and commitment in the process and its results. Underpinning this problem, Koch and Buser (2020) have also identified that the formal quality control system in Sweden (incl. self-inspections) is unable to bridge the gap of quality understanding between the project and company headquarter levels.

Given the above, and as social practices in construction (incl. reactive and proactive problem solving) can exacerbate the reproduction of quality defects (Koch and Schultz, 2019), it can be derived that the way self-inspections are understood, implemented, and shared by the relevant actors, is connected with the recurrence of quality defects in Swedish projects.

Therefore, in this paper we address the research question of how we can improve quality self-inspection in Swedish construction, by proposing the concept of a general cloud quality self-inspection service for clients, designers, and contractors, based on generative pre-trained transformer (GPT) AI. The core proposition is that professionals performing quality controls can be provided with a much larger knowledge basis for planning and executing inspections through GPT systems. GPT systems, while popularized through ChatGPT, are little understood in the construction context, with only few studies mapping relevant opportunities and challenges (e.g., Ghimire et al. (2024)), sparse early stage attempts of leveraging such systems for construction applications (e.g., Zhen and Fischer, 2023), and virtually no efforts explicitly focused on construction quality.

Following this Introduction, the paper's research method is described. Then, a literature review on the limited GPT state-of-art for construction is conducted. Afterwards, our relevant empirical insights, as derived from four consecutive research projects (three concluded and one ongoing) on the development of a Swedish cloud-based service for quality self-inspection, are summarily offered. The insights from the literature review and our empirical studies are then synthesized into our proposed concept. Finally, we conclude with some discussion points, end remarks, and recommendations for future research.

Research method

This paper builds on the aforementioned background, a literature review, and empirical work, to develop a concept attempting to address the stated research question.

The literature review of this study concerns a summary of standing quality-related considerations within the

Swedish construction sector and its self-inspection processes (forming the background for the introductory section), as well as the (very limited) state-of-art-research on using GPT-based tools for construction. It is based on a concept-centric literature review enhanced by units of analysis that was conducted in iterations (Webster and Watson, 2002). The main searched concepts were "construction quality in Sweden", "quality inspection in Sweden", and "application of GPT in construction". The emerging units of analysis included, indicatively, "GPT use for construction quality". Finally, exclusion and inclusion criteria (e.g., contextual relevance) were applied on the found sources (Dundar and Fleeman, 2017) for finally resulting in the ones featured in the current study.

Our empirical material draws from three development projects in Sweden (concluded, respectively, in 2018, 2019, and 2022), as well as an ongoing one (2023-2024), where we have been working on developing a digital tool as a cloud service (software-as-a-service) for quality assurance and self-inspection in construction. This cloud service is intended as a tool for clients, designers and contractors who actively want to work with quality assurance and self-inspection – as it has been shown that this active and systematic work is expected to contribute to better project quality and a reduction in errors and defects. Our empirical insights were obtained in those projects through various qualitative methods (Bell et al., 2019), including, among others, expert interviews, focus group meetings, market observations, conceptualizations of recommender systems based on different (not GPT) algorithms, and an incorporation of methods of analyzing construction quality defects and their sources, like the "stumbling stone" analysis in Apelgren et al. (2005).

Finally, we synthesize the research units of our literature and empirical results (Bell et al., 2019) into our proposed concept of a cloud quality self-inspection service for clients, designers, and contractors, based on GPT-powered AI, and discuss its potential strengths and weaknesses, as well as opportunities and challenges in its implementation.

Literature review

In order to substantiate this paper's background, accompany its empirical material, and inform the conceptual design of the cloud GPT-based platform, this literature review will go through the state-of-art uses of GPT within construction in general, and with regard to quality control in particular.

In short, generative pre-trained transformers (GPT), as a framework of generative AI, are a type of large language model (LLM) – i.e. artificial neural networks used in natural language processing (NLP) tasks (Abdullah et al., 2022). GPTs are based on the transformer architecture – namely, they are pre-trained on very large datasets of unlabeled text in order to generate human-like responses to queries (Abdullah et al., 2022). According to Saka et al. (2023), while in the 2020s other LLMs like BERT have been experimentally applied in construction for a few cases outside of quality management, GPT models are still relatively new in the field. This is indicated in the few retrieved relevant publications describing dedicated systems – with none of them explicitly addressing quality management and control (Abioye et al., 2021; Amer et al., 2021; Prieto et al., 2023; Uddin et al., 2023; You et al., 2023; Zheng and Fischer 2023; Saka et al., 2024). Moreover, the use of GPT in those studies also exhibits particular limitations per case.

In particular, Amer et al. (2021) used the light version of GPT-2 to integrate master schedules with look-ahead plans, with the main limitation being the intense need for manual data pre-processing. Abioye et al. (2021) discussed how GPT models can assist the project team in performing impact analyses on how change orders can affect the project scope, and identified the appropriate representation of fragmented language as a major limitation. Prieto et al. (2023) used ChatGPT-3.5 for supporting the scheduling of construction tasks, while Uddin et al. (2023) implemented it to facilitate site hazard recognition and support construction safety education. However, none of the latter two studies featured a quantitative evaluation of their results, and the systems exhibited inadequacies with zero-shot learning (i.e., the ability of the learner to correctly predict the class of new observed samples, without the latter belonging to a class observed through training (Xian et al. (2020)). Zheng and Fischer (2023) introduced a prompt-based visual assistant integrating ChatGPT-3.5-turbo with BIM for better information retrieval, but the system was limited to single-turn conversations and no quantitative evaluation of the study's results were offered. You et al. (2023) used ChatGPT-4 for automated construction task sequence planning in robot-based assembly, which was however limited to not being able to utilize visual information. Aladağ (2023) assessed the performance of ChatGPT in construction risk management as moderate, with it providing more accurate knowledge in risk response monitoring, and less so in risk identification and analysis. In a later study, Zhang et al. (2024) used ChatGPT-4 for automated data mining connected to building energy management, which showed the potential of the system in energy management, but also identified its limitation connected, mainly, to its demarcated domain knowledge and almost exclusive reliance on the users' own skills to understand and evaluate its prompt results. Finally, Saka et al. (2024) developed a GPT-based material selection and optimization prototype that integrated BIM data through the OpenAI API, with the limitations of it requiring the identification of the specific component to provide accurate responses.

Underpinning the potential exhibited in systems such as the above, Ghimire et al. (2024) identified relevant opportunities for using GPT in construction, as in, indicatively, document and data management, AI-generated designs, task forecasting, project data synthesis, and material assessment. However, they also identified challenges connected to, among others, the GPT learners' limited domain knowledge, the over-reliance on the users' analytical skills to interpret GPT-generated results with regard to their accuracy, generalizability, and interpretability, a high cost of integration, non-updated regulations on implementation, and potentially unethical data use (Ghimire et al. 2024).

Notably, full publications on utilizing GPT systems for construction quality issues could not be found during this review, with only some initial ideas identified in pre-prints like the one by Rane et al. (2023) – where the authors investigate GPT along with augmented reality (AR), virtual reality (VR), and BIM, for identifying defects and deviations from standards in quality control. Also, at this early-stage study, the aforementioned opportunities and challenges identified by Ghimire et al. (2024) are still apparent. Nonetheless, leveraging GPT for issues identified explicitly within the context of quality self-inspection in *Swedish* construction projects (like the "check listing" and a reduction in the clients' involvement in the process, as described in the Introduction), has not been investigated yet. In the latter case, it could be expected that, to an extent, similar opportunities, and challenges as the above should apply – but with a strong contextualization come much more specific considerations, which would require dedicated investigation.

Empirical insights

Corroborating the background studies presented earlier, a central challenge highlighted by our previous projects is that research-based knowledge of quality assurance and self-inspection is limited. Moreover, there are examples in practice where the relevant actors do not know what should be included in a self-inspection procedure, or what a verified self-inspection is. Developing relevant self-inspection lists for specific projects can also be challenging; self-inspection that is not project-adapting can make the control procedure and experience feedback ineffective.

Furthermore, client organizations that do not have tools, knowledge or a process for active quality control may need help addressing queries about construction technology, material selection, standards, and regulations, as well as getting proposals for solutions to technical challenges, analyzing commonly occurring errors and defects, and proposing effective (self-)control.

Designers and contractors may face similar challenges with every new project, and doing this in a valuable way usually requires a review and analysis of previous experiences. Finally, a proposal for self-inspection must be specifically adapted for the project at hand at least up to a requisite point. It has been observed that, normally, clients approve of time allocated for self-inspections, but this time often ends up being utilized in other activities due to the lack of planning skills. This may even mean that quality self-inspections are maybe considered as "non-value-adding" activities by some actors and are thus not prioritized.

Therefore, developing and implementing a solution to the challenges above can accelerate both the interest and understanding of self-inspection as an aid in value creation within the Swedish context. This could result in a construction sector where the customer receives the product they ordered, and the designers and contractors feel professional pride and commitment when delivering projects of high quality.

This ambition has guided our development process so far, which has already resulted in a prototype of a cloud service for quality control. A well-structured system can have a critical impact on the generation of project specific prompts and self-inspection lists. In this vein, the system should be able to use multiple and reliable data sources (with Swedish examples including BBR, Säker Vatten, GVK, PBL, the clients' own local data sources, etc.) to add context to the prompt and list generation. Letting the system interact with such data sources (e.g., by pulling the relevant data for a specific query) will significantly increase the efficiency of content generation. However, AI as such, least of all GPT, has not been part of this platform up until the latest (ongoing) project. During the latter, we have identified that implementing a GPT AI layer on top of the existing cloud service prototype, can potentially help addressing the aforementioned client needs (especially with regard to knowledge requirements for getting value out of self-inspection reports) in an educational and intuitive way. Moreover, it can also help with time savings for contractors, in relation to retrieving lessons learned from previous experiences and adapting the self-inspection template per project for contextualizing the work ahead.

Therefore, implementing GPT AI in the existing cloud service prototype can potentially not only increase the service's area of implementation, but also increase user value. Moreover, communication among the relevant stakeholders can be improved, and a new type of quality data (incl. textual data in queries) can be collected and analyzed. This insights can also be supported by investigating the way currently available GPT models are utilized to explore possible areas of use. Depending on the case, the models have been trained in large datasets, thus becoming suitable for a range of different tasks – which are, however, interrelated within the domain of the use case. In addition to answering questions and generating content, GPT systems can also analyze text, assess probabilities and relevance, suggest improvements, explain complex contexts, and suggest best practices.

As probably the most popular GPT language models, OpenAI's various versions of ChatGPT are trained on vast datasets connected to multiple topics, in order to generate text and answer user queries in a human-like manner. ChatGPT has only been publicly available for a short time, but interest has grown rapidly. This may indicate that, even in niche services, there is a high demand based on the GPT technology. The cloud support for the improvement of quality self-inspection in (Swedish) construction projects can be considered such a niche service with, as of yet, no use cases featuring the implementation of a GPT. Therefore, the uniqueness of such an implementation should not only lie in the implementation of the GPT itself, but in the value that the GPT along with the cloud service and its infrastructure can create for the users. It has been ascertained that by implementing GPT AI in the intended way, the cloud service has the potential to become very attractive to clients, designers, and contractors, and create value for them when engaging in quality assurance and self-inspection through the service.

The insights above have consequently led to some crucial considerations, which in turn reflect those obtained from the literature review. In particular, the results of a potential GPT-powered cloud service should be evaluated in terms of reliability, consistency, interpretability, generalizability, and data demands and usage. Basically, the results from the language model should be interpreted as advice and recommendations that still need to be evaluated by the user – which would in turn require the user (e.g., the client) to have some competence within the field for which the GPT is used. Finally, the implementation of the GPT AI should be evaluated from an ethical perspective (e.g., regarding privacy and ownership of data), in terms of the risks involved in implementing it as a language model or NLP support, and most importantly, by considering what kind of value streams are created and for whom.

Moreover, standing inquiries have emerged in terms of the system's conceptualization, including, but not being limited to, the following:

- Simulated prompts: From where can the system get its inspiration? Is it going to be agglomerating data related to previous similar projects from the same or another client, known errors and defects, professional roles, working tasks, relevant standards on quality management (like ISO 9001:2015) and/or risk management (like ISO 31000:2018) – or a combination thereof?
- System-generated content: Could it be both the self-inspection checklists themselves (e.g., regarding HVAC installations), and, preliminarily, suggestions for the prompts leading to such checklists (which would in turn assist users with a limited knowledge on the relevant domain)?
- The web app perspective: What will each professional role's experience be when using the system? How may the system's interface and content be adapted for the needs of the designers and contractors (who, based on own experience, may anticipate certain quality problems and self-inspection requirements in the project at hand), or the clients (who may not know and be able to predict quality problems that may emerge)?

Addressing the aforementioned insights, considerations, and standing inquiries is still a work in progress. Nonetheless, the proposed concept described in the following section can act as the relevant basis.

Conceptual design

In this section, we will frame the concept of our proposed GPT-based cloud quality self-inspection service for clients, designers, and contractors, based on the context described in the Introduction and the insights and considerations derived from our literature review and empirical project work.

First, the process graph in Fig. 1 (see next page) conceptualizes the interaction of the system's workflow within a project use case, with the different professional roles of the users who intend to use it. In particular, the process is initiated with the client creating a project, by inputting attributes like the project's name and number, sub-projects (i.e., processes connected to either planning/design or construction) and their names (e.g., SP01 Planning, UP02 Production), and dates for self-inspections (also shared with the designer and/or general contractor via emails). Then, the project is kicked off in the app and an invitation is automatically sent to the designer and/or general contractor. After the latter accept the invitation, their work in the project starts by creating a discipline list related to each sub-project, which can either be selected from a drop-down list, or defined by the user. Examples of such disciplines can indicatively include HVAC, plumbing, or electrical system installations. Then, they can invite other users as the lead of one or more of the disciplines. The leads can then create quality self-inspection checklists, either by themselves or by inviting more users to collaborate. Finally, the leads and their invited users (if any) create checks and complete them; with this completion, a progress report is generated into a PDF file, which can then be shared or downloaded.

Then, in Fig. 2 we schematically represent the concept of how GPT should work in the background for the realization of the platform's process steps described previously. Specifically, we show how the system can potentially build its prompts and generate its suggested checklists and reports by interacting with the user, utilizing relevant SQL and Vector databases for relational creation, storing, updating, and retrieval of data, using auxiliary tools like web search, and, primarily, calling and retrieving data from the LLM through its API. The content generation depends on the user's role, the databases used, and the training of the LLM informing the GPT. Over the graph itself, we include the problematization about whether the user input should follow a different generation rule depending on the user's profession, i.e., whether it should be role-based generation (potentially more suitable for designers and/or contractors) or risk-based generation (namely, returning risk analyses based on project description, which is potentially more suitable for clients). Resolving this problematization is still a work in progress, as, for example, we have so far not engaged in correlating potential risks with the presence of quality defects. However, it can be reasonably assumed that it will not affect the general structure of the concept, but rather the content of the prompts, the suggested lists, the informing databases, and even the LLM.

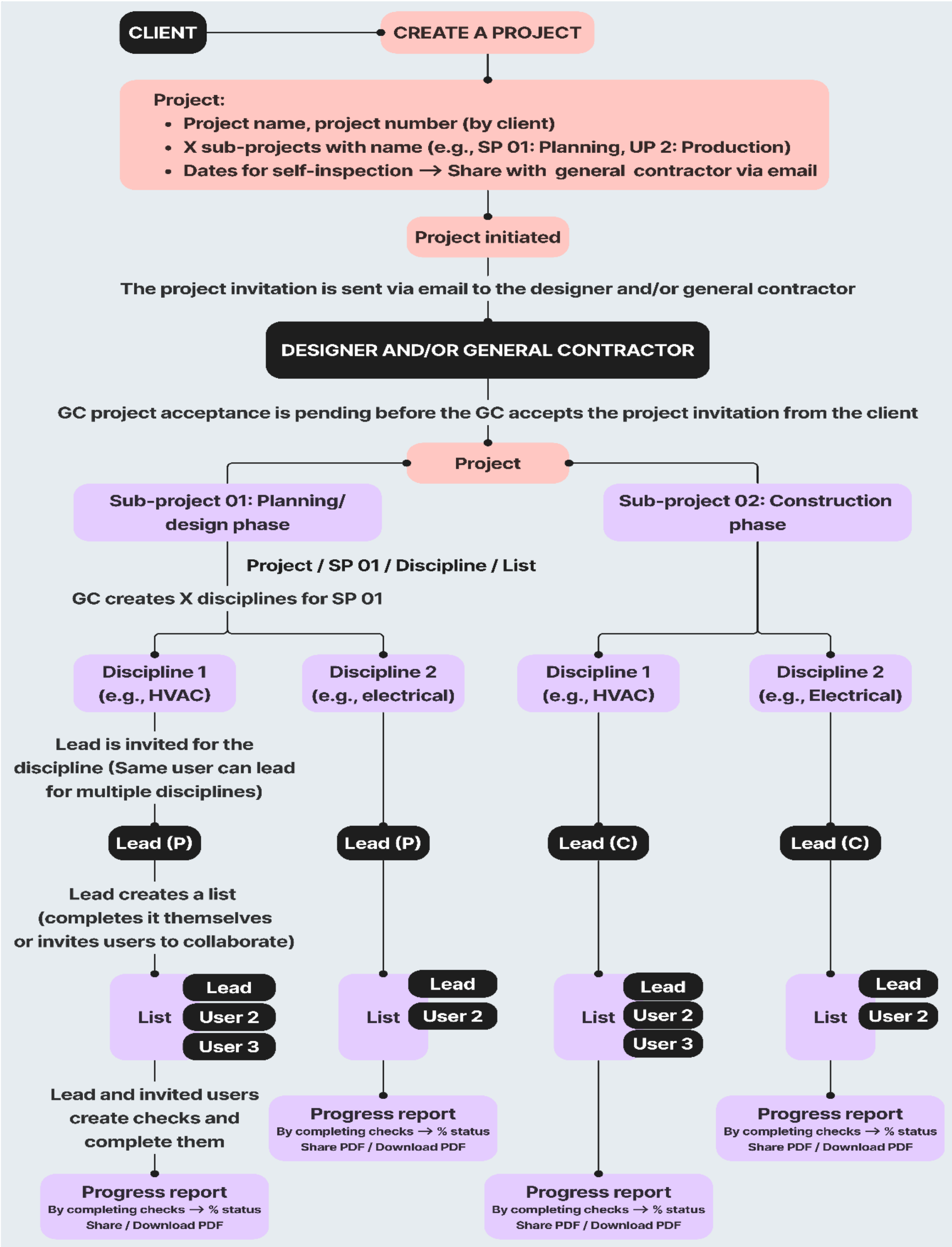

Figure 1: Interaction of the proposed system's workflow with the different professional roles using it

To further enhance the understanding of how the GPT would interface with the user, we offer the following interaction example connected to the project description analysis step:

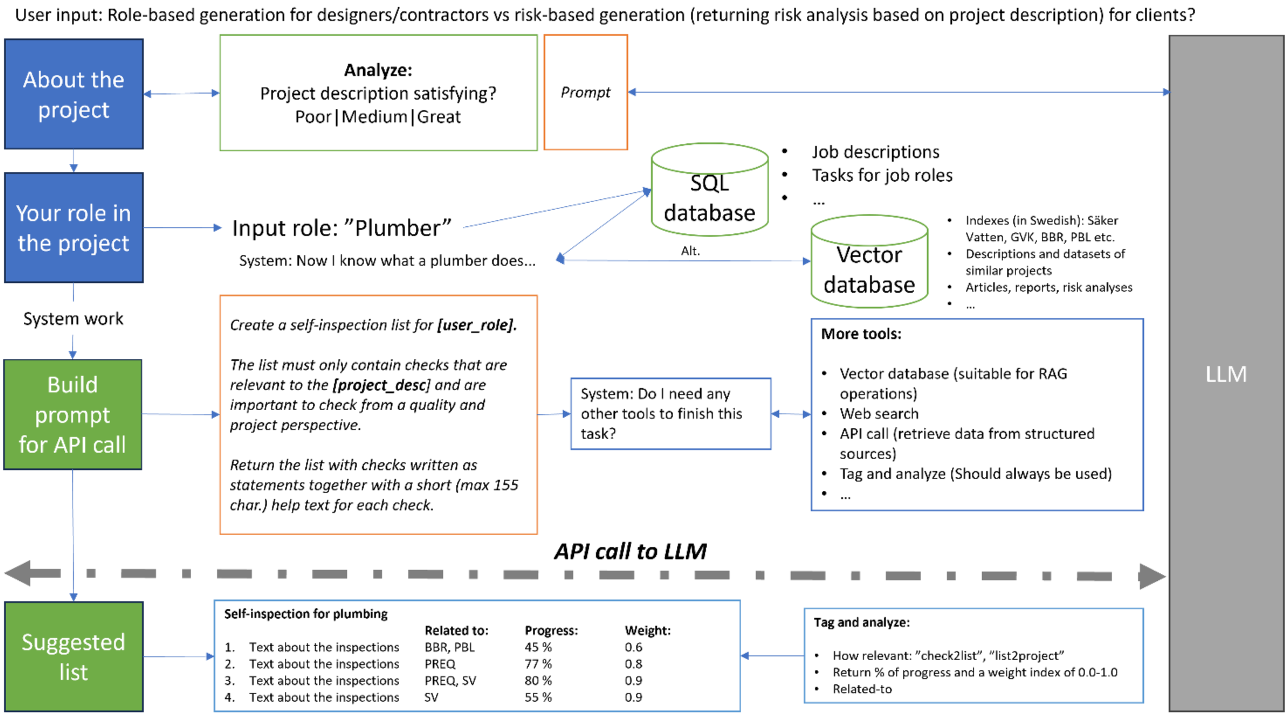

Figure 2: Schematic representation of how GPT should work in the background for the realization of the platform's process steps

You are a semantics and text analyzer, and your task is to understand the meaning of a given text and analyze it.

[text start]

A construction project has been initiated, which involves the raising of a new multi-story residential building commissioned by KKVC. This development will house 50 apartments and will feature comprehensive HVAC and electrical installations to ensure optimal conditions for future residents. The design aims to deliver comfortable, modern living spaces that meet current housing demands. Specific details about the project's size, budget, timeframe, and phases have not been provided, but the core focus will be on delivering a residential building with high-quality internal systems for heating, ventilation, air conditioning, and electrical services.

[text end]

Analyze this text and grade it. You should specifically look for these components:

- *How well does the text describe the project in general?*
- *Is there information in the text about the project budget?*
- *Is there information in the text about the project timeframe?*
- *Is there information in the text about the project and the construction phases involved?*
- *Is there information in the text about the client?*
- *Is there information in the text about the disciplines included in the project?*

Consider all questions above and then grade the text with a qualitative characterization of being Poor, Medium, Great, where:

- *Poor means that the text includes little information addressing the questions above.*
- *Medium means that the text includes a reasonable amount of information addressing the question above.*
- *Great means that the text includes a very adequate amount of information about the project and answers all of the questions above.*

Only return your score and a one-line piece of advice on how to improve the text to get a higher score (i.e., how to provide more information addressing the question above).

In short, Fig. 1 represents a simplified process flow of the cloud service concept, while Fig. 2 summarizes the functionality of the added GPT layer further empowering the service's infrastructure. These schemas are not to be considered separately, as they jointly constitute the concept of our proposed cloud-based service.

Discussion and conclusions

It has been documented that flaws in the way quality self-inspections are practiced can contribute to the recurrence of quality defects in Swedish projects. Addressing this through improving the self-inspection process itself has scarcely been the focus of relevant research. Therefore, in this paper we address the research question of how we can improve quality self-inspection in Swedish construction projects, by proposing the concept of a cloud quality self-inspection service for clients, designers, and contractors. This service is conceived to leverage generative pre-trained transformer (GPT) AI to access, retrieve, share, and create content (in the form of prompts and checklists) about relevant project knowledge and quality issues, on the basis of the understanding that professionals enacting quality controls using GPT can be provided with a much larger knowledge basis for planning and executing quality inspections.

The GPT AI support is expected to help clients, designers, and contractors to address inquiries and generate content for control plans and self-checklists. In addition, this AI could potentially help in calculating the probability and relevance of control plans and self-inspections, as well as suggesting improvement measures and best practices. The effects of this are that the client, designer and contractor can get a tool where qualitative (aggregated knowledge) and quantitative (the number of answers and suggestions) help is available in a cloud service throughout the project. It is even envisioned that, through further development, the users will, through some clicks in the app, get a proposal for a control plan together with a risk assessment and a list of quality-critical elements for both planning and execution. That foundation would be critical when developing functional requirements and requesting documents, as clients, designers and contractors can enter some brief information about the current project and get suggestions for self-checks based on the most quality-critical work steps.

The expected benefits of the cloud service include the addressing of client needs with regard to knowledge requirements for getting value out of self-inspection reports in an educational and intuitive way. Moreover, large time savings for designers and contractors can be potentially manifested, especially in relation to retrieving lessons learned from previous experiences and adapting the self-inspection template per project for contextualizing the work ahead. These benefits can primarily be achieved by having the GPT access, retrieve, share, and create content about project knowledge, experiences, known quality defects, and best practices. The aggregated knowledge to which the language model can potentially have access is in itself almost priceless.

Nonetheless, this research has several limitations. At its current stage of development, our proposed concept is still a work in progress, comprising an existing cloud service base but not a fully formed GPT layer yet. As such, it does not wholly address ongoing challenges connected to, among others, the GPT learners' limited domain knowledge, the over-reliance on the users' analytical skills to interpret and identify potential shortcomings in the content produced by the learner, the results' accuracy, generalizability, and interpretability, the potentially high cost of dedicated integration, non-updated regulations on GPT implementation, and possibly unethical data use. Moreover, there are yet not fully elaborated design considerations related to the knowledge requirements of the system's simulated prompts, the substance of the system-generated content, and the service's different functionalities and interfaces depending on the role of the user accessing it. Furthermore, measures guaranteeing the integrity and quality of the data and information processed by the GPT have not been considered yet. Using the proposed system demands specialized knowledge and expertise, and as such it must be ensured the GPT operates not merely as a linguistic transformer but as an intelligent, knowledge-based quality assessor. Finally, capabilities of assessing images (e.g., of hand-written reports), and data and/or accessor bias have not yet been considered.

Future work on the system will thus comprise, among others, the robustification of the concept for addressing the aforementioned challenges, the development and integration of the GPT layer within the cloud service base (incl. any needed APIs and user interfaces), and several rounds of testing, validation, and re-development, in order to iron out any weaknesses in the system's functionalities (incl. analyzing documents for quality against a human accessor). It is also critical to ensure the repeatability of the application, by comparing different LLM versions and vendors for the suitability informing the GPT layer of the proposed system. The ambition is that, afterwards, the cloud service will be available to all users regardless of geographic or economic conditions. Such an availability is expected to contribute to a more equal social development, as everyone would get the same opportunity and access to the service.

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