LLMs for Public Procurement

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Abstract

Public procurement is an issue of local, national and international importance. Persistent challenges include procedural errors, insufficient time and manpower, and opportunities for corruption and fraud risks. Utilizing a document chatbot approach, we demonstrate the potential applications of LLM technology towards assisting the procurement review process in analyzing high-cost, high-variation proposals.

Results Summary: We *reject* the null hypothesis that LLM-based document chatbots cannot perform better than verbatim in-document search. Our proof-of-concept, GPT-4-enabled chatbot successfully provided answers to both extractive and abstractive questioning, and demonstrated promise when handling object-evaluative questioning. However, the risk of discovery errors and the need for quality contextual data represent ongoing challenges to implementation for this application.

Contents

1 Introduction

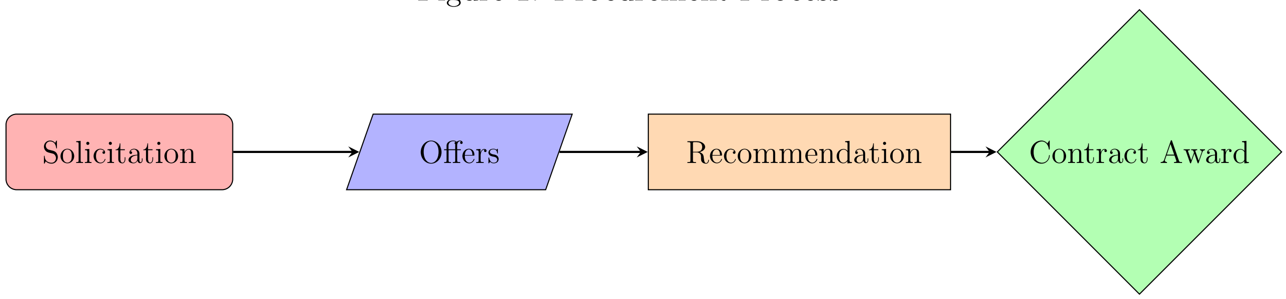
In 2008, during the midst of the Great Recession, the Chicago City Council rubber-stamped a lease on the city's parking meters in exchange for $1.12 billion in cash from private investors [1]. The catch? The lease spanned a whopping 75 years, sold at a price far below expected revenue—in fact, the meters have already turned millions in profit for private investors since then. Not only have taxpayers been deprived of future revenue, but efforts to overhaul the city's transportation infrastructure have been hampered by the city's lack of control over these parking spaces. So what went wrong?

Chicago's parking fiasco highlights an extreme example of the challenges faced within public procurement, the process whereby governments purchase goods and services from private entities. In Chicago's case, the urgent need for funds, rushed nature of the approval process, and lack of due diligence contributed to this serious oversight, with significant knock-on effects for Chicago's taxpayers and environment. How could such a mistake be avoided in the future? Furthermore, how might we apply new technologies towards addressing these oversights?

The emerging utility of generative AI and large language models (LLMs) may provide one such solution. Models such as GPT-4 have demonstrated immense value in summarizing and classifying textual data, features which could greatly help procurement specialists and city officials understand and critique different proposals. In this paper, we explore the use of GPT-powered document chat-bots as assistive tools in the public procurement approval process. Our null hypothesis is as follows: LLM-based document chatbots cannot perform better than basic verbatim in-document search tools currently in use.

2 Background

Figure 1: Procurement Process



Generally, the procurement process at the local level consists of four distinct stages.

1. **Solicitation.** The city procurement office formulates and releases a *solicitation*, whereby specifications for the requested good or service are laid out in detail.

2. **Offers.** In response to the solicitation, vendors, i.e. private entities, will submit offers satisfying the specifications as stated in the solicitation.

3. **Recommendation.** Procurement specialists will then review all offers received, and compare against a predetermined criteria to determine the best fit, then generate a recommendation that reflects these comparisons.

4. **Contract Award.** Based on the size and scope of the solicitation/offer, the procurement office may be able to directly approve the offer and formalize the contract, or it may require approval from the city council.

For the purposes of this experiment, we will be examining the City of Austin's specific procurement processes. The City of Austin's central procurement provide an illustrative example of relevant norms at the local level. The City classifies procurement purchases based on the following dollar ranges [2]:

- **Low-cost purchases ($0-3k)** are conducted at the discretion of the relevant departments, without requiring additional approval.

- **Mid-cost purchases ($3-50k)** require that an informal request for materials be made with at least three quotes (the City of Austin, as part of their diversity and equity efforts, also requires an attempt to obtain at least two quotes from a certified Women or Minority Owned Business).

- **High-cost purchases ($50k+)** are generally made based on a "formal solicitation," i.e. a set of specifications for the product/service in question, and may require approval by the City Council. Entities or businesses ("Offerors") whose proposals are approved are then able to formalize a contract with the city.

Furthermore, solicitations are grouped into the following categories [3]:

- **Invitation for Bids (IFB)**. These are the most straightforward form of solicitation, generally with the lowest cost offer being selected, granted the offer is both responsive to the solicitation criteria and from responsible entity.

- **Request for Proposals (RFP)**. These involve analyzing the merits between different proposals, which may have high-variation due to the broad nature of the request. Price as a factor is not as determinative as for IFBs.

- **Request for Qualifications (RFQ)**. These involve looking for the most qualified offeror rather than only a specific proposal, since there may be a complex set of duties which need to be performed.

For our purposes, we are most interested in addressing issues at the intersection of the high-cost purchase range and the RFPs/RFQs categories. The prioritization of high-cost is self-explanatory: solicitations which require the largest commitments of city funds ought to be most scrutinized. We recognize RFPs and RFQs as the areas of greatest value in applying the summarizing and querying power of LLMs. For IFBs, the criteria is relatively consistent and consequently offer variation is small (largely determined by cost, all else equal); in contrast, for RFPs and RFQs, the same solicitation can often yield high variation between offers, with quality of solution or entity taking greater precedence over direct monetary cost in the evaluation process.

3 Methods

3.1 Materials

Our goal will be to test the potential applications of LLMs to the solicitation-offer process. To that end, we will examine past solicitations and contracts from Austin Finance Online, the City's online repository for active/closed solicitations and their corresponding documents.

Although most documents submitted in Stage 2 of the procurement process, as described in Figure 1, are not by default available on the public database, we were able to file a Public Information Request with the City of Austin's Public Records Center to gain access to some examples, in order to test our document chatbot approach on a realistic dataset. Specifically, we requested and received copies of an unsuccessful response to RFP 8700 KWT3005, which pertains to the design and deployment of a Criminal Intelligence Case Management Software for the Austin Police Department. We were then able to pair this with the original solicitation document, which among other things highlights evaluation factors, defines relevant terms, and describes the overall scope of the project.

Although we were unable to obtain the unredacted final contract for RFP 8700 KWT3005, we still wanted to examine the chatbot's potential for the contract award stage of the procurement process (where city officials may play a role in voting on the contract). To achieve this, we were able to find and download a detailed and unredacted finalized contract example from the online repository, on the topic of implementing an Electronic Patient Care Record Solution for the City of Austin.

Therefore we are examining in total three documents: (a) the original solicitation document for RFP 8700 KWT3005 [4], (b) a complete offer response to said RFP [5], and (c) an unredacted contract award for an Electronic Patient Care Records Solution (EPCRS) [6].

3.2 Study Design

3.2.1 Building the Chatbot

At the start of the design process, we consulted procurement specialists at the City of Austin's Central Procurement section of the Financial Services Department, to gain a better understanding of the overall process, which proved to be helpful in refining the specific use case we envisioned. Once a clear goal was identified, we then began designing and building the chatbot itself. Different approaches for constructing document chatbots are well documented thanks to significant public interest in the applications of LLMs; in building our application-specific chatbot, we draw on a wealth of online tutorials, examples, and GitHub projects [7, 8, 9, 10].

Three priorities emerged during the design process: (1) ability to handle large document sizes, (2) utilization of chat history for future answer formation, and (3) in-document source citation. Since procurement documents and resultant contracts can stretch into hundreds of pages, using the ChatGPT interface manually as it currently exists would not be possible. Incorporating previous chat history into the question-answer process would allow users to build out their searches and questions and elaborate on past queries. Finally, source citation would be necessary for addressing some of the discovery error concerns which we expand upon in Table 2 for the testing stage.

The proof-of-concept document chatbot we created broadly implements the following steps:

1. **Creation of Document Embeddings.** Because the procurement documents that serve as context for the questions and answers are too large for the direct approach of copy-and-pasting into the prompt, an alternative was needed. Embeddings, which are fixed-length vectors which allow us to preserve and transmit the relationships between words in relevant documents, allow us to address both the efficiency and memory issues that arise with understanding such a large amount of text. Text is first stripped from the documents, split into chunks, and then transformed into embeddings, which are finally stored in a vector database (in this proof-of-concept we use the vector database provided by Pinecone).

2. **Contextualization of Query.** Once the document embeddings are stored, we can begin to handle queries (or questions) from the User. We first combine all previous questions/responses thus far with the latest question asked by the user, then feed the combined input into our LLM of choice (in this case ChatGPT-4), in order to return a single question that takes into account any relevant chat history. LangChain, an open source package for wrapping LLM queries, formed the core of this approach.

3. **Question Embedding Comparison to Document Embeddings.** Next, we take the single question generated in the previous step, convert it into embeddings, then return to our database of document embeddings in order to compare and find any relevant documents to the question.

4. **Return Answer Response.** Any relevant documents are then returned along with the single question to OpenAI's ChatGPT API, where a response is generated based on the combined input of the document(s) and question. This answer, along with selected portions of the document, are returned to the user as the final response.

3.2.2 Testing the Chatbot

We utilize the following "ladder of inquiry" in order to formulate questions that test the range of chatbot ability.

Table 1: Ladder of Inquiry

Extractive	Direct keyword search, verbatim in-document text discovery
Abstractive	High-level conceptual understanding of in-document themes
Object Evaluative	Assessment of offer components against predetermined criteria
Predictive	Examination of potential outcomes based on proposed parameters
Context Evaluative	Assessment of offer component interactions with outside knowledge

1. For extractive questions, we focus on developing a set of questions that target different sections of a proposal/solicitation, from beginning to end.

2. For abstractive questions, we focus on developing a set of questions that are focused on identifying groupings of similar concepts within the document, aligning a portion of tests with the topics covered by extractive questions.

3. For object-evaluative questions, we use the solicitation evaluation factors (see Appendix A) as a starting point for question development. Each component of the criteria is then translated to a question for the chatbot.

4. For predictive questions, we would focus on the short-term/long-term impact of proposed items, in categories such as sustainability, congestion, etc. as they relate to stated city priorities that are relevant to the category of procurement. However, in an effort to limit the opportunities for hallucination, we have restricted our prompts to only answer questions from the text. In the future, testing these questions could be conducted by ingesting for context an extensive set of city priority documents and overall goals, which could then inform the chatbot responses.

5. Though we also do not explicitly test context-evaluative questions in this paper, due to a lack of access to unredacted datasets for fair comparison, we highlight this as an area for future testing. Context-evaluative testing could be done by feeding in an array of separate submitted offer proposals responding to the same RFP, then asking questions which refer to points of comparison across the offers in relation to specific criteria.

In assessing the chatbot responses to the designated questions, we are also conscious of potential pitfalls with LLMs as a whole, particularly in its ability to provide convincing answers that are not actually backed by evidence. Hallucination is a well-founded cause for concern [11], particularly for this use case where false interpretations may have significant legal and financial implications. As such we have broadly identified two categories of potential issues which we are cognizant of and consider in the design/testing process: Type I and Type II discovery errors.

Table 2: Discovery Errors

Error Type	Description
Type I Discovery Error	Returns wrong interpretation of information in the text
Type II Discovery Error	Omits crucial information from the search findings

To address concerns with Type I discovery errors, we prioritize the implementation of a “source citation” feature [9], whereby the chatbot, along with its answer, returns a reference to portions of the document that informed that specific answer. While not perfect, this provides a starting point for rectifying misinterpretations of the document contents; by checking the relevant sections of the documents, the user can then verify the accuracy of the understanding, or use those sections as an initial point of departure for identifying the correct interpretation.

For Type II discovery errors, we recognize that the presence of such errors could have serious implications for the quality of a chatbot answer. Particularly in this application, missing just one clause could significantly alter the overall meaning or fail to recognize important exceptions. In our discussions section, we expand on some ideas for reducing the likelihood of such issues, for example through separately loading definitions stated in the document as context for the chatbot in order to make such terms more salient and therefore less likely to be omitted. However, this remains an open question and warrants a disclaimer for users.

4 Results

We test a series of questions for the set of documents we compiled, first with the original solicitation document for RFP 8700 KWT3005 and the a complete offer response, and then with the Electronic Patient Care Records Solution (EPCRS) contract. For the RFP 8700 KWT3005 documents, we asked extractive, abstractive, and object-evaluative questions; for the EPCRS contract, we asked extractive and abstractive questions only (no evaluation factors were included in the contract with which to ask object-evaluative questions with).

Extractive Questioning. On the small sample of questions tested, we found the chatbot to be very effective when asking extractive, verbatim questions, along the lines of the basic ”find” functionality which most document viewers are equipped with, but elevated by the ability to utilize natural language. No Type I errors were identified in the sample; however a few Type II errors with partial omission were identified. Upon further inspection, the source citations attached to each response proved to be a sufficient remedy; in most cases the partially omitted information came immediately after the selected portion, something which the user is readily able to inspect and understand.

Abstractive Questioning. On the small sample of questions tested, we found the chatbot to be very effective when asking abstractive questions, with the exception of some Type II errors similar to those identified in Extractive Questioning. In a minority of cases, the chatbot response started with "The context provided does not include ...," indicating a complete omission of the relevant information, and the source citations provided were not helpful in identifying the omitted text.

Object-Evaluative Questioning. The chatbot struggled the most with questions based on this format. These questions were formulated based on the factors outlined in Appendix A, and at times the chatbot did not answer the questions citing a lack of detail in defining the factors, or when it did, omitted some crucial details which may have altered its rating with the factor. It is important to note that the solicitation documents themselves do not define in great detail these factors, which may have had an overall impact on the response quality.

The raw data on questions, responses, and citations can be found in the data.xlsx file.

5 Discussion

Based on these preliminary findings, we would reject the null hypothesis. Even with the small sample of question tested, this demonstrates that there is significant value added by a chatbot approach which understands natural language and which can cite selected portions of the document in response to questions. The chatbot's ability to provide answers to queries which were more complex than exact text matching is evident, and therefore represents a major improvement over the basic text matching tools most commonly in use. There are a number of key takeaways we gained from the testing:

Source citation is valuable. While we initially envisioned in-document citation for chatbot answers to be helpful primarily for rectifying Type I discovery errors, testing revealed that it could also be useful in addressing Type II discovery errors, by providing a starting point within the document to look for more clarification. Indeed some of the partial omissions we encountered simply missed the additional text in a later section (which we suspect may also have been due to token size issues for the prompt and response). Addressing discovery errors is an important objective, and source citation remains one of the best tools thus far to do so.

Terminology matters. We found during testing that variation in the terminology used to describe actors or objects, even if the terms used were synonymous, could influence the chatbot response. For example, referring to the solicitation as a 'proposal" instead of a “context” or a “document” led to differing results. We found greater success using a consistent set of terms rooted in the prompt design as well as the definitions provided within the document (e.g. in Appendix B).

Chat history and context is influential. Object-evaluative questions had more success when they were split into multiple stages, and chat history played an important role in making that multi-stage approach possible. However, users also need to be mindful of how chat history can cause questions to be misinterpreted; ambiguity in the current question may lead the model to make assumptions based on past chat history that can warp the original intent of the question. Secondly, more context can be valuable in providing more detailed responses. There are many opportunities to load in additional data, for example via city specific regulations or relevant state statutes that would provide the model with more opportunities to elaborate on material. Boilerplate elements of existing solicitation documents (see Appendix B for examples in both the offeror’s proposal and in the original solicitation) could easily be integrated more explicitly into the model. Furthermore, solicitations often come with attached addendums formatted in a question and answer format, which could also easily enhance the chatbot’s capabilities [12].

Recent research finds that multi-document question answering can degrade significantly based on the location and order of relevant information [13]; for applications to public procurement, this poses a serious concern, and indeed we saw some possible signs of this occurring with the Type II errors described in the results section, when important sections were omitted.

We therefore stress the *assistive* role that we envision for this technology and use case: this proof of concept is intended to demonstrate the value that the summarizing and extracting potential of LLMs may bring to this specific procurement process, particularly in time- and resource-constrained environments. Ultimate analysis, review, and decision-making is the responsibility of elected officials and procurement specialists who approve and recommend procurement contracts and proposals.

While the current focus is on local government, both due to the magnitude and diversity of vendor-procurement interaction and engagement, the eventual goal is to expand these findings to other contexts at the state and federal level, and in related applications, such as for parsing and evaluating legislation under strict time-constraints. While the probability for discovery errors continues to be of concern, these results so far demonstrate the immense potential of document chatbots for usage within government, particularly in assisting on extractive and abstractive questioning.

6 Limitations

There were a number of limitations present in this proof-of-concept which could be improved upon in future iterations of this experiment. Firstly, there were some inherent challenges with the quality of the textual data; due to fact that all relevant procurement documents were in PDF format, transforming the document text into embeddings required some optical character recognition work which was not entirely consistent, and there was some information loss due to the poor quality of the scanned pages in the contract. However, this issue is largely secondary to the larger questions we are exploring through this proof-of-concept, as the formatting of proposals and submissions is something that cities can easily update if necessary to make it more conducive for chatbot implementation.

Furthermore, I hope to expand this initial sample with more city-specific data in the future. Specifically bringing in more contextual data, for example in the form of city priority and planning documents, would allow for more detailed testing of predictive and context-evaluative questions. In our testing, insufficient context was not often a fault of the chatbot but due to the constraints of the data.

Finally, testing this with other LLMs besides OpenAI's GPT-4 would also expand the generalizability of the results and demonstrate the feasibility of this idea beyond a single model. Developing an LLM-agnostic framework that can work under a variety of models will be important for remaining up to date with the latest developments in the field. This may also help prevent lock-in to specific vendors/services that in the long run create issues with procurement. That being said, many of the findings discussed in the previous section are likely to hold for other technologies as well.

References

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Appendices

A Solicitation Evaluation Factors

10.8 Service-Disabled Veteran Business Enterprise ("SDVBE") - Pursuant to the interim Service-Disabled Veteran Business Enterprise (SDVBE) Program, Offerors submitting proposals in response to a Request for Proposals shall receive a three point (3 percent) preference if the Offeror, at the same time the proposal is submitted, is certified by the State of Texas, Comptroller of Public Accounts as a Historically Underutilized Business and is a Service-Disabled Veteran Business Enterprise. This preference does not apply to subcontractors. To receive this preference, Offerors shall complete the enclosed Section 0840 Service-Disabled Veterans Business Enterprise Preference Form, in accordance with the Additional Solicitation Instructions included therein.

11. Evaluation of Offers

11.1 Evaluation Factors

RFP Evaluation Factors		**Maximum Points**
1. Demonstrated experience, references, and personnel qualifications		15 Points
2. Project concept and solution		42 Points
3. Project Approach		20 Points
4. Price Sheet		10 Points
5. Local Business Presence		10 Points
Team's Local Business Presence	Points Awarded	
Local business presence of 90% to 100%	10	
Local business presence of 75% to 89%	8	
Local business presence of 50% to 74%	6	
Local business presence of 25% to 49%	4	
Local presence of between 1 and 24%	2	
No local presence	0	
6. Service-Disabled Veteran Business Enterprise		3 Points
Total		**100**

11.2 Interviews and/or presentations, Optional. The City will score proposals on the basis of the criteria listed above. The City may select a "short list" of Proposers based on those scores. "Short-listed" Proposers may be invited for presentations, demonstrations, or discussions with the City. The City reserves the right to re-score "short-listed" proposals as a result, and to make award recommendations on that basis.

B In-Document Definitions

EXHIBIT B TO ATTACHMENT A. THE MASTER SUBSCRIPTION AND LICENSE AGREEMENT
SUPPORT SERVICES ADDENDUM

1. **DEFINITIONS**. Capitalized terms not defined below shall have the same meaning as in the General Terms & Conditions.

1.1. "Enhancement" means a modification, addition or new release of the Software that when added to the Software, materially changes its utility, efficiency, functional capability or application.

1.2. "E-mail Support" means ability to make requests for technical support assistance by e-mail at any time concerning the use of the then-current release of Software.

1.3. "Error" means an error in the Software, which materially degrades performance of such Software as compared to ESO's then-published Documentation.

1.4. "Error Correction" means the use of reasonable commercial efforts to correct Errors.

1.5. "Fix" means the repair or replacement of object code for the Software or Documentation to remedy an Error.

1.6. "Initial Response" means the first contact by a Support Representative after the incident has been logged and a ticket generated. This may include an automated email response depending on when the incident is first communicated.

1.7. "Management Escalation" means, if the initial Workaround or Fix does not resolve the Error, notification of management that such Error(s) have been reported and of steps being taken to correct such Error(s).

1.8. "Severity 1 Error" means an Error which renders the Software completely inoperative (e.g. a User cannot access the Software due to unscheduled downtime or an Outage).

1.9. "Severity 2 Error" means an Error in which Software is still operable; however, one or more significant features or functionality are unavailable (e.g. a User cannot access a core component of the Software).

1.1. "Severity 3 Error" means any other error that does not prevent a User from accessing a significant feature of the Software (e.g. User is experiencing latency in reports).

1.2. "Severity 4 Error" means any error related to Documentation or a Customer Enhancement request.

1.3. "Status Update" means if the initial Workaround or Fix cannot resolve the Error, notification of the Customer regarding the progress of the Workaround or Fix.

1.4. "Online Support" means information available through ESO's website (www.esosolutions.com), including frequently asked questions and bug reporting via Live Chat.

1.5. "Support Representative" shall be ESO employee(s) or agent(s) designated to receive Error notifications from Customer, which Customer's Administrator has been unable to resolve.

1.6. "Update" means an update or revision to Software, typically for Error Correction.

1.7. "Upgrade" means a new version or release of Software or a particular component of Software, which improves the functionality or which adds functional capabilities to the Software and is not included in an Update. Upgrades may include Enhancements.

1.8. "Workaround" means a change in the procedures followed or data supplied by Customer to avoid an Error without substantially impairing Customer's use of the Software.

City are: representatives from the department that requested the purchase, the Department of Law, the Purchasing Office, and other appropriate City staff. You may bring a representative or anyone else that will present information to support the factual grounds for your protest with you to the hearing.

8.4.8 A decision will usually be made within fifteen (15) calendar days after the hearing.

8.4.9 The City will send you a copy of the hearing decision after the appropriate City staff has reviewed the decision.

8.4.10 When a protest is filed, the City usually will not make an award until a decision on the protest is made. However, the City will not delay an award if the City Manager or the Purchasing Officer determines that the City urgently requires the supplies or Services to be purchased, or failure to make an award promptly will unduly delay delivery or performance. In those instances, the City will notify you and make every effort to resolve your protest before the award.

8.5 **Interested Parties Disclosure.** As a condition to entering the Contract, the Business Entity constituting the Offeror must provide the following disclosure of Interested Parties to the City prior to the award of a contract with the City on Form 1295 "Certificate of Interested Parties" as prescribed by the Texas Ethics Commission for any contract award requiring council authorization. The Certificate of Interested Parties Form must be completed on the Texas Ethics Commission website, printed, and signed by the authorized agent of the Business Entity with acknowledgment that disclosure is made under oath and under penalty of perjury. The City will submit the "Certificate of Interested Parties" to the Texas Ethics Commission within 30 days of receipt from the successful Offeror. The Offeror is reminded that the provisions of Local Government Code 176, regarding conflicts of interest between the bidders and local officials remains in place. Link to Texas Ethics Commission Form 1295 process and procedures below:

https://www.ethics.state.tx.us/File/

9 DEFINITIONS

Whenever a term defined by the Uniform Commercial Code, as enacted by the State of Texas, is used in the Contract, the UCC definition shall control, unless otherwise defined in the Contract.

"Addendum" means a written instrument issued by the Contract Awarding Authority that modifies or clarifies the Solicitation prior to the Due Date. "Addenda" is the plural form of the word.

"Best Offer" means the best evaluated Offer in response to a Request for Proposals or Request for Qualifications/Statements.

"Best Offeror" means the Offeror submitting the Best Offer.

"City" means the City of Austin, a Texas home-rule municipal corporation.

"Offer" means a complete signed response to a Solicitation including, but not limited to, a Request for Proposals.

"Offeror" means a person, firm, or entity that submits an Offer in response to this Solicitation. Any Offeror may be represented by an agent after submitting evidence demonstrating the agent's authority. The agent cannot certify as to his own agency status.

"Proposal" means a complete, properly signed Offer to a Request for Proposals.

"Proposer" means a person, firm, or entity that submits an Offer in response to a Request for Proposals.

"Purchasing Office" refers to the Purchasing Office in the Financial Services Department of the City.

"Purchasing Officer" means the director of the Purchasing Office and the principle recipient of procurement authority from the City Manager.