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Human-centered artificial intelligence for the public sector: The gate keeping role of the public procurement professional

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Abstract

The increasing deployment of artificial intelligence (AI) powered solutions for the public sector is hoped to change how developing countries deliver services in key sectors such as agriculture, healthcare, education, and social sectors. And yet AI has a high potential for abuse and creates risks, which if not managed and monitored will jeopardize respect and dignity of the most vulnerable in society. In this study, we argue for delineating public procurements' role in the human-centred AI (HCAI) discourses, focusing on the developing countries.
The study is based on an exploratory inquiry and gathered data among procurement practitioners in Uganda and Kenya, which have similar country procurement regimes: where traditional forms of competition in procurement apply compared to more recent pre-commercial procurement mechanisms that suit AI procurement. We found limited customization in AI technologies, a lack of developed governance frameworks, and little knowledge and distinction between AI procurement and other typical technology procurement processes. We proposed a framework, which in absence of good legal frameworks can allow procurement professionals to embed HCAI principles in AI procurement processes.

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Keywords: Human-centered artificial intelligence (AI); Explainable AI(XAI); public procurement; Ethical AI; Responsible AI; developing countries

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1. Introduction

Artificial intelligence (AI), machine learning (ML), and other data science technologies have become the most ubiquitous innovations of the 21st century. From chatbots and virtual assistants, medical assessments, language translation, credit scoring to more complex applications in manufacturing and supply chain optimization, AI has shown significant promise for companies. In developing countries, AI tools are being used to address the biggest sustainable development challenges in education services, healthcare, public infrastructure, agriculture, and security [1]. AI and ML tools continue to have positive benefits for governments, and millions of people worldwide. Likewise, there are ethical concerns associated with AI solutions, which are not well understood by the man on the street who has no technical understanding of AI or ML [2]. The literature has cited several existential threats of AI such as intrusive surveillance, erosion of privacy, and the use of AI weapons [3]. Nowhere is it more critical to understand the social impacts of AI and data science than in the public sector where job losses due to automation, higher inequality, discrimination, and biased policymaking are likely to affect the most vulnerable, underserved underrepresented communities [31]. So, in this paper we address *the challenge of governance of AI in the public sector* in developing countries.

The public sector represents the biggest market for AI solutions in the developing world: AI governance becomes important especially today as open government and digitization of public services take root [4]. Deployments of AI in the public sector start with public procurement decisions, whose spend represents up to 50% of GDP in most developing countries [5]. So public procurement is essentially a critical bridge for public sector adoption of AI technologies [3,6,7]. However, governments in developing countries have weak regulatory and governance mechanisms to incentivize solution developers and users of AI to develop and deploy human-centered AI (HCAI) innovations that protect users against abuse, social divisions, and government suppression [3,7,8]. Irresponsible and unethical AI has shown the potential to abuse the dignity of people and distorts value systems of the most vulnerable for whom AI solutions are intended [9]. The street bump project in Boston Massachusetts [10]; the COMPAS project for the justice system in Broward County, Florida [11]; the Chinese supplied CloudWalk facial-recognition program for the Zimbabwean government [12] etc, are some of the demonstrable examples of such irresponsible and biased AI solutions.

In this paper, we argue for and investigate public procurement's role in the development and deployment of HCAI in developing countries. Specifically, we address the research question (RQ1): *what role can public procurement and the public procurement professional play in the development and deployment of HCAI?* Human-centered artificial intelligence – HCAI, has been defined by among others [13], [14], [15], and [16] as the extent to which AI systems are designed with a clear purpose of human use and benefit. HCAI is essentially a design concept associated with both ethical AI and responsible AI to allow humans fair and transparent access and control over the data and algorithms from which the solution is based [3]. HCAI contrasts traditional AI where the development of algorithms was based on machine autonomy and properties such as deep learning and self-adaptation [16].

Developers today must think of privacy, accountability, safety & security, transparency & explainability, fairness & non-discrimination, human control of technology, professional responsibility, and promotion of human values [15]. Yet it is still not well understood how pre-AI deployment processes such as government technology procurement have considered HCAI or AI's impact in society. Both [6] and [7] agree that public procurement can be an enabler for the ethical adoption of AI to ensure safe, accountable, and transparent AI adoption for public service delivery.

With the exception of [3], we found no study that addressed HCAI in public procurement. Naudé and Dimitri [3] make the argument that public procurement of innovation through pre-commercial procurement (PCP) processes, can incentivize private agents of innovation to advance HCAI. In this paper we further this argument but specifically address the "how" and "to what extent" questions, i.e., public procurement as an enabler for HCAI. We look at the traditional gatekeeping role of procurement as the basis for negotiating the process and rationalizing rewards with the owners and developers of AI technologies. This to the best of our knowledge has not been studied.

In addressing the above RQ, this study contributes to a better refinement of procurement's role in the implementation of ethical AI for the benefit of citizens and the public good in developing countries. We provide a framework that can be used to incorporate HCAI dimensions in the high-impact public procurement processes.

The paper is organized as follows. In the next section, we briefly review the literature on gatekeeping and HCAI. Then we present the methods used in the study, the results, and discussion thereafter. In the end, we present the conclusion of the study.

1.1. Public procurement's gatekeeping role in the HCAI literature

The public procurement space presents the biggest opportunity to unlock AI usage for the public sector but the nuances in their role present the highest safety and ethical risks in public sector AI [3,6,7]. At the center is the public procurement professional who is the *maître d* of the government procurement process: they are the link between vendors of AI solutions and users [31] (**Fig. 1**). They sit at the junction of many communication paths and are exposed to large amounts of key information for the most vital decisions [2]. Their decisions' failure to promote ethically and technically robust AI procurement tends to be very risky and harmful to the public.

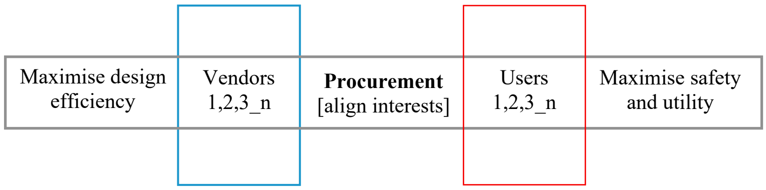

Fig. 1. A conceptual model of procurement's HCAI considerations.

Literature shows that the dangers of procurement and deployment of AI solutions that could harm the public focus mostly on privacy, security, environmental protection, social justice, and human rights concerns [7]. Jobin, Ienca, and Vayena [17] rises fears of unemployment, misuse by malevolent actors, the loss of accountability, and dissemination of bias which undermines fairness. Malhotra and Anand [18] are concerned by the enormous real-time data harvesting by IoT devices which developers use to gain sensitive information about individuals, communities, and related demography. Scheltema [19] notes that AI solutions need to reduce public health and safety risks as well as risks to the environment; should include social responsibility; should protect privacy and should protect stakeholders from undue risk and harm or violation of their rights.

These are aspects that HCAI governance literature has closely investigated. Shneiderman [14] and Shneiderman [16] have particularly provided a framework of three HCAI principles to guide managers involved in technology development, and procurement for that matter. They include: (i) *reliability* which emerges from software design to allow audit trails for analysis of failures, algorithm verification, and validation testing, bias testing to check for fairness, and explainable user interfaces: (ii) *safety as a culture* among solution buyers and vendors to consider how suppliers report failures and how industry standard practices are adopted, and (iii) *trustworthiness* whose focus is on industry-wide efforts on AI regulation should allow for external auditors, researchers, civil society and insurance companies to check, certify and provide input towards responsible AI. These three dimensions are congruent with guidelines that some countries and institutions developed for AI procurement (See: [6,7]). An even more elaborate HCAI framework offered by [16] arguably agrees with [14] by placing the needs of humans at the center of technology development and includes ethics and technology as the other pillars. Other studies also confirm that consumers tend not to trust a solution unless it is auditable and certifiable [20, 32]. Naudé and Dimitri [3] notes that HCAI is a two-way street; while it aims to minimize misuse and negative AI side-effects to society thus societal development, there is a commercial focus too in the safe and ethical AI use when companies avoid costly mistakes. It increases the uptake and diffusion of AI [31].

In sum, the literature shows that the procurement of ethical and responsible AI solutions for public use demands: (a) deeper knowledge of HCAI principles which are currently not well developed or aligned to public procurement processes: (b) better interaction between AI solutions vendors and the public procurement practitioner.

Both (a) and (b) have a significant impact on equitable, fair, transparent, safe, and trusted AI use for the public, including for society's most vulnerable.

2. Methods

The study adopts an exploratory qualitative approach to answer the RQ in section 1. Exploratory research suits relatively new, under-researched, and under-theorized themes like the ones addressed in this paper, where deep and rigorous knowledge is needed to clarify ambiguity or discover ideas that may enhance theory development [21]. Because exploratory research emphasizes discovery, also theory elaboration was is targeted [33]. Our study focuses on the developing country context – specifically Kenya and Uganda, where knowledge on government technology procurement and HCAI are still foundational in an environment where issues of data ethics, data access, and regulation are rather complex [22].

2.1. Material and data collection methods

We adopted a two-pronged approach to data collection. First, we collected and conducted a documentary review analysis of legislations that govern public procurement in both Uganda and Kenya. In Uganda, the public finance procurement regulations of 2000, and its successor the public procurement and disposal of public assets (PPDA) act of 2003 were reviewed. In Kenya, the public procurement and asset disposal (PPAD) act of 2015 (revised 2016) and the supplies practitioners act of 2015 were reviewed. These legislations are the main policy documents that govern public procurement in these two countries

Second, we then collected data from public procurement professionals involved in technology procurement in the period between January 2021 and June 2021. The primary source of data were focus group discussions (FGDs) (in Uganda) and virtual one-on-one interviews (in Kenya). The goal was to understand the participants' actions and experiences through their own stories, perceptions, and motivations based on a research protocol that was developed from the literature on the HCAI frameworks [23].

In Uganda, our target population consisted of the 566 members of the Institute of Procurement Professionals of Uganda. In that group, 32 participants were purposively selected based on experience and availability for the three (3) FGDs rounds. Each FGD with 11 participants lasted between 90 minutes to 2 hours and was conducted by a moderator assisted by one trained research assistant. Permission to tape-record the sessions was also sought.

Both the FGD and interview participants were invited in April 2021 to indicate their interest in participating in this study through an information sheet and consent forms. In the reporting of the FGDs, the findings are not tagged to individual participants' names to assure anonymity. Both the semi-structured questions used and transcribed data files for the FGDs and interviews can be availed as supplementary files.

Table 1. Data sources

Data collection techniques	Uganda (*number of*)	Kenya (*number of*)	Participants
Focus group discussions	3 rounds (32 participants)	0	Contracts committee members, procurement officers, procurement policy experts, public finance experts, data scientists and cyber security experts
Interviews	0	6 (6 participants)	Procurement consultants, procurement officer, public procurement trainers, Chief executive officer, and data scientist

2.2. Data analysis

The data analysis approach considered three phases of [24, 25] including data reduction; first-order coding and data display; second-order analysis; conclusions and verification. Data from the interviews and FGDs were transcribed, thereafter we conducted preliminary analysis (first-order coding) to identify a working framework for the coding needs for the detailed content analysis. To ensure the trustworthiness and credibility of the data analysis process, an independent co-coder reviewed each transcript independently and provided comments to authors to consider for the detailed analysis (second order coding). Using the pattern-matching technique, data was displayed in matrices to facilitate comparisons of interview data from Kenya with that from FGDs in Uganda. Two forms of verification were sought. We sent the transcribed interviews and FGD answers to all the participants for comments on the accuracy of their responses, and thereafter verification of the preliminary analyses among the co-authors was made before identifying common data points of agreement or disagreement and drawing logical connections to inform the discussions and conclusions that we present in the subsequent sections.

3. Results and discussions

First, we report on the results from the documentary review analysis and thereafter, from the first and second-order coding informed by frameworks from [14,16].

The results from the documentary review show that HCAI principles are superficially represented in procurement legislation of both Uganda and Kenya. The four (4) main pieces of legislation we reviewed as shown in **table 2** have not been updated to consider the challenges of sourcing AI in general. They specifically bundle AI procurements into the category of information and communications technology (ICT) procurement which creates ambiguous situations in AI procurements. For example, clause 7(l) provides for the procurement authority in Uganda to determine, develop, introduce, maintain, and update related system-wide databases and technology. Clause of 59b of the PPDA act of 2003 provides for consultation of experts and stakeholders where complex procurements, such as new technology procurements, must be reserved due to their complex nature. In Kenya, Clause 99(1) of the PPAD proposes two-stage tendering processes when, due to complexity, inadequate knowledge, or advancements in technology, the required solution does exist on the market. Clause 155(3b) demands that technology suppliers provide for mechanisms for technological transfer and describe the job creation potential of their solution. Kazim and Koshiyama [26] show AI technologies are different and unique, so the increasing adoption of AI in government demands different and unique standards and regulations. Desouza, Dawson, and Chenok [27] recommend for public organizations to adopt new ways to manage new technologies and particularly address privacy and security concerns.

The results of the first and second-order coding and subsequent analyses confirm that, even if weak, the reviewed legislations have similar orientations but target different HCAI principles. While the PPDA act of 2003 in Uganda is oriented towards trustworthiness where stakeholder input is targeted for more complex procurement, the PPAD in Kenya is more process-oriented to ensure that some HCAI principles are embedded in the procurement process. Moreover, unlike PPAD which is moderately explicit how the procurement professionals may facilitate the AI procurement processes, the PPDA act is rather ambiguous so the public buyers in Uganda seek support from other ICT laws including the Uganda communications act of 2013, the national information technology authority, Uganda act of 2009, computer misuse act of 2011, the Electronics Transactions Act of 2011 and the electronic signatures act of 2011 among others. De Magalhães [28] argues for the need for a specific framework to regulate ethics, inclusion, transparency, and open governance for "political algorithms."

Table 2. HCAI considerations in public procurement legislation

Country	Legislation	*reliability*	*safety as a culture*	*trustworthiness*
Uganda	Public procurement and disposal of public assets act of 2003	○	○	⦿
	Public finance procurement regulations of 2000	○	○	○
Kenya	Public procurement & asset disposal act of 2015 (rev. 2016)	⦿	○	○
	Supplies practitioners act of 2007 (rev.2015)	○	○	○

● = fulfilled. ⦿ = Partially fulfilled. ○ = not fulfilled

Building on the earlier argument we made, consistent with Naudé and Dimitri [3] on the role of public procurement in incentivizing the adoption of ethical and responsible AI in the public sector, the results of this study confirm this view and further suggest that the developing country procurement professionals can play an essential gatekeeping role to ensure that the outcomes of the procurement process benefit and safeguards the well-being of society.

The FGDs and interviews all show that the procurement professional is actively but implicitly involved procurement of AI solutions as complete hardware or turn-key solutions rather than novel-ground-up solutions. In Kenya, the example of medical diagnostic equipment for public hospitals is cited, while in Uganda civil service payroll solutions, e-learning technologies, asset tracking and tachometers devices, street and face recognition cameras, biometric access controls, drones were cited. All procurement professionals agree to the benefits of AI technologies in tracking dubious deals, promoting transparent relationships with the suppliers, minimization of conflicts within the system, restoration of trust in the public system, environmental friendliness, and cost reduction. They also cite the dangers of bad AI that had not been considered in the purchase decisions of all the technologies mentioned above. Data use, consent and privacy were cited as the biggest challenge given that most suppliers' servers were hosted in China and India and not locally. Most public institutions did not have control of the source-code of some of the software used; non-disclosure agreements with suppliers and data sharing agreements were not adequately enforced in contracts. The typical public procurement professional lacked ICT knowledge and skills to negotiate with suppliers and depended a lot on IT experts from auxiliary government agencies and consultants. The ambiguity of and the absence of legal frameworks to govern the AI procurement processes was cited as the biggest challenge.

These results suggest that HCAI principles are difficult to embed in traditional public procurement processes that lack appropriate supporting legislation and knowledge of AI among procurement professionals. Unlike in procurement of innovation processes as proposed by Naudé and Dimitri [3] where market dialogue and PCP processes demand closer interaction between the owners of the solution and the potential users of the solution, traditional source-to-pay processes are too rigid to negotiate ethical requirements with suppliers of turn-key solutions. Chopra [29] maintains that governance of AI in procurement requires collaboration between procurement, asset management, with finance and vendor relationship management. Jobin et al [17] propose a concept called 'reflective equilibrium' which demands mutual adjustment of ethical principles alongside judgments contained in the policy documents as would in PCP processes. As a proponent for open government, De Magalhães [28] describes the necessity to invest in "collaborative data" between civil society, private organizations, and the government to support decision-making that's in the interest of the public. Scheltema [19] draws our attention to issues of human rights norms and privacy that are generic but can be embedded in AI procurement if a framework for that exists.

From a procurement process perspective, the results suggest a difficulty in how and what buyers communicate with technology vendors on key procurement decisions. In both countries, the procurement professionals involve users, data scientists, IT experts, and suppliers much earlier in the sourcing to discuss the expectations of government in AI projects but in most cases, the focus is the performance needs and cost of the solution and rarely the potential risks of that technology to the public. The assumption is that users have sufficient knowledge of that technology which is not always true. In one FGD a participant notes: "*…in this part of the world, who cares about the dangers of these technologies?".* Even for the complete turn-key solutions, Scheltema [19] recommends that procurement's due diligence also implies embedded due diligence in the design phase of the technology. Wirtz, Weyerer and Geyer [30] show that procurement should not focus on just cost and financial feasibility in the implementation of AI technology but rather also AI safety, system and data quality and integration as well as specialization and expertise.

From interviews and The procurement professionals identified four (4) processes shown also in **Fig.2** where they exert the most influence in technology procurement processes and therefore the most AI for impact decisions can be made. These include at solicitation, at supplier selection and award, commissioning and installation, and post-contract management. Based on this, we propose a framework in **Fig. 2** where user needs are aligned with data governance standards at preparation and planning, society benefit and ethical requirements in design are demanded at solicitation, the documentation of trustable certification and oversight possibilities, descriptions of technical auditability of the solution, and documentation of the safety culture of vendors are provided at selection, evaluation, and award, while in contract implementation and ongoing management, vendors provide mechanisms for transparency and ease of audit, and asses explainable user interfaces. This framework underscores how procurement teams, data scientists, together with AI-solution providers can embed the HCAI principles proposed by Shneiderman [14] and Shneiderman [15] in the key public procurement processes in safeguarding public benefit and well-being.

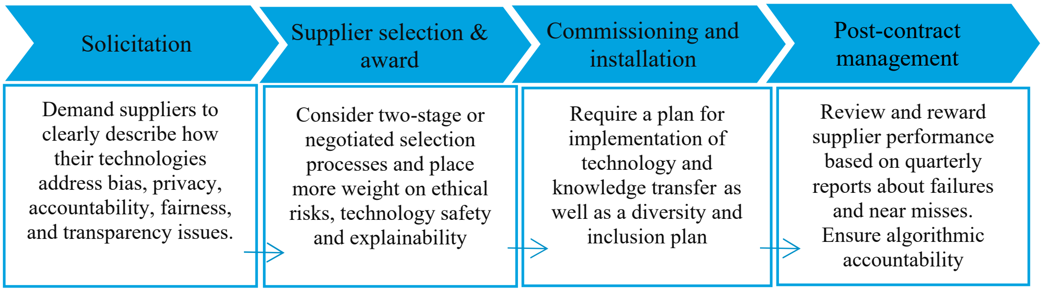

Fig. 2. How to embed HCAI in the key procurement impact processes.

4. Conclusion

In this paper, we examined the governance of artificial intelligence technologies in the public sector in developing countries. We explored the role of the procurement professional as the gatekeeper of the public sector procurement processes and their contribution towards aligning the interests of AI vendors with those of AI consumers. Specifically, we examined the role of public procurement and procurement professionals in the development and deployment of human-centered artificial intelligence – HCAI. We developed the paper around three HCAI principles from Shneiderman [14] and Shneiderman [16].

The study concludes that in principle, the procurement professional recognizes the significance of HCAI for the benefit and safety of the public yet is limited by weak procurement legislation, lack of skills, and knowledge gaps within the AI procurement teams, which include procurement leaders, data scientists, IT professionals and AI solution vendors.

In the absence of clear AI procurement legislation in developing countries, the study provides a framework of how to embed HCAI principles, which are essentially design concepts, into the existing procurement processes to allow users and process owners a much fairer, transparent, and accountable control of their data and vendor solutions than currently is.

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