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Article

What AI Cannot Know: Agri-Cultural Relational Knowledge, Embodied Practices, and the Limits of Automation

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Abstract

Agriculture and cultural heritage generate knowledge in similar ways as they are both rooted in land-based, intergenerational, and tacit forms of transmission. This is complicated when generative AI systems are used to replicate these forms of knowledge but often struggle to fully capture relational forms of knowing. As generative AI becomes increasingly more ubiquitous in society, it becomes more important to understand not only how this technology is being used within these respective fields of study but also how it represents these bodies of knowledge. To this effect, this paper uses a case study approach to examine how generative AI like ChatGPT responds to questions related to farming and cultural heritage. Utilizing Critical Discourse Analysis and autoethnography, we critically interrogate ChatGPT prompts that require an understanding of relational knowledge. We show the limitations of ChatGPT and the need to honour relational knowledge practices.

Keywords: relational knowledge; agriculture; cultural heritage; ChatGPT; generative AI; knowledge practice; critical discourse analysis

1. Introduction

1.1. Ethnographic Vignettes

The father of Author 1 learned to farm not through formal instruction or written guidelines, but through sustained participation in a network of relationships with land, with animals, and with those who had worked the land before him. He grew up on a family farm in southwestern Ontario, Canada. This part of the country was and still is known for its agricultural ties with much of the land committed to farming.

When he was a teenager, he was often sent to his uncle's farm to work during the early spring and summer. He credits much of his time on that farm that shaped him into the farmer he became. Once, in mid-April, when many farmers were set to begin working their fields for planting season, his uncle led him out into the field. The surface of the soil appeared ready: dry enough to walk on, the season turning toward planting. Yet his uncle paused, bent down, and lifted a handful of earth. Pressing it between his fingers, he showed how it held its shape—too wet, too compact. He handed it over: "You have to feel it. If it doesn't break right, the seeds won't grow."

No measurement was given. No universal threshold defined. The knowledge did not reside in an abstract rule but in the act itself: in sensing, comparing, and remembering. It was something that could not be acquired through description alone; it required participation. To know the soil was to engage it.

On another day, the same field appeared empty until his uncle began walking it slowly, scanning the ground. Rocks emerged—not as obvious objects, but as latent problems. "You don't see them now," he said, "but the machine will." Together, they carried them to the edges of the field. This was not simply preparation; it was a form of anticipatory knowledge grounded in experience. The

consequences of inattention were already known—not abstractly, but through lived memory of broken equipment, delayed planting, and lost yield.

Later, in caring for cattle, knowledge shifted again. Feed was adjusted not by fixed formula but in response to subtle changes: how the animals moved, how they ate, how they held their bodies. “You have to read them,” his uncle would say. These signs were not always verbalized. They were recognized through familiarity, through long-term engagement with particular animals in particular conditions.

Across these moments—feeling soil, clearing stones, reading animals—knowledge does not appear as a stable body of information that can be extracted, stored, and reapplied. It emerges through embodied practice, intergenerational transmission, and ongoing relationships with more-than-human worlds. It is not reducible to representation because it is constituted through relation. It is not simply *held*; it is *lived*.

While contemplating the lived experience of Author 1’s father and his long held relationship to the land around him, we recalled Robin Wall Kimmerer’s relationship with land as she chronicled her own journey in revitalizing Indigenous knowledge [1] (p. 149). It echoed how Author 2 learned about her culture through Uyghur mazars, which are cultural gathering spaces in Xinjiang that translate as “holy site” or “tomb” [2]. One such example, the mazar of Imam Asim, offers a look at how people continuously reestablish their connection to their culture through interaction with land. Imam Asim was once a great leader in the 11th century. When he was martyred, his tomb became a popular pilgrimage site and for a thousand years after, people by the tens of thousands would go to his shrine for an annual festival. But his shrine was more than just the place where he was buried. The entirety of the landscape surrounding the mazar was considered sacred.

Along the road to the mazar of Imam Asim, was a great tree that rose up. It was said that Imam Asim’s wife gave birth there, and because of this, for years after, pilgrims would make offerings at the tree when they were hoping for a child. If they prayed for a son, they would leave a gift of a small knife. If they prayed for a daughter, they would place a bundle of needles there. Even on the hill nearby, women would roll down the slopes in hopes of a good and healthy pregnancy. It is never just about the stories these sites hold; it is about the connection to the land; and how these stories have become embedded in the land. Rian Thum has written that the stories told at mazars “helped foster a sense of the past that could be shared across people of all backgrounds. The shrine system circumvented a major barrier to the creation of such shared views on the past, a barrier common to most premodern societies: the specialized localization of education along lines of class and profession” [3] (p. 116).

But within both these experiences, these knowledge practices have been disrupted, altered by the integration of technology that is used to either make processes more efficient as is the case with farming or as a means to preserve historical cultural places by freezing it in time. The emergence of generative artificial intelligence (AI) has greatly begun to change our relationship with the physical world. In some highly urbanized spaces, and especially online, AI has almost become inescapable. Major tech companies like Meta, Alphabet, and Microsoft have woven AI into the very fabric of their devices and services. AI has become so engrained within the classroom that there are now questions of how we properly prepare students for the future where AI is constant and how do we account for the ethical, privacy, and safety concerns when using it in these spaces [4,5]. In this way, AI is no longer optional or distant. It has quickly become embedded in our everyday lives and has greatly changed how we come to “know” and acquire “knowledge.”

1.2. Conceptual Foregrounding

What generative AI systems like OpenAI’s ChatGPT, Google’s Gemini, and Microsoft’s CoPilot bring to agriculture will fundamentally change the way we understand agriculture not only as production but as a form of knowledge, a form of life, and as a form of culture. As Lewis et al. demonstrate, dominant AI paradigms conceptualize intelligence as an abstract property of an individual agent, detached from the social and ecological relations that make knowledge possible [6].

This abstraction becomes particularly problematic in domains such as agriculture and cultural heritage, where knowledge is not possessed but enacted through ongoing engagement with land, climate, and more-than-human relations. In this way, many of the current concerns around generative AI are often epistemic in nature. How will this technology change the knowledge inherent in farming? The knowledge that was once passed down from parent to child? This relational knowledge?

At the heart of these experiences is how we come to know and apply knowledge from land-based contexts. The term “knowledge” is often treated as self-evident, yet it carries fundamentally different meanings across disciplinary and epistemological traditions. Knowledge within Western epistemology is abstracted, decontextualized. Knowledge in Indigenous frameworks is relational, embodied, accountable. Knowledge in the field of AI is seen as a probabilistic representation, a data point.

This distinction can be further understood through the concept of knowledge-practice. Rather than viewing knowledge as a static body of information, knowledge-practice emphasizes that knowing emerges through embodied action—through sensing, observing, participating, and responding within particular contexts. It is intergenerational, transmitted through shared practice rather than solely through formal instruction. It is situated, shaped by specific environments and histories. It is relational, inseparable from the networks of human and more-than-human relations that sustain it.

In this paper, we adopt this relational understanding and define knowledge as relational knowledge-practice: a form of knowing that is enacted through embodied, intergenerational, and land-based relationships. This definition stands in contrast to computational models of knowledge as abstract, decontextualized data. The distinction is not merely semantic; it is foundational to our argument. If knowledge is understood as relational knowledge-practice, then systems that operate through abstraction, prediction, and data processing cannot fully engage with it. The limitation of generative AI, therefore, is not only a matter of accuracy or completeness, but of ontology and epistemology. It reflects a fundamental mismatch between two different ways of knowing—one grounded in representation, the other in relation.

We approach the topic of generative AI from a discussion on how it impacts relational knowledge systems. As Shawn Wilson asserts, our relationships with those around us are our reality [7]. We seek to build a dialogue between Cultural Heritage Studies and Agricultural Studies to critically interrogate the way generative AI is used within Indigenous and agricultural communities. In doing so, we approach the topic from an epistemic frame: how does AI impact relational knowledge-practice systems like that of farming and that of language revitalization? This paper seeks to reframe debates on AI away from questions of capability and toward questions of epistemology, relation, and responsibility. We build on recent calls to reconceptualize AI through Indigenous epistemologies [6,8,9], but argue more specifically that generative AI is ill-equipped at engaging in relational knowledge-practice systems because such knowledge is constituted through embodied, intergenerational, and land-based relations that exceed computational abstraction.

While Lewis et al. call for a relational reconceptualization of intelligence grounded in Indigenous epistemologies [6], this paper operationalizes that insight through the concept of agri-cultural relational knowledge-practice systems (ACRKPS), emphasizing how knowledge emerges through embodied, intergenerational engagement with specific ecologies. Indigenous knowledge systems are not primarily stored as abstract information but are enacted through practice, ceremony, and relational processes [6]. Following this, we adopt the term knowledge-practice to emphasize that knowing emerges through doing, sensing, and participating within specific relational contexts. While the Abundant Intelligences framework proposes a broad reorientation of AI toward Indigenous epistemologies [6], this paper contributes a domain-specific analysis by examining how generative AI intervenes in ACRKPS.

To this end, we position our research questions: 1) How does generative AI attempt to replicate relational knowledge practices through its predicted responses? 2) What happens to relational-knowledge when it is reduced to being data?

2. Scope and Method

The scope of this paper is to theorize the impact generative AI has on ACRKPS. When generative AI systems are built, they are trained with data sets extracted from existing bodies of work, whether that is books, videos, or audio recordings. These often-creative forms of expression are then broken down into data that trains the AI on how to respond to queries. When reducing the complex relational knowledge systems between humans and other humans or humans and the non-human to merely data, much is lost in the way we conceive of knowledge not merely as an abstract concept but as a lived experience.

As previously mentioned, we frame our concept as ACRKPS. This borrows much from the work conducted on Indigenous relationality and the interdependence between humans and the land and the more than human land systems [10,11]. Within this paper, we focus specifically on cultural practices and knowledge that is intergenerational, land-based, more than human, and practice based. This knowledge requires years' worth of lived experience with a deep connection to the land in order for it to be passed down from one generation to the next. Knowledge like this is often situated in specific places. It is performed. It is shared by senior, veteran farmers or Elders and cultural knowledge keepers. This type of relational knowledge is inseparable from 'doing' it, from practicing it.

As co-authors, we engage in frequent discussions and document each other's life history through an autoethnographic approach, which offers an alternative perspective to research by "providing an authoritative voice that offers insight into otherwise unknowable worlds" [12] (p. 45). We build our argument on the body of Critical Indigenous Studies such as Leanne Simpson, Robbin Wall Kimmerer, Shawn Wilson, Linda Tuhiwhai-Smith, and Jason Lewis [1,6,7,11,13]. We recognize that we are engaging in a non-Indigenous farmers' community in southwestern Ontario and a minoritized community from China. This specific localized context and relationality have given us a deeper understanding of how we further understand and complicate agricultural and traditional knowledge in the space of generative AI through the application of Indigenous epistemological frameworks.

Our method here is two-fold. First, we conduct a literature review to foreground our conceptual framework of ACRKPS. We engaged studies in both Agricultural Studies and Cultural Heritage Studies that focused on the transmission and generation of knowledge and how those practices are carried. The second part we examined studies and examples of how generative AI is used within the communities, noting both the applications and limitations of this technology as it currently exists.

Second, we engage with ChatGPT to critically interrogate how it replicates ACRKPS. To do this, we employ Critical Discourse Analysis (CDA) as our methodology. As theorized by Fairclough, CDA provides us a tool through which we can address various social wrongs [14]. CDA is used to examine social wrongs like that of poverty, racism, or gender inequality [14–16], and generative AI often has a problem of reproducing these social wrongs through the way it spreads misinformation, contributes to racial stereotypes, or is used to generate material that is harmful [17–19]. Here, we will apply CDA to interrogate the responses we receive to better understand how generative AI like ChatGPT contributes to discourse within our fields.

We informally interviewed interlocutors from the farming community in Ontario, Canada and Uyghur language learners in the diaspora. We conducted a scoping review of papers about the applications of generative AI in agriculture and language revitalization. We then engaged in a critical analysis with ChatGPT to examine how it attempts to replicate ACRKPS.

3. Literature Review

3.1. Knowledge, Responsibility, and Relational Accountability

A defining feature of relational knowledge-practice systems is that they are not only epistemological but also ethical. Knowing is inseparable from responsibility [7,11,20]. To hold knowledge is to be accountable to the relationships through which that knowledge is constituted—relationships with community members, with ancestors, and with the more-than-human world [20,21]. This contrasts sharply with dominant models of knowledge being seen as neutral, transferable, and value-free. In relational frameworks, knowledge cannot be separated from the obligations it entails [22]. Practices of learning and transmission are governed by protocols that determine who can know, how knowledge is shared, and under what conditions it can be used. These protocols are not restrictions but mechanisms for sustaining the integrity of knowledge within its relational context [20].

Such perspectives challenge the assumption that increased access to information necessarily leads to better knowledge. When knowledge is detached from its relational and ethical grounding, it risks becoming decontextualized and misapplied. As Ingold and Kurttila argue, knowledge is not constructed as an external system to be stored or transmitted but is cultivated through processes of dwelling and skilled practice [23]. This distinction is critical when evaluating the epistemic limits of generative AI, which depends on the abstraction and recombination of decontextualized information.

Allen et al.'s approach to knowledge-practice systems is that relational approaches recognize "the interconnections across the different elements of agriculture" [24] (p. 2). This framing asks us to think of agriculture beyond its associations with pure production and that it is also the relationships between humans and ecosystems, humans and the non-human [18]. Viewing agriculture as a system of relationships, of knowledge can help us realize the inherent interconnected nature of the work that farmers and farm labourers do. By thinking of agriculture as a system of knowledge, of our relation to the land, to the animals, to the water, this can help us to understand the work that we do to be much more sustainable and in a way that honours these relationships.

Expanding this notion of the relational approach between the human and non-human, Pakarinen and Huising view relational knowledge as something that is "generated in and resides within the ties or links among actors and is thus fluid, fluctuating, and evolving" [25] (p. 2065). This further expands our understanding of agri-culture as a form of relational knowledge systems that are passed down from generation to the next and require constant maintenance and connections between people and between the non-human. These relations must always be established for the system to work.

3.2. Agri-Culture as Relational Knowledge-Practice

What we refer to as ACRKPS, we are speaking to the intergenerational, land-based, and more-than-human knowledge practices through which agricultural lifeways and cultural heritage are co-produced, transmitted, and sustained as living relations rather than discrete domains of information [26]. ACRKPS is not limited to human interactions; it is constituted through relationships with more-than-human beings, including animals, plants, soil, water, and climate systems. Farmers do not operate on land as passive managers of resources; they engage with dynamic, responsive environments that require ongoing negotiation and care [27]. Crops respond to weather conditions, soil conditions shift over time, and animals exhibit behaviors that signal health or distress. Knowledge emerges through attention to these interactions.

This relational orientation resonates with Indigenous epistemologies that emphasize the interconnectedness of human and more-than-human worlds. As Leanne Betasamosake Simpson argues, land is not merely a setting for human activity but a site of pedagogy, where knowledge is produced through reciprocal relationships with the environment [11]. Learning, in this framework, is not extractive but relational; it involves responsibility, care, and ongoing engagement. Understanding agriculture in this way shifts its conceptualization from resource management to

relational practice. The farmer is not an external agent applying knowledge to the land but a participant within a system of relations that shapes what can be known and done.

Agricultural knowledge is also intergenerational. It is transmitted not primarily through formal instruction or textual documentation, but through participation in shared practices over time [27]. Children learn by working alongside parents, Elders, and community members, gradually acquiring skills through observation, imitation, and guided experience. This mode of transmission produces what is often described as *tacit knowledge*: forms of knowing that are difficult to articulate explicitly but are nonetheless essential to practice [27,28]. Tacit knowledge is not simply knowledge that has not yet been codified; it is knowledge that cannot be fully codified without losing its meaning. The timing of planting, the reading of weather patterns, the interpretation of animal behavior—these are learned through repeated engagement within specific contexts. They depend on memory, judgment, and responsiveness rather than fixed rules.

This aligns with Shawn Wilson’s articulation of knowledge as fundamentally relational, where learning occurs through relationships with people, land, and community, and where accountability to those relationships shapes how knowledge is held and shared [7]. In this sense, knowledge is not owned by individuals but sustained through networks of relations across generations.

From this, we should consider agriculture and cultural heritage as one and the same: agriculture. Both are inherently tied to land, to inter-generational relationships, to an ecosystem of relations with the non-human. If we frame agriculture, the act of farming, through the lens of Indigenous relationality, we see the same dynamics: its intergenerational transmission, its grounding in land-based practice, and its reliance on embodied skill. These same structures underpin what is often categorized separately as cultural heritage. Practices such as language use, ritual participation, and oral storytelling similarly emerge through sustained engagement, repetition, and relational contexts. Rather than treating agriculture and cultural heritage as distinct domains, we can then understand them as co-constituted within ACRKPS. Our approach is demonstrated in Figure 1.

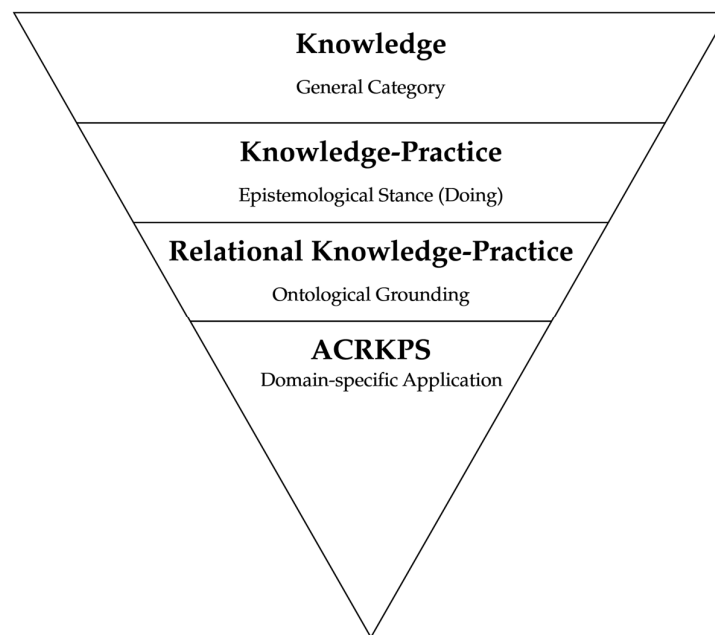


Figure 1. Conceptual framing of ACRKPS. This figure visualizes the different domains of knowledge that become increasingly more specialized. In visualizing ACRKPS this way, we seek to draw connections between Cultural Heritage and Agricultural Studies as being related bodies of knowledge.

As scholars who have been deeply engaged with Indigenous Epistemologies that guide us to think more relational accountability and account the colonial temporality and land as pedagogy, we see epistemic deficiency in AI to this ACRKPS. In the paper we shift the analytical focus from what knowledge is to how knowledge comes into being and is sustained. This shift is critical for examining the role of AI, as it reveals that the limitations of such systems are not merely technical but epistemological [29]. AI can process and generate information about agricultural and cultural practices, but it struggles to adequately capture the relational, embodied, and intergenerational processes through which such knowledge is formed.

4. Applications of Generative AI in Agri-Culture

Now that we have established the connection between agriculture and cultural heritage and what it is we mean by ACRKPS, we seek to foreground some of the uses of generative AI within these fields. On the side of agriculture, generative AI use will be examined from how farmers can utilize these systems to improve their connection to the land and the more than human. On the side of cultural heritage, generative AI will be examined as it has been applied to language revitalization efforts where we often see the most advances in technological adoption within cultural heritage.

4.1. Farming and Generative AI

During the American Superbowl, an OpenAI commercial played to millions about how Racheal Sharp, a family seed farmer from South Carolina, was using ChatGPT as part of her work practices as she inherited the farm from her father [30]. The two-and-a-half minute long ad showed how Sharp was using ChatGPT, from notetaking to confirming problems with equipment and crops on the field. In the official description on OpenAI's website, Sharp was struggling to apply her father's "hard-earned knowledge" that included a hand-written crop ledger since 1971. As she said, "It's so much data, it almost scares you away" [31]. The ad shows how Sharp is not only trying to learn from her father but apply new working tools in anticipation of running the farm on her own. As confirmed in the ad and on the website, there has been a dramatic decrease of certified seed farmers in South Carolina, from 200 to 7. In many ways, the use of ChatGPT here is framed as a tool for success, but what it's replacing is the inter-generational relationship that has been key to farming for thousands of years. The knowledge of Sharp's father is boiled down to "data"

AI has often been posed as a benefit to farmers and another tool for them to use so they can optimize their farming practices [32]. Javaid et al. highlight how rising labour demands, a growing global population, and increased automation on farms has demonstrated how much AI is needed on farms [33]. And even now, in an era of increased climate change disasters, AI could even be used to cut down on the amount of stress farmers exhibit just by being able to provide them with more refined data points on how they can farm more efficiently [33].

But AI isn't always beneficial. In their examination of AI applications within agriculture, Oliveria and Silva note both the many benefits and many challenges AI brings to farming [34]. Many of the benefits connect to similar studies done within the area, noting how AI can optimize the farm and make it more efficient. But many of the challenges highlight the ongoing issues facing AI more broadly. Some of these challenges include issues of data privacy and sovereignty, the AI systems are often too complex to understand, and that some of the systems are too expensive to use [34] (p. 12). These challenges make it so only farmers who have the means necessary to invest in AI will be able to reap the rewards of it, while smaller and poorer farmers will continue to struggle, thereby increasing the divide between large scale and small-scale farms.

The studies mentioned above, however, largely account for highly specialized AI systems that examine agricultural information more broadly. For systems like chatbots, specifically ChatGPT, Alobid and Szűcs suggest that use of ChatGPT within agriculture has led to a high yield per hectare within countries in the European Union [35]. The usage of ChatGPT is related to better resource allocation among water use, suggesting that farmers are using ChatGPT to guide their decision-

making process. Other applications of ChatGPT within farming are, again, focused on increased efficiency, crop yield, and improved resource management [36].

Ibrahim et al.'s study demonstrates how farmers can use ChatGPT specifically for accessing agricultural knowledge [37]. In this case, it focused on the quality of information ChatGPT provided on rice cultivation in Nigeria. The study compared the responses provided by a human extension agent and ChatGPT. The results of this study discovered that ChatGPT responses to agricultural questions were more detailed than those from an extension agent, and that evaluators preferred the ChatGPT responses over those from the agents. This could be because ChatGPT, at the time of this study, was programmed to display more empathy and emotion. But in its criticisms of ChatGPT, Ibrahim et al. did note that the responses from ChatGPT did contain false information about rice cultivation in Nigeria, which means that it could lead farmers astray in the information it provides [36]. In this way, the human element of having that deep, familiar knowledge of agriculture is still required. This is a similar finding from Calone et al. who also concluded that ChatGPT generates information that is often too generic and impractical for specific uses [38]. This remains a consistent problem in applying ChatGPT within areas that require specialized and regional knowledge with some researchers developing much more agricultural specific platforms that are trained on agricultural data for more in-depth responses [39].

This poses challenges for how generative AI like ChatGPT are continuously rolled out as means to replace the human element in many different industries from customer service to health systems. In reducing generative AI's responses to merely data, we lose the relational knowledge that is so fundamental to this livelihood.

4.2. Cultural Heritage and Generative AI

When speaking of cultural heritage, we are referring to the notion of sacred knowledge. Kealiikanakaoleohaililan and Giardina offer an understanding of the notion of sacred within Indigenous epistemologies and how it contributes to knowledge capacity [40]. The sacred is "tightly coupled to place-based knowledge systems and culturally driven management practices" [40] (p. 59). Uyghur mazars offer a salient example of this where these spaces and the stories that are told in them hold "a special power to create sacred geographies and systems of belonging" [3] (p. 14). It is often through mazars that one comes to know about Uyghurs as a people [2,3,41].

With this sort of tacit knowledge in mind, it is often difficult to accurately capture or translate this into the realm of the digital. Information is lost in translation. Context is often missing, and text descriptions are often ill-equipped at fully capturing a cultural practice that is based off embodied practice. There have been different attempts at applying AI to cultural heritage. Gîrbacia identifies several uses largely with the use of 3D reconstruction of heritage artifacts like music, dance, and historical texts to better preserve and study these forms of culture [42], but Ming and Xia identify several constraints when attempting to apply generative AI to cultural heritage [43]. They note that cultural heritage can only provide limited amounts of training data, especially for intangible cultural heritage like forms of dance, songs, and oral storytelling [43] (p. 14). This makes it difficult to trust that generative AI would have accurate responses in regards to generative AI.

There are also questions as to whether what is created using generative AI can be considered cultural heritage on its own [44], but we are here to examine the limits of generative AI in the space of cultural heritage. Researchers have raised concerns when using technologies like that of AI in relation to cultural heritage practices. Pansoni et al. state that "cultural and historical bias, attribution of responsibility, high economic investment, authenticity, privacy, and the risk of physical cultural heritage replacement arise from the use of AI in cultural heritage and the resulting digitization process" [45] (p. 1151). Their response to these issues is seven prerequisites an AI system must meet to be considered trustworthy to use in cultural heritage. These prerequisites are:

1. Technical robustness and safety;
2. Privacy and data governance;
3. Transparency and explainability;

4. Diversity, nondiscrimination and fairness;
5. Societal and environmental well being;
6. Accountability. [45] (p. 1153)

The emphasis on transparency, equity, accessibility, and accountability address many of the issues Cultural Heritage as a field has faced over the past few decades where researchers have been increasingly involving community members in the research process to ensure there is an equal exchange of knowledge [46].

We can point to an example where generative AI has been used in a way that honours the prerequisites noted by Pansoni et al. Language provides a particularly clear example of relational knowledge-practice. It is frequently approached as a system of grammar and vocabulary that can be documented, taught, and learned through formal instruction. In many Indigenous language contexts, linguistic knowledge is inseparable from place. Words encode ecological relationships, seasonal cycles, and culturally specific ways of relating to the environment. To learn a language, therefore, is not only to acquire a set of linguistic forms but to enter into a network of relations that gives those forms meaning. Language revitalization efforts often recognize this, emphasizing immersion, intergenerational exchange, and community-based learning rather than purely classroom-based instruction. This aligns with the work of Simpson, who conceptualizes land as pedagogy, where knowledge is produced through direct engagement with place and through relationships that extend beyond the human [11]. In this framework, language is not a detachable system but a mode of relating—one that emerges through lived interaction with land and community.

Danielle Boyer, an Ojibwe robotics engineer, created SkoBot as a means of teaching Indigenous languages. SkoBot is a ten-inch wearable robot that sits on the shoulders of users and teachers Anishinaabemowin through speaking small phrases and singing. In designing the robot, Boyer intended for the robots to “reimagine a future with Anishinaabe toys and were made to supplement community language learning (never replace it)” [47]. Boyer’s work highlights a unique case facing the intersections of language revitalization, cultural heritage, and technological innovation within Indigenous communities.

SkoBot is a successful example of how applications of AI within cultural heritage can be done in a way that is ethical. In an article with CNN, Boyer details how the robot works in replicating back-and-forth conversation in Anishinaabemowin [48]. The robot utilizes recorded audio files, some from Boyer’s own grandmother, and uses AI speech recognition technology—like that of Whisper developed by OpenAI—to identify what word a user speaks at it before responding in the corresponding Anishinaabemowin word.

SkoBots are programmed to use other voices as well, including that of children as they can be employed in grade schools to better connect to children of a similar age. This is an important part of Indigenous language revitalization efforts, bringing language to children so they can grow up immersed in their culture’s language. To this, Boyer has said, “We bring the SkoBots into classrooms, and the students build the robots themselves, which is really exciting,” she said. “They get to design their own aspects of it, they get to wire the robot, and then from there ... you speak to it” [48].

This perspective resonates with relational approaches to knowledge that emphasize the inseparability of knowledge from practice and context, but the limitations of generative AI remain the same as they are in agriculture studies. It misses the relational aspects of cultural heritage. This is why Boyer’s approach is so important to highlight as she insists on embedding relational knowledge throughout the entire project of SkoBot from the design to the development and deployment of SkoBot.

5. The Systems of Generative AI

Generative AI systems operate through pattern recognition and probabilistic prediction, drawing on large-scale datasets to produce responses that are often coherent and technically useful. However, these outputs remain fundamentally detached from the embodied, relational, and temporal processes through which knowledge is formed in practice. As a result, generative AI does

not merely assist existing knowledge systems; it reconfigures them by translating relational knowledge-practice into flat information that is removed from reciprocal practices.

This is often how generative AI systems are built and trained through a process of abstraction. Being built on a large language model, these systems are trained off of massive datasets that are gathered from a wide variety of sources. There has been considerable criticism of how these datasets are sourced and used with considerable concerns surrounding a lack of standards around them [49]. It is known that generative AI has used copyrighted material that has been the focus of lawsuits to properly attribute credit to people's works that were used to build and train these systems [50].

Beyond the structural problems generative AI poses, there are also concerns of how reliable a source of information it can be. There are deeper concerns that ChatGPT falsifies and "hallucinates" information [51–53], providing a platform that is rife with misinformation. Contrast this against Indigenous epistemologies where learners are encouraged to say "I don't know" [54,55]. Generative AI does not say "I don't know"; instead, it hallucinates, fills gaps with unrelated knowledge, or brushes over uncertainty. Not knowing is a relational and ethical position but AI replaces this with probabilistic completion.

To exemplify our arguments about the need for ACRKPS, we turn to ChatGPT to better understand how it handles domain specific knowledge. We developed two example questions used to prompt ChatGPT. These two questions are:

1. Why are my tomatoes so small?
2. How can I learn about Uyghur mazzars?

These examples pull from both authors years of lived experience having applied ACRKPS within practical settings that demonstrate this concept in action: hands-on experience, communal learning, and intergenerational transmission.

We each asked ChatGPT the same question on separate machines to compare the different results presented. We take a case study approach to analyzing the content of the responses. While we were asking questions and experimenting with ChatGPT, Author 1 resided in Ontario; Author 2 was in Turkey. It is unclear for use if the following answers were at all influenced based on previous user data that ChatGPT may have access to. Once given the answers, we critically interrogated the responses, reflecting on what it is that ChatGPT was knowledgeable on and what it did not include. We used ChatGPT-5.4 as the model for our inquiries as that was the model available at the time.

As previously stated, we employ CDA as our methodology. We do this by critiquing the text ChatGPT produced for us as CDA acknowledges that all texts "are produced and read (or heard) not in isolation but in some real-world context with all of its complexity" [16] (p. 87). As we have argued thus far, context like that of place is extremely important within ACRKPS. This is why when using ChatGPT, we should all be aware of how generative AI contributes to discourse about our society.

5.1. ChatGPT and Agricultural Knowledge

Upon initial view, we are both surprised that ChatGPT did not ask where we were farming and in what conditions. These are often the most important conditions within farming as it dictates what can and cannot be grown. For example, growing tomatoes in a backyard garden versus a hydroponic greenhouse versus a large field all provide very different growing conditions that must be taken into consideration. These different growing conditions would also dictate other aspects like the amount of nutrients, sunlight, and water the plants would have access to. Farming is an interconnected practice where many things must be considered all at once.

Table 1. Responses generated by ChatGPT from two different users based on agriculture.

Why are my tomatoes so small?	
Author 1	Author 2
Small tomatoes are usually a sign that one or more growing conditions aren't quite right. Here are the most common	Small tomatoes are usually the result of growth stress rather than a single

<p>reasons, from most likely to least, and what you can do about each:</p> <p>1. Not enough water (most common)</p> <p>Tomatoes need consistent moisture, especially while fruits are forming.</p> <ul style="list-style-type: none"> Irregular watering can cause plants to survive but produce small fruit. Fix: Water deeply 2–3 times per week (more often in hot weather), and mulch to keep soil moisture steady. <p>2. Too much nitrogen</p> <p>High nitrogen makes plants very leafy but poor at fruiting.</p> <ul style="list-style-type: none"> You'll see lots of green growth, few flowers, and small tomatoes. Fix: Use a fertilizer labeled for tomatoes or fruiting plants (lower N, higher P & K). <p>3. Lack of sunlight</p> <p>Tomatoes need at least 6–8 hours of direct sun daily.</p> <ul style="list-style-type: none"> Less sun = less energy for fruit growth. Fix: Move plants (if in containers) or remove shading plants. <p>4. Poor pollination</p> <p>Stress, lack of pollinators, or very high heat can reduce pollination.</p> <p>Fix: Gently shake plants occasionally, and avoid pesticides during flowering.</p>	<p>problem. The most likely causes can be narrowed down quickly:</p> <p>1. Water inconsistency</p> <p>If the soil cycles between very dry and very wet, fruit stays small. Tomatoes need steady, deep watering. Irregular watering limits fruit expansion.</p> <p>2. Nutrient imbalance</p> <ul style="list-style-type: none"> Too much nitrogen → lots of leaves, small fruit Too little phosphorus/potassium → poor fruit development <p>A fertilizer formulated for tomatoes (lower nitrogen, higher P/K) helps</p> <p>3. Insufficient sunlight</p> <p>Tomatoes need at least 6–8 hours of direct sun. Less light reduces energy for fruit growth.</p> <p>4. Root restriction (often overlooked)</p> <p>If growing in a small container or compacted soil, roots cannot support large fruit.</p>
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Another aspect we noticed was the quality of the information provided by ChatGPT. The information was often quite generic and not specific enough. The responses were often delivered in point form and quite brief. For example, both responses state that tomatoes need 6-8 hours of direct sunlight. This is an underestimate as tomato plants can regularly require anywhere from 10–14 hours of direct sunlight per day. Not knowing where ChatGPT may be pulling its information from to generate these responses poses problems as it may be generating information from false data. It is with prior knowledge that Author 1 is able to identify what it is that ChatGPT does not get right.

Another way we can analyze this is when the issue of water is brought up in both responses. Both responses talk about the need for consistent watering and provide some measures on how much water is needed. Response 2 mentions “deep watering” whereas response 1 says to “water deeply 2–3 times per week”. It is difficult to determine what “deep watering” means without hands-on, practice experience to show what deep watering is within the soil, and this is where ChatGPT struggles to replicate within its responses as it is attempting to respond to tacit knowledge.

5.2. ChatGPT and Cultural Knowledge

Like with the first case study, we first noticed the lack of context that places the user. Understanding who a user is, where they are coming from, would typically guide the answer to this sort of question. Are we a heritage learner? Are we an outsider? Are we a member of the community? Our positionality is important to consider, especially when learning about sacred knowledge that may be closed practice. As a member of the community, Author 2 expressed that there is nothing about cultural protocols within ChatGPT's answers. These cultural protocols would consider the aspects of privacy and ethics; not all knowledge is for everyone. Uyghur mazars are very specific to not only place but also time. Large festivals can only be held at certain times of year [2] (p. 60). Others are specific to certain communities like that of different religious orders [41]; and others are

exclusively attended by men or women, such the tomb of Büwi Märyäm, which is held in high regard by women [2] (p. 57). This context is important to consider when beginning to learn about mazars.

Table 2. Responses generated from ChatGPT from two users based on cultural heritage.

How can I learn about Uyghur mazars?	
Author 1	Author 2
<p>Learning about Uyghur shrines is a fascinating way to explore Central Asian history, religion, and culture. These shrines—often called <i>mazars</i>—are deeply tied to pilgrimage traditions, Sufism, and local identity among Uyghur Muslims.</p> <p>Here’s a clear path you can follow, depending on how deep you want to go:</p> <ol style="list-style-type: none"> 1. Start with the basics Uyghur shrines are mostly associated with Islamic saints and spiritual figures, especially within Sufi traditions. A good foundation includes: <ul style="list-style-type: none"> • Understanding Islam, especially Sufism • Learning about Xinjiang, where most Uyghurs live • The concept of pilgrimage beyond Mecca (local sacred sites) 2. Read key books and academic work Some well-regarded scholars and books: <ul style="list-style-type: none"> • Rian Thum – <i>The Sacred Routes of Uyghur History</i> → One of the best modern studies on shrine pilgrimage and storytelling traditions. • Rahile Dawut – Research on mazars and folklore → Focuses on rituals, oral traditions, and sacred landscapes. • Look into topics like: <ul style="list-style-type: none"> ○ “Uyghur mazars” ○ “Central Asian shrine pilgrimage” ○ “Sufi saints in Xinjiang” 3. Be aware of modern context Discussion of Uyghur shrines today is often connected to broader political and cultural issues in China. Reading multiple perspectives will give you a more balanced understanding. 	<p>Learning about Uyghur shrines is a fascinating way to explore Central Asian history, spirituality, and culture. These shrines—often called <i>mazars</i>—are deeply tied to Sufi traditions and local community life in the Xinjiang region.</p> <p>Here are some good ways to approach learning about them:</p> <ol style="list-style-type: none"> 1. Start with the cultural and religious context Uyghur shrines are closely connected to Sufism, a mystical branch of Islam. Many shrines are tombs of saints, scholars, or revered figures. Key concepts to explore: <ul style="list-style-type: none"> • Sufi pilgrimage traditions • Ancestor veneration in Islamic cultures • Local ritual practices and festivals 2. Read books and academic work Some well-regarded scholars have studied Uyghur religious life and shrines: <ul style="list-style-type: none"> • Rian Thum – wrote <i>The Sacred Routes of Uyghur History</i>, a highly recommended introduction to shrine pilgrimage and storytelling traditions. • Rahile Dawut – extensively documented mazar traditions (her work is especially valuable, though harder to access). <p>Search for topics like:</p> <ul style="list-style-type: none"> • “Uyghur mazars” • “Islamic pilgrimage in Central Asia” • “Xinjiang religious practices” <ol style="list-style-type: none"> 3. If you want deeper study You could: <ul style="list-style-type: none"> • Read ethnographies (anthropology-focused books) • Learn some Uyghur or related Turkic language basics • Explore Sufi poetry and oral storytelling traditions.

What really stands out for us is that learning about Uyghur mazars is that it is a very active practice, involving visitations and pilgrimages to various shrines. Learning and visitation, being physically present, are inseparable [2,3,41]. There is knowledge that can only be learned when at these mazars during a pilgrimage or annual mazar festivals [2,3]. For example, Harris and Dawut mention the performance of a musical piece called *Tashway*, which is performed at the tomb of a 19th century musician (ashiq) named Tash [41] (p. 105). It is appropriate for this song to be played here as this is the resting place for Tash. The song and the place are therefore inseparable. To learn about Tash, one must not only experience the music but also his shrine.

In expanding further on this notion of place and context, one of the responses from ChatGPT does vaguely mention “exploring” specific shrines with some examples, there is no further elaboration on what exploring entails. Researchers like Rahile Dawut, Rian Thum, or Rachel Harris have demonstrated the level of care, attention, and involvement that is required when engaging with mazar culture [2,3,41]. While we can glean information on what mazars are through books, there is a limit to what these texts can offer when the culture that surrounds mazars is, like agriculture, tacit in nature. There is no suggestion that the learner makes a pilgrimage to those shrines and connect with that land and learn those stories about the land, the saint, the geography, which is needed and necessary to truly know these sacred spaces.

6. Discussion: The Epistemic Limits of AI and the Inability to “Not Know”

For both examples with farming and mazar culture, ChatGPT produced a numbered list, a quantifiable measure of things for the user to learn and take away from, but for both responses they demonstrate the same pattern; that 1) generative AI produces coherent but decontextualized responses; and 2) it fails to engage relational conditions of knowing. These cases demonstrate not only isolated limitations of generative AI, but a consistent epistemic pattern. Here generative AI produces responses that are informationally adequate yet relationally deficient. This distinction is critical. Generative AI operates through generalization, whereas relational knowledge is inherently situated. Relational knowledge requires accountability whereas AI has none. This is why we should encourage the limitations of our own knowledge and be confident in saying “I don’t know”; this sentiment is also put forth to recognize the vast amounts of knowledge that has been stolen through colonization and kept from Indigenous communities from “knowing” [52,53]. In many ways, generative AI continues to act as a colonizing force [54], consuming knowledge without respecting, honoring, or recognizing where that knowledge has come from in the first place.

To address these limitations, we advocate for an inclusion of grounded normativity. As put forward by Coulthard and Simpson, grounded normativity instructs us on how to live our lives in connection to the other people and more-than-human life forms around us in a way that is not exploitative [56]. Just as colonial knowledge systems have historically stripped context from the land, extracting knowledge from its place, so too does ChatGPT repeat this decontextualization.

There are of course limitations to our critical analysis of ChatGPT. First, this does not replicate typical use of ChatGPT for everyday users. These responses were not built up over sustained and repeated use. Second, understanding the inadequacies of generative AI in these communities would require much more rigorous study to better understand what it is both farmers and Uyghur language learners are looking for when using ChatGPT. While we know ChatGPT can be used for general inquiries, what are the cases where ChatGPT is inadequate and where users must turn to more traditional forms of knowledge gathering, namely speaking with senior farmers and community Elders.

7. Conclusions

When using ChatGPT in this way to ask about deeply relational, land-based knowledge, both responses provided several points of varying specificity and generality. By breaking down ACRKPS into points, into data, it is often missing the more holistic practice of language and farming that is

intrinsically tied to knowledge and cultural production. As Simpson states, “Meaning then is derived not through content or data, or even theory in a western context, which by nature is decontextualized knowledge, but through a compassionate web of interdependent relationships that are different and valuable because of that difference. Individuals carry the responsibility for generating meaning within their own lives – they carry the responsibility for engaging their minds, bodies and spirits in a practice of generating meaning” [11]. This is what we are at risk of losing when we use generative AI to produce knowledge for us and circumvent the relationships that are vital for knowledge generation and knowledge practice. The relationships we may build with generative AI are not the same as the ones we build and nurture with people in our communities.

We have argued for not only seeing how cultural heritage and agriculture are connected through the relational, land-based practices, but also how generative AI reconfigures rather than replaces relational knowledge. If knowledge is relational, then the expansion of AI into domains of agriculture and cultural heritage does not simply introduce a new tool; it transforms the conditions under which knowledge is produced, transmitted, and recognized. The question, then, is not whether AI can be made more accurate, but whether it can coexist with relational knowledge systems without eroding the relationships that sustain them.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
CDA	Critical Discourse Analysis
ACRKPS	Agri-cultural Relational Knowledge Practice Systems

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