Ethical Perspectives on Generative AI in Computing Education in the Global South

Claudia Szabo[*]
The University of Adelaide
Adelaide, Australia
claudia.szabo@adelaide.edu.au

Nickolas Falkner[*]
The University of Adelaide
Adelaide, Australia
nickolas.falkner@adelaide.edu.au

Munienge Mbodila[*]
Walter Sisulu University
Buffalo City, South Africa
mmbodila@wsu.ac.za

Judithe Sheard[*]
Monash University
Melbourne, Australia
judy.sheard@monash.edu

Tony Clear
Auckland University of Technology
Auckland, New Zealand
tony.clear@aut.ac.nz

Delali Kwasi Dake
University of Education, Winneba
Winneba, Ghana
dkdake@uew.edu.gh

Enock Mabberi
University of Eastern Finland
Joensuu, Finland
emabberi@student.uef.fi

Omowumi Ogunyemi
Pan-Atlantic University
Lagos, Nigeria
oogunyemi@pau.edu.ng

Oluwakemi Ola
University of British Columbia
Vancouver, Canada
kemiola@cs.ubc.ca

Bimlesh Wadhwa
National University of Singapore
Singapore, Singapore
bimlesh@nus.edu.sg

Abstract

Generative AI has a wide range of impacts on how we access and use information, particularly as educational settings and perspectives differ greatly across different locations. These effects extend broadly across our society and include negative impacts on intellectual and creative works and the potential infringement of authorship. They also include positive effects on engagement with social responsibility and the societal role of computing. The differences in institutional Generative AI policies, available funding, accessibility to tools translated in relevant languages may create challenges to equal and equitable tool access, their responsible use, and ethical questions about the use of AI tools and the impact of uneven student knowledge of their benefits and limitations. In addition, Generative AI introduces questions concerning academic integrity, bias, and data provenance. All these aspects have increasingly been the focus of computing education research studies, however our analysis has found that Global South perspectives are largely missing from the corpus of work. In this paper we conduct a landscape analysis on Global South ethical perspectives related to the use of Generative AI tools in computing education contexts. We identify critical supports of Global South ethical frameworks and explore how these are considered across the Global South computing education literature.

[*]Co-Leader

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CCS Concepts

• **Social and professional topics → Computer science education**; **Cultural characteristics**; **Codes of ethics**.

Keywords

computing education, ethics, Generative AI, Global South

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1 Introduction

The rapid expansion of Generative Artificial Intelligence (Generative AI) tools has sparked intense debate about their ethical and educational implications [29, 82, 98, 144]. Generative AI technologies have the potential for innovating learning, teaching, and research, but their use raises equally complex questions about integrity, equity, and responsibility. While global discourse around the ethics of AI has been extensive [54, 103, 146, 199], it has remained largely anchored in Eurocentric frameworks that may overlook the lived realities, educational priorities, and value systems of the Global South. This imbalance risks reproducing historical asymmetries in knowledge production, data sovereignty, and technology governance, perpetuating dependency rather than enabling agency.

Existing works on the use of Generative AI in computing education primarily focus on personalised learning systems [85, 107], code generation assistance [100, 128], code comprehension [31, 124], and automated assessment tools [63, 123]. However, there is a lack of comprehensive studies on secondary education contexts, non-English environments, and the impact of Generative AI on long-term educational outcomes. Furthermore, ethical perspectives are rarely the main focus of investigation [32, 113, 146]. Although there are several surveys that analyse ethical considerations within the Global South [79, 129, 172, 178], none, to the best of our knowledge, contextualise these within computing education, and few address the breadth and depth of the many Global South and Indigenous ethical frameworks.

To address this challenge, the focus of this working group has been on identifying the ethical perspectives on Generative AI in computing education as they are framed and discussed within the Global South.

There are many documents produced that discuss and define how ethical principles can be applied in the area of artificial intelligence, with two leading examples from UNESCO and the OECD [171, 190], but such documents reflect, by default, the societal and governmental paradigm of those states and communities that dominate global discourse, values, and trade: the Global North. The values, principles, and ethical expectations of the countries in the Global North do not necessarily reflect, include, or even acknowledge the same aspects of the Global South. While existing ethical documents, theoretical and applied, can be very useful, we risk disenfranchising the large and diverse populations of the Global South if we do not determine what their fundamental understanding is of key ethical values and principles.

There are many ways to identify how concepts are understood and applied but one of the key research approaches is the use of descriptive research [58], where researchers identify *what* is happening in an area, which provides a foundation to understand *why* this is occurring and *how* it is occurring. Descriptive research is already an established approach in Computer Science Education Research, providing the basis for later hypothesis driven work, as well as assisting in gaining insight into an area that is not fully understood [49]. Two useful tools for undertaking descriptive research are discourse analysis of relevant texts, to treat a text as language in action to identify cultural and social structures, and landscape analysis, where the results of our discourse analysis are considered in terms of their connections and how they then map to the cultures or communities under study [25]. The landscape analysis sets our focus out to a wider view, while each individual contribution to the landscape is analysed to determine how it all connects.

In this paper, we conduct a landscape analysis of ethical frameworks across countries in the Global South and identify several 'support concepts' that are used to frame each perspective. Ethical frameworks are constructed atop an identified set of values and key principles, where the values and principles provide the support for the overarching framework. Given the known diversity of values and principles at the global and regional level, classifying these all as support concepts allows us to recognise how and why ethical frameworks may be more or less suitable for a given community seeking this knowledge. These supports present an extensive view of the ethical school of thought across the Global South, and cover many aspects that are either not present in a Western perspective or framed in a significantly different manner. To contextualise these supports within the topic of Generative AI and computing education, we then present an analysis of the different perspectives of Global South researchers on the topic, as framed by these supports. Our analysis places the discussion within broader questions about fair access to technology, data sovereignty, language diversity, and the power structures that shape digital systems. These issues are especially important in contexts with limited resources, unequal access, and diverse cultural ways of knowing. Our contribution is twofold:

- A list of ethical concepts extracted from various Global South ethical frameworks.
- An in-depth analysis of how these concepts are contextualised in discussing Generative AI in computing education in the Global South.

2 Ethical Perspectives in the Global South

We present in this section several ethical perspectives across the Global South. We discuss first the term Global South and highlight its many facets. We then present an overview of some of the ethical perspectives and frameworks present in the Global South and discuss their diversity. We also highlight a principle-based approach to considering ethics and discuss how it shapes our method.

2.1 The Global South

The term "Global South" broadly refers to regions in Latin America, Africa, Asia, and Oceania. It is used to describe areas outside Europe and North America that are mostly, though not always, lower-income and often politically or culturally marginalized [53].

Brooke-Holland [37] of the UK parliament claims that the term 'Global South' "has become a widely used term in discussions of international politics and diplomacy, but not everyone thinks it is a helpful term". She goes on to add:

> There is no definitive definition of the Global South, which means there is no definitive list of countries. One way of identifying countries is to look at the membership of the G77, a group of developing countries established in the 1960s to articulate and promote their collective interests at the United Nations. The group now numbers 134 states from Central and South America, Africa, Asia and Oceania, and refers to itself as the 'Global South'.

As such using the term in the context of computing education, as noted by Wong-Villacres et al. [186] surfaces a range of complexities when considering ethics in teaching and learning computing

> in the Global Souths when curricula are oriented by Western traditions. We use the plural of Global Souths to indicate that there are multiple and overlapping 'Souths', or geographic and conceptual spaces, that are negatively impacted by contemporary capitalist globalization…and the US–European norms and values exported in computing products, processes, and education.

A list of countries deemed to be within the Global South is maintained by the charitable organisation *The British International Studies Association*[1]. In establishing the ethical framework supports discussed below we have also added indigenous communities within nation states (such as New Zealand Māori, Australian Aboriginal and Torres Islander peoples), as southern hemisphere examples.

2.2 Ubuntu and other African Ethical Perspectives

Ubuntu, a well known philosophy prevalent in Southern Africa, guides ethics from the traditional standpoint. It emphasizes humaneness, the interconnectedness of humanity, deep kindness and the importance of compassion, empathy and communal well-being, while recognising the importance of individual contributions to social good [14]. Ubuntu highlights relational personhood and social responsibility [114].

There are, however, other lesser-known principles that support ethical action in Africa that could enrich the discourse on the continent. Gyekye [70] gives an overview of African ethical principles and emphasizes individual good character and community-centred ethics. African ethical perspectives explore concepts such as ethical and moral personhood, the common good, and communal values, displaying the social character of African ethics that can be contrasted with individualistic ethics.

For example, within the Akan repertoire: 'The well-being of man depends on his fellow man (*onipa yieye firi onipa*)" [70]. Other accounts of African ethics from the east, and west of the continent are also characterized by communal flourishing. Such concepts include *Hunhu, Harambee, Ujamaa, Ukama* and *Sankofa*. *Ukama*, literally means kinship and relatedness. *Ujamaa* is the Swahili word for 'familyhood', or 'extended family' or 'brotherhood'. It was developed and popularized by the former President of Tanzania, Julius Kambarage Nyerere, who employed it as the basis for a national development program and agenda [60].

Folk wisdom and idiomatic phrases found in oral tradition are also sources of ethical principles. For example, *Hu Ìwà Sí i bí Ènìyàn Ẹlé·ran-Ara*, which means to act towards the other as one with human flesh, is part of a Yoruba theory of social interactions in west Africa and guides ethical approaches to interactions [6].

The *Ma'at* ethics from north Africa is the application of the principle of balance, harmony, and order. *Ma'at* is a set of standards which defines proper ethics, morality, and conduct, and an ethical person behaves in accordance with*ma'at* when they follow these principles [132]. Overall, the principles explored above highlight a tendency to ground ethics on human interconnectedness and personal character traits that contribute to individual development and societal growth. These principles offer a foundation for the development of context-specific guides for ethics in computing education. At present, however, there is limited work that explicitly integrates these concepts into computing ethics education.

2.3 South American Ethical Perspectives

South American ethical perspectives are frequently articulated through relational ontologies that foreground *Buen Vivir* ("living well") as an alternative framework to individualistic models of development [41]. *Buen Vivir* emphasizes harmonious relationships among humans, communities, and nature, grounding ethics in reciprocity, solidarity, and collective responsibility rather than accumulation or growth [179]. Across Ecuador, Bolivia, Peru, Colombia, Chile, and Argentina, these ideas draw on Indigenous epistemologies that understand wellbeing as inherently relational and ecological, where nature is a living subject rather than an exploitable object, and social life is sustained through mutual care and interdependence [41]. Within this tradition, *Suma qamaña* (Aymara) in Peru and Chile emphasizes collaboration, reciprocity, and respect for traditions enacted through everyday communal practices and ethical obligations toward the natural world [137]. Similarly, *Sumak kawsay* (Quechua) in Ecuador and Peru emphasises communal identity, social cohesion, and solidarity, framing life as the collective continuity of community and culture rather than individual success [52, 137], and orienting this vision towards a sustainable future across much of South America [179].

2.4 South East Asian Ethical Perspectives

South East Asian ethical perspectives are deeply shaped by relational, communitarian, and harmony-oriented world-views that emphasise social cohesion, moral self-cultivation, and balanced relationships between individuals, community, and nature. Drawing on Confucianism, Buddhism, Islam, and indigenous perspectives such as *adat*, ethical frameworks and perspectives in countries including Indonesia, Malaysia, Thailand, Vietnam, Cambodia, and the Philippines prioritises reciprocity, respect for hierarchy with a focus on responsibility, and maintaining social harmony over individual autonomy [36, 101, 118]. Buddhist ethics include concepts such as compassion (*karuṇā*) and non-harm (*ahiṃsā*), encouraging moral action that reduces suffering for both human and non-human life [101]. In maritime South East Asia (Brunei, Indonesia, Malaysia, the Philippines, Singapore), ethical traditions emphasise communal obligation, social justice, stewardship of nature (*khalifah*), and solidarity (*ummah*) together with the idea of interconnectedness and community, with respect for all life [36]. This is often considered together with indigenous *adat* norms that regulate reciprocity, land use, and collective responsibility rather than individual maximisation [118].

2.5 Māori and Indigenous Perspectives

Tikanga refers to the practices and customary law of the Māori communities of Aotearoa [116], which are deeply embedded in social practice. Ethical considerations are framed as a relational, collective, and place-based practice grounded in community authority, reciprocity, and responsibility. In Māori perspectives, frameworks such as *Te Ara Tika* emphasise *whakapapa* (relationships and connectedness), *tika* (doing things in the right way), *manaakitanga* (care, respect, and cultural responsibility), and *mana* (justice, equity, and the protection of dignity), highlighting that ethical action must sustain both people and relationships across time. Likewise, for Aboriginal and Torres Strait Islander peoples in Australia, ethical guidance stresses Indigenous self-determination, Indigenous leadership, meaningful benefit, sustainability, accountability, and respect for diverse knowledge systems [21]. Across these perspectives, a

[1] https://www.bisa.ac.uk/become-a-member/global-south-countries

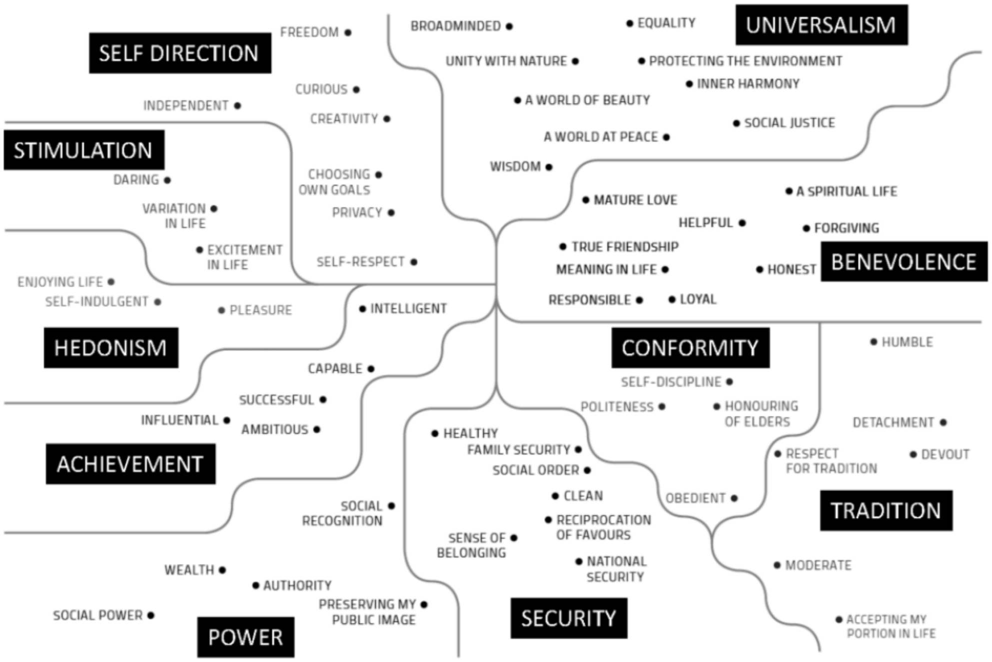

Figure 1: Schwartz Values Structure ex [138] Words in black boxes are values categories, each subdivided into values.

shared theme is that knowledge is embedded in Country, kinship, culture, and collective custodianship [87]. Similar world-views encompassing respect for local knowledge and one another; valuing family and community; and preserving the ecologies of land, people and relations over time can be observed in indigenous communities in the Pacific [145] and Peru [192]. While the focus of this work rests on the needs of the Global South, including the concerns of indigenous groups within that grouping is legitimate, even if somewhat occluded through membership within being geographically located within the borders of countries that are not considered to be within the Global South. Indigenous communities have more often been the target of Eurocentric colonialism [46], the Global North, thus their needs and value systems must equally be considered.

2.6 Diversity of Ethical Frameworks

The overview of the various ethical perspectives presented above highlights the impossibility of identifying a single ethical perspective that can be uniquely classified as 'Global South'. Such a monolithic model would not be effective or acceptable, and as Wong-Villacres et al. [186] have argued: "no single ethics code or set of guidelines can reconcile the diverse ethical principles, orientations, and questions that arise" [186]. Similarly critiquing universal models, as bluntly phrased by Karaitiana Taiuru "we do not force our tikanga [customs] on another group"[165]. In addition, it is important to note that influential computing curricula, such as reported in [43], have produced sets of guidelines that could be adapted and used globally, however:

> they reflect US–European norms and values and do not clearly acknowledge the ethical paradox in assuming these should hold in the Global Souths. Indeed, no single ethics code or set of guidelines can reconcile the diverse ethical principles, orientations, and questions that arise amongst the many different philosophical, constitutional, and administrative systems, religions, languages, and ethnicities around the world…nor the complex politics that shape the priorities of international computing curricula [186].

In this paper, we deliberately highlight the tension between the predominant value systems driving the Global North and those of the Global South. While a high level classification of values across a range of countries cannot be definitively inclusive or exclusive of any value or value set, we can speak in terms of aggregate presentation of values and the tendencies of these nations as a whole. The Global North tends to be driven primarily by individual stakeholder focus and the historical colonialism that accompanies and underpins settler societies [28]. In the context of technology and Generative AI, this is manifested in the desire to homogenise heterogeneity of culture, data, and practice, in order to achieve efficiencies. This perspective does not apply to the Global South, where the concerns are closer to family, Country, and groups such as tribes and sub-tribes. As such, in this paper we focus on highlighting the *diversity* of ethical perspectives in the Global South, the pillars and concepts that define them, and their relationship with Generative AI.

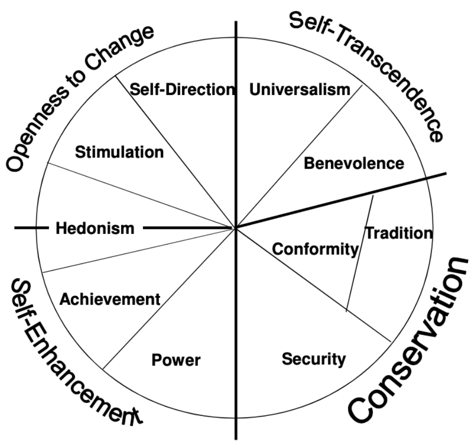

Figure 2: Schwartz Higher Order Values Grouping the Ten Basic Values ex [155]

2.7 Theory of Human Values

Value systems have a range of impacts upon individuals, groups, and society as whole, where achieving outcomes in alignment with our values can serve a wide range of interests as outlined in Schwartz' development of a theory of human values [155]. In this work, Schwartz identified some clear distinctions with ten basic value categories that could regulate individual and social expression as shown in However, it is possible to apply additional grouping categories through two approaches, higher abstraction and the recognition of the impact of anxiety on human value attainment. In Figure 1, the anxiety value dimensions are polarised as we can only meaningful hold one of the pair of values. Thus, two polar value dimensions for values include people's interests and their own level of anxiety. In the diagram, those values towards the top of the diagram are in the area of personal expression, whereas those values below the midpoint are more on relating to others, social interactions, and how their interests are affected. On the figure, those values to the right of the centre are more focused on growth, when the ones to the left are more focused on self-protection. It is important to note that these boundaries have significant space of overlap and that the categorisation system chosen has a very large influence on any meaningful groupings. [155]. Figure 1. Schwartz recognised that these categories of motivational values could be grouped into four higher order values: openness to change, self-transcendence, conservation, and self-enhancement, as shown in Figure 2.

This distinction has been highlighted in a critique analysing *Values in Computing and the 'Sharing Economy'* and the behaviour of Uber as a company [45]. Clear [45] identified a clear skew of values exhibited by Uber, based on the Schwartz model [154] as a value set primarily based on an individualistic mindset, oriented to power and achievement, but competing value systems do exist and a balance should be struck. An example of such values are offered by the Ubuntu perspective when applied for example to the Uber case study. Ubuntu occupies a spectrum opposite to that of Uber as a company, emphasising self-transcendence (universalism and Benevolence from figure 1) and conservation (conformity, tradition and security from figure 1) with a social focus as driving values. So in a sense we see a clash between an individualistic and capitalistic set of values and one with a communitarian, human and sustainability focus. These in turn represent the tensions between a "big-tech" driven form of AI and computing and a model based on Ubuntu such as [16, 117] or one supporting indigenous sovereignty values [38].

2.8 Principles-based Approaches

The diversity of the ethical frameworks described above leads to an understanding that no 'Global South' ethical framework can be extracted and generalised from existing frameworks, without generalising and wrongfully framing those existing ethical frameworks, often through a Westernised, colonialism-focused perspective [38]. A more suitable approach is one that identifies concepts or supports and discusses how they are considered geographically. The field of biomedical ethics advanced what has since been termed a 'principles-based approach', where moral principles or derivative rules are typically applied to typically novel situations or moral conflicts [26]. A similar principles-based approach has been adopted in the ACM approved IEEE-CS Software Engineering Code of Ethics [68], with statements such as:

> Ethical tensions can best be addressed by thoughtful consideration of fundamental principles, rather than blind reliance on detailed regulations. These Principles should influence software engineers to consider broadly who is affected by their work [68]

So, a principles-based approach aims to support both broad principles for a general ethical code and their specific application in a context demanding ethical deliberation.

In surveying AI ethics guidelines around the world, notably predating the advent of Generative AI, Jobin et al. [93] identified a set of ethical principles in existing AI guidelines, including transparency, justice and fairness, non-maleficence, responsibility, privacy, beneficence, and freedom and autonomy among others. An example of the use of a principles-based approach is taking the above global principles and reframing them as *Responsible Algorithm Principles*, which allowed them to be mapped in a New Zealand Māori indigenous context as *Māori Algorithmic Sovereignty (MASov) Principles* [38]. The motivation for Māori Algorithmic Sovereignty discussed above has arisen from concerns about how systemic biases from algorithms tend to impact marginalised communities and reinforce historical and current injustices, with 'colonising bias' a particular concern, defined as:

> Colonising Bias: Prejudice or injustices against an indigenous group due to the effects of colonisation, that results in negative outcomes for that group [38]

The global *Responsible Algorithm Principles* within a New Zealand Māori indigenous context then, were mapped against the *Māori Algorithmic Sovereignty (MASov) Principles* [38]. The broader Māori terms such as *Rangatiratanga* were seen to encompass a group of the *Responsible Algorithm Principles* - (Fairness and justice, responsibility, beneficence, freedom, trust and dignity)[38]. Likewise, Māori terms reflecting broader notions of guardianship or care such as *Kaitiakitanga* were mapped to (Transparency, fairness and justice, responsibility, privacy, trust, sustainability, solidarity) [38].

Another important point to highlight is that when working with a principles-based approach to ethics and professionalism in computing and AI, differences in languages and perspectives must be navigated. But, it appears that bridging through some commonality of language and terms across the Global North and Souths may be possible through the idea of highlighting and contextualising the discussion of principles and supports as discussed below in our research method.

2.9 A Principles-Based Approach to Landscape Analysis

We have identified that we seek to identify global ethical principles in this area and then seek their matches, contradictions, and extensions, in the practice, principles, and cultural contexts of the Global South. The global ethical principles provide us with a base search vocabulary and thus a starting point for discourse analysis, where we treat each document or written artefact as an expression of the local interpretation of a set of concepts, moderated by an individual author or organisation. Each document is then a source of potential matches for the unaltered words used to describe global principles but, through context and association, they are also a source of related contexts, local vocabulary, and local cultural, ethical, and societal concepts. A semiotic lens, where the narrative is examined in terms of what it signifies and how this reflects local interpretation, also provides a pathway to understanding how locally introduced concepts discussed around a global principle can then be associated with them.

Consider the Finnish term *sisu*, which has no strict translation into English, but encapsulates a national sentiment of resilience, toughness, indefatigability, and stoicism. A Finnish document that explored concepts of individual resilience is highly likely to use the term *sisu*, allowing a non-Finnish reader to identify that the term is at least adjacent to resilience, if not confirmed as a synonym. Similarly, a document from certain countries in Africa would be likely to associate *Ubuntu* with community and harmony, reflecting the cultural context, the association, and identifying a local cultural concept that can be associated with a Global Principle.

Landscape analyses, where we seek to unify or at least collate what has been extracted through discourse analysis, do not merely identify matches but also may identify concepts important to the culture surveyed that have no definition at the global area - or are not considered sufficiently significant to be included in a list of principles unless it is exhaustively long. Thus, the research methodology we have followed is based on a notion of discovery and representation, rather than requiring confirmation in terms of alignment with existing concepts or excluding terms that have a small number of occurences.

3 Research Method

Our method for identifying ethical perspectives on Generative AI in the Global South is focused on inclusion and contextualisation. Specifically, rather than imposing predefined Western ethical models, the coding process sought to recognise contextually grounded interpretations of ethics, such as responsibility, accountability, or collective benefit. This ensured that ethical perspectives were interpreted not only through normative frameworks but also through the lived realities and local knowledge systems represented in the papers. In the following, we present our methodology, focusing on initial coding, categorisation, analysis and discussion.

3.1 Overview

The method was conducted in two phases, where the operations took place over two quite distinct datasets.

- In Phase One, publications that addressed ethical concepts within the Global South and associated communities were analysed to extract all of the terms for principles and concepts that were considered to be important and valuable.
- In Phase Two, these identified terms were then used as search terms within papers that had been produced by authors from the Global South around Generative AI in computing education in the context of the Global South. The occurrence of a term could indicate a meaningful use of term in a way that aligned with its original meaning in Phase One or it could be an incidental, non-significant, usage of the term.

This two phase process meant that there were four possible outcomes for any term identified in Phase One.

(1) A term identified in Phase One could be found in literature examined as part of Phase Two, carrying its original meaning in the context of an ethical concept.
(2) A term identified in Phase One could be found in literature examined as part of Phase Two, but with a different meaning or used in a different way that did not indicate contextual alignment with the original term.
(3) A term identified in Phase One might not be found in literature examined as part of Phase Two, as the term was so localised or specific that, although its meaning may be present, the exact term could not be found.
(4) A term identified in Phase One could be might not be found in literature examined as part of Phase Two and this would indicate no aligned conceptual content in the corpus.

It should now be clear that this means that the number of terms originally determined in Phase One does not prescribe the number of terms that would be located and be contextually significant in Phase Two. As we will discuss, some terms had very high elimination rates, as their alternative meanings were commonly used in ways that did not match the original ethical concept.

3.2 Process

Our process is summarised in Figure 3 and contains four main steps:

- Phase 1

Step 1 Identification of ethical concepts:
  - Identify the candidate materials to review to extract valid ethical supports for the Global South

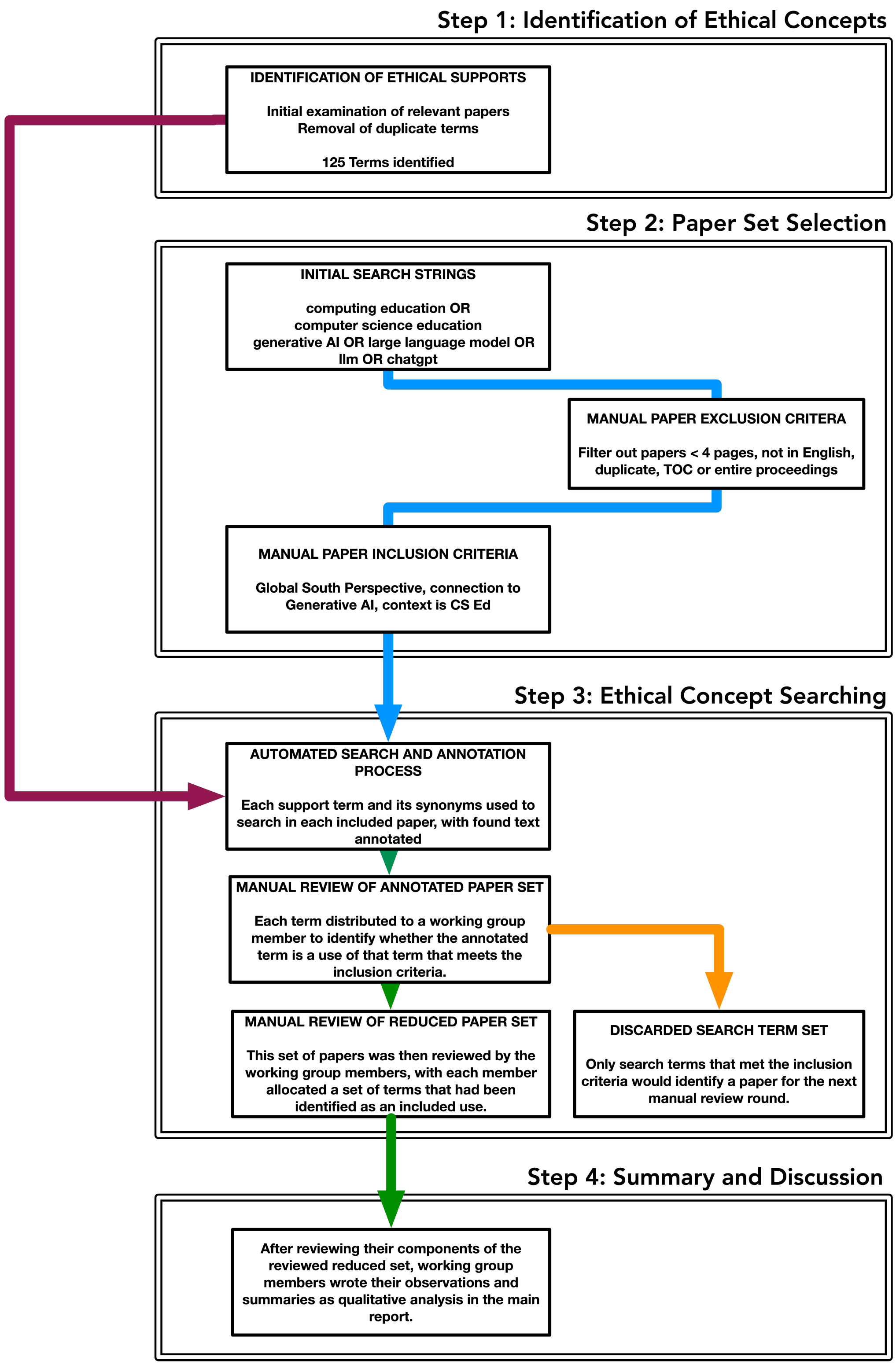

Figure 3: Overview of Search Process

  - Select the ethical supports
- Phase 2

Step 2 Paper set selection: Identify a large body of relevant papers from ACM, IEEE, and Scopus using well-crafted search strings and with:
  - well-defined exclusion criteria
  - well-defined inclusion criteria

Step 3 Ethical concept searching:
  - Apply an automated search process to identify papers that contained references of any kind to the identified supports
  - Review each identified term in each paper to establish whether the use of the term is valid and contextualised within the Global South.
  - Reduce the paper set to contain only valid term uses

Step 4 Summary and Discussion: Summarise the specific issues relating to each term that had been identified in the paper corpus.

3.3 Step 1 Identification of Ethical Concepts

We discuss in this section our approach to identifying the range of underpinnings, supports, concepts or other pillars of ethical principles within the Global South. We used a variety of resources that discuss various ethical perspectives distributed geographically across the Global South. Each member of the group was responsible for a geographic region, and collected relevant papers that were then discussed with the entire group, and relevant concepts extracted. These concepts were then evaluated by a four person subset of the group, with a mutual review of terms discussed in meetings and through shared collaboration tools. These terms are as shown in Table 1

Building on the ideas of ethical diversity discussed in Section 2.6, we avoided a thematic analysis as the implicit abstraction to a theme can mean that the original subtlety in the semantic difference between terms can be lost, and that the contribution of any individual element to a corpus can be overshadowed if other themes dominate. An example of subtlety in term meaning is given in Section 3.3.1.

Thus, rather than seeking themes, based on a semantic grouping for abstraction and occlusion, we used syntactic comparison of the concepts identified to reduce complexity and duplication without reducing the contribution of elements that only arose once. This would mean that concepts such as ’collaboration’ and ’collaborative’ would be selected together under the same label. In contrast, the process of systematic synthesis reported in [50] is depicted in Figure 4, where the process of concentration tends to compress and inherently lose local ownership of important but discrete concepts.

The initial work in identifying terms that underpin ethical discussions from the existing literature revealed 161 distinct supports. Grouping terms that were identical reduced this number to 143 terms, attached as an Appendix, Section A, and then grouping these further by the leading single word in any cluster reduced the number of unique terms to 125 terms. These were then grouped by similarity of terms to provide an indicative frequency of similar terms. It is important to note that this grouping is not meant to suggest or support a subordination of any of the contributing terms,

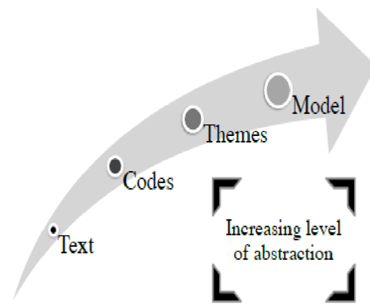

Figure 4: Thematic Synthesis Progression (Cruzes and Dyba [50])

as each of these terms was derived from a paper that represented one or more cultures as shown in Table 1.

In addition, even the grouping of geographical locations into shared concepts referred to as “countries” is potentially reductive, as Hau’Ofa [76] notes. Original inhabitants of the islands in the Pacific Ocean would refer to seas of islands in a pre-colonial view, rather than grouping the islands into larger administrative, political, and cultural organisations that could then be labelled as countries. Further, the supra-national groupings of countries based on a post-colonial set of relationships and common language, can also be seen in the unifying phenomenon of the “Anglosphere” as explored in the book on settler societies by Belich [28].

We note that our underlying assumption is not that we can unify all of these disparate ethical frameworks into a unified whole, as this is at odds with a great deal of indigenous knowledge and practice.

3.3.1 Complexity of Terms. As noted, a risk with thematic abstraction is that we do not just reduce the overall complexity inherent in the multidimensional thematic space defined by a rich variety of terms, but that we simplify individual terms to a point where they lose their individual semantic richness. For example, the grouping ‘time’ associates the extracted support components:

- conceptualization of time
- theory of space and time
- time, context and the environment

It is immediately clear why grouping these as time has identified a concept that connects them, yet all of these uses of the term are different. Time as a convenient container for describing a concept that arises in several source works is useful but not as a thematic abstraction that can capture the nuance of the cited works. However, searching for papers that have authors or research located in the Global South, and that contain content that can be associated with one of the container terms is likely to increase the overall diversity of the literature in a way that aligns with existing identified supports.

Elaborating on this issue, the ‘concept of Time’ for instance, presents a very complex research phenomenon. As observed in a global collaborative educational context [47], time can be seen to encompass multiple dimensions such as: ‘cyclical time’ as expressed in the cycles of seasons or semesters; ‘clock time’ as in

Table 1: Ethical concepts mapped across Indigenous, cultural, and AI governance frameworks

Framework	Region	Ethical concept group
AIATSIS Code of Ethics [21, 22]	Australia	impact; sustainability; tradition
Buen Vivir [179]	Ecuador, Bolivia, Peru, Colombia, Chile, and Argentina	nature; reciprocity; relationship; solidarity
Fonofale [136, 145]	Samoa	community; health; holism; relationship; spirit; time; tradition
Ga [14]	Western Africa (Ghana)	communal; justice; longitudinal responsibility; responsbility
Global AI ethics guidelines [93]	Global	agency; choice; clarity; communal; dignity; freedom; harm; health; integrity; justice; liability; liberty; nature; privacy; protection; responsibility; safety; transparency; trust; virtue
Harambee [184]	Eastern Africa (Kenya)	communal; community; generosity; responsbility
Hu Ìwà síi bí Ènìyàn Ẹ̀léṛan-Ara [6]	Western Africa (Nigeria)	dignity; justice; reciprocity
ICT4D–Indigenous Quechuan People in Peru [192]	Peru	community; family; nature
Indigenous Standpoint Theory [89]	Tanzania	collaboration; presence; reciprocity; respect; responsibility; safety; virtue
Ma'at [132]	Northern Africa (Egypt)	harmony; health; integrity; justice; structure
Māori Algorithmic Sovereignty Principles [38, 119]	New Zealand	beneficence; dignity; freedom; justice; responsibility; solidarity; transparency; trust; agency; ethics; privacy; truth; care; family; health; reciprocity; tapu; tradition
Menkiti's Philosophy [130]		communal; community; identity
NHMRC [125]	Australia	reciprocity; respect; spirit; tradition; virtue
Nnobaa [20]	Western Africa (Ghana)	collaboration; communal; dignity
Omoluabi [23]	Western Africa (Nigeria)	freedom; integrity; responsbility; virtue
Pacific World-views & Frameworks [167]	Samoa, Tokelau, and Tonga	family; holism; spirit
Principles of Biomedical Ethics [26]	Global	beneficence; non-maleficence; autonomy; justice; veracity; confidentiality; privacy; fidelity; professional ethics
Safuu [7]	Eastern Africa	dignity; justice; reciprocity
Sankofa [20]	Western Africa (Ghana)	fidelity; reconciliation; time
Schwartz Basic Values Framework [154–156]	Global	achievement; safety; status; tradition
Suma qamaña (Aymara) [137]	Peru and Chile	collaboration; nature; reciprocity; tradition
Sumak kawsay (Quechua) [137]	Ecuador and Peru	communal; community; identity
TKI Conduct of Indigenous Health Research [168]	Australia	collaboration
Ubuntu [16, 114, 161, 191]	Africa	care; communal; community; harmony; solidarity
Ujamaa [60]	Eastern Africa	communal; community; family; relationship
Ukaama [60]	Southern Africa (Zimbabwe)	family; nature; spirit

Greenwich Mean Time (GMT) and calculated through time-zones; time covering 'predictable events' such as religious holidays and 'unpredictable events' such as through delays, storms, epidemics or earthquakes; the notion of time as 'life-cycle' such as through phases in a project, time as 'duration', and even time experienced as 'pressure' through deadlines.

The cultural aspects of time have been categorized through Western notions of 'monochronic' time expressed through clock time, time as a means for measuring economic productivity, and 'polychronic' time, where time is considered intangible, and activities are timed by events rather than a clock. Time is viewed as a backdrop against which events unfold. Cultures who view time as cyclical, continuous (holistic), and epochal tend to match with perspectives about time held in the Global South.

As one, albeit more complex example, the notions of *Va* and *Te Wa* are held across the Pacific, in Samoan, Tongan and Māori world views. Here the concept of *Va* incorporates not only time but space, and relationships with humanity and the natural world spanning those dimensions:

> [...] it symbolises woven connections of space and time that hold things together. [...] Va is the space between, the betweenness, not empty space, not space that separates but space that relates, that holds separate entities and things together in the Unity-that-is-All, the space that is context, giving meaning to

> things. The meanings change as the relationships/the contexts change…A well-known Samoan expression is “Ia teu le va”: “Cherish/nurse/care for the va, the relationships”. This is crucial in communal cultures that value group, unity, more than individualism: who perceive the individual person/creature/thing in terms of group, in terms of va, relationships...The notion of space “connecting”, rather than “separating”, is central for those seeking to understand how Pacific peoples view the world.

[167].

So, while the supports and terms for ethical concerns relevant for the Global Souths have been identified and mapped in the selected papers, the differences in local languages, concepts and interpretations of those terms means an imperfect mapping can be achieved at best. But more positively, this reinforces the need for any ethical framework for the Global Souths to support agency of the diverse user groups. It must be able to be interpreted in their situation and operate effectively in the local context, rather than being globally imposed.

3.4 Step 2 Paper Set Selection

To establish a set of papers from which we would search for use of the support terms, we used the following process: 1) develop a search string, 2) select databases to search, 3) filter based on page count and publication type, 4) apply an inclusion criterion based on Global South authorship or context. Following the process in a precursor working group [113] we established a search string that would ensure a broad range of papers, focused on the domain of computing education and the topic of Generative AI using the following keywords for each:

- “computing education” OR “computer science education”
- “Generative AI” OR “large language model” OR “llm” OR “chatgpt”

3.4.1 Databases. In line with recent literature reviews in computing education research [143, 144, 193] we searched three databases: ACM Digital Library, IEEE Xplore, and Scopus. This ensured a broad coverage of papers in computing education. The search returned a total of 2543 papers from all three databases. The searches were conducted on 19th September 2025. The results are shown in Table 2.

3.4.2 Paper Filtering Process. In the filtering process papers were excluded according to the following exclusion criteria:

(1) less than 4 pages in length, OR
(2) not written in English, OR
(3) the type of publication is a table of contents or entire conference proceedings, OR
(4) a duplicate between databases.

Papers were included according to the inclusion criteria:

(1) there is a connection to Generative AI, AND
(2) the context of the work is in computing education.

Applying the inclusion criteria involved a read of each paper. After this filtering, 276 papers remained (see Table 2). The filtering process was done by two group members, with one group member doing the initial filtering and the another group member checking the filtering

Table 2: Paper counts at each stage of building the dataset

Venue	Initial search	Filtering	GS authorship	Dominant GS authorship
ACM	1817	112	81	62
IEEE	402	109	56	49
Scopus	324	55	19	14
Overall	2543	276	156	125

3.4.3 Global South Authorship or context. The next filter was applied to identify papers where one of the authors was from the Global South and/or the work reported was set in the Global South. The Global South countries were determined from the *The British International Studies Association* (see footnote 1). This left 156 papers in the data set (see Table 2).

The final filter was applied to include only papers that were predominantly Global South authored.

Papers were included according to the inclusion criteria:

(1) the majority of authors have Global South affiliations, OR
(2) the first author has a Global South affiliation.

This left 125 papers as our final data set, with 62 from the ACM, 49 from the IEEE and 14 from Scopus (see Table 2).

3.4.4 Handling Review Papers. In analyzing the papers, we noted that some papers constituted literature reviews of various forms, e.g. [1]. This would inherently inflate the number of terms identified, were we engaged in conducting a systematic literature review, so typically would have been excluded as part of our exclusion criteria, given usual practice e.g. [27]. But, as this report aims to elicit perspectives from the Global South, the perspectives of authors commissioning such reviews were deemed of equal value, so were included for analysis in the paper set.

The working group identified a larger narrative associated with the inherent bias of a systematic literature review (SLR), because such reviews favour well-established, so-called ‘high impact’ venues that are not globally accessible, even with the increased use of Open Access approaches. Thus, any SLR that follows protocols such as [27] is likely to overlook community venues that are not considered to be at the same standard, to avoid alternative interpretations of existing works through culturally located literature surveys, and fail to include works that are written in languages other than English. Solving the problems associated with this are well beyond the scope of this working group.

3.5 Step 3 Ethical Concept Searching

To support the review, an automated search and annotation process was developed to identify key ethical and contextual terms across the corpus. This process had several steps.

Firstly, the set of 125 ethical concept terms identified in section 3.3 were enhanced with a set of synonyms extracted from the Merriam-Webster dictionary [115], to broaden the capture of relevant text in papers. For example, the initial term ‘consensus’ had the synonyms ‘agreement’, ‘unison’, ‘unanimity’. Two of the authorial team worked to identify and confirm the three most commonly used synonyms from Merriam-Webster, and these were used to augment searches in the primary term had no hits.

Then, a Python program was developed to search the full-text PDFs for predefined ethical and contextual terms. The software was developed on a Mac OS X 15.7.1 machine under Python 3.9.6, Pandas 2.1.0, and PyMuPDF 1.26.4. Frequently, the ability to search inside PDFs is unreliable as producers can go to some lengths to prevent text extraction. However, the papers downloaded from the ACM, IEEE, and SCOPUS research databases were all well-formed and the PyMuPDF package could be used to search for, highlight, and extract text and entire pages from scanned PDFs [2]. While some PDFs can be hard to read, as they are either using images in place of text, or have been produced by scanning, none of the PDFs in the set were of this type, as the software was designed to report any situations where the text was not readable on file opening and it did not report any of these errors in the live dataset after confirmation of function during testing.

The script generated paired outputs: 1. a CSV file listing each occurrence of a target term (including source file title, page numbers) and 2. a corresponding PDF file containing only the extracted pages with the terms marked through underlining and a yellow highlight for rapid review. The name of the parent file was printed onto the top of each page to avoid confusion. Using this process the 125 papers identified in Section 3.4 were scanned and marked for each of the terms.

This workflow significantly reduced manual screening time while preserving contextual visibility. Reviewers then validated each extracted segment by cross-referencing the highlighted PDFs and corresponding CSVs, removing instances where terms appeared only in bibliographies, generic contexts, or unrelated discussions. Following the review we found that a number of terms did not appear in any of the papers, resulting in a final set of 110 terms that had occurred at least once in one of the 125 papers in the paper set. These terms are listed in Appendix B. We also found that each of the 125 papers was marked with at least one of the 110 terms.

The resulting verified records provide a curated dataset of 125 papers and passages that directly engage with ethical questions, values, and practices surrounding Generative AI in higher education within Global South contexts.

3.6 Step 4 Summary and Discussion

This step happened in two phases. In phase 1, each group member was allocated a group of terms to analyse. They carefully read the subset of papers that contained relevant discussions contextualised around Generative AI and summarised these perspectives. During this process the group discussed novel or unexpected views, as well as overloaded terms or terms with multiple meanings.

In phase 2, three working group members reviewed each term and the analysis. This brought more consistency to the writing of the summaries and more rigour to the analysis.

Overall, every paper that was read and had a relevant use of a term was included in our interpretive analysis summary (see Appendix C). Ninety eight terms listed in Table 6 were found to have relevant discussion. A further 13 terms where no relevant discussion was found have not been included. These are listed at the start of Appendix C).

A total of 97 (74%) of the papers in the paper set are cited in the summary.

[2]Some file fragility was noted in saving modified files, as file repair was taking place without discernible pattern, potentially related to a race condition or timing issue in either the library or the executed code. While this was addressed through code refactoring, the final structure affected the overall speed of execution.

4 Results

We focus in this section on highlighting the insights that guided the methodology for landscape analysis and the descriptive research framework that was adopted for this trans-cultural project, to facilitate other researchers using this method. We discuss the assembly of relevant terms, identification of those terms in the paper set, and the methodology for establishing relevance and provide an introductory descriptive framework for this important area of research. We also present a summary of our search process results, describing the identified terms and their refinement. The interpretive analysis, which is the last and potentially our most significant contribution, is presented separately, in Appendix C, for two reasons:

(1) The interpretive analysis is presented as a glossary with alphabetical entries, each supported by relevant text and citations. It is not designed to be read in a linear manner but as a reference, highlighting how each ethical concept frames Generative AI in the Global South.
(2) The interpretive analysis provides information of 110 terms, and spans 16 pages. Even if were not in glossary format, it is too long to insert at this point without placing undue burden on the reader.

The choice of a glossary as a mean of data presentation supports the wider discussion of the terms by practitioners and researchers interested in how considerations about a particular term and Generative AI are framed within the Global South. The size of the glossary and the in-depth discussions framing most terms means that the entries cannot be meaningfully summarised due to the number of terms, the varying levels of engagement with the theme of Generative AI and ethics in computing education, and the variety of cultures from which the works have been taken. We provide an example of an entry from Appendix C at the end of this results section, along with clarifying text on the nature of the entries in the Appendix.

Our analysis found 110 search terms located across the 125 papers in the final paper set. Many terms were found on multiple occasions in different papers. The list of terms in Appendix B shows the number of papers that each term appeared in and the total occurrence of each term. The 10 terms with the greatest occurrence are shown in Table 4 and the 10 terms appearing in the greatest number of papers are shown in Table 5.

It is important to note here that Tables 4, 5 and Appendix B show the occurrences of the terms but the actual numbers of relevant terms is much lower. After a careful analysis of each term's specific treatment within a paper there was a substantial reduction in the number of relevant term hits within our paper set. This is because of several aspects, including:

(1) For example, words such as 'choice' and 'community' were often found in relevant texts but not used in a way that was specific to Global South interpretations of these terms.

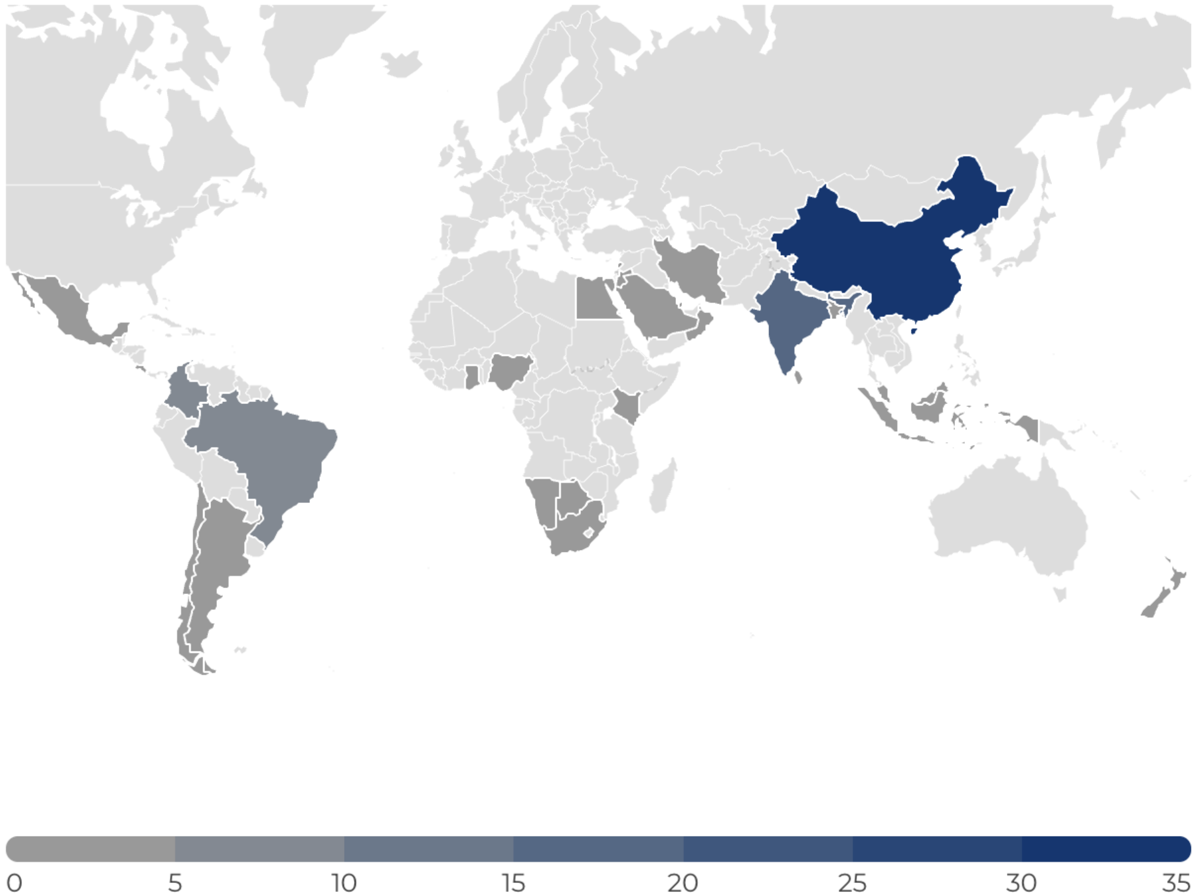

Figure 5: Distribution of Countries in the Paper Set

(2) Some terms were strongly associated with one venue in a non-relevant way. For example, the phrase 'IEEE society' is a valid use of the term 'society' but is not relevant to the Global South context.
(3) Some terms were also found as stems or elements of other words, for example 'unity' found in the word 'comm*unity*'.
(4) Some terms were associated with all of the above problems. Again, the word 'unity' could be seen in a non-Global South localised sense of union, as a reference to the Unity software package, and as a component of the word 'community'.

Across the paper set there were authors from 36 different Global South countries (see Table 3). The greatest representation was from China and India. Figure 5 presents a visualisation of this distribution.

4.1 Interpretive Analysis

The qualitative analysis was not, as noted earlier, a straightforward thematic analysis as there was a high risk that the coding into themes would occlude important concepts that had only been identified in a single paper or by a single community. While TF-IDF (term frequency/inverse document frequency) [5] might capture key words that could lead to the generation of sufficiently broad themes, an automated approach was not adopted due to the high risk of losing the fine, individually culturally-located structure. Thus, each term that had been identified in the first pass and then validated as relevant in the second pass was used to identify papers that contained a discussion of theme that could be elaborated for a descriptive basis of that theme in a relevant environment.

The results of the qualitative analysis phase are described in detail in Appendix C, where we describe how each term is considered by Global South authors and either within or framing a Generative AI perspective. As an example, we reproduce the entry on 'socialisation' here:

> **C.81: Socialisation**
> A scoping review by Boubaker and Fang [35] analysed the implications of integrating Generative AI in engineering and computing education from K-12 to tertiary levels. Areas of focus were the development of learning outcomes in the cognitive, affective, or behavioural (e.g., socialisation) domains of learning.

It is important to note that the identified supports can be used in a wide range of other studies focused on Global South perspectives, which is why we considered important to highlight the treatment

Table 3: Global South countries represented by the authors in the final paper set

Global South country
Argentina
Bahrain
Bangladesh
Botswana
Brazil
Chile
China
Colombia
Costa Rica
Ecuador
Egypt
Ghana
India
Indonesia
Iran
Jordan
Kenya
Korea
Lebanon
Malaysia
Mexico
Namibia
Nigeria
Oman
Pakistan
Palestine
Peru
Philippines
Saudi Arabia
Sri Lanka
Trinidad
Turkey
UAE
Vietnam

Table 4: Top ten terms according to their occurrence in the final data set

Top 10 Rank	Term
1	support
2	engagement
3	choice
4	environment
5	cognitive
6	fairness
7	privacy
8	order
9	individual
10	nature

of each of them individually in the literature. Readers will note that not all of the terms used were explicitly connected to ethics in

Table 5: Top ten terms according to their paper coverage in the final data set

Top 10 Rank	Term
1	support
2	individual
3	environment
4	engagement
5	personal
6	cognitive
7	order
8	choice
9	collaboration
10	society

Generative AI but these terms were discussed by authors from the Global South in the context of the Global South, which provides an association with this overarching context. We have worked from a principle that, not being from the communities or cultures producing these works, our external interpretation of how strong an association is not sufficient grounds for exclusion unless it is completely clear that the use of a term is explicitly outside of the area under study. Rather than remove terms that have an arguably weaker connection, we have included these more loosely connected discussions to represent the widest possible inclusive set. In using the results of Appendix C, future authors may be able to determine more exact contexts and either reinforce the inclusion of this term or make a better case for its removal.

5 Discussion

The interpretive analysis of the support terms gave broad insights into the Global South perspective on the use of Generative AI and related ethical and societal issues. Overall, the influences on ethics have many sources, from philosophy, religion, cultural experience, tradition, and precedent, but the regional variations in which of these have the most weight are significant. Any ethical code must take into account the local contributions to ethical reasoning, especially where violations of ethical (or moral) codes can lead to severe repercussions. Among the many issues raised, the following stood out as matters to both inform the wider community and identify opportunities for education, training, resource allocation, and co-operation as a global community to reduce the distance between the Global North and the Global South.

The Digital Divide is real and large [135, 153, 175, 198] There is not the same level of access to infrastructure, resources, and education in the Global South as is found in the North. Even where any other knowledge or will to take action is present, this resourcing shortfall reduces the capability of those in the Global South to make the required changes at the desired level of scale. In addition, the vast majority of mature Generative AI systems are built in the Global North and thus tend to reflect Global North values, because they are built in a Global North context by Global North aligned employees. Given that internationalisation, the provision of alternative languages than English, has to be cost-justified and is often lacking any other than mainstream languages, there is no guaranteed driver for addressing contexts found in the Global South.

Regulations are key [105, 135, 170, 186, 198] Regulatory drivers in many areas will drive the degree to which key aspects of ethics, such as transparency, accountability, and harm metrics, are considered. While the Global North has, for the most part, mature and wide-ranging regulatory systems with supportive powers of fine and punishment, the Global South is not at the same level and, in some cases, such regulations have no real enforcement, leading to the difficult situation where everyone is aware what the regulations and laws should be doing but it is not what is done.

The importance of cultural contexts [44, 72, 186] If a project is launched from outside a community, and does not acknowledge and incorporate the values, ethics, and norms of that community, it is far less likely to succeed, to engage students, and to provide the solutions that are needed by that community. Similar are the perceptions on learning. Learner autonomy, agency, and expectations of integrity can vary widely, as some cultures adopt a more didactic and recitative model, reducing learning autonomy and agency. This can be at odds with Global North expectations around Socratic interaction and the synthesis of new knowledge. See the interpretive analysis of related terms in Sections C.23, C.24, and C.25.

The importance of community Community, and participation between members of a community, is often more highly valued in the Global South, which has a direct impact on perceived ethical issues such as academic dishonesty. If sharing is the best way to achieve a result, then it is potentially wasteful to conduct individual work when a group solution can or does exist. There is also the value of work that contributes to the community, making culturally located authentic tasks of more importance and reducing the ability to re-use examples and teaching materials from outside of the community. See the interpretative analysis of the term 'community' in Section C.17.

Protecting information Privacy, security, and the way that trust is constructed and supported have a wide range of different interpretations in the Global South. In some communities, honesty is more important than security or privacy, and, in others, the privacy of sacred, secret, or gendered information is so important that it transcends all other requirements. The epistemology of a community is key to the way that their ethical praxis will develop. See the sections on privacy (Section C.63) and protection (Section C.64) in the interpretative analysis appendix.

5.1 Term Meaning

The identified supports are common worldwide; however, it is worth noting that their meanings are not always consistent. Both language and culture influence the different connotations associated with how people across the globe perceive certain terms. For instance, in our work, we observed that supports like community, choice, and health, to name a few, sometimes conflict or are more nuanced in their meaning than initially envisaged. We discuss these in the subsections below.

5.1.1 Community. In the Global North context, the term "community" typically refers to groups, digital communities, or affiliations where individuals are loosely connected by their shared beliefs, disciplines, or interests. These groups typically involve voluntary participation and are not bound by family-like ties or responsibilities. Within the Global South, a broader meaning exists. There is an implicit understanding that the community carries moral and sometimes economic weight. In this setting, the focus is interdependence, in addition to belonging. While it may still be regarded as a social bond, there is an obligation that goes beyond personal interests. In the Global South, communities can be viewed as extensions of the family, with a shared sense of purpose and connection.

5.1.2 Choice. In many Western countries, having a choice means being free to do what you want without undue interference. This view on choice is based on the idea that each individual is a rational decision-maker and should have control over their life. In many traditions of the Global South, choice is not independent of society; rather, it is symbiotic. Based on social systems that emphasize harmony and duty, both African and Asia-Pacific ideas of choice are not isolated, but a negotiation between the desires of the individual and what is best for their community. Decisions are often guided by what sustains balance within the integral relationships of the extended family. "Choosing" ends up being a confluence of moral negotiation rather than an isolated act of will. Freedom is meaningful only when exercised responsibly within the network of obligations that unite the community.

Considering these two meanings of 'choice', we see a potential ethical conflict. Choice is usually seen as user control, and the more control a user has, the more we value such systems. However, with this broader view of choice, we understand that technologies promoting personalised choice might unintentionally disrupt collective norms, like harmony. For example, what is the point of learning individually with a Generative AI tutor if it benefits the individual but harms the communal spirit among students? From this perspective, the ethical AI choice would be to support both the individual and maintain community goals and social balance. We did not notice this dichotomy in the literature we reviewed, as all the references to choice were rooted in Western ideas of autonomy and independence. However, it is important to think about this potential conflict as such tools become more common.

5.1.3 Health. Generally, in the context of the Global North, health typically refers to an individual's physical well-being; over the past three decades, it has also come to include mental well-being. Conversely, many cultures in Africa and Asia do not see health as separate from the land and communal stability. What the Global North describes as individual well-being appears in Global South literature as an integrated condition supported by both personal cognition and communal ethical infrastructure. Educational health, as discussed in the literature, examines how it depends on managing inclusion, transparency, and responsibility with AI tools. Health in this context highlights disparities in digital access and how the inclusion of AI tools can further deepen educational health inequalities by increasing the gaps.

5.2 Overloaded Words

We also noted that the meaning of several supports were overloaded. Understanding overloaded words in the context of Generative AI in computer education is crucial due to their numerous and diverse meanings, which become particularly significant when establishing foundational pillars for integration that respect specific institutional or national contexts, especially in the Global South. The interpretation of a pillar like 'equity' or 'autonomy' can vary dramatically based on local resources, cultural values, and educational priorities; what constitutes 'achievement' in a well-resourced university may differ profoundly from its meaning in a context with infrastructural constraints. Therefore, dissecting this lexical complexity is not a semantic exercise but a foundational necessity for ensuring that the integration of AI tools is purposeful, equitable, and effectively enhances both learning and teaching, enabling the construction of a robust and context-sensitive framework that avoids imposing external assumptions and instead builds on locally relevant definitions and goals. We discuss several examples of overloaded words in the following.

An example is the word 'affect' which routinely switches in meaning between denoting the measurable impact of AI on learning outcomes and the deeply personal emotional experience of using these tools. This ambiguity is central, as it forces us to ask: Are we evaluating AI solely by metrics, or by how it affects students and teachers? Generally, 'affect' relates to having an influence on or making a difference to. This can be applied to Generative AI in the context of teaching and learning. However, the word can also be related to emotions, feelings, or moods. In line with this, it is also worth noting that students and educators experience a range of emotions when interacting with Generative AI, including excitement, frustration, confidence, and curiosity about utilising the tool.

Similarly, the concept of 'achievement' is contested, with students' subjective perceptions of learning efficiency pitted against objective, quantifiable evidence of improvement, as measured by metrics such as improved test scores or coding proficiency. This leads directly to a discussion on 'action' which is far more than merely the technical deployment of Generative AI; it is a moral imperative that demands consideration of how AI reconfigures pedagogical roles and whether our actions promote equity or perpetuate disparities. Even a term like 'appreciation' oscillates between a conventional academic courtesy and a deeper, culturally situated educational goal of fostering genuine value for heritage and the environment in some context.

Finally, this lexical richness extending to 'autonomy' (of the student, the system, or the institution) and 'attainment' (as a static goal versus a continuous process) is not merely semantic. It reflects the complex, multi-faceted nature of integrating AI into the human-centric realm of education, where every technical decision is intertwined with pedagogical, ethical, and social dimensions.

5.3 Missing Perspectives from Lived Experiences in the Global South

While Generative AI continues to shape educational practice globally, much of the ethical discourse remains abstracted from the lived realities of educators, students, and researchers in the Global South. The absence of detailed country-level perspectives has created a homogenised view of the region, where Ghana, Kenya, Bangladesh, and Pacific Island states are treated as a single ethical space rather than diverse moral ecosystems with unique institutional and cultural contexts [141]. The result is a literature that discusses global issues such as fairness, accountability, and access, but rarely engages with how these are experienced differently in classrooms, universities, and local communities. These omissions reveal how ethics is still predominantly framed through the lens of the Global North, where principles are defined universally, and lived experiences are treated as peripheral. Beyond missing representation, there is also a missing school of thought that situates ethics within the everyday realities of institution, funding, and culture. Many Global South universities navigate donor driven governance, externally prescribed curricula, and limited policy autonomy, all of which shape how ethical norms are internalised and taught [150]. Funding constraints influence which technologies can be adopted, while institutional hierarchies affect how responsibility and decision making are distributed. At the same time, local cultures provide rich moral vocabularies grounded in values such as communal care, reciprocity, and respect that could serve as the foundation for a distinct Southern approach to AI ethics. However, these have not been adequately theorised or integrated into global frameworks. The same silence extends to climate and ecological ethics. The environmental implications of AI, including energy and water consumption [106], data centre expansion, and e waste accumulation, disproportionately affect low emission nations in the Global South, yet sustainability remains marginal in computing education discourse [69].

The lived ethics of social responsibility and data sovereignty are equally under-explored. Educators and learners in the South often express social responsibility through collective practices of care, mentorship, and resource sharing, forms of moral agency that rarely appear in policy documents or academic models. As digital infrastructures expand, the question of who controls data and whose interests are served by AI systems becomes central to institutional ethics and national sovereignty [62, 150]. Re-centring these themes, including specific national contexts, differing experiences, institutional realities, environmental accountability, social practice, and data governance, invites a richer, experience based ethics. Such a framework recognises the Global South not as a site of ethical deficiency but as a source of original thought, where moral imagination is shaped by lived struggle, cultural continuity, and aspirations for technological justice. In addition to themes of cultural continuity, technologies used in teaching must continue to support learning when formal schooling ends or the location where the technology was introduced becomes unavailable, allowing students to take their learning environment with them [91].

5.4 Values in Computing and the Ethics of Generative AI

Computer science and software engineering papers with a focus on programming largely present a techno-centric perspective on the computing disciplines, and largely do not focus on ethical dimensions. But with the rise of AI and the embedding of technologies such as Generative AI within typical development platforms, the unifying of programming practices and the reliance on data and algorithms at scale demands an increased focus on the ethics of programming [59]. Indeed, commentators such as Ozkaya, the Editor in Chief of the journal *IEEE Software*, have asserted that "ethics is a software design concern" [134], and Vardi, the former Editor

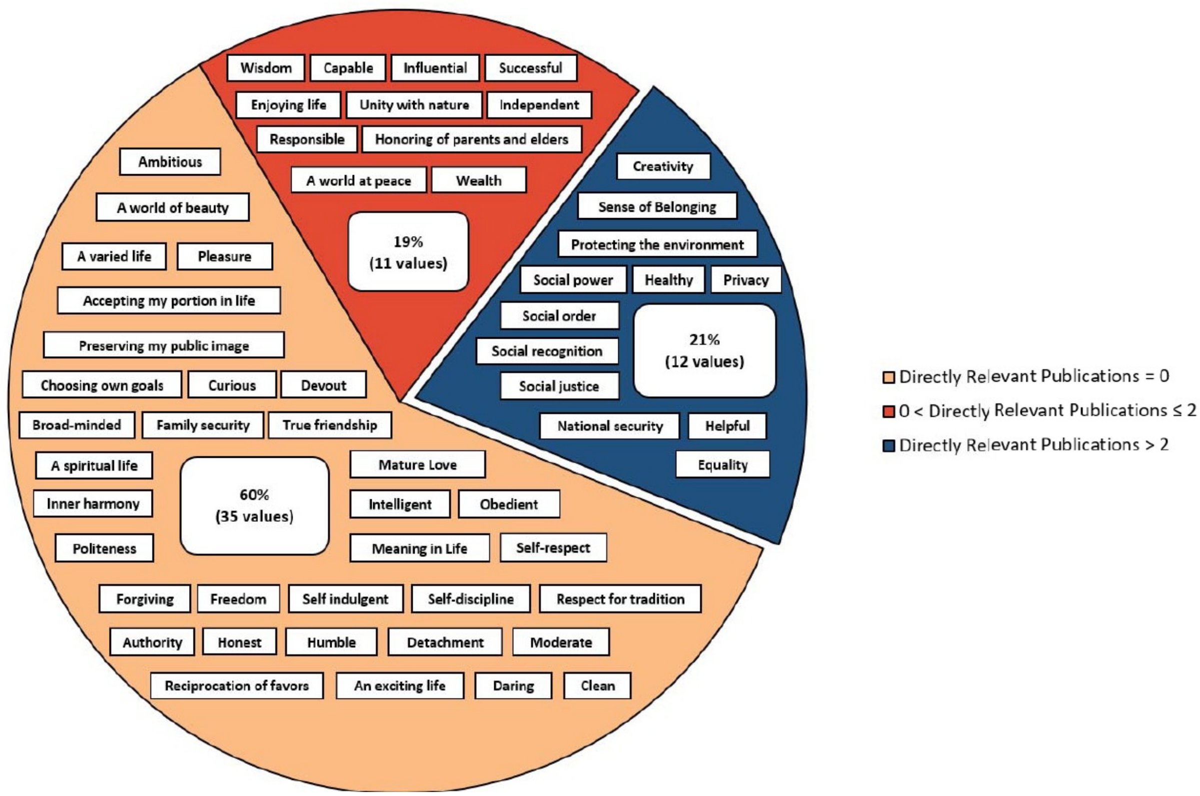

Figure 6: Level of Attention Given to 58 values in the Schwartz value structure according to Perera et al. [138]

in Chief of *Communications of the ACM*, has asserted even more strongly: "By and large, Big Tech workers do not seem to be asking themselves hard questions, I believe, hence my conclusion that we do indeed suffer from an ethics crisis" [173]. These authors conclude that we need to address the actions within our disciplines and profession from a more conscious ethical perspective and understand, and perhaps regulate, whose data, what assumptions, for whom and what purpose, who benefits and what decision making capabilities can be assumed or embedded.

A study by Perera et al. [138] focused on the prevalence of human values in software engineering publications, based on the Schwartz set of values [154, 155], discussed in Section 2.7 and Figure 1. The authors found that for the majority of the values, very few or no directly relevant publications were found. For instance, 60% of the Schwartz set of values were not reported in the set of papers analysed. Moreover, the study found that 82% of publications (1105 out of 1350 papers) were not directly relevant to Schwartz values [138]. This value-free perspective is in contrast with our discipline context, which is heavily-value laden. In addition, and critical to this study, we observe in Figure 6 that not only are references to values relatively rare but also, most importantly, the values that are not present also reflect those more reflective of a Global South perspective.

These aspects further the Digital Divide described above and highlights the critical role of computing educators in the Global Southsm who face an ethical and power imbalance which must be surmounted to participate in adopting this technology in our teaching and learning on any equitable basis [152].

5.5 Resolving Global and Local Tensions: Co-existence Strategies with Generative AIs?

A critical issue for many communities in the Global South remains the retention of data and algorithm sovereignty. To frame this issue, from a Māori perspective (Section 2.5, Te Taka Keegan has been quoted as saying:

> He thought if it could be isolated, trained by Māori, and controlled at an *iwi* [tribe] level, Māori could retain sovereignty and use it as a helpful tool...We need to make sure it is cut off from the mothership, that it wasn't feeding everything back to the mothership, because everyone loses if that's the case [102].

This quote highlights the tensions in the Global South between colonising global forces and local data governance. To address this, the balance in Generative AIs, especially LLMs, between Foundation Models and Retrieval Augmented Generation (RAG) models may provide a way forward. To build on this, Munn sets five tests for evaluating AI, addressing concerns over what is "prohibited" in the context of a specific community; risks to the lifeworld of participants - such as ecological risks of AI "stressing the dense connections between care for the earth, care for community, and care for family"[119] ; the principle of 'reciprocity'; the test of 'precedent' such as maintaining control over traditional knowledge, expressed as "Our Data, Our Sovereignty, Our Future"[119] ; and a further set of principles including "whether something is ethically, culturally, spiritually, and medically right" [119].

In an example addressing the notion of 'values debt' by Hussain [88], generic foundation model algorithms and data were augmented with local data and algorithms to give more focus to their needs. Similarly in the study of the contribution of a Spanish-based RAG assistant [104], and in the study of a RAG-based chatbot that accesses *Stack Overflow* information [174] we see computing education examples of such collaborations.

As such, collaborative technology models may meet the challenge for constructive coexistence posed by Te Taka Keegan, who stresses the importance of ensuring such systems remain independent from centralised control and do not continuously transmit data back to external sources, as this would be detrimental for all involved. It may prove viable to adopt collaborative strategies such as these, based on orchestrating combinations of decentralized RAG architectural models as outlined by Hecking et al. [78] and Lu and colleagues [111]. Approaches where data is queried from the global model, where inputs are not shared externally, and those global outputs are then augmented by a firewalled local data set and set of secure local outputs, may meet these needs, noting the question of consideration and how are those needs satisfied by collaborating parties [75]:

> At present we have a serious problem with the business model of these data hoarders [Google, Baidu, Tiktok]. While we pay our physicians and lawyers for their services, we usually don't pay Google and TikTok. They make their money by exploiting our personal information. That's a problematic business model, one that we would hardly tolerate in other contexts Why should we agree to get free email services, social connections and entertainment from the tech giants in exchange for giving them control of our most sensitive data?

When viewed from a Global South perspective, these larger questions must be addressed if more equitable outcomes from partnership with large global corporations are ever to be based on more human values.

5.6 Limitations and Considerations

When reading this work, the following considerations and limitations should be taken into account. The scope of analysis for this work is broad, spanning multiple countries, cultures, regions, and languages. The working group report authors recognise that the papers considered for inclusion and analysis do not represent the entire corpus for several key reasons.

In this report, we were guided by institutional affiliation as a manageable mechanism for allocating the paper as potentially representing a voice from the Global South. But in making this determination, we necessarily omitted the considerations of the inherent intersectionality [48] of many authors from the Global South, who have relocated to institutions in the Global North and though dislocated, may still retain their own world views originating from the South.

Searching was undertaken for English language papers only. This excludes a number of languages that dominate in the Global South, including Chinese, French, Portuguese, and Spanish. Additionally, there is a risk that the selected papers lack the authenticity of papers written in the languages local people traditionally use, thus restricting the range of voices, and risking the introduction of a Global North perspective through translation training.

Academic publication cultures can vary, where some areas favour a focus on the quality of venue, while others favour the number of publications. This can have a direct impact on the perceived quality of work or the required degree of detail or depth in a given publication. In addition, in some countries and academic cultures, career advancement and promotion can depend upon the number and quality of publications and this can have a significant impact on how many publications emerge from a given region.

Several significant publishers have continued to operate closed access models, where access to previous publications and conference proceedings require a paid licence or subscription. In some cases, where there is an OpenAccess model, authors are required to pay to cover the Open Access fees. In both cases, many academics in the Global South have restricted resources, which may limit their publication to low-cost or more available venues, which can be harder to locate, may be in local language, and may not be available online. The existence of predatory journals, with lower bars to entry from a quality perspective, and a model akin to vanity publishing can lead to published work being unlikely to reach the mainstream corpus. These journals can prey on smaller, more isolated communities. These tensions made determining what to include complex; trying to balance the requirements of the environment with identifying best practice. Measures such as whether a venue is Scopus Indexed can be a proxy for venue quality, however these research and publication quality metrics can differ on a per-country basis for publication standards including iCore ranks, SciMago journal ranks, and the level of accompanying funding. We did not impose explicit quality assessment criteria, as this would have immediately restricted the search to a much smaller set of venues, many of which do not frequently include Global South authors. Hence any paper that met the inclusion criteria was used to extract relevant information. This does, however, introduce the risk that some papers may introduce concepts or unsupported concept interpretations that could reduce corpus credibility due to different levels of peer review.

6 Conclusion

In this paper we address a critical gap in existing literature by bringing to the foreground ethical perspectives and considerations of Generative AI in computing education in the Global South. Our study has identified 110 ethical concepts from a variety of Global South ethical frameworks and has presented a deep analysis of how each of these concepts are considered in the literature in relation to Generative AI. This work surfaces values frameworks and systems and local priorities and concerns that are not often found in Western, prevailing narratives. We highlight how responsibility, a community-centered focus, and data sovereignty shape ethical reasoning about Generative AI in computing education.

Our analysis has also highlighted significant challenges that have yet to be addressed. Firstly, the Digital Divide across infrastructure, resources, and language representation means that Global South values and concerns might not necessarily be easily addressed. Secondly, the lack of regulatory infrastructure might lead to critical aspects of ethics such as transparency, accountability and harm metrics to not be enforced, even if a regulatory framework exists. Lastly, community and cultural contexts are critical when considering teaching with Generative AI in computing education and beyond.

This work provides educators, researchers, and policymakers with a systematically grounded ethical lens for engaging with Generative AI in computing education that extends beyond dominant Western frameworks. Beyond the focus on Generative AI within our interpretative analysis presented in an extensive glossary of ethical concepts and their relationship with Generative AI, the ethical supports identified are useful in providing a non-Western focus and contextualisation of ethical concerns within computing education, framing conversations on how we teach, learn, build and deploy software and computer systems with a more diverse and inclusive perspective.

References

[1] Yasir Abdelgadir Mohamed, Abdul Hakim H. M. Mohamed, Akbar Khanan, Mohamed Bashir, Mousab A. E. Adiel, and Muawia A. Elsadig. 2024. Navigating the Ethical Terrain of AI-Generated Text Tools: A Review. *IEEE Access* 12 (2024), 197061–197120. doi:10.1109/ACCESS.2024.3521945

[2] Mohammad Abolnejadian, Sharareh Alipour, and Kamyar Taeb. 2024. Leveraging chatgpt for adaptive learning through personalized prompt-based instruction: A cs1 education case study. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*. 1–8.

[3] Ibrahim Adam, Muftawu Dzang Alhassan, and Abdoulaye Diack. 2024. Exploring the Pedagogical Approaches for Generative AI Integration in Computing Education in Ghana: A Constructivist Perspective.

[4] Nimisha Agarwal, Viraj Kumar, Arun Raman, and Amey Karkare. 2023. A Bug's New Life: Creating Refute Questions from Filtered CS1 Student Code Snapshots. In *Proceedings of the ACM Conference on Global Computing Education Vol 1*. 7–14.

[5] Akiko Aizawa. 2003. An information-theoretic perspective of tf–idf measures. *Information Processing & Management* 39, 1 (2003), 45–65.

[6] Akinmayowa Akin-Otiko. 2024. Hu Ìwà Sí i bí Ènìyàn Ẹlé-ran-Ara a (act towards the other as one with human flesh): A Yoruba theory of social interactions. *Social Sciences & Humanities Open* 10 (2024), 100936. doi:10.1016/j.ssaho.2024.100936

[7] Dasta Alamayo. 2021. Safuu: The indigenous Oromo moral thought. *Journal of Philosophy and Culture* 9, 1 (2021), 1–10.

[8] May Alashwal. 2025. Generative AI in Computer Science Education: Insights from Topic Modeling and Text Network Analysis. In *2025 2nd International Conference on Advanced Innovations in Smart Cities (ICAISC)*. IEEE, 1–5.

[9] Sara Alaswad, Tatiana Kalganova, and Wasan Awad. 2025. Developing a Framework for Using Large Language Models for Viva Assessments in Higher Education. In *2024 International Conference on IT Innovation and Knowledge Discovery (ITIKD)*. IEEE, 1–7.

[10] Chris Jordan G Aliac, Meachelle Nicole A Abella, Jun Cyric Shane S Dela Torre, and Sheer Jay A Piodos. 2025. LitterBox: A Teaching Assistant ChatBot for Computer Organization and Architecture. In *2025 11th International Conference on Education and Training Technologies (ICETT)*. IEEE, 153–161.

[11] Wajdi Aljedaani, Marcelo Medeiros Eler, and PD Parthasarathy. 2025. Enhancing accessibility in software engineering projects with large language models (llms). In *Proceedings of the 56th ACM Technical Symposium on Computer Science Education V. 1*. 25–31.

[12] Isaac Alpizar-Chacon and Hieke Keuning. 2025. Student's Use of Generative AI as a Support Tool in an Advanced Web Development Course. In *Proceedings of the 30th ACM Conference on Innovation and Technology in Computer Science Education V. 1*. 312–318.

[13] Sihem Amer-Yahia, Angela Bonifati, Lei Chen, Guoliang Li, Kyuseok Shim, Jianliang Xu, and Xiaochun Yang. 2023. From large language models to databases and back: A discussion on research and education. *ACM SIGMOD Record* 52, 3 (2023), 49–56.

[14] Laud Nii Attoh Ammah, Christoph Lütge, Alexander Kriebitz, and Lavina Ramkissoon. 2024. AI4people - an ethical framework for a good AI society: the Ghana (Ga) perspective. 22, 4 (2024), 453–465. doi:10.1108/JICES-06-2024-0072

[15] Joanah Pwanedo Amos, Oluwatosin Ahmed Amodu, Raja Azlina Raja Mahmood, Akanbi Bolakale Abdulqudus, Anies Faziehan Zakaria, Abimbola Rhoda Iyanda, Umar Ali Bukar, and Zurina Mohd Hanapi. 2025. A bibliometric exposition and review on leveraging LLMs for Programming Education. *IEEE Access* (2025).

[16] Lameck Mbangula Amugongo, Nicola J. Bidwell, and Caitlin C. Corrigan. 2023. Invigorating Ubuntu Ethics in AI for healthcare: Enabling equitable care. 583–592 pages. doi:10.1145/3593013.3594024

[17] Ronald E Anderson. 1992. ACM code of ethics and professional conduct. *Commun. ACM* 35, 5 (1992), 94–99.

[18] J. Á. Ariza, M. B. Restrepo, and C. H. Hernández. 2025. Generative AI in engineering and computing education: A scoping review of empirical studies and educational practices. *IEEE Access* (2025).

[19] Utkarsh Arora, Anupam Garg, Aryan Gupta, Samyak Jain, Ronit Mehta, Rupin Oberoi, Prachi, Aryaman Raina, Manav Saini, Sachin Sharma, et al. 2025. Analyzing llm usage in an advanced computing class in india. In *Proceedings of the 27th Australasian Computing Education Conference*. 154–163.

[20] Douglas Asante and Thomas Archibald. 2023. Beyond Ubuntu: Nnoboa and Sankofa as decolonizing and Indigenous evaluation epistemic foundations from Ghana. *Journal of MultiDisciplinary Evaluation* 19, 44 (2023), 156–165.

[21] Australian Institute of Aboriginal and Torres Strait Islander Studies. 2020. Access and Use Policy: AIATSIS Collection. https://aiatsis.gov.au/sites/default/files/2020-09/aiatsis-access-and-use-policy-20180.pdf. Accessed on 9 January 2026.

[22] Australian Institute of Aboriginal and Torres Strait Islander Studies. 2020. AIATSIS Code of Ethics for Aboriginal and Torres Strait Islander Research. https://aiatsis.gov.au/sites/default/files/2020-10/aiatsis-code-ethics.pdf. Accessed on 9 January 2026.

[23] Godwin Azenabor. 2022. Omoluabi: An African Conception of moral values. *Thought and Practice* 8, 2 (2022), 63–81.

[24] Rishabh Balse, Viraj Kumar, Prajish Prasad, and Jayakrishnan Madathil Warriem. 2023. Evaluating the quality of llm-generated explanations for logical errors in cs1 student programs. In *Proceedings of the 16th annual ACM India compute conference*. 49–54.

[25] Jamie Baxter. 2020. Text and Textual Analysis. In *International Encyclopedia of Human Geography (Second Edition)* (second edition ed.), Audrey Kobayashi (Ed.). Elsevier, Oxford, 239–243. doi:10.1016/B978-0-08-102295-5.10872-8

[26] Tom Beauchamp and James Childress. 2019. Principles of biomedical ethics: marking its fortieth anniversary. *The American journal of bioethics* 19, 11 (2019), 9–12. doi:10.1080/15265161.2019.16654

[27] Sarah Beecham, Tony Clear, John Barr, and John Noll. 2015. *Protocol for Challenges and Recommendations for the Design and Conduct of Global Software Engineering Courses: A Systematic Review.* Report "ITiCSE Working Group One: Technical Report No. Lero_TR_2015_01). Lero.

[28] James Belich. 2011. *Replenishing the earth: The settler revolution and the rise of the Angloworld.* OUP Oxford.

[29] Emily M Bender, Timnit Gebru, Angelina McMillan-Major, and Shmargaret Shmitchell. 2021. On the dangers of stochastic parrots: Can language models be too big?. In *Proceedings of the 2021 ACM conference on fairness, accountability, and transparency*. 610–623.

[30] Maicon Bernardino, Rodrigo Cargnelutti, Renato de Souza Garcia, and Williamson Silva. 2024. The use of ChatGPT in improving and reviewing scientific paper writing: an exploratory study. *IEEE Revista Iberoamericana de Tecnologias del Aprendizaje* (2024).

[31] Seth Bernstein, Paul Denny, Juho Leinonen, Lauren Kan, Arto Hellas, Matt Littlefield, Sami Sarsa, and Stephen Macneil. 2024. " Like a Nesting Doll": Analyzing Recursion Analogies Generated by CS Students Using Large Language Models. In *Proceedings of the 2024 on Innovation and Technology in Computer Science Education V. 1*. 122–128.

[32] Seth Bernstein, Ashfin Rahman, Nadia Sharifi, Ariunjargal Terbish, and Stephen MacNeil. 2025. Beyond the Benefits: A Systematic Review of the Harms and Consequences of Generative AI in Computing Education. In *Proceedings of the 25th Koli Calling International Conference on Computing Education Research*. 1–18.

[33] Humnath Bhandari and Kumi Yasunobu. 2009. What is social capital? A comprehensive review of the concept. *Asian Journal of Social Science* 37, 3 (2009), 480–510.

[34] Esdras L Bispo Jr, Simone Cristiane dos Santos, and Marcus VAB De Matos. 2023. Equity issues derived from use of large language models in education. In *International Conference on New Media Pedagogy*. Springer, 425–440.

[35] Anis Boubaker and Ying Fang. 2025. Automated Generation of Challenge Questions for Student Code Evaluation Using Abstract Syntax Tree Embeddings and RAG: An Exploratory Study. In *Proceedings of the 2024 7th International Conference on Educational Technology Management (ICETM '24)*. Association for Computing Machinery, New York, NY, USA, 277–282. doi:10.1145/3711403.3711450

[36] John R Bowen. 2003. *Islam, law, and equality in Indonesia: An anthropology of public reasoning.* Cambridge University Press.

[37] Louisa Brooke-Holland. 2024. *What is the Global South?* Report. UK Parliament - House of Commons Library. https://commonslibrary.parliament.uk/what-is-the-global-south/

[38] Paul T Brown, Daniel Wilson, Kiri West, Kirita-Rose Escott, Kiya Basabas, Ben Ritchie, Danielle Lucas, Ivy Taia, Natalie Kusabs, and Te Taka Keegan. 2023. Maori algorithmic sovereignty: idea, principles, and use. *arXiv* (2023). doi:10.48550/arXiv.2311.15473 Brown, Paul T., Daniel Wilson, Kiri West, Kirita-Rose Escott, Kiya Basabas, Ben Ritchie, Danielle Lucas, Ivy Taia, Natalie Kusabs, and Te Taka Keegan. "Māori algorithmic sovereignty: idea, principles, and use." arXiv preprint arXiv:2311.15473 (2023)..

[39] Ritvik Budhiraja, Ishika Joshi, Jagat Sesh Challa, Harshal D Akolekar, and Dhruv Kumar. 2024. "It's not like Jarvis, but it's pretty close!"-Examining ChatGPT's Usage among Undergraduate Students in Computer Science. In *Proceedings of the 26th Australasian Computing Education Conference.* 124–133.

[40] Santhush Chandrasekara, Dileep Hewavitharana, Maleesha Weerasinghe, Binod Gayasri, Dinuka Wijendra, and Dilshan De Silva. 2025. Gamifying Coding Education for Beginners: Empowering Learners with HTML, CSS and JavaScript. In *2025 International Research Conference on Smart Computing and Systems Engineering (SCSE).* IEEE, 1–7.

[41] Natasha Chassagne. 2020. *Buen Vivir as an alternative to sustainable development: Lessons from Ecuador.* Routledge.

[42] Liuqing Chen, Shuhong Xiao, Yunnong Chen, Yaxuan Song, Ruoyu Wu, and Lingyun Sun. 2024. ChatScratch: An AI-augmented system toward autonomous visual programming learning for children aged 6-12. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems.* 1–19.

[43] Alison Clear, Allen Parrish, and CC2020 Task Force. 2020. *Computing Curricula 2020 - CC2020 - Paradigms for Future Computing Curricula.* Report. ACM. doi:DOI: 10.1145/3467967

[44] Tony Clear. 2011. Exploring the notion of 'cultural fit' in global virtual collaborations. *ACM Inroads* 1, 3 (2011), 58–65. doi:10.1145/1835428.1835444

[45] Tony Clear. 2017. THINKING ISSUES: What's Driving Uber? Values in Computing and the 'Sharing Economy'. *ACM Inroads* 8, 4 (2017), 38–40. doi:10.1145/3148547

[46] Tony Clear. 2024. THINKING ISSUES: Large Language Models, the 'Doctrine of Discovery' and 'Terra Nullius' Declared Again? *ACM Inroads* 15, 2 (2024), 6–9. doi:10.1145/3638564

[47] Tony Clear and Stephen G. MacDonell. 2010. Beyond "Temponomics" - The Many Dimensions of Time in Globally Distributed Project Teams. 297-304 pages. 10.1109/ICGSE.2010.56

[48] Patricia Hill Collins, Elaini Cristina Gonzaga da Silva, Emek Ergun, Inger Furseth, Kanisha D Bond, and Jone Martínez-Palacios. 2021. Intersectionality as critical social theory: Intersectionality as critical social theory, Patricia Hill Collins, Duke University Press, 2019. *Contemporary Political Theory* 20, 3 (2021), 690.

[49] Tom Crick, Tom Prickett, Christina Vasiliou, Neeranjan Chitare, and Ian Watson. 2023. Exploring Computing Students' Post-Pandemic Learning Preferences with Workshops: A UK Institutional Case Study. In *Proceedings of the 2023 Conference on Innovation and Technology in Computer Science Education V. 1* (Turku, Finland) *(ITiCSE 2023).* Association for Computing Machinery, New York, NY, USA, 173–179. doi:10.1145/3587102.3588807

[50] Daniela S Cruzes and Tore Dyba. 2011. *Recommended steps for thematic synthesis in software engineering.* IEEE, 275–284.

[51] Claudio Cubillos, Rafael Mellado, Daniel Cabrera-Paniagua, and Enrique Urra. 2025. Generative Artificial Intelligence in Computer Programming: Does it enhance learning, motivation, and the learning environment? *IEEE Access* (2025).

[52] Javier Cuestas-Caza. 2018. Sumak kawsay is not buen vivir. *Alternautas* 5, 1 (2018).

[53] Nour Dados and Raewyn Connell. 2012. The global south. *Contexts* 11, 1 (2012), 12–13.

[54] Karl de Fine Licht. 2025. Rethinking the Ethics of GenAI in Higher Education: A Critique of Moral Arguments and Policy Implications. *Journal of Applied Philosophy* (2025).

[55] Imed Ben Dhaou, Hannu Tenhunen, Jouni Isoaho, Xing Guo, and Zhuo Zou. 2025. Rethinking ICT Engineering with Transformative Impact of AI-Based Innovation and Co-Creation. In *2025 IEEE 5th International Conference on Human-Machine Systems (ICHMS).* IEEE, 397–402.

[56] Otávio Lube Dos Santos and Davidson Cury. 2023. Challenging the confirmation bias: Using ChatGPT as a virtual peer for peer instruction in computer programming education. In *2023 IEEE Frontiers in Education Conference (FIE).* IEEE, 1–7.

[57] Haizhou Du, Wenhao Li, Xiaoyu Ding, and Huan Huo. 2024. Can LLMs Understand Parallel and Distributed Machine Learning Algorithms in AIoT?. In *2024 8th Asian Conference on Artificial Intelligence Technology (ACAIT).* IEEE, 501–510.

[58] Helen L. Dulock. 1993. Research Design: Descriptive Research. *Journal of Pediatric Oncology Nursing* 10, 4 (1993), 154–157. arXiv:https://doi.org/10.1177/104345429301000406 doi:10.1177/104345429301000406 PMID: 8251123.

[59] Severin Engelmann, Madiha Zahrah Choksi, Angelina Wang, and Casey Fiesler. 2024. Visions of a discipline: Analyzing introductory AI courses on YouTube. In *Proceedings of the 2024 ACM Conference on Fairness, Accountability, and Transparency.* 2400–2420.

[60] Edwin Etieyibo. 2022. *On the One Concept and Many Accounts of African Ethics.* Springer International Publishing, Cham, 125–143. doi:10.1007/978-3-030-70436-0_9

[61] Anna Lyza Felipe, Ushik Shrestha Khwakhali, and Thanh Ngoc Nguyen. 2025. A Framework for Assessment Design in the Era of Generative AI: Case Study of Take-Home Assignment in Software-related Courses. In *2025 10th International STEM Education Conference (iSTEM-Ed).* IEEE, 1–6.

[62] Anna Fischer. 2023. Data Sovereignty and E-Governance: The Legal Implications of National Laws on Digital Government Systems. *Legal Studies in Digital Age* 2, 4 (2023), 1–12.

[63] Eduard Frankford, Clemens Sauerwein, Patrick Bassner, Stephan Krusche, and Ruth Breu. 2024. Ai-tutoring in software engineering education. In *Proceedings of the 46th International Conference on Software Engineering: Software Engineering Education and Training.* 309–319.

[64] André Pimenta Freire, Paula Christina Figueira Cardoso, and André de Lima Salgado. 2023. May we consult chatgpt in our human-computer interaction written exam? an experience report after a professor answered yes. In *Proceedings of the XXII Brazilian Symposium on Human Factors in Computing Systems.* 1–11.

[65] Rong Gao, Qin Ni, and Bingying Hu. 2024. Fairness of large language models in education. In *Proceedings of the 2024 International Conference on Intelligent Education and Computer Technology.* 1.

[66] Çağdaş Evren Gerede. 2024. Are We Asking the Right Questions to ChatGPT for Learning Software Design Patterns?. In *2024 9th International Conference on Computer Science and Engineering (UBMK).* IEEE, 1092–1097.

[67] Sebastian Gomez-Jaramillo, Omar Cardona-Zapata, Manuel Valbuena-Henao, and Valeria Poliche. 2025. Guided Learning with AI: A Didactic Strategy Using Sequential Tutoring via ChatGPT for Object-Oriented Programming. *International Journal of Learning, Teaching and Educational Research* 24, 7 (2025), 717–736. doi:10.26803/ijlter.24.7.35

[68] Don Gotterbarn, Keith Miller, and Simon Rogerson. 1999. Computer society and ACM approve software engineering code of ethics. *Computer* 32, 10 (1999), 84–88.

[69] Ali Asker Guenduez, Nora Walker, and Mehmet Akif Demircioglu. 2025. Digital ethics: Global trends and divergent paths. *Government Information Quarterly* 42, 3 (2025), 102050.

[70] Kwame Gyekye. 2025. African Ethics. In *The Stanford Encyclopedia of Philosophy* (Summer 2025 ed.), Edward N. Zalta and Uri Nodelman (Eds.). Metaphysics Research Lab, Stanford University.

[71] Avval Halani, Prajish Prasad, and Aamod Sane. 2024. Exploring the Effectiveness of a Multilingual Generative AI Programming Chatbot for Vernacular Medium CS Students. In *Annual ACM India Compute Conference.* Springer, 44–57.

[72] Sally Hamouda, Ethel Tshukudu, Linda Marshall, Kehinde Aruleba, Cleverence Kombe, Janet Shufor Bih Fofang, Joseph Kizito Bada, Emmanuel Okyere Ekwam, Nils Timm, and Tessema Mengistu. 2025. Expanding Contextualized Computer Science Education in Africa: A Collaborative Initiative. In *Proceedings of the ACM Global on Computing Education Conference 2025 Vol 2.* 376–378.

[73] Kuntong Han, Keyang Tang, and Meng Wang. 2025. Stage Wizard: Enhancing Tangible Storytelling with Multimodal LLMs. In *Proceedings of the Nineteenth International Conference on Tangible, Embedded, and Embodied Interaction.* 1–13.

[74] Ching Nam Hang, Chee Wei Tan, and Pei-Duo Yu. 2024. MCQGen: A large language model-driven MCQ generator for personalized learning. *IEEE Access* 12 (2024), 102261–102273.

[75] Yuval Noah Harari. 2024. *Nexus: A brief history of information networks from the Stone Age to AI.* Fern Press.

[76] Epeli Hau'Ofa. 2017. *Our sea of islands.* Routledge, 429–442.

[77] Sannidhi V Hebbar, Sasmita Harini S, and Viraj Kumar. 2025. Refuting LLM-generated Code with Reactive Task Comprehension. In *Proceedings of the 30th ACM Conference on Innovation and Technology in Computer Science Education V. 1.* 30–36.

[78] Tobias Hecking, Thorsten Sommer, and Michael Felderer. 2025. An Architecture and Protocol for Decentralized Retrieval Augmented Generation. In *2025 IEEE 22nd International Conference on Software Architecture Companion (ICSA-C).* IEEE, 31–35. doi:10.1109/ICSA-C65153.2025.00012

[79] Andrés Domínguez Hernández, Diana Mosquera, and Francisco Gallegos. 2025. Lessons from the margins: Contextualizing, reimagining, and hacking generative AI in the Global South. *Harvard Data Science Review* 7, 4 (2025).

[80] Hilene E Hernandez, Ranie B Canlas, Madilaine Claire B Nacianceno, Jordan L Salenga, Jaymark A Yambao, Juvy C Grume, Aileen P De Leon, Freneil R Pampo, and John Paul P Miranda. 2025. Trust, Usefulness, and Dependency on AI in Programming: A Hierarchical Clustering Approach. In *2025 7th International Conference on Computer Science and Technologies in Education (CSTE).* IEEE, 30–34.

[81] Dalia Walid Hewedy and Aya Salama Abdelhady. 2025. PETRA: A Personalized Educational Tutoring Tool for Recursive Assistance Leveraging Multi-model LLMs for Dynamic Programming Learning. In *2025 15th International Conference on Electrical Engineering (ICEENG)*. IEEE, 1–6.

[82] Wayne Holmes, Fengchun Miao, et al. 2023. *Guidance for generative AI in education and research*. Unesco Publishing.

[83] Nan Hong and Jiao Huang. 2024. Large Language Models in Teaching and Learning: Bibliometrics, Educational Paradigms, Risks and Challenges and Coping Strategies. In *2024 International Conference on Artificial Intelligence and Digital Libraries (AIDL)*. IEEE, 32–37.

[84] Zichang Hong. 2025. Research on the Innovative Application of AIGC in Programming Education: A Case Study of Code Generation and Intelligent Feedback System Design. In *Proceedings of the 2nd Guangdong-Hong Kong-Macao Greater Bay Area International Conference on Digital Economy and Artificial Intelligence*. 1368–1373.

[85] Xinying Hou, Zihan Wu, Xu Wang, and Barbara J Ericson. 2024. Codetailor: Llm-powered personalized parsons puzzles for engaging support while learning programming. In *Proceedings of the Eleventh ACM Conference on Learning@ Scale*. 51–62.

[86] Bingying Hu, Qin Ni, and Rong Gao. 2024. Development Strategies and Practical Insights of Teachers' Artificial Intelligence Competence. In *Proceedings of the 2024 International Conference on Intelligent Education and Computer Technology*. 1.

[87] Maui Hudson, Moe Milne, Paul Reynolds, Khyla Russell, and Barry Smith. 2010. Te Ara Tika: Guidelines for Māori research ethics: A framework for researchers and ethics committee members. *Health Research Council of New Zealand* 9 (2010), 1–29.

[88] W. Hussain. 2025. Mitigating Values Debt in Generative AI: Responsible Engineering with Graph RAG. In *2025 IEEE/ACM International Workshop on Responsible AI Engineering (RAIE)*. 9–12. doi:10.1109/RAIE66699.2025.00006

[89] Hassan Iddy. 2021. Indigenous standpoint theory: ethical principles and practices for studying Sukuma people in Tanzania. *The Australian Journal of Indigenous Education* 50, 2 (2021), 385–392.

[90] Pooriya Jamie, Reyhaneh Hajihashemi, and Sharareh Alipour. 2025. Utilizing ChatGPT in a Data Structures and Algorithms Course: A Teaching Assistant's Perspective. In *Proceedings of the Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*. 1–7.

[91] Kaiyue Jia and Junnan Yu. 2025. Technologies for Children's AI Learning: Design Features and Future Opportunities. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems (CHI '25)*. Association for Computing Machinery, New York, NY, USA, Article 1196, 22 pages. doi:10.1145/3706598.3713443

[92] Hyoungwook Jin, Yoonsu Kim, Yeon Su Park, Bekzat Tilekbay, Jinho Son, and Juho Kim. 2024. Using large language models to diagnose math problem-solving skills at scale. In *Proceedings of the eleventh ACM conference on learning@ scale*. 471–475.

[93] Anna Jobin, Marcello Ienca, and Effy Vayena. 2019. The global landscape of AI ethics guidelines. *Nature machine intelligence* 1, 9 (2019), 389–399. doi:10.1038/s42256-019-0088-2

[94] Ishika Joshi, Ritvik Budhiraja, Harshal Dev, Jahnvi Kadia, Mohammad Osama Ataullah, Sayan Mitra, Harshal D Akolekar, and Dhruv Kumar. 2024. ChatGPT in the classroom: An analysis of its strengths and weaknesses for solving undergraduate computer science questions. In *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1*. 625–631.

[95] Guo Jun, Guo Yan Ting, and Zheng Yan Song. 2024. A question-and-answer system based on artificial intelligence. In *Proceedings of the 2024 the 12th International Conference on Information Technology (ICIT)*. 299–305.

[96] Asha Gowda Karegowda, Shreetha Bhat, Vineeth S Naidu, et al. 2025. Enriching Learning Experience Using Gemma-the Intelligent Chat Companion. In *2025 3rd International Conference on Smart Systems for applications in Electrical Sciences (ICSSES)*. IEEE, 1–6.

[97] Oscar Karnalim, Hapnes Toba, Meliana Christianti Johan, Erico Darmawan Handoyo, Yehezkiel David Setiawan, and Josephine Alvina Luwia. 2023. Plagiarism and AI Assistance Misuse in Web Programming: Unfair Benefits and Characteristics. In *2023 IEEE International Conference on Teaching, Assessment and Learning for Engineering (TALE)*. 1–5. doi:10.1109/TALE56641.2023.10398397

[98] Enkelejda Kasneci, Kathrin Seßler, Stefan Küchemann, Maria Bannert, Daryna Dementieva, Frank Fischer, Urs Gasser, Georg Groh, Stephan Günnemann, Eyke Hüllermeier, et al. 2023. ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and individual differences* 103 (2023), 102274.

[99] Marzooqa Naeema Kather, R Srimathi, et al. 2025. GDT: Generate, Debug, and Translate Code. In *2025 International Conference on Innovative Trends in Information Technology (ICITIIT)*. IEEE, 1–6.

[100] Majeed Kazemitabaar, Justin Chow, Carl Ka To Ma, Barbara J Ericson, David Weintrop, and Tovi Grossman. 2023. Studying the effect of AI code generators on supporting novice learners in introductory programming. In *Proceedings of the 2023 CHI conference on human factors in computing systems*. 1–23.

[101] Damien Keown. 2020. *Buddhist ethics: A very short introduction*. Oxford University Press.

[102] Libby Kirkby-McLeod. 2023. How will ChatGPT impact te reo Māori? Data sovereignty experts weigh in. *RNZ* (June 13, 2023 2023). https://www.rnz.co.nz/news/te-manu-korihi/491925/how-will-chatgpt-impact-te-reo-maori-data-sovereignty-experts-weigh-in

[103] Joakim Laine, Matti Minkkinen, and Matti Mäntymäki. 2025. Understanding the ethics of generative AI: Established and new ethical principles. *Communications of the Association for Information Systems* 56, 1 (2025), 7.

[104] Gabriel A León-Paredes, Luis A Alba-Narváez, and Kelly D Paltin-Guzmán. 2025. NOVA: A Retrieval-Augmented Generation Assistant in Spanish for Parallel Computing Education with Large Language Models. *Applied Sciences* 15, 15 (2025), 8175.

[105] Linze Li, Cixiao Wang, Jiaqi Chen, Haozhi Sun, and Hanbo Zhang. 2024. Artificial Intelligence Education Policy Analysis From International Perspective. In *Proceedings of the 2024 7th International Conference on Educational Technology Management*. 264–270.

[106] Pengfei Li, Jianyi Yang, Mohammad A Islam, and Shaolei Ren. 2023. Making ai less" thirsty": Uncovering and addressing the secret water footprint of ai models. *arXiv preprint arXiv:2304.03271* (2023).

[107] Mark Liffiton, Brad E Sheese, Jaromir Savelka, and Paul Denny. 2023. Codehelp: Using large language models with guardrails for scalable support in programming classes. In *Proceedings of the 23rd Koli Calling International Conference on Computing Education Research*. 1–11.

[108] Yumi Chin Yin Lim and Kai Weng. 2024. Automated Coding Challenges Assembly Using Pre-trained Programming Language Models. In *Proceedings of the 2024 on ACM Virtual Global Computing Education Conference V. 1*. 123–129.

[109] Runda Liu, Shengqi Chen, Jiajie Chen, Songjie Niu, Yuchun Ma, and Xiaofeng Tang. 2025. Iterative Design of a Teaching Assistant Training Program in Computer Science Using the Agile Method. In *Proceedings of the 56th ACM Technical Symposium on Computer Science Education V. 1*. 680–686.

[110] Yangtao Liu, Hengyuan Liu, Zezhong Yang, Zheng Li, and Yong Liu. 2024. Empirical Evaluation of Large Language Models for Novice Program Fault Localization. In *2024 IEEE 24th International Conference on Software Quality, Reliability and Security (QRS)*. IEEE, 180–191.

[111] Qinghua Lu, Liming Zhu, Xiwei Xu, Zhenchang Xing, and Jon Whittle. 2024. Toward responsible AI in the era of generative AI: A reference architecture for designing foundation model-based systems. *IEEE Software* 41, 6 (2024), 91–100. doi:10.1109/MS.2024.3406333

[112] Subhankar Maity, Aniket Deroy, and Sudeshna Sarkar. 2023. Harnessing the power of prompt-based techniques for generating school-level questions using large language models. In *Proceedings of the 15th annual meeting of the forum for information retrieval evaluation*. 30–39.

[113] Janice Mak, Joyce Nakatumba-Nabende, Tony Clear, Alison Clear, Ibrahim Albluwi, Oana Andrei, Lorenzo Angeli, Stephen MacNeil, Solomon Sunday Oyelere, Matthew Hale Rattigan, et al. 2025. Navigating the Ethical and Societal Impacts of Generative AI in Higher Computing Education. *arXiv preprint arXiv:2511.15768* (2025).

[114] Fainos Mangena. 2016. African Ethics through Ubuntu: A Postmodern Exposition. *The Journal of Pan-African Studies* 9 (2016), 66. https://api.semanticscholar.org/CorpusID:202893438

[115] Merriam-Webster. 2025. Merriam-Webster.com. https://www.merriam-webster.com. Accessed 22 Sep 2025.

[116] Ani Mikaere. 2007. Tikanga as the first law of Aotearoa. *Yearbook of New Zealand Jurisprudence* 10 (2007), 24–31.

[117] Katleho Karabo Mokoena. 2023. *Towards an Ubuntu/Botho Ethics of Technology*. Thesis. doi:Disclaimerletter Copyright - Database copyright ProQuest LLC; ProQuest does not claim copyright in the individual underlying works. Last updated - 2025-02-03.

[118] Niels Mulder. 2000. *Inside Southeast Asia: Religion, everyday life, cultural change*. Silkworm Books.

[119] Luke Munn. 2024. The five tests: designing and evaluating AI according to indigenous Māori principles. *AI & SOCIETY* 39, 4 (2024), 1673–1681. doi:10.1007/s00146-023-01636-x

[120] Ritwik Murali, Nitin Ravi, and Amruthiyu Surendran. 2024. Augmenting Virtual Labs with Artificial Intelligence for Hybrid Learning. In *2024 IEEE Global Engineering Education Conference (EDUCON)*. IEEE, 1–10.

[121] Abdullah Mushtaq, Rafay Naeem, Ibrahim Ghaznavi, Imran Taj, Imran Hashmi, and Junaid Qadir. 2025. Harnessing Multi-Agent LLMs for Complex Engineering Problem-Solving: A Framework for Senior Design Projects. In *2025 IEEE Global Engineering Education Conference (EDUCON)*. IEEE, 1–10.

[122] Susan Mwaniki, Eric Araka, Benson Kituku, and Elizaphan Maina. 2025. Students' Perceptions on the Use of Generative AI in Enhancing Teaching and Learning Computer Science Courses. In *2025 IST-Africa Conference (IST-Africa)*. IEEE, 1–11.

[123] Goda Nagakalyani, Saurav Chaudhary, Varsha Apte, Ganesh Ramakrishnan, and Srikanth Tamilselvam. 2025. Design and Evaluation of an AI-Assisted Grading Tool for Introductory Programming Assignments: An Experience Report. In

Proceedings of the 56th ACM Technical Symposium on Computer Science Education V. 1. 805–811.
[124] Daye Nam, Andrew Macvean, Vincent Hellendoorn, Bogdan Vasilescu, and Brad Myers. 2024. Using an llm to help with code understanding. In *Proceedings of the IEEE/ACM 46th International Conference on Software Engineering*. 1–13.
[125] National Health and Medical Research Council. 2018. *Ethical conduct in research with Aboriginal and Torres Strait Islander Peoples and communities*. Australian Government.
[126] Mamoun Nawahdah, Hadeel Sawalha, Rana Salameh, and Mohammad Taha. 2025. Evaluating the Accuracy and Effectiveness of AI-Based Grading in Computer Science Education. In *2025 International Conference on Smart Learning Courses (SCME)*. IEEE, 1–6.
[127] Andres Neyem, Juan Pablo Sandoval Alcocer, Marcelo Mendoza, Leonardo Centellas-Claros, Luis A Gonzalez, and Carlos Paredes-Robles. 2024. Exploring the impact of generative ai for standup report recommendations in software capstone project development. In *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1*. 951–957.
[128] Sydney Nguyen, Hannah McLean Babe, Yangtian Zi, Arjun Guha, Carolyn Jane Anderson, and Molly Q Feldman. 2024. How beginning programmers and code llms (mis) read each other. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*. 1–26.
[129] Yaw Ofosu-Asare. 2025. Guiding the future: developing an ethical framework for generative AI use in education. *The International Journal of Information and Learning Technology* (2025), 1–19.
[130] Online Consortium of Oklahoma. 2025. African Ethics. https://open.ocolearnok.org/ethics/chapter/traditional-african-ethics/. Accessed on 9 January 2026.
[131] Ana Carolina Oran, Letícia Braga Montenegro, Hellmut Alencar Schuster, José Carlos Duarte, Williamson Silva, and Rayfran Rocha Lima. 2024. Integrating ChatGPT in Project Management Education: Benefits and Challenges in the Academic Environment. In *Proceedings of the XXIII Brazilian Symposium on Software Quality (SBQS '24)*. Association for Computing Machinery, New York, NY, USA, 596–604. doi:10.1145/3701625.3701684
[132] Ikechukwu Monday Osebor and Carol C. Ohen. 2024. Egyptian Idea of Ma'at into the Healthcare to Cultivate Balance and Harmony. 9, 3 (2024), 151–156. doi:10.58709/niujhu.v9i3.1960
[133] Solomon Sunday Oyelere and Kehinde Aruleba. 2025. A comparative study of student perceptions on generative AI in programming education across Sub-Saharan Africa. *Computers and Education Open* 8 (2025).
[134] Ipek Ozkaya. 2019. Ethics is a software design concern. *IEEE Software* 36, 3 (2019), 4–8.
[135] Shengwu Pan, Qi Zeng, Mingjiang Li, and Na Yan. 2025. *Global and Domestic Perspectives on AI in Education: A Knowledge Mapping Analysis Using CiteSpace*. Association for Computing Machinery, New York, NY, USA, 404–415. https://doi.org/10.1145/3718491.3718558
[136] Teuila Percival and Alistair Woodward. 2011. *From Typhoid To Tsunamis: Samoan Children In A Changing World*. Nova Science Publishers, 189. http://ndl.ethernet.edu.et/bitstream/123456789/46617/1/23.pdf#page=208 Climate Change and Rural Health ISBN: Ed: E. Bell, B. M. Seidel and J. Merrick © 2011 Nova Science Publishers, In.
[137] Fabricio Pereira da Silva. 2020. The Community and the Paths of Critical Thinking in the Global Periphery: The Cases of sumak kawsay/suma qamaña and Ubuntu. In *New Paths of Development: Perspectives from the Global South*. Springer, 169–178.
[138] Harsha Perera, Waqar Hussain, Jon Whittle, Arif Nurwidyantoro, Davoud Mougouei, Rifat Ara Shams, and Gillian Oliver. 2020. A study on the prevalence of human values in software engineering publications, 2015 – 2018. 409–420 pages. doi:10.1145/3377811.3380393
[139] Marcelo Pias, Ernesto Cuadros-Vargas, and Rodrigo Duran. 2024. Computer Science Education in Latin America and the Caribbean. *ACM Inroads* 15, 1 (2024), 38–47.
[140] Farman Ali Pirzado, Awais Ahmed, Román Alejandro Mendoza-Urdiales, and Hugo Terashima-Marin. 2024. Navigating the pitfalls: analyzing the behavior of LLMs as a coding assistant for computer science students—a systematic review of the literature. *IEEE Access* 12 (2024), 112605–112625.
[141] Marie-Therese Png. 2022. At the tensions of south and north: Critical roles of global south stakeholders in AI governance. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*. 1434–1445.
[142] P. Prasad and A. Sane. 2024. A self-regulated learning framework using generative AI and its application in CS educational intervention design. In *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V.1 (SIGCSE 2024)*. ACM, 1–7. doi:10.1145/3626252.3630828
[143] James Prather, Paul Denny, Juho Leinonen, Brett A Becker, Ibrahim Albluwi, Michelle Craig, Hieke Keuning, Natalie Kiesler, Tobias Kohn, and Andrew Luxton-Reilly. 2023. *The robots are here: Navigating the generative ai revolution in computing education*. ACM, 108–159.
[144] James Prather, Juho Leinonen, Natalie Kiesler, Jamie Gorson Benario, Sam Lau, Stephen MacNeil, Narges Norouzi, Simone Opel, Vee Pettit, Leo Porter, Brent N. Reeves, Jaromir Savelka, David H. Smith, Sven Strickroth, and Daniel Zingaro. 2025. Beyond the Hype: A Comprehensive Review of Current Trends in Generative AI Research, Teaching Practices, and Tools. In *2024 Working Group Reports on Innovation and Technology in Computer Science Education (ITiCSE 2024)*. ACM, 300–338. doi:10.1145/3689187.3709614
[145] FK Pulotu-Endemann. 2009. Fonofale Model of Health. http://www.hpforum.org.nz/resources/Fonofalemodel.pdf Health Promotion Forum: Pacific Health Promotion Models 2009 Sep 7; Massey University Campus, Wellington. Wellington: Massey University, 2009]. Accessed 2009 Sep.
[146] Zachery Quince, Kathy Petkoff, Ruby N Michael, Scott Daniel, and Sasha Nikolic. 2024. The current ethical considerations of using GenAI in engineering education and practice: A systematic literature review. In *Proceedings of the 35th Annual Conference of the Australasian Association for Engineering Education (AAEE 2024)*. Engineers Australia Christchurch, New Zealand, 509–517.
[147] Chathura Rajapakse, Wathsala Ariyarathna, and Shanmugalingam Selvakan. 2024. A Self-Efficacy Theory-Based Study on the Teachers' Readiness to Teach Artificial Intelligence in Public Schools in Sri Lanka. *ACM Trans. Comput. Educ.* 24, 4, Article 47 (Nov. 2024), 25 pages. doi:10.1145/3691354
[148] Arun Raman and Viraj Kumar. 2022. Programming pedagogy and assessment in the era of AI/ML: A position paper. In *Proceedings of the 15th Annual ACM India Compute Conference*. 29–34.
[149] X. Ren, L. Tong, J. Zeng, and C. Zhang. 2023. AIGC scenario analysis and research on technology roadmap of Internet industry application. *China Communications* 20, 10 (2023), 292–304.
[150] Jennafer Shae Roberts and Laura N Montoya. 2023. In Consideration of Indigenous Data Sovereignty: Data Mining as a Colonial Practice. In *Proceedings of the Future Technologies Conference*. Springer, 180–196.
[151] Pramodya Samarakoon, Dinesh Asanka, Shantha Jayalal, and Nirasha Jayalath. 2024. Analyzing the Learning Effectiveness of Generative AI for Software Development for Undergraduates in Sri Lanka. In *2024 International Research Conference on Smart Computing and Systems Engineering (SCSE)*, Vol. 7. IEEE, 1–7.
[152] Morgan Klaus Scheuerman. 2024. In the walled garden: Challenges and opportunities for research on the practices of the AI tech industry. In *Proceedings of the 2024 ACM Conference on Fairness, Accountability, and Transparency*. 456–466.
[153] Carsten Schulte, Sue Sentance, Sören Sparmann, Rukiye Altin, Mor Friebroon-Yesharim, Martina Landman, Michael T. Rücker, Spruha Satavlekar, Angela Siegel, Matti Tedre, Laura Tubino, Henriikka Vartiainen, J. Ángel VelÁzquez-Iturbide, Jane Waite, and Zihan Wu. 2025. What We Talk About When We Talk About K-12 Computing Education *(ITiCSE 2024)*. Association for Computing Machinery, New York, NY, USA, 226–257. doi:10.1145/3689187.3709612
[154] Shalom H Schwartz. 1992. *Universals in the content and structure of values: Theoretical advances and empirical tests in 20 countries*. Vol. 25. Elsevier, 1–65. doi:10.1016/S0065-2601(08)60281-6
[155] Shalom H Schwartz. 2012. An overview of the Schwartz theory of basic values. *Online readings in Psychology and Culture* 2, 1 (2012), 11. doi:10.9707/2307-0919.1116
[156] Shalom H Schwartz. 2017. The refined theory of basic values. In *Values and behavior: Taking a cross cultural perspective*. Springer, 51–72.
[157] Priyanka Sebastian, Sumita Sharma, Netta Iivari, Marianne Kinnula, Charu Monga, Deepanshu Verma, and Muhammad Shahroz Abbas. 2024. Emerging technologies in global south classrooms: Teachers imagining future of education. In *Proceedings of the Participatory Design Conference 2024: Full Papers-Volume 1*. 234–247.
[158] Muhammad Shoaib, Ghassan Hasnain, Nasir Sayed, Yazeed Yasin Ghadi, Masoud Alajmi, and Ayman Qahmash. 2025. Automated Generation of Multiple-Choice Questions for Computer Science Education Using Conditional Generative Adversarial Networks. *IEEE Access* (2025).
[159] Muhtasim Ibteda Shochcho, Mohammad Ashfaq Ur Rahman, Shadman Rohan, Ashraful Islam, Hasnain Heickal, AKM Mahbubur Rahman, M Ashraful Amin, and Amin Ahsan Ali. 2025. Improving User Engagement and Learning Outcomes in LLM-Based Python Tutor: A Study of PACE. In *Proceedings of the Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*. 1–12.
[160] Mario Simaremare, Chandro Pardede, Irma Tampubolon, Putri Manurung, and Daniel Simangunsong. 2024. Pair Programming in Programming Courses in the Era of Generative AI: Students' Perspective. In *2024 31st Asia-Pacific Software Engineering Conference (APSEC)*. IEEE, 507–511.
[161] Zuleika Suliman, Ntshimane Elphas Mohale, Kgabo Bridget Maphoto, and Kershnee Sevnarayan. 2024. The interconnectedness between Ubuntu principles and generative artificial intelligence in distance higher education institutions. *Discover Education* 3, 1 (Oct. 2024), 188. doi:10.1007/s44217-024-00289-2
[162] Lu Sun. 2024. Human-Centered AI-Based Integrated Approach to Personalized Teaching and Assessment. In *2024 5th International Conference on Information Science and Education (ICISE-IE)*. IEEE, 379–386.
[163] Yuling Sun, Jiaju Chen, Bingsheng Yao, Jiali Liu, Dakuo Wang, Xiaojuan Ma, Yuxuan Lu, Ying Xu, and Liang He. 2024. Exploring Parent's Needs for Children-Centered AI to Support Preschoolers' Interactive Storytelling and Reading Activities. *Proceedings of the ACM on Human-Computer Interaction* 8, CSCW2 (2024), 1–25.

[164] Archana Pown T, Marzooqa Naeema Kather, Vazhan Arul Santhiya R, Pappathi Jancy Rani M, and Srimathi R. 2025. GDT: Generate, Debug, and Translate Code. In *2025 International Conference on Innovative Trends in Information Technology (ICITIIT)*. 1–6. doi:10.1109/ICITIIT64777.2025.11041511

[165] Karaitiana Taiuru. 2025. *State of the Nation – Māori Data Sovereignty/ Māori Data Governance in 2025 - Tino Rangatiratanga Raraunga ki Aotearoa 2025*. Taiuru & Associates Ltd. https://www.taiuru.co.nz/wp-content/uploads/2025/08/State-of-the-Nation-Report-FINAL.pdf

[166] Reza Tavasoli, Arya VarastehNezhad, Mostafa Masumi, and Fattaneh Taghiyareh. 2025. Analyzing the Mathematical Proficiency of Large Language Models in Computer Science Graduate Admission Tests. In *2025 29th International Computer Conference, Computer Society of Iran (CSICC)*. IEEE, 1–5.

[167] Mary Anne Teariki and Eseta Leau. 2024. Understanding Pacific worldviews: principles and connections for research. *Kōtuitui: New Zealand Journal of Social Sciences Online* 19, 2 (2024), 132–151.

[168] Telethon Kids Institute. 2022. Guidelines for the Standards for the Conduct of Aboriginal Health Research. https://www.thekids.org.au/globalassets/media/documents/aboriginal-standards-guidelines---july-2022.pdf. Accessed on 9 January 2026.

[169] Hapnes Toba, Laurentius Gusti Ontoseno Panata Yudha, Oscar Karnalim, Hendra Bunyamin, and Terutoshi Tada. 2024. A Large Language Model Question Generator Based on Bloom's Taxonomy Template. In *Proceeding of the 2024 8th International Conference on Education and E-Learning*. 25–31.

[170] Janette B. Torrato, Genevieve A. Pillar, Dave Arthur R. Robledo, Socorro E. Aguja, and Maricar S. Prudente. 2024. Knowledge, Attitudes, and Practices on ChatGPT:Perspectives from Students and Teachers of De La Salle Santiago Zobel School *(IC4E '24)*. Association for Computing Machinery, New York, NY, USA, 107–116. doi:10.1145/3670013.3670058

[171] UNESCO. 2023. *UNESCO's Recommendation on the Ethics of Artificial Intelligence: Key Facts*. United Nations Educational, Scientific and Cultural Organization.

[172] Tizziana Valdivieso and Oscar González. 2025. Generative AI Tools in Salvadoran Higher Education: Balancing Equity, Ethics, and Knowledge Management in the Global South. *Education Sciences* 15, 2 (2025).

[173] Moshe Y. Vardi. 2024. I Was Wrong about the Ethics Crisis. *Commun. ACM* 68, 1 (2024), 5. doi:10.1145/3704959

[174] Raj Vasaniya, Meet Visodiya, and Anand K Patel. 2025. TechAssist: A RAG-Based Chatbot for Accessing Technical Information from StackOverflow. In *2025 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS)*. IEEE, 1–6.

[175] Riti Verma, Ingmar Weber, and Vikram Kamath Cannanure. 2025. Exploring AI in Education: Child-Computer Interaction in the Global South. *ACM J. Comput. Sustain. Soc.* 3, 3, Article 20 (July 2025), 23 pages. doi:10.1145/3736645

[176] Abhijit Vhatkar, Vilis Pawar, and Pravin Chavan. 2024. Generative AI in Education: A Bibliometric and Thematic Analysis. In *2024 8th International Conference on Computing, Communication, Control and Automation (ICCUBEA)*. IEEE, 1–6.

[177] Ronnie Videla, Simon Penny, and Wendy Ross. 2025. 'If you can't dance your program, you can't write it': Challenges and Implications for AI in Education. *ACM Transactions on Computing Education* (2025).

[178] Kutoma Wakunuma and Damian Eke. 2024. Africa, ChatGPT, and generative AI systems: Ethical benefits, concerns, and the need for governance. *Philosophies* 9, 3 (2024), 80.

[179] Johannes M Waldmüller. 2014. Buen vivir, sumak kawsay,'good living': an introduction and overview. *Alternautas* 1, 1 (2014).

[180] Bingshu Wang, Shenyu Li, Yan Dong, and Han Zhang. 2024. ChatGPT-aided education teaching. In *2024 6th International Conference on Computer Science and Technologies in Education (CSTE)*. IEEE, 141–145.

[181] Hanling Wang, Banghao Chi, Yufei Wu, Kexin Chen, Di Wu, Songning Liu, Yiwei Li, Hanyan Niu, and Xiaohui Zhu. 2025. LLMarking: Adaptive Automatic Short-Answer Grading Using Large Language Models. In *Proceedings of the Twelfth ACM Conference on Learning@ Scale*. 105–115.

[182] Shuai Wang. 2025. Algorithm Design and Analysis Instruction Using the BOPPPS-ACPS Model: Dynamic Programming Algorithm: A Case Study. In *Proceedings of the 2nd Guangdong-Hong Kong-Macao Greater Bay Area Education Digitalization and Computer Science International Conference*. 324–330.

[183] Zongxuan Wei, Lei Chen, Liting Sun, Jinli Li, Lin Wang, Liting Liu, and Jiawei Meng. 2025. Research on Teaching Methods for Computer Operating Systems Integrating AI and Structured Seminars. In *Proceedings of the 2025 International Conference on Artificial Intelligence and Educational Systems*. 1–7.

[184] Tom Mboya Were, Paul Kamau, Sara Kinsbergen, and Dirk-Jan Koch. 2024. How distance and technology affected philanthropy in Kenya: A review of the journey of Harambee. *International Review of Philanthropy & Social Investment* 3, 1 (2024).

[185] Cheong Weng Luen William and Tong Ming Lim. 2024. Comparative Studies: Leveraging Large Language Model In Theoritical and Practical Assessment Sample Question-Answer Bank on Programming Related Subjects. In *2024 IEEE 4th International Conference on Electronic Communications, Internet of Things and Big Data (ICEIB)*. IEEE, 331–335.

[186] Marisol Wong-Villacres, Cat Kutay, Shaimaa Lazem, Nova Ahmed, Cristina Abad, Cesar Collazos, Shady Elbassuoni, Farzana Islam, Deepa Singh, Tasmiah Tahsin Mayeesha, et al. 2024. Making ethics at home in Global CS Education: Provoking stories from the Souths. *ACM Journal on Computing and Sustainable Societies* 2, 1 (2024), 1–26.

[187] Yubing Wu, Yang Wu, Tong Ji, Yuxin Luo, Yifeng Lin, Yuer Yang, and Yingying Liu. 2025. Bibliometric Analysis of Artificial Intelligence Literacy Research Status Based on Clustering. In *2025 8th International Conference on Artificial Intelligence and Big Data (ICAIBD)*. IEEE, 782–788.

[188] Qiao Xiang, Yuling Lin, Mingjun Fang, Bang Huang, Siyong Huang, Ridi Wen, Franck Le, Linghe Kong, and Jiwu Shu. 2023. Toward reproducing network research results using large language models. In *Proceedings of the 22nd ACM Workshop on Hot Topics in Networks*. 56–62.

[189] Zhijie Yang, Mingxi Liao, Yibing Li, Lei Wang, Kaipu Wang, and Yiying Wei. 2025. Research and Practice on the Teaching Reform of General Programming Courses for Non-Computer Science Majors. In *Proceedings of the 2025 2nd International Conference on Innovation Management and Information System*. 343–348.

[190] Karen Yeung. 2020. Recommendation of the council on artificial intelligence (OECD). *International legal materials* 59, 1 (2020), 27–34.

[191] Kinfe Yilma. 2025. Ethics of AI in Africa: Interrogating the role of Ubuntu and AI governance initiatives. *Ethics and Information Technology* 27, 2 (May 2025), 24. doi:10.1007/s10676-025-09834-5

[192] Young, Alison, and Clear, Tony and McCarthy, Chris and Muller, Logan. 2010. ICT4D: A model for engagement with indigenous communities for ICT-enabled change. In *CITRENZ2010*.

[193] Cynthia Zastudil, IV Smith, David H., Yusef Tohamy, Rayhona Nasimova, Gavin Montross, and Stephen MacNeil. 2025. Neurodiversity in Computing Education Research: A Systematic Literature Review. In *Proceedings of the 30th ACM Conference on Innovation and Technology in Computer Science Education V. 1* (Nijmegen, Netherlands) *(ITiCSE 2025)*. Association for Computing Machinery, New York, NY, USA, 114–120. doi:10.1145/3724363.3729088

[194] Hanjie Zhang. 2025. Exploring AI-Integrated Curriculum Reform in University Computer Science Program. In *2025 11th International Symposium on System Security, Safety, and Reliability (ISSSR)*. IEEE, 41–50.

[195] Ming Zhang and Virginia M Lo. 2010. Undergraduate computer science education in China. In *Proceedings of the 41st ACM technical symposium on computer science education*. 396–400.

[196] Yifan Zhang, Xinkui Zhao, Zuxin Wang, Zhengyi Zhou, Guanjie Cheng, Shuiguang Deng, and Jianwei Yin. 2025. SortingHat: Redefining Operating Systems Education with a Tailored Digital Teaching Assistant. In *Companion Proceedings of the ACM on Web Conference 2025*. 2951–2954.

[197] Yi Zhou, Zhenyu Shan, Zeyao Dai, and Zhao Zhang. 2025. CodeEduBench: A Multidimensional Benchmark for Evaluating AI-Driven Code Generation Models in C Programming Education. In *Proceedings of the 2025 International Conference on Artificial Intelligence and Educational Systems*. 217–222.

[198] Irina Zlotnikova and Hlomani Hlomani. 2025. GenAI in the context of African universities: a crisis of tertiary education or its new dawn? *Digital Government: Research and Practice* 6, 2 (2025), 1–11.

[199] Irina Zlotnikova, Hlomani Hlomani, Tshepiso Mokgetse, and Kelebonye Bagai. 2025. Establishing ethical standards for GenAI in university education: a roadmap for academic integrity and fairness. *Journal of Information, Communication and Ethics in Society* 23, 2 (2025), 188–216.

A Initial terms identified in ethical support scan

accountability
achievement
actions to birth a virtous society
ancestral practices
autonomy
beneficence
benevolence-caring
benevolence-dependability
brotherhood
care or hospitality
character
collaboration
collaborative approach
collective coexistence
collective family
collective well-being
common labour
communal flourishing; humanness
communal harmony and social cohesion
communal labour
communal living
communal self-reliance
community
complementarity
conceptualization of time
confidentiality
conformity-interpersonal
conformity-rules
connection to the natural world
consensus
contextual morality
continuous engagement and relationship building
cooperation
cultural continuity
culture
deep listening
diginity and personhood
dignity
doing what is right
ecological harmony
environmental wellbeing
equality
equity
expanded community
extended family socialization
face
face-to-face interaction
fairness & justice
family
family or kinship
familyhood
feelings
fidelity
freedom
freedom with destiny
generosity
harmony
harmony of thought
hedonism
holism
holism/holistic systems
holistic harmony
holitistic morality
hospitality
humility
impact and value
indigenous leadership
indigenous self-determination
inherent individual worth
integenerational responsiblity and sustainability
integrity
integrity and veracity
intelligilbility
interconnectedness
interculturality
intergenerational justice
interpersonal connections
justice
justice and social order
kinship
loyalty
maintaining boundaries
mental
mutual assistance
non-maleficence
normalising
order
other aspects bearing on health
personhood
physical
plurinationality
power-dominance
power-resources
precedent
preserving life
principle of reciprocity
principles
privacy
professional ethics
prohibited or sacred
reciprocal relationship with god
reciprocity
reciprocity and duty
reciprocity with all beings
reconciliation
relatedness
relational relationships
relationality
respect
respect for pachamama (mother earth)
responsibility
responsibility and accountability

security-personal
security-societal
self-direction-action
self-direction-thought
self-reliances & dignity
shared prosperity
social harmony
social responsibility
solidarity
spirit and integrity
spiritual
spirituality
standing or dignity
stimulation
survival and protection
sustainability
sustainability and accountability
territorial harmony
the environment
the family
theory of space and time
time; context and the environment
totemic and spiritual connections
tradition
transparency
trust
universalism-concern
universalism-nature
universalism-tolerance
veracity
wholistic approach to wellbeing

B Interpretive Analysis Terms and Occurrences

Table 6: Interpretive analysis terms with the number of papers in which they were found and total number of occurrences

Term	#Papers	Occurrence
Accomplishment	6	7
Accountability	13	41
Achievement	29	44
Action	25	59
Affect	38	74
Ancestral	1	1
Answerability	3	6
Appreciation	10	12
Attainment	5	10
Autonomy	22	71
Benevolence	1	1
Care	17	29
Character	22	100
Choice	57	295
Cognitive	68	265
Cohesion	4	10
Collaboration	56	205
Commitment	14	23
Community	50	128
Completeness	12	30
Compliance	13	26
Conceptual Alignment	1	1
Confidentiality	12	25
Consensus	19	34
Cooperation	18	61
Cross-Cultural	5	6
Cultural	31	148
Culture	14	28
Dedication	3	8
Dignity	1	1
Duty	4	6
Ecological	6	8
Emotions	14	19
Empathetic	1	3
Engagement	76	396
Environment	80	280
Equality	7	46
Equilibrium	3	16
Equity	23	144
Excitement	4	5
Face-To-Face	6	6
Fairness	38	255
Faith	4	6
Family	14	24
Fate	1	1
Feelings	3	3
Fellowship	1	1
Fidelity	4	12
Freedom	12	18
Generosity	2	2
Harm	5	24
Health	26	52
Honesty	4	8
Hospitality	2	2
House	3	4
Humanity	7	9
Individual	82	218

Term	#Papers	Occurrence
Integrity	36	144
Interpersonal	7	7
Justice	6	16
Liability	4	4
Liberty	2	2
License	35	42
Listening	4	6
Mental	25	34
Moral	12	36
Nature	78	207
Obligation	1	1
Order	66	227
Partnership	6	7
Personal	70	143
Privacy	42	249
Protection	20	60
Reciprocity	1	1
Reconciliation	2	2
Regard	18	25
Regulation	19	91
Relatedness	4	4
Relationship	31	65
Resilience	11	21
Respect	25	41
Responsibility	23	57
Right	44	111
Rules	35	101
Security	47	180
Self-Determination	4	11
Self-Regulation	9	53
Sentiments	8	10
Social-Capital	1	3
Social-Cohesion	1	1
Social-Responsibility	6	10
Socialization	1	1
Society	52	169
Spirit	8	9
Stimulation	2	2
Success	51	96
Support	111	716
Sustainability	38	72
Teamwork	20	51
Temporal	11	14
Thought	33	87
Tradition	3	8
Transparency	32	101
Trust	31	98
Understandability	3	4
Unity	2	3
Values	52	201
Virtue	1	5
Welcoming	1	1
Well-Being	9	16

C Ethical Supports of Generative AI in Computing Education in the Global South

The following is the summary of the analysis of 98 support terms listed in Table 6. Thirteen terms where no relevant discussion was found have not been included. These were: care, cohesion, consensus, fellowship, health, hospitality, house, integrating, liability, listening, reciprocity, self-determination, solidarity, temporal.

C.1 Accomplishment

A study by Chen et al. [42] of students using ChatScratch, an AI-augmented system, found that personalised learning experiences could increase both self-efficacy and a sense of accomplishment, especially when the projects they engage with were personally meaningful. Grounding material and pedagogy within a local culture can engage students with the familiar to ensure that these meaningful interactions can have the greatest benefit [194]. Other ways to increase a sense of accomplishment with AI is to use puzzles or games that constructively employ competitiveness [159, 175].

C.2 Accountability

Shoaib et al. [158] present an AI-driven architecture for generating contextually relevant multiple-choice questions (MCQ). They claim their architecture ensures fairness, transparency, and accountability in MCQ generation. Accountability and transparency is achieved through providing clear documentation of the model's decision-making process, disclosing data sources, and establishing mechanisms for feedback and recourse in case of errors or discrepancies.

Others mention the importance of transparency and accountability when using Generative AIs in algorithm reproduction [57] and in grading [126]. Abdelgadir Mohamed et al. [1] stress the importance of human oversight in verifying information provided by Generative AI, aligning this with ethical principles of accountability and transparency. Gao et al. [65] propose that using Generative AIS to improve fairness often necessitates a trade-off with transparency and accountability.

C.3 Achievement

A study by Samarakoon et al. [151] investigated the effectiveness of Generative AI in enhancing coding proficiency. Their study framed achievement as both a measure of cognitive growth and educational effectiveness as evidenced through improvements in coding proficiency and learning outcomes. Toba et al. [169] generated pre-test questions using ChatGPT-3.5-Turbo. Using a comparative study they found that the pre-test questions improved student post-test achievement significantly.

An analysis of publications on AI in education by Pan et al. [135] found that the achievement of educational equity in the use of AI in education was a key research focus.

C.4 Action

AI in education is viewed as a catalyst for transformation, where 'action' signifies not only technological deployment but the reconfiguration of pedagogy.

Industry-focused analyses indicate that sustainable AI adoption should align with strategic educational roadmaps that integrate technological progress with human-centered design [149]. In this way, action in AI-mediated education becomes both a technical and moral enterprise—anchoring progress in accountability, inclusiveness, and the cultivation of shared competence.

C.5 Affect

The term 'affect' appears frequently with two distinct meanings: the first relating to the impact of Generative AI in a teaching and learning context, and the second relating to the feelings and emotions engendered when working with Generative AI.

C.5.1 Affect as 'impact'. Prasad and Sane [142] propose that students' over-reliance on Generative AI tools is likely to affect self-regulated learning (SLR), hampering their ability to regulate their programming problem solving. However, they claim that "these technologies also open up the possibility to design new interventions that promote better SRL strategies".

Student demographics may affect learning. From their study of Sri Lankan software development students use of the Generative AI, [151] recommended "tailored interventions to address specific demographic variables, fostering a more inclusive and effective learning environment".

Design decisions in Generative AI tools can affect the quality and effectiveness of generated responses and learning outcomes. These decisions include the selection of training or fine-tuning data, which may introduce bias, and the choice of model, which have differing capabilities. A study by Tavasoli et al. [166] found variations across different languages in Generative AI's ability to solve mathematical problems. The interpretation of code by Generative AI tools may also affect student learning as the tools may struggle with fault localization [110].

Ethically addressing the affect of bias on 'AI safety' is challenging. As Abdelgadir Mohamed et al. [1] have observed "truly confronting bias requires embracing AI safety as an interdisciplinary, transparent and participatory process engaging affected populations – not just a statistical challenge solvable through datasets or algorithms". But discussions of participative, interdisciplinary processes engaging affected groups appear limited, and "we need to consider our moral obligations to different stakeholders in society, including vulnerable populations who may be disproportionately affected by these technologies".

C.5.2 Affect as 'emotion'. In addition to having affect on learning, Generative AI technologies elicit emotions in their users. In a paper reviewing self-regulated learning, Prasad and Sane [142] found that Code generation using Generative AIs such as Codex elicit positive sentiments (e.g., joy, wonder) as well as negative sentiments (e.g., fear, confusion) in learners. They propose that "Learners must be taught to see themselves in the driver seat, with the Generative AI as a copilot".

In a scoping review on Generative AI use in education, the prevalence of student-centered computing education proposals focused on cognitive learning outcomes at the university level was observed. In contrast, there was an emphasis on affective learning outcomes for elementary and middle school students [18]. The review also found issues such as: students manifested self-esteem and frustration problems because their task efforts were affected by rapid

Generative AI tool answers; some methodologies focused on affective outcomes because activities were linked with the students' identities, creativity, and cultural practices; many studies focus on the affordances and technical features of the Generative AI tools and do not consider how these tools could be a catalyst for learning, affective and behavioral skills, or a potential risk for students and teachers based on the evidence [18].

A study investigating affective constructs using the Intrinsic Motivation Inventory, found no differences in learning between the groups that used Generative AI and videos; however, distinct impacts were observed on motivational and affective aspects. For the group that used Generative AI there was "a significant increase in perceived autonomy (choice) from pretest to post test and a significant reduction in perceived effort and perceived pressure" [51]. Whether these findings are positive or negative depends, of course, on whether effort expended corresponds to learning gained.

So the affective dimensions of learning with Generative AI technologies raise several issues, which have had relatively limited attention.

C.6 Ancestral

Videla et al. [177] propose a paradigm shift towards embodied AI grounded in situationality and sensorimotor coupling with a focus on advancing an inclusive vision of AI in education that fosters creative, critical, and situated learning. The authors propose that the use of Generative AI in education should not only focus on producing outputs but on creating spaces for discussion and political imagination that encourage diversity and value ancestral knowledge. The goal is to design technologies that do not repress cultural differences. Pedagogy that lacks such design concerns risks devaluing ancestral knowledge and thus undermining the positive transformative capabilities of education.

C.7 Answerability

Answerability is one of the criteria that Hang et al. [74] use to evaluate multiple choice questions developed using MCQGen, their 'large language model' (LLM) driven generator.

C.8 Appreciation

A study by Indian teachers' views of the implications of emerging technologies by Sebastian et al. [157], found that AI was viewed by teachers as a tool for fostering an appreciation for nature and the environment, which they identified as a highly desirable outcome for students.

C.9 Attainment

Abdelgadir Mohamed et al. [1] emphasize the need to continuously monitor and audit Generative AI systems in order to ensure that they maintain fairness. They propose that the attainment of justice requires continuous vigilance and calibration. The implication here is that the attainment of equity is not just a technical obstacle but requires the deep inclusion of all human aspects, contextualised to specific cultures.

C.10 Autonomy

Cubillos et al. [51] identified 'autonomy' as a valuable characteristic of the developing student, tying confidence and choice to a sense of autonomy and control, with links back to self-determination theory. Their study found that Generative AI significantly increased students' perceived autonomy. Oran et al. [131] affirm that proper use of Generative AI tools can help students develop critical skills and autonomy, although improper use could pose a threat to autonomy.

A study by Sun et al. [163] explored how parents of children aged 3-6 perceived AI-based tools to support parent-child interactive storytelling. Autonomous learning capability was identified as important in the cultivation of "well-rounded individuals".

C.11 Benevolence

Abdelgadir Mohamed et al. [1] propose a virtue ethics approach to guide developers of AI systems toward transparency and social good. They explicitly emphasize benevolence as a trait to instil in AI systems.

C.12 Character

The term character was used in descriptions of characters developed in AI systems designed to engage and support children. An analysis of design features of AI tools for children by Jia and Yu [91] proposed characters that could take on various roles: a tutor to explain concepts, a non-playing character in a game to explain fairness and encourage participation, and a non-human character to strengthen emotional connections.

ChatScratch, an AI-augmented system developed by Chen et al. [42] for teaching young children programming, provided a Scratch-Cat character to allow students to create personally meaningful projects. Although, a limitation was raised during an interview study when a child related a situation where they had imagined a unique character that they could not find in the system.

C.13 Choice

From a study of the use of Generative AI in programming education in a university in Chile, Cubillos et al. [51] found that perceived choice increased significantly for students using Generative AI, suggesting that AI fosters self-directed learning and autonomy.

C.14 Cognitive

Shochcho et al. [159] define the pedagogical role of Generative AIs in supporting "reasoning, problem-solving, and programming comprehension". They argue that Generative AIs reduce cognitive load and promote metacognitive learning by providing immediate feedback and explanations.

The ChatScratch system Chen et al. [42] developed was designed to reduce cognitive load and facilitate autonomous programming learning for 6-12 year old children. However, Videla et al. [177] cautions that intensive use of Generative AI, such as ChatGPT, in educational contexts may weaken critical thinking, leading to "cognitive deskilling and dependency".

The study by Samarakoon et al. [151] discusses cognitive engagement through AI-based problem-solving and comprehension improvement, highlighting AI's capacity to enhance retention, understanding, and adaptability of coding concepts. Toba et al. [169] found that Generative AI enhanced lower Bloom's level learning experiences and they concluded that it has the capacity for the development of higher-order cognitive tasks.

Videla et al. [177] argue that “that human pedagogy is rooted in shared, embodied experience”, which is at odds with contemporary AI. They propose the concept of embodied cognition as a “framework for rethinking both computational development and educational design with AI”. Bispo Jr et al. [34] cite metacognitive and lifelong learning competencies as necessary for equitable Generative AI use: “Generative AI can help students and teachers to build a road of metacognitive strategies”. The implication is that using AI fairly can support students’ cognitive development.

C.15 Collaboration

Videla et al. [177] promote distributed creativity and co-agency between humans and AI systems, viewing learning as a collaborative process between bodies, technologies, and environments. A study by Oyelere and Aruleba [133] that explored student perceptions of Generative AI across Kenya, Nigeria, and South Africa, found that AI tools such as ChatGPT and GitHub Copilot were seen to “encourage collaboration and learning among students from different cultural background”, fostering a sense of belonging and mutual support. The results of this study suggest that AI-driven platforms can act as collaborative partners in learning, but are not replacements for peer collaboration.

Abdelgadir Mohamed et al. [1] highlight collaborative and multidisciplinary approaches as essential for addressing AI ethics. ‘AI ethics hubs’ are proposed as collaborative environments uniting technologists, policymakers, and communities. The study by Sebastian et al. [157] is grounded in participatory design, a collaborative research approach. The paper calls for “collaborative networks across borders” and “partnerships among educators, policymakers, and researchers” to shape ethical technology use.

Collaboration in computing education can even take place at the policy and regulatory levels in the Global South, where curricular development is often multi-national to address resource and community requirements [139]. Given the often strongly collaborative nature of many communities in the Global South, it is unsurprising that there is often an emphasis on collaborative projects in educational courses, for engagement and cultural localisation [153].

However, collaboration needs to be supported with sufficient resources and time, which can be challenging in the often-resource-reduced spaces of the Global South [186]. Additionally, the ethics created in collaborative spaces are often both iterative and generative, as shared commitments are negotiated. The final note, from Verma et al. [175], is that all collaborations involving the Global South should prioritise the empowerment of the local communities, which will then lead to better decision making that incorporates and respects local knowledge – their “unique realities” in the words of the authors.

C.16 Commitment

A study by Aljedaani et al. [11] used Generative AI capabilities to enhance students’ awareness, knowledge, and skills in addressing accessibility issues, fostering a lasting commitment to accessibility. Another study by Gao et al. [65] investigated the fairness of Generative AIs when used in education. The authors concluded that a multidimensional strategy for AI use in education is needed to ensure a balance between technology advancements and a commitment to inclusivity and fairness.

C.17 Community

Community was used frequently across the paper set in reference to different groups involved with Generative AI: academic [42], computer science [39], computer science education [24], minority [34], networking [188], programming [1], social [42], student [133].

In their study of ethics and computing in Global South regions, Wong-Villacres et al. [186] report on a community engagement project used to promote science engagement in disadvantaged communities, reinforcing the value of the familiar in not just the sense of community but familiarity of language. Introducing students to the community values and experiences of other communities can raise awareness of a wider range of problems that could be addressed by computer science. But involving community goes beyond understanding what their requirements could be, where an informed and enabled community can identify and advocate for their specific needs, as well as deepening their own understanding of their relationship with technology. The authors conclude, "Enabling a community to lead a project according to their needs includes ongoing training to deepen a community’s understanding of technical possibilities and their control and ownership, within their own values and culture".

A study, Bispo Jr et al. [34] discuss the “digital divide” and disparities in digital access and algorithmic transparency that risk perpetuating structural inequalities. They present some mitigation actions for reducing the digital divide. One suggested action is to foster active involvement of minority communities in the creation of technologies. Another study by Oyelere and Aruleba [133] examined the impact of AI tools on fostering inclusive education in Kenya, Nigeria, and South Africa and found mixed opinions about whether AI tools foster a sense of belonging and community.

Several studies mentioned communities within an education context. A survey by Budhiraja et al. [39] sought to understand how undergraduate computer science students use ChatGPT. They found that only 0.2% of the students reported that they were unaware of ChatGPT, evidencing its widespread recognition within the undergraduate computer science community. Jia and Yu [91] analysed the design features of 64 different AI learning tools for children. The found that “some tools create community-based learning networks, which enable students to access AI learning resources by sharing, using, and building upon each other’s work”.

Torrato et al. [170] argue that the misuse of ChatGPT in scientific research has sparked significant concern and opposition within the academic community, leading to widespread discussion across educational institutions globally. Similarly, Prasad and Sane [142] observe that investigations into the use of large language models (LLMs) have emerged organically, shaped by community perceptions of both their potential and the risks they pose in computer science education.

From a security perspective, Abdelgadir Mohamed et al. [1] emphasise that the implications of automated code generation must be carefully managed. They suggest that establishing clear standards and implementing robust safeguards can help ensure that tools such as Copilot positively contribute to the programming community while mitigating associated risks.

At a broader level, Li et al. [105] highlight that international policy efforts stress the importance of fostering global collaboration in the AI era, encouraging countries to work together to address the challenges of integrating AI into education.

As noted earlier in the studies of Māori culture, data sovereignty cannot be applied hegemonically but must take into account the individual community values, rather than assuming some level of aggregation.

C.18 Completeness

Completeness is a common evaluation measure in AI performance studies. Freire et al. [64] and Oran et al. [131] use completeness as a criterion to measure ChatGPT output; Alaswad et al. [9] use completeness to analyse ChatGPT's self-judgment; Shochcho et al. [159] use completeness to assess tutor bot effectiveness via user responses; and Du et al. [57] and León-Paredes et al. [104] evaluate virtual assistant prompts with completeness as a key criterion. However, Generative AI often fall short in completeness. Pirzado et al. [140] highlight Generative AIs limitations, and Abdelgadir Mohamed et al. [1] emphasize the need to improve Generative AIs' completeness.

C.19 Compliance

Compliance with rules as part of meeting industry expectations is considered part of student learning, and forms of compliance may also assist in quality validation. A bibliometric analysis of LLM research in programming education by Amos et al. [15] discussed the use of ChatGPT in education. A concern raised was that code produced by ChatGPT was frequently non-compliant with standards, citing the ChatGPT's disclaimer that "while AI can assist in the code development, human validation and oversight are still essential to ensure code quality, security, and compliance with project requirements". Another concern was the risks of relying on ChatGPT as a primary resource for teaching secure coding, particularly if students will be working in industries with stringent security and compliance requirements.

More negatively, compliance can be seen as engaging in a rules-based exercise which may result in outcomes counter to the intentions of the initiators of the rules or frameworks, as observed by Wong-Villacres et al. [186]. The authors note that a 'thin' notion of ethics as a list of discrete criteria can reduce corporate professional ethics to a rote compliance exercise, and warn against modelling this approach in ethics courses as it can lead to shallow engagement with ethical questions, and does not prepare students to engage with ethics in a professional setting.

C.20 Conceptual Alignment

León-Paredes et al. [104] present NOVA, an educational AI-driven virtual assistant for a parallel computing course. Built on a Retrieval-Augmented Generation architecture, the virtual assistant integrates curated course material and Generative AIs, which the authors claim ensures conceptual alignment with curricular objectives.

C.21 Confidentiality

Confidentiality in relation to Generative AI was was mentioned in the context of education and research studies, ususally in relation to the protection of participants' data and privacy. In their study of the effectiveness of Generative AI in enhancing coding proficiency, Samarakoon et al. [151] used Google Classroom claiming that platform's security features ensured a secure environment for participants to submit their assessments, which fostered a sense of trust and confidentiality.

Wong-Villacres et al. [186] noted that attempts to replicate surveillance and business models from the Global North could interfere with culturally located efforts to maintain an appropriate level of confidentiality. There is existing pressure in many areas to dismiss confidentiality for reasons of expediency, government regulatory and reporting requirements, or the commercialisation of data. Concerns about commitment to confidentiality are growing in the Global North as evidenced by some of the requirements of the European Union's General Data Protection Regulation.

A study of the integration of AI into education in the Global South by Verma et al. [175] found that children had contradictory views regarding the confidentiality of AI. Their study of smart speakers in India found that while "children did not perceive their interactions with these devices as private, closed-door conversations, they nonetheless regarded the speakers as safe". Mwaniki et al. [122] explored the perceptions of third-year computer science students in Kenya towards the use of Generative Artificial Intelligence tools. They found a low level of students (4.4%) were concerned about data security and confidentiality when using these tools.

C.22 Cooperation

Framed as crucial for guiding Generative AI adoption, Torrato et al. [170] propose there needs to be a cooperative effort from instructors, students, and AI research and development staff in order to obtain the best educational outcomes. Abdelgadir Mohamed et al. [1] stress the importance of concentrating on the moral and legal concerns raised by AI technology, arguing the need for a cooperative effort by stakeholders to create effective regulatory frameworks.

C.23 Cross-Cultural

From an analysis of the current state of Generative AIs in education, Hong and Huang [83] conclude that Generative AIs expand learning boundaries and facilitate cross-cultural communication and multidisciplinary collaboration. A core focus of the study by Oyelere and Aruleba [133] is to examine the impact of AI tools on fostering inclusive education in Kenya, Nigeria, and South Africa. It explicitly treats programming education as a cross-cultural context, examining how attitudes toward AI tools differ by country. The findings show largely uniform motivation but varied attitudes toward AI tools depending on local technological conditions.

C.24 Cultural

The term 'cultural' is discussed in the context of regional and contextual influences on students' acceptance, use, and access to Generative AI. Sebastian et al. [157] situate technology adoption within local cultural frameworks, discussing how educators adapt global tools to regional norms, traditions, and identities. Verma et al. [175]

propose that integrating AI technology into the education curriculum in developing regions can be complicated by "technological disparities and cultural nuances".

A study by Oyelere and Aruleba [133] found that socio-cultural factors shape how learners engage with technology across African universities.

Zlotnikova and Hlomani [198] identify a lack of customization for local needs and cultural contexts as threats from Generative AI in African universities. They stress there is a need for "robust guidelines that balance technological advances with traditional teaching methods in African universities". Recognising the varying situations in AI across different parts of the world Hu et al. [86] present a strategy for improving teachers' AI capabilities that considers relevant ethical, social, and cultural factors, to inform the construction of teachers' AI competence.

From another perspective Gao et al. [65] discuss racial and cultural biases in Generative AIs that can lead to unfair treatment or resource allocation.

C.25 Culture

Culture refers to the institutional and learning culture within universities, encompassing teaching practices, values, and access to educational technology that influence how students perceive and use Generative AI. Verma et al. [175] propose that "culture plays a crucial role in shaping technology adoption in the Global South". A study by Oyelere and Aruleba [133] showed the capacity of AI-driven programming tools to provide for students from different cultures.

C.26 Dedication

Dedication is a moral and forcing mechanism that makes ethical considerations fundamental for AI development. Abdelgadir Mohamed et al. [1] see dedication as vital for societal benefit, emphasizing that growth requires commitment to ethical, accountable, and transparent practices to maximize benefits and reduce risks. They stress that responsible AI development must prioritise ethics as a central driver.

C.27 Dignity

Abdelgadir Mohamed et al. [1] argue that the development and deployment of AI-generated text tools should prioritise alignment with core ethical principles, including respect for human dignity and autonomy.

C.28 Duty

Abdelgadir Mohamed et al. [1] discuss the societal impacts and challenges of Generative AI tools, proposing that it is our duty to protect vulnerable individuals and groups from possible harm that may arise from AI misuse.

Wang [182] describe a model for an algorithm design and analysis course that uses AI scaffolding and introduces ethical issues through case studies. The authors argue that "Algorithm engineers must rely on technology's judgment to correct societal disparities, so a higher standard must be set: not only for excelling in technology, but also for servicing the values of humanism".

In addition to social duty, there are religious and philosophical frameworks that may guide whether a person is expected to judge which of the many duties they should undertake where this is a clash between moral guides and secular ethics [186]. This tension between potentially conflicting duties is seen in a number of socio-cultural spaces, affecting areas such as the participation of young women in education or the ability to work with items that would be considered forbidden (*tapu* or *haram*, for example) in a given cultural setting.

C.29 Ecological

The study by Dhaou et al. [55] links ecology to systems and frames AI as a transformative force within the educational ecosystem, highlighting the integration of humans and AI systems in co-creation, innovation, and curricular reform. Ariza et al. [18] refer to the learning ecosystem as an interactive and adaptive network formed by learners, educators, and AI tools that collectively shape educational practices and assessment.

In preparing teachers for an AI curriculum, Rajapakse et al. [147] propose a socio-technical system for teacher training, an approach they claim aligns with the ecological perspective of learning.

The term 'Ecological' is also used metaphorically by Sebastian et al. [157] to describe the systemic nature of educational innovation, emphasizing inclusion, access, and interconnectivity in resource-limited contexts.

C.30 Emotions

Advances in AI technologies enable the development of AI-driven virtual humans that can simulate emotions. Ren et al. [149] describe 'virtual digital people' with 'empathy ability' that express, identify, and feed back emotions built from large emotion databases. In an education context, Sun [162] proposes the implementation of digital humans that can "simulate real teaching behaviours, offering students a more vivid and intuitive learning experience". Cubillos et al. [51] suggest AI-generated virtual instructors based on admired figures can "increase student motivation and foster positive emotions".

Emotion is both promising and risky: Prasad and Sane [142] advise that students using agent-based tools should be aware of their motivations and emotions in response to Generative AI-generated artifacts.

C.31 Empathetic

Zhang et al. [196] present SortingHat, a personalised educational assistant that uses advanced AI technologies. A feature of SortingHat is a 3D digital human interface that provides personalised, empathetic, and context-aware guidance.

C.32 Engagement

The impact of Generative AI on student engagement is widely reported and often associated with enhanced learning outcomes, self-efficacy and student satisfaction. A number of studies use behavioural engagement to evaluate tools or resources. Murali et al. [120] use engagement in an evaluation of AI-supported virtual labs, highlighting engagement as a key metric for learning effectiveness. A study by Gomez-Jaramillo et al. [67] that investigated the effectiveness of ChatGPT in teaching object-oriented using an

AI-assisted sequential tutoring strategy found enhanced learner engagement and self-efficacy. Aliac et al. [10] measured engagement time, including time spent interacting with a teaching assistant chatbot, connecting it to learning depth and user satisfaction. A study by Chen et al. [42] using ChatScratch, an AI-augmented system they developed for teaching young children programming, found that children had a heightened sense of engagement and satisfaction when using the system.

Toba et al. [169] generated pre-test questions using ChatGPT-3.5-Turbo. Using a comparative study they found that the generated pre-test questions were successful in maintaining student engagement. However Videla et al. [177] claims that Generative AIs users can "exhibit lower brain connectivity, reduced intellectual engagement, and difficulty citing their own ideas".

A review of the integration of AI in education in the Global South by Verma et al. [175] highlights the importance of "involving children, educators, and parents in AI design to ensure culturally and educationally relevant solutions ...[to] improve student engagement and safety in AI-driven learning environments".

Simaremare et al. [160] explored a student-Generative AI pair programming approach. While the Generative AI support was appreciated, some students reported missing the dynamic in-person engagement of traditional student-student pair programming, claiming "it limited depth of discussion, empathy and collaborative problem solving".

C.33 Environment

Environment as a term occurred primarily in the context of measuring and improving the learning environment, and focusing on several aspects that facilitate an excellent learning experience and are conducive of learning, such as accessibility [151], group interaction. and collaboration [40, 91], conversation [174, 196], humanistic care [162], safety and security [175], and personalisation [51, 176] including specific language localisation [104]. There is also an emphasis on creating learning environments that are supportive of tutors rather than becoming 'short-cut' tools [90].

While broader environmental concerns seem to be addressed under the concept of sustainability, environmental accountability is considered across a handful of studies [55, 112, 121, 139, 149, 157]. Maity et al. [112] create LLMs to store and analyse environmental data, while Sebastian et al. [157] use LLMs to support students creating enviornmental connections in the classroom, similar to Pias et al. [139] who consider a critical role for Generative AI in promoting environmental connections. Generative AI supports the generation of environmental issues-focused senior student projects in the work by Mushtaq et al. [121].

C.34 Equality

Bispo et al. [34] discuss equality in the context of the 'digital divide' and accessibility, noting that while Generative AIs offer educational potential, unequal access to technology and infrastructure exacerbates pre-existing inequalities. They describe equality in the context of equal access and opportunity and distinguish it from equity, which achieves fairness through targeted support.

A study by Oyelere and Aruleba [133] examined the impact of Generative AI tools on fostering inclusive education in Kenya, Nigeria, and South Africa. They found that higher educational levels and more programming experience were associated with more favourable perceptions of the ability of AI tools to provide equality in learning opportunities and bridge the digital divide.

Guo et al. [65] propose that the pursuit of equality in education needs to consider three dimensions, namely, equality of opportunities, outcomes, and resources. From an equality of opportunity perspective, Generative AIs can help disadvantaged students gain access to similar opportunities of those more privileged. Considering equality of outcomes, machine learning techniques can be used to analyse student learning data to identify and address external influences that may affect academic performance. Lastly, in regard to equality of resources, the strategic use of Generative AIs ensures that all students have access to the necessary support they need to thrive.

C.35 Equilibrium

Equilibrium functions as a recurring framework for navigating AI's inherent tensions. It is often characterised as "harmonious", or "optimal", and must be actively maintained rather than assumed to occur naturally. Abdelgadir Mohamed et al. [1] describe equilibrium across several critical dimensions: between AI's transformative potential and the need for careful governance and ethical deliberation; between creativity and control in generative systems such as DALL·E 2; between the powerful capabilities of these models and their limitations and societal impacts; between the use of AI and the development of essential academic skills; and between leveraging synthetic data to advance medical research and ensuring the authenticity and reliability of resulting insights.

C.36 Equity

Bispo Jr et al. [34] define Generative AI equity issues as gaps in access, prompt literacy, and social-environmental conditions that limit educational freedom. Cubillos et al. [51] highlight equity in access to technology as an emerging concern and emphasize inclusive design to avoid deepening educational divides. In agreement, Pan et al. [135] argue for increased focus on educational equity to ensure the benefits are available to a broader demographic. Equity policies for AI use are discussed in [86] and [105].

Gao et al. [65] proposes that Generative AIs can assist educators in understanding and addressing the needs of students from different cultural contexts, achieving more equitable outcomes. A study by Indian teachers' views of the implications of emerging technologies by Sebastian et al. [157] found that teachers advocated for "inclusive and equitable access to high-quality education" and recognised language barriers and socio-economic divides as major equity challenges in India.

Abdelgadir Mohamed et al. [1] view equity as a guiding principle that should be built into every part of AI development. It means ensuring data and teams include people from diverse backgrounds, creating shared and transparent ways to check how algorithms make decisions and ensuring global and inclusive participation in how AI systems are governed. The authors view equity as both an ethical value and a practical requirement. Equity is about designing AI tools that benefit everyone fairly, instead of increasing existing inequalities.

C.37 Excitement

The capacity of Generative AI to spark excitement is mentioned by Gerede [66], Samarakoon et al. [151], and Zlotnikova and Hlomani [198]. When excitement is mentioned in relation to Generative AI, it is often tempered by cautions about inappropriate use and negative impact on learning, for example, scepticism regarding its code-generation capabilities [15], being too generous when used for marking [198] and copyright issues [151]

C.38 Face-To-Face

Amos et al. [15] argue that while AI tools can be highly effective for learning, their benefits are most evident when they are used to supplement traditional face-to-face instruction, and are supported by careful guidance and supervision to promote optimal outcomes. Hang et al. [74] explain how blended learning combines online flexibility with the structure of face-to-face instruction, allowing for personalised learning paths. While face-to-face may be a preferred mode for many reasons, a study of Sri Lankan teachers' readiness to teach AI by Rajapakse et al. [147] found that a requirement for face-to-face instruction for teacher training can cause resource bottlenecks in regions where travel is difficult or the area covered by a teaching team is very large.

A study by Simaremare et al. [160] that explored a student-Generative AI pair programming approach found that when Generative AI replaced human partners in pair programming, students experienced a significant loss—they missed the "dynamic in-person interaction and engagement of traditional student-student pairing" and identified the "lack of interpersonal interaction with Generative AI" as a critical drawback that "limited the depth of discussion, empathy, and collaborative problem-solving".

Cubillos et al. [51] emphasize the importance of conducting comparative studies between in-person and video-based programming classes when examining Generative AI integration, as student interaction and motivation may vary across formats, and highlight the need for longitudinal research to assess long-term impacts.

C.39 Fairness

A study of student perceptions of AI tools in programming education in Kenya, Nigeria, and South Africa by Oyelere and Aruleba [133] found concerns about fairness of assessment, particularly with perceived lack of impartiality of AI-driven assessments.

To safeguard fair treatment, Alaswad et al. [9] propose complementing AI-driven evaluation with essential human oversight and establishing systematic, transparent frameworks, such as well-defined rubrics and clear grading criteria, to validate AI content and ensure consistency. A study by Nawahdah et al. [126] that compared human and AI-based grading in a university in Palestine shows that AI grading systems which are guided by well defined criteria, are able to match or exceed human grading in fairness and consistency.

A bibliometric analysis by Vhatkar et al. [176] to identify the status and future trends in the research concluded that resolving bias and ensuring fairness were key priorities for advancing Generative AI in education.

C.40 Faith

Wong-Villacres et al. [186] highlight a critical assumption in the ACM guidelines for Professional Conduct [17] , as well as in codes of conduct in the engineering field, namely that technology is created by good designers and introduced to society in good faith. While the meaning of 'good' might not necessarily be the same across contexts, the concept of 'introduced in good faith' shapes technologies and their use across societies in the world. Abdelgadir Mohamed et al. [1] contend that disinformation produced by Generative AI tools and the growing difficulty of identifying Generative AI content has caused an undermining of faith in online communication.

Another perspective on faith, this time in a religious context, is presented by Sun et al. [163], who investigated parents' perception of how Generative AI can be effectively used in practical storytelling and reading scenarios. Their study also explored how parents view these technologies more broadly. One participant noted that the value orientation promoted by ChatGPT might not align with the family's religious beliefs. As noted by Wong-Villacres et al. [186], there is ongoing religious concern about the decline in reflection on faith-based morals, which may further heighten sensitivity to potential mismatches between religious beliefs and the values suggested by Generative AI.

C.41 Family

In the Global South context, the family situation has an impact on students' ability to access Generative AI tools, as families and villages with fewer resources may use shared devices. Verma et al. [175] found this has a direct impact on how interfaces and lesson plans are personalised, as a one-person-per-device model cannot be assumed. A study by Sun et al. [163] showed that family value orientation is a factor in whether AI may be used, as parents may be concerned that the perspectives promoted by Generative AI tools may not align with their own views,

C.42 Fate

The fate of democratic discourse, scientific integrity and cultural authenticity is mentioned by Abdelgadir Mohamed et al. [1] as dependent on our shared capacity to negotiate the increasing overlap between Generative AI and human created content.

C.43 Feelings

A study by Torrato et al. [170] investigated the perspectives of teachers and students about ChatGPT to better appreciate its role in advancing teaching and learning. They concluded that to encourage the advancement and use of AI technology to benefit humans it is important to understand and respect the feelings of students and educators who will be using this technology.

C.44 Fidelity

Abdelgadir Mohamed et al. [1] examine fidelity in image generation, using it as a metric to compare OpenAI's DALL-E 2 and Luna. They identify ongoing challenges in managing intricate motivations and cultural sensitivity, advocating for broader evaluation that includes conceptual correctness and creative quality, since technical fidelity alone cannot ensure culturally appropriate outputs Gomez-Jaramillo et al. [67] demonstrate how, with a carefully designed master prompt, AI can be used as a virtual tutor. Through reducing variability in AI responses they achieved instructional reliability and fidelity similar to an intelligent tutoring system.

C.45 Freedom

Freedom appears as a multifaceted concept across the literature, operating simultaneously as a pedagogical principle, a technological concern, and a moral imperative. At the classroom level, freedom manifests as learner autonomy, both as a measurable dimension of intrinsic motivation that captures students' "perceived autonomy and freedom" in learning environments [51] and as a transformative vision where students have the "freedom to study whatever they want, wherever they want" [157]. Students also have the freedom to choose their desired creative topic, with the Generative AI tool providing the necessary support to create a required theme [39, 73]. This pedagogical freedom influences educators' practices, with Ren et al. [149] advocating for more openness in exploring unstructured data like lesson notes for AI content. However, this raises concerns about equity in the Global South. Bispo Jr et al. [34] argue that freedoms to achieve well-being and be educated are vital but can be threatened when AI literacy skills are unevenly shared. Outside the classroom, Abdelgadir Mohamed et al. [1] discuss how digital rights, privacy, and data protection influence public trust in AI.

C.46 Generosity

In their empirical study comparing human and AI-based grading approaches Nawahdah et al. [126] found that human and AI graders differ in their generosity. Human graders demonstrate generosity by awarding partial credit, whereas strict AI tends to be overly harsh and tolerant AI can be overly generous. They concluded that a tolerant AI, when guided by a rubric, most closely aligns with human grading while maintaining fair and controlled generosity.

C.47 Harm

Abdelgadir Mohamed et al. [1] discuss harm that may arise from biased AI systems or unequal access to systems. They claim there is a moral duty "to prevent harm and protect vulnerable individuals and groups from the negative consequences of AI misuse". Verma et al. [175] propose that AI systems can subtly erode learners' confidence in their reasoning and autonomy, replacing curiosity with convenience. Certain communities have identified that anthropomorphic attribution of human-like characters to AI and robots can lead younger children to assume that such devices/systems are going to act ethically, ultimately expecting a stance of "do not harm" from systems that have no concept or mechanism for understanding harm.

C.48 Honesty

The term honesty appeared both in a cultural context and a technical context, which separates honesty as a cultural practice or value from the lens of academic honesty, which is usually associated with student academic integrity issues and the accurate representation of research investigation and results.

Focusing on the cultural practice, ethical expectations can vary widely based on the perceived primacy of honesty. In their study of ethics and computing in Global South regions, Wong-Villacres et al. [186] found that some regions placed the highest value on honesty in professional and general life to the extent that an ethical code that prioritised personal privacy above honesty would appear unnecessary, or even unintelligible, in such a region.

In the academic honesty framing, some papers discussed honesty in terms of its inverse, "dishonesty", along with suitable uses of techniques for plagiarism detection, for example, "Specifically, there is the potential for students to misuse ChatGPT to generate coding solutions for assignments, leading to academic dishonesty, cheating, and an unhealthy dependency on AI tools" [15], and "It challenges the notion, too, that plagiarism detection tools alone might have to address academic dishonesty, advocating enhanced learning analytics techniques that can be supported by GPT model integration" [176]. The responsibility for academic honesty however can be placed in part with the institutions and their policy vacuums, for instance "there is growing concern about authorship, plagiarism, and academic dishonesty". While there is clear connection between honesty as a cultural practice and the presence of academic dishonesty in a teaching and research environment, it is not presented in any of the papers as analysed to show a clear relationship between the cultural values of the community and the direct impact on academic practices.

C.49 Humanity

Several papers mentioned benefits to humanity from Generative AI tools: fostering high-quality educational development [83]; enhancing productivity and preparing society for a more AI-integrated future [170]; foster high-quality educational development [83]; augmenting human autonomy, nurturing innovation, and advancing comprehension [1].

However, there are also threats. Hong and Huang [83] and Torrato et al. [170] discuss negative effects on human behaviour, communication, and students' skills and learning. Abdelgadir Mohamed et al. [1] propose that it should be our priority to ensure that the AI revolution enhances rather than reduces our humanity, stressing the importance of technology and ethics progressing in synchronization for the benefit of society as a whole.

C.50 Individual

Generative AI tools have been shown to support individualised learning and assessment across a range of educational contexts. Hong [84] proposes a novel coding education framework that integrates intelligent, computer-aided tools that guide students through personalised learning journeys and assesses them individually. In operating systems education, Zhang et al. [196] introduce SortingHat, an Generative AI-based system that generates customised exercises based on students' individual learning histories, performance, and feedback, transforming learning into a more engaging, immersive, and scalable experience. An exploratory study by Oran et al. [131] on the use of ChatGPT in project management education found that students viewed the tool as a valuable complement for structuring academic content; however, there were concerns about over-reliance and the potential impact on individual creativity.

The integration of Generative AI enables greater customization of assessment processes, as questions can be tailored to students' individual skill levels, thereby fostering more personalised learning experiences [185]. In their study of Generative AI use for advanced computer programming assignments, Arora et al. [19] found that students strongly valued personalization, with a number expressing a desire for learning experiences that adapt to individual needs, learning paces, particularly for challenging coding tasks.

Several studies emphasize the implications of Generative AIs for instructors workload and the benefits for individual students. Wang et al. [180] claim that ChatGPT can alleviate teachers' workload in manual test design while tailoring learning plans to students' individual requirements, study habits, capabilities, and performance. Hu et al. [86] show that real-time data feedback from AI-supported systems enhances instructors' ability to adjust teaching approaches for individual students. Jamie et al. [90] highlight the benefits of a balanced instructional model in which ChatGPT supports routine tasks, while human teaching assistants focus on critical thinking, complex instruction, and addressing individual student needs.

C.51 Integrity

The concept of integrity was often expressed as "academic integrity" when discussing various perspectives on the connections between generative AI technologies, learning practices, and ethical issues.

Several articles frame integrity as an ethical standard, discussing the importance of integrity in preserving the credibility of educational systems against the misuse of Generative AI. Hong and Huang [83] and **?**] warn of an undermining of academic integrity through plagiarism and ghostwriting and the potential threat of reputational damage to universities. Similar concerns are echoed by Amos et al. [15], who highlight ongoing challenges in detecting AI-generated code and text, and the associated risk of compromising academic standards. Karnalim et al. [97] claim that plagiarism detection technologies are essential for maintaining academic integrity. Torrato et al. [170] stress the importance of implementing guidelines for the use of Generative AI to safeguard academic integrity and education quality

Many articles discuss integrity in terms of the impact on student learning. Joshi et al. [94] warn of the hindrance to learning when students plagiarise responses from ChatGPT. As well as missing out on the learning experience, their study showed that responses from ChatGPT could not be relied upon due to a high variability in responses. Other studies caution that unregulated or excessive use of Generative AI can reduce student motivation [175] and can have a negative impact on critical thinking [158].

However, a number of articles promote the view that there can be benefits to learning through responsible and transparent integration of AI tools. Studies such as [10, 61, 140, 160] advocate for actively promoting academic integrity by embedding ethical awareness and guided learning into Generative AI-assisted coursework. The work by Felipe et al. [61], for example, proposes a framework for designing take-home assignments that incorporate Generative AI while upholding integrity principles. Similarly, Bernardino et al. [30] argue that students should be encouraged to use ChatGPT responsibly and with integrity, ensuring transparency and ethical awareness in their learning practices. Mwaniki et al. [122] add a Global South perspective, noting that students in Kenya recognise the need for a balanced use of Generative AI to avoid compromising integrity, critical thinking, and creativity. In these studies, maintaining integrity is strongly connected to enhancing learning outcomes.

In some articles there was evidence of a gradual reframing of integrity in relation to Generative AI. Liu et al. [109] propose that initial fears of Generative AIs as threats to academic integrity have evolved into more nuanced discussions of their potential to support learning when used responsibly. This shift reflects a broader recognition that integrity is not inherently in opposition to Generative AI use, but rather contingent upon how these tools are contextualized within ethical, curricular, and assessment frameworks. Amos et al. [15] similarly emphasise the importance of maintaining a balance between AI assistance and traditional educational practices, suggesting that such equilibrium maximizes the benefits of AI while minimizing risks to integrity and essential skill development. Amos et al. [15] propose that ChatGPT should be used cautiously and always with human oversight.

Taking a broader stance, several articles extend the notion of integrity beyond the classroom, situating it within societal ethics. Authors such as Abdelgadir Mohamed et al. [1], Du et al. [57] and Wong-Villacres et al. [186] broaden the discussion to include scientific integrity, cultural authenticity, and moral responsibility in the development and application of AI systems. Integrity in this sense denotes not merely compliance with academic rules but a moral disposition encompassing responsibility, authenticity, and respect for human values within the computing education context.

C.52 Interpersonal

Several papers explore the use of AI to mediate the interpersonal dynamics of learning, focusing on feedback and collaboration. Abdelgadir Mohamed et al. [1] show that Generative AI influences not only what students learn but also how they relate to peers and instructors.

Dos Santos and Cury [56] show the use of Generative AI in a peer-instruction model. The Generative AI tool promoted dialogue and mutual reflection, encouraging students to confront biases and clarify reasoning through conversational exchange. Students who used the Generative AI tool outperformed the traditionally instructed group, demonstrating better programming skills and a deeper understanding of fundamental concepts. However, difficulties were encountered for more abstract problems.

Simaremare et al. [160] studied the integration of Generative AI into pair programming. They found that many students missed the interpersonal interactions and exchange of ideas of traditional pair programming, limiting the depth of discussion, empathy, and collaborative problem-solving. Amos et al. [15] caution that over-reliance on AI systems may impede the development of essential interpersonal interactions

Zlotnikova and Hlomani [198] offer a different perspective on the effect of using Generative AI in African universities, highlighting that the overuse of technology might lead to a potential neglect of the importance of interpersonal skills, in the context of the increased pressure on African students to achieve high grades and graduate on schedule.

C.53 Justice

Abdelgadir Mohamed et al. [1] explore various ethical considerations in AI technologies through their Virtue Ethics framework. They view justice and prejudice as intricately connected to transparency, accountability, and benevolence. An example they give is where the provision of openness in AI decision-making procedures is connected to concerns about justice. They caution that principles of justice may be violated by unfair AI systems. Pan et al. [135] propose there is future work in addressing ethical challenges to assure justice and safety in AI applications.

C.54 Liberty

Presenting a set of guidelines for ethical teaching with AI, Hong [84] proposes that learning with AI-generated content tools bring concerns about liberty, reliance on automated tasks, and responsible usage.

C.55 License

Bispo Jr et al. [34] highlight licensing concerns, noting that AI-generated content may include material "licensed exclusively for non-commercial use", making copyright and data ownership key ethical issues in educational AI use and in ethical AI deployment.

C.56 Mental

Generative AI tools have the potential to observe changes in attention and motivation and adjust the rhythm of interaction to sustain student engagement and focus. Karegowda et al. [96] showed that when AI models trace how learners process knowledge, they can identify engagement patterns and can help students become self-aware and recognise the flow of their own thinking. Such learning environments do not replace human reasoning but extend it, allowing thought to unfold with greater clarity and continuity. The authors make an important point that the mental models the students may be building may be fragile [77].

Mental health and well-being aspects can be integrated into Generative AI tools. For example, the tools may be designed to respond to linguistic and affective cues to reduce anxiety, particularly among learners navigating complex or multilingual contexts [71, 91]. However, a tool that is sensitive to mental states also invites ethical caution, as the boundaries between support and surveillance grow less distinct [1].

C.57 Moral

The importance of aligning the moral aspects of AI-based education with ethical and societal concerns for the local culture and region was mentioned by Wong-Villacres et al. [186], especially where there was a religious emphasis on a particular moral code.

C.58 Nature

A study of software engineering students' use of AI in Brazil, India and Saudi Arabia by Aljedaani et al. [11] showed that "the nature of ChatGPT interactions can help students delve deeper into the topics they need to grasp".

C.59 Obligation

While discussing the importance of self-efficacy, Rajapakse et al. [147] explain that a government policy created the obligation to teach AI in Sri Lankan public schools, making it a mandatory task rather than a planned, self-efficacious behaviour for teachers.

C.60 Order

The term 'order' was used in relation to lower-order and higher-order cognitive skills often relating these to Bloom's taxonomy [51, 169]. Freire et al. [64] used Bloom's taxonomy to analyse different questions and abilities according to their cognitive level and assessed how they can be solved solely by using ChatGPT. Joshi et al. [94] recommend that instructors design "questions that require critical thinking and higher-order cognitive skills that cannot be easily solved by simply providing a prompt to ChatGPT".

A study by Gerede [66] investigated the effectiveness of prompts that students construct when working with ChatGPT. They found that students initially asked more lower-order thinking questions of ChatGPT, but as they became more familiar with the tool they moved towards higher-order thinking questions.

Arora et al. [19] propose that AI integration requires a reevaluation of assessment methods with a shift in focus from solely assessing the correctness of code to "evaluating higher-order thinking skills, such as problem-solving, creativity, critical analysis, and the ability to explain design decisions and address limitations".

C.61 Partnership

Reflecting on approaches to align curriculum with the needs of industry, Dhaou et al. [55] propose collaborative partnerships between academia and industry as a strategy to ensure that computing education remains adaptive and responsive to advances with technology. They argue that this is especially important with the current AI revolution.

Bispo Jr et al. [34] claim that the emergence of LLMs and Generative AI is creating a digital divide within education systems. They propose the formation of technology communities of practice as a strategy to forge connections and support. They cite an example of a partnership between universities and schools in Brazil, which aims to teach computing through digital games.

With the advent of Generative AI, many programming tasks and assessments can now be completed by these AI tools either automatically or in partnership with humans. Through observing how these tools perform Raman and Kumar [148] propose a set of changes to introductory programming pedagogy and assessment, which will incorporate use of these tools.

Hong [84] presents a hybrid model for programming assessment involving automated grading and manual reviewing, which they propose is a "partnership between human intelligence and machine accuracy" and is a robust and comprehensive strategy for a grading system.

C.62 Personal

There is a general sense of the importance of personalisation across the literature surveyed, with a large number of statements about the possibility for personalised learning offered by Generative AIs, and ChatGPT in particular. The value of creating projects that have personal meaning is identified by Chen et al. [42] with their AI-augmented system, ChatScratch, which they used to show the value of the generative and customisable aspects of their tool. Another study by Sun et al. [163] explored how parents of children aged 3-6 perceived AI technologies. Parents claimed that personalised interaction was a basic requirement of AI-based storytelling technologies, although they acknowledged that each child had different characteristics, interests and questions and would a change as they grew older.

The personal connections that are often culturally significant may also hamper a community's understanding of how far their data can travel - that it can transcend the personal communications that are familiar and end up in remote places with total strangers [186].

Personalisation was used as a means of overcoming cultural and language barriers in Namibia by using the child's name in personalised learning materials, allowing them to identify with the narrative and the use of technology [175]. This use of personalisation to overcome resource issues, to recognise and support diversity, and to improve academic in outcomes was also identified in [198]. The language translation options offered by Generative AI systems, reducing the blanket use of English which is rarely the first language of the Global Souths.

The idea of AI enabled personalised learning at scale, taking into account local cultural perspectives, is an implicit theme that is not well-developed in detail. Cubillos et al. [51] claim that "personalised interventions based on demographic variables may foster inclusive and effective programming learning environments" but provide no supporting evidence.

C.63 Privacy

Privacy associated with Generative AI technologies in Africa can be made more severe due to inconsistent and maturing regulatory frameworks, comparatively lower levels of cybersecurity technology, and lower levels of digital literacy and training [198]. From an analysis of publications on AI in education, Pan et al. [135] found that privacy can be achieved in many ways but usually depends upon both regulatory support and technological advancement. The notion of the value of supporting diverse approaches to privacy is at the heart of work by Wong-Villacres et al. [186], where structural factors can complicate discussions around privacy when cultural and existing approaches are in conflict or are not considered. Again, in the absence of regulation, privacy can be overlooked, leading to serious consequences in the short and long term.

C.64 Protection

Across the reviewed articles the concept of protection is a key ethical and practical consideration in discussions surrounding Generative AI. For Hong and Huang [83] and Abdelgadir Mohamed et al. [1], protection is both technical and ethical, encompassing data encryption, privacy safeguards, and cybersecurity mechanisms designed to defend individuals and their privacy.

Alashwal [8], Vhatkar et al. [176], Zhang [194] extend the notion of protection into the regulatory sphere, framing protection as a matter of governance and discuss policies needed to ensure transparency, fairness, and accountability in Generative AI use. Wong-Villacres et al. [186] highlight the Global South's efforts to develop data protection frameworks amid uneven infrastructure.

Jia and Yu [91] and Pias et al. [139] broaden the term protection to include environmental protection through AI applications in wildlife monitoring and sustainable "green" coding practices. Verma et al. [175] link protection to children's rights, emphasizing safety, privacy, and equitable participation. Hong and Huang [83] propose strengthening security education for teenagers to enhance their ability to discern information and their awareness of self-protection.

C.65 Reconciliation

For Abdelgadir Mohamed et al. [1], reconciliation is a process of balancing AI technology innovation with ethical considerations, societal values, and regulatory frameworks. Wong-Villacres et al. [186] propose there are problems with institutionalised regulations for ethical behaviour in the Global South claiming they can be too restrictive, ineffective, not enforced, or non-existent. The authors propose reflective practice of a way of reconciling institutional requirements with local practice; however, they argue that there are deep post-colonial power-related issues that are not easily addressable via reflective reconciliation.

C.66 Regard

The study by Abdelgadir Mohamed et al. [1] adopted the word regard as a technical construct in AI ethics research, referring to a measure of social bias in AI generated text especially in language models. It is part of the framework that evaluate how models express bias towards demographic groups.

C.67 Regulation

With teachers' and students' growing dependence on Generative AIs, Gao et al. [65] propose there is a need for regulatory guidance on Generative AI use in education. It is concerning therefore that a content analysis of 26 AI education policies from international organizations by Li et al. [105] found an unbalanced development of AI ethics and regulations across various countries. Another review by Abdelgadir Mohamed et al. [1] found shortcomings in some current regulatory structures for AI generated text tools. They "stress the importance of globally coordinated regulatory strategies that are flexible enough to respond to new technologies as they emerge".

A particular issue with regulations developed in the Global North being used in the Global South was highlighted by Wong-Villacres et al. [186]. From their study of ethics and computing in the Global South, the authors found that harm may be caused if regulations do not accommodate local realities.

In regard to unethical use of Generative AI, Zlotnikova and Hlomani [198] claim that lack of reliable Generative AI detection tools complicates the integration and regulation of Generative AI technologies into educational institutions in African countries.

C.68 Relatedness

Chandrasekara et al. [40] identified relatedness as a psychological need of learners, which could be fulfilled by certain types of gamified learning and challenges. They designed an innovative platform that used gamification, AI-driven adaptability, and collaborative learning to teach Hypertext Markup Language, Cascading Style Sheets, and JavaScript.

C.69 Relationship

A study by Oyelere and Aruleba [133] that examined the impact of AI tools on fostering inclusive education in Kenya, Nigeria, and

South Africa found a strong and interconnected relationship between students' motivation and their heavy reliance on AI tools, such as ChatGPT, for teaching and learning, particularly in programming tasks, highlighting their prominent role in computing education for these Global South countries. Rajapakse et al. [147] identified social networks and relationships between people as important contributors to social capital.

C.70 Resilience

The term resilience was used by authors in different ways ranging from technical robustness to human adaptability. Du et al. [57] use resilience to describe the ability of ChatGPT-generated code to withstand adversarial interference and demonstrate reliability under stress. In contrast, Videla et al. [177] define resilience as an educational quality, describing a learner's capacity to resist intellectual dependency on AI and sustain curiosity, creativity, and critical inquiry. Similarly, Chen et al. [42] situate resilience within creative learning, showing how children's commitment to realizing imaginative coding projects fosters perseverance through difficulty. Li et al. [105] and Rajapakse et al. [147] link resilience to teachers' self-efficacy and adaptability in facing the challenges of integrating AI into education. Finally, Cubillos et al. [51] view resilience as a pedagogical outcome, warning that excessive AI support may weaken students' independence and problem-solving endurance.

C.71 Respect

A study by Torrato et al. [170] that investigated the perspectives of teachers and students about ChatGPT found that both groups were positive about the technology but there were concerns. The authors concluded that with the rapid advances of the technology, its use in education should be regulated, and for this it is important to respect and comprehend both teachers and students feelings and viewpoints.

A study of ethics and computing in the Global South by Wong-Villacres et al. [186] mentioned respect as an important concept when understanding different approaches to ethics across cultures. As an example they claim that projects with First Nations people "require respect for their data sovereignty, which can flourish only if people understand what sovereignty means in relation to community control". As another example, "introducing clear regulations might not necessarily translate to respect toward citizens' data privacy" in countries with authoritarian governments.

C.72 Responsibility

A pedagogical model for teaching algorithms proposed by Wang [182] uses outcome-based methods that equip students with both creative problem-solving capacities and social responsibility. Wang proposes "comprehensive assessments of technical competence, innovation ability and ethical responsibility for students", in a way that shifts a focus from exclusively technical proficiency to emphasize "socio-ethical responsibility in Algorithmic problem solving". Du et al. [57] propose a need for a hybrid approach that mixes technical efficiency with human ethical judgements, where "responsibility for ethical and privacy outcomes is clearly defined". Similarly, Sebastian et al. [157] advocates for "blending technological proficiency with a deep appreciation for the environment and a sense of responsibility toward humanity's welfare" within computing education for children.

Adam et al. [3] propose that "responsibility awareness" is one ethical consideration that is important for pedagogical approaches that can support Generative AI integration in higher education institutions. Zhang [194] argue that "universities should integrate ethics and social responsibility into their curricula, cultivating students' ability to consider these issues during technology development, ensuring they can make responsible technical decisions in their future careers".

C.73 Right

The term 'right' was used in two distinct senses: "right" as meaning correct, and "right" as referring to an individual's rights.

A study by Gerede [66] investigated the effectiveness of prompts students construct when working with ChatGPT to determine whether students can ask the "right variety of questions to foster deep understanding". They found a relationship between asking a broad range of questions at different Bloom's levels and performance. Budhiraja et al. [39] explored ChatGPT usage in three universities in India. They found that writing well-structured prompts that would yield the right answer was challenging for many participants.

Verma et al. [175] reviewed the integration of AI in education in the Global South, with a particular focus on children's "rightful participation in AI contexts". They argue that children often have limited understanding of the implications of AI technologies and fewer opportunities to express their views or access appropriate advocacy. The review highlights key considerations for supporting children's rights, including the provision of adequate resources, protection from potential AI-related harm, and the promotion of equitable participation in AI integration.

A study of ethics and computing in the Global South by Wong-Villacres et al. [186] found that computer science professionals in the Global South often face two forms of inequity: discriminating against those who are not of "the right" gender or do not hold "the right" type of knowledge to practise the profession.

C.74 Rules

Alpizar-Chacon and Keuning [12] explored the use of Generative AI as a support tool for learning. In a survey, students were asked their views on rules or policies regarding using Generative AI. They found that "Some students assigned responsibility to teachers (e.g., creating Generative AI-proof assignments) or individuals, emphasizing the need for self-monitoring to ensure they are still learning while using these tools. Others compared its regulation to traditional plagiarism policies or expressed more liberal views advocating for fewer restrictions."

C.75 Security

A review of the integration of AI in education in the Global South by Verma et al. [175] identified privacy and security as barriers to using AI in the classroom. They found that AI can expose learners to various risks including cyberbullying, trolling, flaming and online grooming. While psychological security is a known consideration for effective team work and opening up dialogue, it is often not prioritised in the Global North, due to perceptions around its value. Prioritising this as a value is seen in [55]. A study by Mwaniki et al. [122] of the perceptions of third-year computer science students in Kenya towards the use of Generative AI tools in their studies found that students were concerned about the security of their data Zlotnikova and Hlomani [198] claim that in Africa, the "privacy and security concerns associated with Generative AI are especially severe due to limited cybersecurity infrastructure, insufficient regulatory frameworks, resource constraints, low digital literacy, inadequate awareness and training, rapid digitalization without safeguards, and dependence on external technologies".

C.76 Self-Regulation

Prasad and Sane [142] discuss challenges and opportunities that Generative AI technologies pose for the self-regulation strategies of novice programming students. They conclude that the use of Generative AI could hamper students' self-regulation skills; however, Generative AI tools also offer affordances and features to enable design of interventions that promote self-regulation. A study by Gomez-Jaramillo et al. [67] investigated the pedagogical effectiveness of Generative AI tools when used in the teaching of object-oriented programming. Using an AI-assisted sequential tutoring strategy structured around a master prompt, the design encouraged progressive mastery and fostered self-regulation.

C.77 Sentiments

Studies of sentiments in relation to Generative AI in the Global South concern both negative and positive perspectives about interactions with Generative AIs and Generative AI. A study by Bernardino et al. [30] to assess students' perceptions of using ChatGPT to support scientific paper writing found positive sentiments, including interest, admiration, motivation, and optimism, as well as negative sentiments such as uncertainty and concern about the impact of ChatGPT. Prasad and Sane [142] discuss challenges and opportunities that Generative AI poses for novice programmers' self-regulation strategies. They propose that Generative AI tools may elicit both positive sentiments such as joy and wonder and negative sentiments such as fear and confusion.

C.78 Social Capital

Bhandari and Yasunobu [33] defines Social capital as "a collective asset in the form of shared norms, values, beliefs, trust, networks, social relations, and institutions that facilitate cooperation and collective action for mutual benefits". Given the focus on cultural and value systems in this work, we must recognise that there is a great diversity in the social norms that span the multi-cultural educational environment. These have to be carefully navigated and recognised as the level of agency that teachers may have in a given space can be limited by cultural issues, social norms, and the extent of their interpersonal networks. While this issue was not discussed extensively in the context of Generative AI, the 'social capital' that teachers have in the Global South, focused on their networks and relationships, have been identified as being potentially insufficient to grant them agency to engage in relevant study to support the teaching of more advanced topics such as AI [147].

C.79 Social Cohesion

Wu et al. [187] claim that the uneven geographical and cultural distribution of AI knowledge creates an AI knowledge gap, exacerbating AI development inequalities between the different countries and regions and also affecting the achievement of social cohesion. Wu et al. [187] propose that inequities in the geographical and cultural concentration of AI knowledge could cause an "AI knowledge gap", exacerbating inequalities in the development of AI between different countries and regions and may have a negative effect on the achievement of social cohesion. Wu et al. [187] propose that in order to bring more balance, researchers and scholars globally should participate in AI literacy research and practice.

C.80 Social Responsibility

Yang et al. [189] propose that social responsibility is something that computing educators can focus on as the challenges of low engagement and inadequate practice conditions have largely been solved through the use of Generative AI. Wei et al. [183] observed in a classroom session where students were using Generative AI in a structured way, that this allowed them to deepen their subject understanding and heighten their social responsibility, although it is important to note that the experiments were not focused on that.

Zhang [194] advocates for computing curriculum to include ethics and social responsibility, ensuring students can make responsible technical decisions. A focus of responsible decisions is the green economy, in particular in Latin America and Caribbean, where a growing focus is on utilizing computing to promote environmental protection through energy-efficient coding and using computing to help tackle challenges related to climate change [139]. Wang [182] applies such an integration by combining the BOPPPS model (Bridge-in, Objective, Pre-test, Participatory Learning, Post-test, Summary) with ACPS elements (Algorithm Cases, Political Education, Coding Platform, and Chaoxing Learning System) in an algorithms course. The approach uses a case study of dynamic programming and introduces national strategies, such as public health management and intelligent logistics scheduling, to the teaching exercises. Experimental results show that this model has encouraged students' practices on algorithm modelling and enhanced students' awareness of ethical choice and social responsibility, at a higher level than traditional methods.

C.81 Socialisation

A scoping review by Ariza et al. [18] analysed the implications of integrating Generative AI in engineering and computing education from K-12 to tertiary levels. Areas of focus were the development of learning outcomes in the cognitive, affective, or behavioural (e.g., socialisation) domains of learning.

C.82 Society

As AI technologies become increasingly embedded in everyday life, Sebastian et al. [157] stresses the importance of empowering children to become critical users of digital technologies and "critically reflect on their consequences, in their everyday life as well as in society". Based on a bibliometric review of AI research, Wu et al. [187] conclude that fostering AI literacy is a shared responsibility of educators, policymakers, and society at large. Similarly, Zlotnikova and Hlomani [198] emphasise the importance of coherent national policy and strategic planning for the integration of AI in education, particularly for countries such as Botswana that aspire to become knowledge-based societies.

At the institutional level, Sebastian et al. [157] highlight the need for teachers to be supported through professional development opportunities, access to appropriate resources, and ongoing institutional backing in order to keep pace with rapid technological change. They also stress that educators must be valued and recognised for their broader contribution to society. From a societal perspective, Amos et al. [15] argue that maximising the benefits of AI technologies requires maintaining a balance between AI-assisted approaches and traditional educational methods. In this context, understanding the societal impacts of AI-enabled education is crucial for promoting long-term societal well-being [176].

Societal benefits and ramifications are clearly identified as ongoing and important considerations in the deployment, development, and use of Generative AI systems. Abdelgadir Mohamed et al. [1] stress the importance of considering societal causes in addressing inequity, to inform change that is beyond "statistical adjustments". The issue of an abstracted ethics, which is not grounded in the societal wishes and norms of communities in the Global South was raised as an argument against static ethical codes, applied without cultural consideration and hence often at odds with the cultures of the Global South [186]. Pan et al. [135] argue that addressing societal acceptance is an important for equitable and sustainable educational development.

Papers also recognised the influence of local societal structures on student perception towards AI, beyond technical and cultural issues [133].

C.83 Spirit

Use of the term 'spirit' identified a dichotomy in the perception of its relationship with Generative AI. On one hand, authors focused on how Generative AI can support or enhance high-quality talent and innovative [183, 189], entrepreneurial [194] and teamwork and collaborative spirit [183, 195]. For example, Wei et al. [183] found that their model of integrating Generative AI in all aspects of a course (defining seminar topics, organizing group divisions, conducting "Introduction-Exposition-Summary" three-part seminars, group presentations and feedback, and teacher summaries and feedback) had significantly enhanced the student interest in operating system concepts and improved innovative and critical thinking.

On the other hand, Hong and Huang [83] warn of a risk of extensive reliance on Generative AI leading to decline in critical thinking, creating a superficial understanding of topics, and leading to a lack of deep thinking and innovative spirit. Of note is that the connection between the use of Generative AI and other aspects of student identity such as geographical or spiritual is not discussed in the context of the term 'spirit'.

Matters that are *of* the spirit, thus spiritual, have been identified as one anchor of socialisation, which affects how students can internalise concepts and values [153]. This has also been raised as a concern where the answers given by Generative AI are at odds with the culture/spiritual traditions or expectations of a community.

C.84 Stimulation

Stimulation of interest was one of six key teacher conceptions identified in a phenomenological study by Rajapakse et al. [147]. Most of the participants were ICT teachers with an ICT-related educational background, which Rajapakse et al. [147] propose is the reason for their generally positive attitude towards AI education

C.85 Success

Oyelere and Aruleba [133] links student success to motivation, engagement, and accessibility of AI tools. Students view AI tools as enhancing learning speed and efficiency, suggesting that equitable access to these tools contributes to academic success in programming education. In view of the widespread adoption of Generative AIs in industry, Arora et al. [19] stresses the importance of introducing these tools to students to help them build the "critical thinking skills needed for professional success".

In Bispo Jr et al. [34], success is discussed in terms of educational opportunity and capability. It is not framed as grades but as the "freedom to achieve well-being" and the capability to be educated, and equitable access to opportunities for meaningful learning. Rajapakse et al. [147] explored the readiness of teachers to teach AI into Sri Lankan schools and found them unprepared. The authors argue that the success of the introduction of AI is strongly linked to teacher preparedness and recommended a professional development program.

Gao et al. [65] propose that big data and ML techniques provide a means for more accurately analysing student learning data to determine factors that "affect academic performance, ensuring a more equitable measurement of educational success".

C.86 Support

Across the articles, support is used as both a pedagogical construct to describe how learning is facilitated and as a technical construct to describe capabilities of AI tools.

Many articles use support to describe pedagogical scaffolding, helping students learn by offering explanations, feedback, motivation, and opportunities for exploration. For example, Generative AI guides students through critical thinking and helps them formulate answers [10], supports brainstorming and creativity [39], enhances learning through personalised support and deeper conceptual exploration [19], assists with pre-test preparation [4], and provides debugging assistance and support for diverse learning modalities [81].

Another frequent use of "support" is related to teaching. Generative AI supports instructors by performing routine tasks, generating content and assessment tasks, or assisting with grading and guidance to students. Examples include educators using AI to monitor learners and deliver more personalised interventions [127], tools that help teachers design content, conduct research, and generate assessments [2, 3], AI-generated explanations that free teachers to focus on emotional and motivational support [24], and grading or analytics systems that streamline evaluation processes [13]. Some studies show that teachers still need systemic support to use AI effectively in practice [157].

The term "support" is also used in relation to institutional policies and resources necessary for successful Generative AI integration. Some studies highlight the need for educational policy support to enable AI adoption in computing curricula [170, 194] or describe how effective scaling of AI-mediated instruction requires pedagogical oversight in addition to institutional support [67].

A further use of "support" refers to technical capabilities or functional affordances of AI systems. This includes AI systems supporting personalised learning resources [65], Generative AI systems supporting MCQ creation [74], and AI supporting data cleaning, data integration, and prediction analytics [13].

Some articles use "support" to describe social, community, or mentoring roles traditionally filled by people. AI can substitute for mentors by providing tutoring and motivational support [8, 9], act as a virtual peer that boosts engagement and conceptual understanding [56], offer support to empower communities [164].

Finally, "support" sometimes refers to infrastructure-level contributions within educational systems. This includes AI-based tools supporting interdisciplinary collaboration and real-time feedback [121], intelligent Q&A systems supporting knowledge acquisition [95] and model selection strategies providing methodological support for scientific use of Generative AIs in programming education [197].

C.87 Sustainability

Rajapakse et al. [147] claim that many Global South nations take a fragmented approach to the adoption of AI, frequently missing the social, economic, and cultural context of local communities. They propose that this lack of a coordinated approach and context-aware strategies for AI in education poses a significant barrier to sustainable integration in the Global South argues. Dos Santos and Cury [56] propose the use of ChatGPT as a virtual peer for peer instruction in programming courses, arguing that the these could bring long term benefits for students learning but this needs to be evaluated.

C.88 Teamwork

A study of the use of Generative AIs for advanced level computer programming assignments by Arora et al. [19] reported mixed effects on teamwork. Some students found Generative AIs produced good solutions for team members, others found there were incompatibilities in Generative AI-generated code between team members. A study by Oran et al. [131] explored the use of ChatGPT in teaching project management. For the aspect of teamwork, they found that ChatGPT improved communication and provided a more collaborative learning experience. Neyem et al. [127] explored the impact of stand-up reports on software engineering projects. They found the AI-powered tools, helped students produce better StandUp reports, resulting in improved project management and teamwork. Abdelgadir Mohamed et al. [1] proposes that to ensure effective teamwork in the age of AI, it is important to incorporate AI tools that enhance and support, rather than undermine, their vital human-centric collaborative processes.

C.89 Thought

The different thought processes used by students when working with Generative AI have been discussed in a number of studies. In their AI-augmented system, ChatScratch, for teaching young children programming, Chen et al. [42] introduced the chain-of-thought reasoning approach in which rationales are integrated as intermediate steps with examples. A study of undergraduate and graduate students' use of large language models for programming assignments in advanced computing courses by Arora et al. [19] found that students employed a range of prompting strategies, from simple contextual prompts to more sophisticated techniques such as chain-of-thought prompting. The use of chain-of-thought approaches has also been reported in other studies, where it was found to foster student engagement and critical thinking [90, 92].

At the same time, there is ongoing debate regarding the role and potential of AI tools in supporting creative thought [177]. Torrato et al. [170] caution against the risk of over-reliance on AI technologies in educational contexts, arguing that such dependence "may impair pupils' capacity for autonomous thought".

From a broader perspective, considerations of ethical frameworks for AI use must also account for cultural variation and the "messy" realities of educational practice. Wong-Villacres et al. [186] emphasises that differing cultural perceptions of what constitutes valid knowledge, and who is recognised as a legitimate knower, necessitate culturally situated modes of thinking.

C.90 Tradition

Traditional education methodologies are presented as fundamentally constrained by their human-centric, static, and non-scalable nature [149]. Generative AI extends the learning and teaching options from traditional classrooms through access to a large number of resources [180]. Videla et al. [177] claim that Generative AI's application in education has been positively received by advocates of "traditional and top-down pedagogical approach in which knowledge is conceived as a deposit that the teacher 'transfers' to students". However, they caution that the intensive use of Generative AIs in education is leading to concerns about "cognitive deskilling and dependency".

In domains such as programming education, traditional teaching and assessment approaches use labor-intensive practices such as instructor-written unit tests, manual plagiarism checks, which are often error-prone and incapable of providing personalised or dynamic support. The advent of AI has fundamentally redefined these possibilities, shifting the context from one of constraint to one of generation and adaptation. For example, Lim and Weng [108] present an automated coding challenges assembly method, combining the "strengths of traditional manual problem assembly with modern computational technology", resulting in an efficient system with fairer challenges for students. Another example, Jun et al. [95] present an using AI technology-based Q&A system for computer courses and their study shows it outperforms traditional methods in performance and efficiency.

Amos et al. [15] propose that AI systems act as force multipliers and cognitive partners, automating scalable, repetitive tasks while augmenting human intelligence with unprecedented levels of personalisation, creativity, and real-time feedback. This transformation repositions educators and developers from the traditional roles of the primary sources of knowledge and execution to becoming curators and guides who interpret and leverage AI-generated outputs.

C.91 Transparency

Several studies [86, 99, 163] raise concerns about how transparency with using Generative AI tools in learning can be supported, framing the challenge as a trust issue on behalf of the educator of the content generated. In addition, a lack of explainability of the models leads to usability and fairness challenges [13]. In marking, transparency of the Generative AI tools, rubrics and prompting used in automated grading supports trust in the marking process and thus enhances learning [181].

Transparency is also as a critical issue in Jia and Yu's study [91], who highlight that the responsible design of AI tools, where inclusivitiy, transparency and accountability is emphasized, has the potential to significantly increase the positive impact of Generative AI on society. Similarly, Pias et al. [139] recognise the potential of computer science, and Generative AI, to promote fairness, transparency and justice across Latin America.

C.92 Trust

Trust was seen as an area warranting particular attention when dealing with Generative AI. Torrato et al. [170] highlight a potential dichotomy in the trust in Generative AI responses, with over 81% of students in a Santiago school saying they trust Generative AI responses, versus 64% of teachers. Karegowda et al. [96] studied intelligent chatbots and reported that "the alignment of personality features between users and chatbots…was shown to greatly enhance trust and pleasure". Beyond affinity, Kather et al. [99] focus on building trust in the data using trusted reviews from past developers, in a study of a platform augmenting Generative AI models. This strategy responded to a growing need for transparency and control, ensuring that students and educators can trust the content recommendations being made.

In addition to the inability to assess trustworthiness of Generative AI, the issue of dependency may arise. A study investigating the AI dependency profiles of Filipino first-year programming students, focused on their backgrounds, perceived usefulness of AI, and trust in AI tools [80]. AI trust in that study referred to the confidence that students had that the AI tool will provide reliable, accurate, and helpful suggestions. Trust was seen as a crucial in relation to dependency, as it reduces hesitation and can increase the likelihood of AI tool adoption. Verma et al. [175] introduce an external dimension to the interaction between primary school students and Generative AI, highlighting that students could ask for a second opinion of a trusted adult as prompted by the Generative AI tools.

C.93 Understandability

Understandability is a criterion in a framework developed by Alaswad et al. [9] for evaluating Generative AIs based on their educational performance. A study by Pirzado et al. [140] compared content generated by Generative AIs with student-generated content, and found differences in understandability.

C.94 Unity

A review by Abdelgadir Mohamed et al. [1] that explored ethical, social, and technical challenges posed by Generative AI proposed that the capacity of the tools for generating misinformation and the difficulty people face in differentiating between human and AI generated material present dangers for societal unity.

C.95 Values

According to Oyelere and Aruleba [133], in the Global South the universally recognised value of programming skills is driving a uniform demand for AI educational tools. These Generative AI applications deliver significant value by creating dynamic, personalised resources that maximise learning through customisation and reuse, allowing motivated students to efficiently master high-value tasks, such as code logic [149].

The study by Oyelere and Aruleba [133] found that students from different backgrounds perceived the value of AI-driven tools differently. The authors claim that "students from under-represented groups might see more value in Generative AI tools for creating opportunities and leveling the playing field, as these tools can provide personalised learning experiences and access to resources that might otherwise be inaccessible".

The document "Future of Education and Skills" from the Organization for Economic Co-operation and Development (OCED) stresses that AI cannot replace humans and emphasises the "return to human-centred values" in the age of AI [105]. Hu et al. [86] propose that "AI education should uphold human-centered AI values and principles related to ethics, trustworthiness, responsible AI, and fairness". However, a study of ethics and computing in the Global South by Wong-Villacres et al. [186], found there was a tension in translating explicit or implicit values into formal ethics codes, with participants describing gaps between local realities and globalised formal ethics codes and rules.

C.96 Virtue

Abdelgadir Mohamed et al. [1] employ a multifaceted ethical framework for their review of the ethical terrain on the use of Generative AI tools. They focus, however, on virtue ethics and consider the traits they want AI systems to embody. Examples of such traits include transparency, accountability, and benevolence. They claim that the virtue ethics perspective prompted reflection on "the kind of society we aim to cultivate through the development and deployment of AI systems". The perspective addresses several issues such as societal consequences of the tools (often influenced by the levels of the equity, inclusivity in those tools), trustworthiness, respect, public trust, digital rights and freedoms, fairness and bias . Integrity, responsibility, avoiding harm with AI use are more offshoots of virtue ethics perspectives in the Global South.

C.97 Welcoming

Samarakoon et al. [151] investigate the effectiveness of using Generative AI to enhance coding proficiency across a diverse cohort of undergraduates at a Sri Lankan university. The authors used Google Classroom which is presented as a welcoming technology and an accessible, secure, and inclusive digital environment. Google Classroom presented users with an environment that they felt comfortable using, regardless of their technical expertise.

C.98 Well-Being

Verma et al. [175] propose that Generative AI can have both positive and negative impact on emotional well-being and stress the need for privacy protection and digital literacy education to ensure that "students can safely interact with AI tools without compromising their well-being". From their study of the use of Generative AI in programming education, Cubillos et al. [51] concluded that AI can reduce pressure in programming learning, which may be beneficial for students' emotional well-being; however, it can also lead to excessive dependence on AI and impede the development of independent problem-solving skills. The dangers of negative impact of Ai on students' mental well-being was also mentioned by Sebastian et al. [157]

A study by Rajapakse et al. [147] exploring readiness of teachers to teach AI found that emotional well-being was an important factor in shaping their self-efficacy. Abdelgadir Mohamed et al. [1] propose that it is important to evaluate how AI tools can contribute to overall societal well-being and how possible harmful effects can be mitigated..