10P-Health: A Conceptual Framework for Continuous, Digitally Enabled Precision Health and Wellness

10P-Health: A Framework for Precision Health and Wellness

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ABSTRACT

Personalized medicine has advanced individualized prevention, diagnosis, and treatment through genomics, multi-omics, and artificial intelligence. Nevertheless, its implementation remains constrained by fragmented data, limited interoperability, episodic care, privacy concerns, and the insufficient use of behavioral, environmental, social, and continuously generated health information. Building on the evolution from P4 to later "P" models, this position paper proposes 10P-Health as a broader conceptual framework for holistic, continuous, individual-centered, and digitally enabled health and wellness.

The framework integrates ten core principles: Predictive, Preventive, Personalized/Precision, Proactive, Participatory, Pertinent, Pervasive, Permanent, Privacy-Preserving, and Platform-Based. Together, these principles connect individualized risk assessment and intervention with individual participation, longitudinal monitoring, contextual relevance, responsible data use, and interoperable digital infrastructure. To translate the concept into practice, the paper presents a layered reference architecture linking multimodal data acquisition, harmonization, secure integration, analytics, decision support, individual engagement, and controlled secondary research.

Real-world adoption requires balancing the framework's principles while addressing technological, operational, ethical, and legal challenges, including data generation and usage, data quality, clinical validation, workflow redesign, professional accountability, consent, equity, reimbursement, and sustainable governance. The paper recommends implementing 10P-Health through defined use cases, stakeholder-led pilots, continuous evaluation, and progressive scaling. It offers a structured direction for transforming advances in digital health and multimodal data into responsible, continuous, and sustainable personalized health and care.

KEYWORDS

10P-Health, precision health, digital health, AI for health, continuity of care

1. Introduction

1.1 Background and Context

Conventional medicine is designed largely around the "average" patient, applying standardized protocols even though individuals differ substantially in how they develop disease and respond to therapy. Personalized medicine departs from this one-size-fits-all model by tailoring prevention, diagnosis, and treatment to each patient's genetic, molecular, environmental, and lifestyle characteristics, so that diagnostic and therapeutic decisions are guided by individual molecular profiling rather than population averages [1,2]. The growing accessibility of multi-omics data spanning genomics, epigenomics, transcriptomics, proteomics, and metabolomics has been central to this shift, since integrating these layers yields a more comprehensive picture of individual health and enables more precise, better-tolerated therapeutic strategies [3].

Personalized medicine has advanced in many areas. In pharmacogenomics, genetic variation in drug metabolism, efficacy, and toxicity informs prescribing in oncology, so that genotype-guided dosing can reduce severe adverse reactions, however routine implementation of such testing is still limited [4]. Oncology remains one of the leading domains, where next-generation sequencing and bioinformatics have made it faster to detect mutations for which targeted agents exist, although incorporating genomic profiles into routine clinical workflows remains difficult [5].

Artificial intelligence is widely expected to enable the next stage of this shift by integrating heterogeneous, multimodal data such as electronic health records, medical imaging, genomics and other omics, environmental exposures, and wearable sensor streams within a single analytical framework [2]. Machine learning and deep learning models can detect intricate, non-linear relationships that span these modalities, strengthening early detection, patient stratification, clinical decision support, and treatment response prediction [2]. Integrating molecular, phenotypic, and environmental data across omics layers is in turn expected to sharpen risk assessment and enable earlier intervention [3].

These advances remain constrained by interdependent barriers. Even setting artificial intelligence (AI) aside, realizing personalized healthcare is hindered by the complexity of integrating data across omics layers, heavy computational demands, high generation costs, and the need for standardization and robust validation in diverse populations [3]. For AI specifically, clinical translation is further limited by fragmented and poorly interoperable data, insufficient real-world validation, algorithmic bias, limited transparency, and privacy concerns [2]. Among these, privacy is especially consequential: the sensitive patient data most valuable for such modeling is typically locked within isolated institutional silos, and regulatory and ethical constraints impede the large-scale centralization on which conventional model training depends [6].

1.2 The Evolution of "P" Concepts in Personalized Medicine

P4 medicine is an early and influential formulation of the reorientation from traditional to personalized care. Its four attributes are predictive, preventive, personalized, and participatory. Hood and Galas [7] articulated it as a shift from reactive care, which waits for illness to appear, toward a preventive and increasingly wellness-oriented model. Their case was framed in concrete benefits: earlier detection, stratification of patients into groups amenable to optimal therapy, fewer adverse drug reactions, better drug target selection, and cheaper clinical trials.

Hood [8] later grounded the same vision in systems medicine, where omics technologies, network models of disease, and blood-based biomarkers make it possible to detect perturbations before symptoms appear. Flores et al. [9] traced P4 to the convergence of three megatrends: systems biology and systems medicine, the digital revolution, and consumers' growing determination to manage their own health, and specified the infrastructure, including personalized data clouds and analytic techniques for deriving actionable knowledge.

Subsequent models preserve this core and extend it along additional dimensions. P5 medicine introduces a psycho-cognitive component. Its proponents argue that a predominantly biological account neglects the manner in which individuals experience illness, cope, and reach decisions [10]. P6 medicine retains this dimension and adds a public one, reframing medical practice as population-based, shared, and open-source [11]. P9 medicine was advanced within a health-information-technology context. It augments the P4 foundation with pervasive, precise, privacy-preserving, protective, and priced-reasonably attributes. In doing so, it incorporates precision medicine considerations together with the infrastructural, security, and affordability requirements of a networked health system [12].

1.3 Problem Statement

Despite the advances described above, several structural limitations continue to constrain the field. The first limitation is data fragmentation. Clinical records, genomic data, and imaging results are typically held by separate institutions under separate governance regimes, with no shared architecture for integration. Data silos therefore remain a structural constraint on any framework that aims to integrate multimodal data.

The second is the limited scope of current clinical applications that mainly focus on biomarker-guided oncology, genomic diagnosis of rare diseases, and selected pharmacogenomic decisions. The third limitation is that care remains episodic rather than continuous. Current health systems are organized around the clinical encounter as the basic unit of care, and depend on it as the main source of individual data, while the use of remote and continuous monitoring, including wearable devices, home-based sensors, and related digital health technologies as a routine source of data between encounters remains behind. Fourth is that personalized medicine today relies mainly on omics and clinical data. Other factors known to influence health outcomes, including environmental exposure, data from the Internet of Things, social media, and behavioral data, and broader social determinants of health, are not utilized in their full capacity in the creation of personalized health solutions.

1.4 Aim, Methodology and Structure of the Paper

This position paper responds to the limitations set out above by proposing the 10P-Health framework, a conceptual extension of the 4P model of personalized medicine. Where the 4P model established the shift from reactive care to predictive, preventive, personalized, and participatory care, 10P-Health reframes that vision around the continuity of care, using digital health technologies and multimodal health data to inform decisions beyond the individual clinical encounter.

This paper pursues two objectives. First, it develops the 10P-Health concept into a scholarly framework, defining its ten principles. Second, it outlines a layered reference architecture that specifies the principal functional requirements for exploiting multimodal data.

Methodologically, the framework was developed through a narrative synthesis of the literature on the evolution of "P" models in personalized medicine (Section 1.2), which was used to further describe the 10P-Health concept originally formulated by Chaltikyan (Section 2.1). Each principle was then examined for the functional requirements it places on data, services, and governance, and these requirements were organized into the layered reference architecture presented in Section 2.2. The framework is intended as a reference for future research and design in personalized health, not as an empirically validated system.

2. The 10P-Health Framework

2.1 Overview

The 10P-Health framework described by Georgi Chaltikyan [13] (G. Chaltikyan, personal communication, November 14, 2019), brings together ten complementary principles that define a continuous, individual-

centered, and digitally enabled model of health. Personalized and Precision form the foundation of the framework. Precision uses molecular, biological, clinical, environmental, and lifestyle data to support risk stratification, disease classification, and treatment selection, whereas personalized extends this approach by adapting care to the individual's psychological, social, environmental, and broader life-context characteristics. Predictive builds on these data to estimate future disease risks, health trajectories, treatment responses, and potential complications before they become clinically evident.

These predictions are translated into action through Preventive, which uses long-term risk forecasts to support actions that reduce the likelihood of future health problems before symptoms develop. Proactive initiates timely and personalized responses to identified risks rather than waiting for disease to emerge or for the individual to seek care. Pertinent focuses on delivering relevant and timely healthcare interventions. This involves real-time data analysis, quick adaptation to changing health conditions, and ensuring that interventions align with the specific needs of the individual or population.

Participatory positions individuals as active partners in their care by involving them in decision-making, health-data contribution, self-management, and care planning. Pervasive extends health support beyond conventional clinical settings by embedding it into everyday life through remote care, ubiquitous technologies, and connected devices. Permanent adds a longitudinal dimension by maintaining continuity of health information, monitoring, and support across the life course, healthcare providers, care settings, and clinical episodes.

These principles require both technological coordination and responsible data governance. Privacy-Preserving protects personal health information throughout its collection, storage, analysis, and exchange through data minimization, secure computation, access control, transparency, and accountable governance. Platform-Based provides the coordinating foundation through which heterogeneous data sources, analytical services, digital technologies, care processes, and stakeholders can interact within an interoperable, modular, and individual-centered health ecosystem.

Although several principles are closely related, each has a distinct operational role (Table 1). Predictive, Preventive, Proactive, and Pertinent form a sequence rather than overlapping labels: Predictive estimates risk, Preventive targets the long-term reduction of that risk, Proactive determines when action is initiated without waiting for the individual to seek care, and Pertinent adapts the content of that action to the individual's current context. Similarly, Pervasive and Permanent describe two different dimensions of continuity: Pervasive concerns where health support is available, across everyday settings, whereas Permanent concerns how long it is maintained, across the life course and successive care episodes.

Principle	Distinct operational role	Main output
Personalized/ Precision	Tailors risk stratification, classification, and care to the individual's biological and life-context characteristics	Individual-specific stratification and care options
Predictive	Estimates future risks, health trajectories, and treatment responses	Risk estimates and forecasts
Preventive	Reduces the long-term likelihood of disease before symptoms develop	Preventive options and goals
Proactive	Initiates timely action on identified risks without waiting for the individual to seek care	Timely prompts and referrals
Participatory	Involves the individual as an active partner in decisions and self-management	Shared decisions and self-management plans
Pertinent	Delivers relevant and timely interventions that adapt to changing health conditions and to the specific needs of the individual or population	Relevant, context-adapted interventions
Pervasive	Extends health support across everyday settings (where support is available)	Support outside clinical settings
Permanent	Maintains continuity of information and support over time (how long support is maintained)	Life-course health record and follow-up
Privacy-Preserving	Protects personal health information throughout its collection, analysis, and exchange	Minimum authorized data and auditable use
Platform-Based	Enables interoperable, modular interaction of data, services, and stakeholders	Interoperable, replaceable services

Table 1: Distinct operational roles of the ten 10P-Health principles.

Realizing this vision depends on advances in data analytics and on the large volumes of information generated by sensors and Internet of Things devices outside traditional clinical encounters. Such data may be produced continuously across smart homes, hospital-at-home programs, smart cities, and connected hospital environments such as intensive care units. The framework integrates these real-world data streams with clinical and genomic information to create a unified and continuously updated view of the individual. In this way, personalized healthcare can become part of everyday life rather than remain confined to episodic clinical visits, with the broader aim of improving quality of life and extending healthy life expectancy.

2.2 Implications and Applications

10P-Health is a paradigm for organizing health and wellness. At its center is the individual, who serves as the organizing point around which health information, analytical capabilities, preventive support, and decisions concerning data use are coordinated. This individual-centered orientation can be embodied in a personal health companion, a conceptual individual-facing function through which a person connects relevant sources of health information and manages which data can be used, for what purpose, and for how long.

The companion is intended to provide continuity across everyday life and changes in health status. It can support different use cases such as understanding personal measurements and longitudinal trends, obtaining health information, exploring future risks, considering preventive options, setting goals, and recognizing when professional assessment may be required. These needs can use different combinations of data analysis, health-domain knowledge, behavior support, and professional input.

Individuals can interact with the framework through different digital interfaces, including conversational interfaces enabled by large language models. Such interfaces provide an accessible point of interaction by interpreting the individual's request and communicating it to the coordination and orchestration function, which identifies the relevant information and services. Relevant multimodal personal health data may originate from wearables, home-based sensors, mobile and consumer devices, self-reported information, personal or electronic health records, healthcare providers, laboratories, medical-imaging systems, genomic and other omics repositories, and environmental, behavioral, psychological, and social sources. Validated, use-case-specific analytical models process the relevant multimodal data to generate risk estimates, forecasts, classifications, or other health-related outputs, while the personalized health companion communicates the results in understandable language.

A coordination and orchestration function links the companion to these distributed data sources to analytical, knowledge-based, and behavior-support services. Based on the individual's request, permissions, and intended purpose, it identifies the appropriate services and the minimum authorized information required. Interoperability, data quality, privacy, and governance operate across these connections. Information should be technically and semantically interpretable and accompanied, where relevant, by details concerning its source, timing, completeness, quality, and permitted use. This is particularly relevant for data from consumer wearables and home-based sensors, which are affected by measurement error, motion artefacts, and missing data arising, for example, from non-wear or device charging [14]. Such data should therefore undergo quality control, including the handling of missing values and the flagging or filtering of implausible measurements, before they are made available to analytical services. Access should remain proportionate to the intended purpose and subject to appropriate requirements concerning identity, authorization, consent, purpose limitation, data minimization, transparency, auditability, and accountability.

The framework relies on modular and purpose-specific services rather than a single model or service intended to address every health need. Different conditions, populations, prediction periods, and data combinations may require different analytical models. Each service should therefore have a defined purpose, required inputs, validation status, limitations, and conditions of use. Models and services should also be governed, monitored, and applied only within their intended scope. This modular structure

allows individual services to be updated or replaced without redefining the wider 10P-Health paradigm.

Depending on the legal, organizational, privacy, and governance requirements of the context, multimodal model development may use governed central environments, distributed analysis, federated methods, or hybrid arrangements. The selection of a specific technical architecture for developing and applying multimodal models across distributed data sources lies beyond the scope of this conceptual framework. Before analytical outputs are communicated to the individual, they should be assessed for data sufficiency, evidential grounding, relevance, consistency, uncertainty, and alignment with the intended use. A predictive multimodal model may estimate a risk or future trajectory, but translating that estimate into an appropriate response requires health knowledge, safety considerations, individual preferences, and, where necessary, professional judgement. The companion can therefore explain the result, the factors that contributed to it, the limitations of the available information, the degree of uncertainty, and the possible next steps.

Beyond presenting information, the companion may help individuals translate insights into action by setting meaningful goals, selecting feasible preventive steps, and monitoring progress. With appropriate consent and governance, relevant goals and prior actions can be retained to support continuity while preserving individual autonomy. The functions described above are organized into the layered conceptual reference architecture shown in Figure 1.

Healthcare professionals and caregivers remain important within this model. Their involvement occurs through controlled access when required. Selected information may be shared for preventive assessment, diagnosis, treatment, emergency care, or shared decision-making. When a professional assessment is necessary, the companion should facilitate an appropriate connection to healthcare services. For secondary purposes, individuals can choose to contribute by giving permission for the use of selected data to research, public-health, or multimodal model development activities under legal, ethical, and governance arrangements.

An illustrative scenario demonstrates how these functions may interact. An individual may ask how their biological, clinical, behavioral, environmental, or social circumstances influence their risk of developing a condition and what actions could reduce that risk. The companion would interpret the request, identify an appropriate validated model and supporting services, and determine which authorized information is required. Relevant data could be accessed or analyzed where they are held, and the resulting forecast would be reviewed for quality, relevance, and uncertainty before being explained with its contributing factors, limitations, and possible preventive options. Box 1 illustrates these interactions step by step across the reference architecture.

Box 1. Illustrative walkthrough across the reference architecture

1. Distributed data sources. An individual uses a wearable device and home-based sensors that record physiological and activity data. They have consented to these data being linked with their laboratory results and the records held by their healthcare provider.

2. Data access and interoperability. Incoming sensor data are checked for gaps and implausible values, labelled with their source and time, and harmonized with laboratory and record data using common standards. Only the data streams covered by the individual's current consent are made available.

3. Coordination and orchestration. When the individual asks the companion why a monitored measure has recently changed, or when a sustained deviation from their personal baseline is detected, the coordination function identifies a validated, use-case-specific risk model and requests only the minimum data it requires.

4. Validated services. The model is applied where the data are held and returns a risk estimate together with its uncertainty and contributing factors, which may include changes in physiological measurements, physical activity, or other behavioral and environmental factors.

5. Personal AI health companion. The companion explains the result in understandable language, states its limitations, and suggests feasible preventive options, such as changes in physical activity or daily routines, while recording the goals the individual agrees to pursue.

6. Professional services. If the estimate exceeds the level defined for the model's intended use, or persists despite the agreed actions, the case is escalated or referred to a healthcare provider or professional, as appropriate. With the individual's permission, a summary is shared with that provider, who confirms or rejects the finding through an appropriate assessment and determines any further care. The outcome is returned to the companion and added to the individual's longitudinal record.

This example is illustrative only. It has not been implemented or validated.

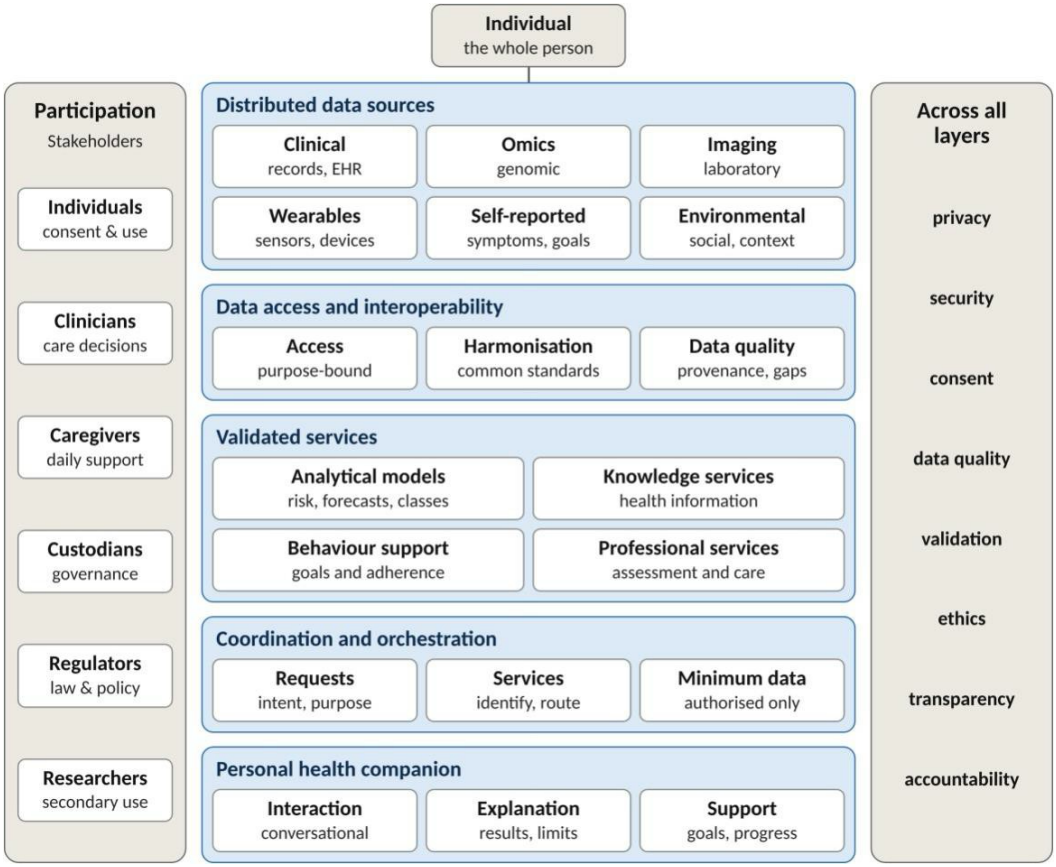


Figure 1. Conceptual architecture of the 10P-Health framework: Multimodal data from the individual are continuously acquired, harmonized through interoperability standards, and securely integrated within the 10P-Health platform to support a unified longitudinal health record, analytics, decision support, individual-facing applications, and research. Stakeholder participation, governance, and privacy-preserving design operate across all layers.

3. Challenges to Real-World Adoption of 10P-Health

Adopting 10P-Health in practice requires translating its ten principles into coordinated clinical and organizational processes instead of treating them as independent objectives. Tensions may arise between principles, for example, pervasive and permanent monitoring may be deemed conflicting with privacy-preserving aspects, while proactive intervention may increase unnecessary testing or overmedicalization. Participatory care must also be balanced with professional responsibility and individual preferences.

Technologically, adoption depends on the reliable integration of longitudinal clinical, genomic, behavioral, environmental, and sensor-generated data. Key barriers include limited interoperability, variable data quality, algorithmic bias, and insufficient external validation across diverse populations and care settings.

Operationally, healthcare organizations must redesign workflows, define responsibilities, train professionals, establish reimbursement mechanisms, and secure long-term funding. Clinician resistance, individual digital literacy differences, additional workload, and unclear ownership of continuous monitoring may further limit routine adoption. Realizing this vision also depends on sustained collaboration across stakeholders, regulators, healthcare providers, payers, technology developers, researchers, and individuals whose aligned incentives, shared governance, and coordinated standards are needed to move the framework from concept to routine practice.

Legally, the framework raises questions concerning continuous consent, data protection, secondary data use, cross-institutional and cross-border exchange, and liability for algorithm-supported decisions. Clear governance is therefore required to determine who may access data, who is accountable for recommendations, and how individual rights are preserved throughout lifelong data use. Because permanent monitoring may extend over many years, consent should be dynamic and granular rather than a single, all-or-nothing decision, allowing individuals to set different preferences for different data streams and uses and to modify these preferences over time [15]. For example, an individual could withdraw consent for a specific wearable or home-sensor stream while maintaining clinicians' access to their health records. In the European context, such arrangements must comply with the General Data Protection Regulation.

Psychological and behavioral effects also require particular consideration. Continuous monitoring and repeated communication of possible future risks may increase anxiety, encourage excessive attention to normal physiological variation, or create a sense of being continuously medically evaluated. False-positive alerts may further increase anxiety and unnecessary use of healthcare services, whereas false reassurance may delay appropriate professional assessment. In addition, wearable-based assessment of stress, anxiety, and depression remains limited by small study populations, short follow-up periods, and inconsistent validation, raising concerns about the reliability of psychological predictions.

4. Conclusion and Recommendations

The 10P-Health framework extends personalized medicine beyond isolated genomic applications and episodic clinical encounters toward a holistic, continuous, multimodal, participatory, and digitally enabled model of health. Its ten principles connect personalization, prediction, prevention, participation, pertinence, proactivity, pervasiveness, permanence, privacy preservation, and platform-based delivery within a single conceptual framework. The central position of this paper is that these principles should not be implemented as separate technological functions, but as interdependent requirements for designing the health and wellness journey of an individual across settings, providers, and stages of life. Realizing the 10P-Health paradigm does not necessarily entail immediate implementation at a large scale. Adoption can begin with a clearly defined clinical or population-health use case, such as remote chronic-disease monitoring, hospital-at-home care, preventive risk assessment, or personalized treatment support. The relevant 10P principles can then be translated into measurable clinical, technical, regulatory, ethical, and operational requirements. Organizations can identify the necessary data sources, establish interoperability and governance arrangements, define professional and individual responsibilities, and select an appropriate centralized, federated, or hybrid architecture.

The framework can subsequently be introduced through a limited pilot that integrates selected clinical and individual-generated data into existing workflows. Analytical outputs should be externally validated, clinically interpretable, and evaluated for safety, utility, equity, privacy, individual experience, workload, and cost. Individuals, clinicians, regulators, data custodians, payers, researchers, and technology providers should be involved throughout the design and evaluation, rather than consulted only after implementation. Successful pilots may then be expanded progressively across user groups, organizations, regions, or cross-border networks, while preserving common interoperability, accountability, and privacy requirements.

Implementation should therefore be viewed as an iterative learning process rather than a single technology deployment. Throughout implementation, data quality, analytical model performance, health outcomes, unintended consequences, cybersecurity risks, and changes in individual preferences should be continuously monitored. Evidence generated through routine care and controlled secondary research can inform the refinement of the implemented services and applications.

Future research should develop measurable indicators for each principle and evaluate whether different implementations improve health outcomes, quality of life, continuity of care, individual participation, equity, and healthy life expectancy. The contribution of the 10P-Health concept is therefore not a fixed technical solution, but a structured direction for translating advances in digital health, multimodal data,

and artificial intelligence into responsible and sustainable personalized healthcare.

Declarations

The authors declare that there is no conflict of interests regarding the publication of this paper.

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