

Human-Centered AI in FinTech: A Conceptual Model and Strategic Research Agenda

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Abstract—The introduction of human-centered artificial intelligence (HCAI) in the financial technology (FinTech) industry was borne out of the need to have an AI system that has the interest of humans at its heart. The deployment of HCAI thus heralded a new ease of doing work. This paper presents a conceptual model on the applications of human-centered AI within the FinTech domain, drawing on insights from an interactive management workshop. Three trigger questions were raised with experts in the field in developing a conceptual model for applying HCAI in the FinTech industry to understand the ongoing research efforts; current challenges, limitations and gaps that are restricting research in this domain; and key areas that should be prioritized in developing a strategic research agenda for HCAI in FinTech. Our findings, based on the output from the IM session revealed that focus in HCAI should focus more on areas such as ethics, fairness and bias, transparency and accountability, regulation and governance, cost of implementing AI-driven systems, cybersecurity, trust, maliciously developed AI systems, climate change challenges, and expertise of AI model developer.

Keywords— *interactive management, conceptual model, FinTech, human-centered AI*

I. INTRODUCTION

Technological progress has been accelerated, leading to the development of big data analytics, machine learning (ML), and artificial intelligence (AI). These developments have made it possible to automate financial procedures, improve data analysis capabilities, and support better-informed financial decision-making. Financial technology (FinTech) applies technology and cutting-edge techniques to improve financial activities and automate financial services [1,2]. Hence, the FinTech sector has benefited greatly from the ongoing advances in AI. This is because the sector has continuously been at the forefront of technological innovation, quickly improving client experiences and preserving a competitive advantage in the market. Considering this, the banking industry's adoption of AI has created new opportunities for breakthroughs in risk management, fraud detection, and regulatory compliance. AI technology is being adopted by financial institutions, whether internally, externally, or through ecosystem-based collaborations.

Many advantages come with AI-powered solutions, including greater security measures, better customer identification procedures, real-time fraud detection, and thorough creditworthiness assessments. By utilizing AI, financial organizations may optimize their processes, cut expenses, and guarantee regulatory compliance. AI algorithms can analyze client data to create personalized financial apps that cater to individual needs, including risk profiles, investment objectives, and spending patterns. Financial institutions may now obtain deeper insights into the demands of their consumers by utilizing modern data analytics, ML,

and natural language processing. This allows for the development of customized financial solutions that cater to specific requirements.

Technology companies and e-commerce platforms are among the many new market entrants in the financial industry that are taking use of their technological prowess and customer-centric methods. FinTech is gaining traction among entrepreneurs, researchers, and regulators due to its revolutionary technologies like blockchain and AI, which are driving its rapid development. The term "AI-empowered" is becoming more and more common. Currently, machines make up a sizable fraction of the important players in modern finance rather than only humans. They take over systematic and regular duties like standard analysis.

The integration of AI technologies within the financial technology sector, with a primary emphasis on enhancing user experience and prioritizing consumer needs and preferences, is referred to as human-centered AI (HCAI) in FinTech. Indeed, HCAI emphasizes the design of AI systems with the user's needs and preferences at the core. The main benefit of HCAI is its ability to provide personalized financial solutions, replacing the "one-size-fits-all" approach. As the FinTech industry rapidly evolves, the widespread adoption of AI technologies has become increasingly prevalent. HCAI in FinTech now extends beyond the application of technology and underscores the significance of prioritizing user experience. Thus, FinTech companies are deploying AI to customize their services and cater to the specific requirements of users, ultimately leading to improved customer satisfaction and loyalty.

This approach involves a thorough understanding of human behavior, financial decision-making processes, preferences, demands, and the psychology of money management in addition to the development of sophisticated computing algorithms and forecasting models. FinTech businesses are creating AI-powered solutions that match how people think about and make financial decisions by combining insights from cognitive psychology and behavioral economics. Comprehending user emotions, objectives, and decision-making procedures to develop AI-powered financial services that are not only effective but also user-friendly and empowering results in a seamless user experience [3]. Financial institutions have revolutionized their consumer engagement and interaction strategies by integrating these insights into AI-based solutions.

One notable example is the AI-driven robo-advisor, which is becoming more and more popular in the market due to its ability to offer individualized financial advice and portfolio management services. Studies conducted by Pal et al. [4] and Chen [5] demonstrate the increasing acceptance of these AI-driven robo-advisors due to their ability to provide

individualized investment advice and portfolio management services. Comparably, AI is used in fraud detection, emphasizing how it can spot suspicious patterns and instantly reduce financial risks [6]. Also, the integration of AI into mobile banking and online finance platforms enhances user experience by streamlining processes, providing real-time insights, and offering personalized recommendations. This is achieved through the integration of natural language processing and machine learning algorithms, that personalize and automate customer interactions, ultimately benefiting users and enhancing trust in the financial system.

Research has demonstrated how these AI algorithms improve user experience and decision-making processes in HCAI in FinTech solutions, featuring the disruptive potential of AI [6,7]. This paper seeks to develop a conceptual model that is based on outputs from an interactive management workshop held on HCAI in FinTech organizations to ensure better user experience.

II. LITERATURE REVIEW

The deployment of AI in FinTech is a field that has enjoyed considerable deliberation by scholars. Some scholars have even taken off by examining the impact of deploying technology in FinTech. Making informed decisions requires an understanding of how technology adoption in the financial industry affects things. It enables financial institutions to evaluate the possible advantages and dangers of integrating AI into their daily operations. AI can result in major advancements in several commercial banking domains such as lowering loan loss rates, boosting payment processing security, automating tasks linked to compliance, and enhancing client targeting [8]. Financial organizations can improve their risk management skills by utilizing AI and deep learning models. This involves anticipating stock market movements by analyzing and learning from past market situations, predicting loan defaults by analyzing borrowers' financial histories, and integrating other data streams such as news articles and chat bots to offer a more proactive risk management approach.

There is a lot of promise that comes with using AI in risk management in the financial industry. It makes it possible to analyze massive amounts of data and spot patterns that conventional models would miss. This results in proactive decision-making and more accurate risk assessments, which help businesses and financial institutions better anticipate and reduce future uncertainties. The accuracy, speed, and cost-effectiveness of FinTech decision-making processes can all be improved by using AI and deep learning. The use of AI and deep learning to FinTech decision-making processes makes risk assessments more precise, increases regulatory compliance, strengthens fraud prevention strategies, and permits more focused consumer interaction. Consequently, risk can be significantly increased by FinTech decision-making processes that use AI and deep learning models.

The application of AI in the finance sectors may assist company leaders in automating labor-intensive and time-consuming processes and allow enterprises to provide clients with novel services [9]. Organizations that were traditionally financial institutions are changing into information technology firms, and vice versa, as the industry is transforming [10]. Given these changes and AI's potential, it will be critical for businesses to determine the tasks that must be completed for AI to reach its full potential. FinTech

“encompasses innovative financial solutions enabled by IT” [11]. The newest wave of finance is being driven by AI and data analytics, which can uncover previously undiscovered correlations between variables [12]. As AI changes how financial organizations operate, participant interaction shifts, and new financial mechanisms arise, concepts and tasks in the FinTech space are redefined.

A new era of risk management, lending, and intelligent digital currencies has been ushered in by AI-powered finance [13]. AI holds great significance due to the financial services industry's vast amount and variety of data [14]. FinTech applications of AI, for instance, use neural networks to evaluate loan applications and rule-based expert systems to approve loans. By lowering costs, raising productivity, and encouraging more customized goods, the development of AI contributes to the improvement of financial organizations' efficiency as well as the caliber of financial services and products [15]. For example, FinTech lenders make loan decisions fast by utilizing sophisticated AI algorithms [16]. Additionally, investors use AI to evaluate big data to determine client investment preferences and obtain information about customer demand [17,18].

Contrary to common perceptions, AI serves to enhance and augment the capabilities of financial professionals rather than replacing them, thereby improving the efficiency and accuracy of financial processes [19]. This collaborative approach emphasizes the importance of human judgment and ethical decision-making alongside AI-driven insights, ensuring a balance between technological advancements and human values. The integration of AI and human expertise is therefore essential for the successful and responsible implementation of AI in FinTech. By promoting an environment that values both human judgment and ethical deliberation, financial institutions can maintain ethical standards while leveraging the potential of AI technologies. This enables institutions to enhance human capabilities, rather than replace them, ensuring a balanced and responsible deployment of AI in financial services. As a result, financial institutions should invest in training programs and resources to support this collaborative approach, emphasizing the ethical implications of AI-driven insights and promoting a human-centric decision-making process.

In addition, as HCAI in FinTech develops, exploring ways to incorporate AI into regulatory compliance, improve cybersecurity with AI-based solutions, and use AI for predictive customer analysis presents promising future opportunities and directions. Also, ensuring the quality and integrity of data is fundamental to the responsible implementation of AI in FinTech. Therefore, financial institutions should develop diverse and representative datasets while actively mitigating biases and discriminatory patterns. Lastly, robust data governance practices, including regular audits and transparent data sourcing, should be implemented to build trust and integrity in AI-driven decision-making.

Previous studies have been able to identify the factors that are responsible for the successes associated with adopting AI in FinTech. These success factors include having the appropriate resources, like data, and support from top management [20], as well as employees' behaviors and orientations before the adoption and integration of AI [21]. It must however be said that these literatures however failed to identify the actionable objectives that are needed if one will get top value from AI adoption.

It must however be said that AI is a new technology that presents dangers and challenges for the FinTech. Wall [22] asserted that non-causative links might be identified by the AI algorithm. Biases against specific protected classes (such as gender and ethnicity) may result from this. Humans find it difficult to control and intervene in these complicated, imperceptible decision processes [15]. It can be challenging to persuade consumers to trust financial advice and services that are only offered by automated systems [21]. Additionally, researchers discovered that FinTech lenders might circumvent current financial laws. Consequently, laws that support consumer protection measures and stimulate the creation of innovative technologies must be further enhanced [15]. It will be critical to determine the value that AI can offer and the goals that can be met to realize this value if the technology is to fulfill its full potential. Other areas of AI in FinTech include algorithmic trading systems that incorporate investor dispositions [23] and investor dependence on humanized robo-advisors [7].

III. METHODOLOGY

The purpose of this study is to construct a conceptual model, based on the responses from the interactive management (IM) workshop on HCAI in FinTech. This approach supports consensus decision making through idea generation, structuring and conceptualizing design alternatives [24].

The methodology employed is a review of these responses in comparison with existing literature. This will be a guide for future research and practice in designing a conceptual model for HCAI solutions for FinTech organizations. This paper presents an analysis of the diverse viewpoints expressed in response to the selected questions on current research in HCAI FinTech. The key thematic areas that were identified from the participants' inputs are discussed herein.

IV. FINDINGS AND DISCUSSION

Three trigger questions were raised in developing a conceptual model for HCAI application in the FinTech industry: (1) what are the current HCAI in FinTech research that people are working on; (2) what are the current challenges, limitations and gaps that are restricting research in this domain; and (3) what key areas that should be prioritized in developing a strategic research agenda for HCAI in FinTech. Participants (n=30) were researchers and practitioners in the FinTech domain. The first question was used as an icebreaker activity and resulted the research project outputs (n=15) such as usability and security trade-offs, anti-money laundering, machine learning for transaction monitoring, Automated KYC (Know Your Customer) onboarding using AI, trustworthiness, explainable AI, data protection and ownership, human-centered risk assessment, HCAI in credit allocations, and loan default prediction, just to name some examples. The outputs from the second (n=16) and third (n=12) trigger responses were analyzed by using an excel spreadsheet and coding the key themes. The results from Q2 and Q3 are presented below.

A. Current Challenges, Limitations, and Gaps Restricting Research in HCAI in FinTech

The second question asked during the Interactive Management session was on the current challenges, limitations and gaps that are restricting research in Human centered AI in FinTech. In response to this, the panel

mentioned areas of ethics, fairness and bias, transparency and accountability, regulation and governance, cost of implementing AI-driven systems, maliciously developed AI systems, climate change challenges, and expertise of AI model developer (Fig. 1).



Fig. 1. Conceptual model of potential challenges of HCAI in FinTech.

The position of the participants in the IM session that ethical considerations is one of the challenges restricting research in HCAI in FinTech aligns with previous research in this field. The intricacy of ethical considerations in AI is discussed by [25], who highlights issues like the multiplicity of ethical principles, cultural differences, regulatory challenges, and cognitive biases. These challenges highlight the difficulty of creating a universal ethical framework for AI applications, reflecting the diversity of societal norms and the rapid pace of technological advancement. Borenstein and Howard [26] explore the need for AI ethics education, arguing that the emerging challenges in AI necessitate a structured approach to ethics pedagogy. Their work indicates that the incorporation of AI ethics into educational curricula is essential for preparing future generations to deal with the ethical dilemmas presented by AI technologies. This method highlights how crucial it is to give people the information and abilities they need to evaluate the moral implications of AI systems. Rezwana and Maher [27] use a design fiction study to examine the moral conundrums and difficulties in human-AI co-creativity. Their study highlights the need for frameworks that help direct moral decision-making in collaborative AI applications by offering insights into user perspectives on ethical issues in co-creative processes. This study emphasizes how crucial it is to comprehend user expectations and experiences while creating AI systems that are ethically sound.

Mittelstadt [28], pointing out important distinctions between medical practice and AI research, contends that ethical AI cannot be ensured by principles alone. According to this viewpoint, a moral strategy might not work well in the case of AI, highlighting the bottlenecks in operationalizing ethical principles within AI, nay HCAI. With discussion of the operationalization of AI ethics principles, Canca [29] offers a framework for developers to comprehend the ethical and financial trade-offs. To ensure that ethical concepts are not only theoretical but are actively included into the decision-making and operational processes of AI development, this method is essential for integrating ethical considerations into the design and development stages of AI systems. Transparency, accountability, equity, and privacy are just a

few of the many factors that are considered by the ethical AI use principles.

However, one of the main limitations in the current discourse on ethical AI in finance is the dynamic nature of technological evolution [30,31]. The rapid pace of technological evolution often outpaces the development of corresponding ethical frameworks and regulatory standards, highlighting the need for ongoing research into adaptive ethical guidelines that can keep up with technological advancements and ensure that AI applications in finance remain in line with societal values and norms.

The mention of fairness and bias as one of the challenges identified by the participants in the IM session aligns with the position of previous research. The ethical landscape of AI is full of conundrums, particularly regarding bias and fairness. Weber [32] highlights the crucial role societal biases play in shaping AI technologies, highlighting the deficiencies and dangers posed by lack of diversity within the field. This absence of diversity does not only perpetuate the existing societal biases but also makes them more pronounced through HCAI systems, thereby accentuating the need for inclusive engineering teams more urgent than ever. Finding these biases and putting strong safeguards in place to lessen their influence on AI applications are both difficult tasks. The significance of matching AI principles to detect and lessen toxicity in online chats is covered by [33]. This strategy is a prime example of the larger problem of guaranteeing equity and responsibility in AI systems, where moral and social ramifications transcend the technical sphere. Navigating the issues of fairness and prejudice in AI requires careful human moderation in addition to machine learning. There is a need for collaboration of all stakeholders towards addressing issues of bias and fairness using both ethical rules as well as technological innovations [34]. The moral consequences of this are much and thus demands a multidisciplinary approach.

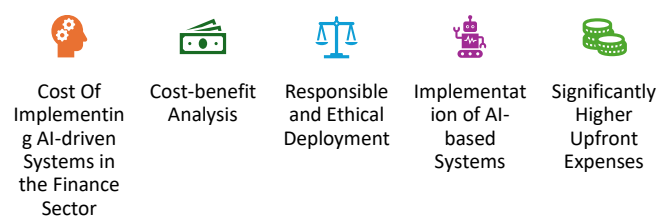
For AI systems to foster confidence and support responsible decision-making, transparency and accountability are essential. As shown in Indonesian manufacturing organizations, [35] examined how trust and accountability in AI systems have improved. Their study emphasizes the importance of reliability and openness in promoting a high level of trust in AI technology. Robust perceived accountability frameworks are crucial for promoting responsible decision-making, highlighting the necessity of transparent and easily available processes for comprehending and assessing AI choices. The difficulty of guaranteeing accountability and transparency in AI applications is further highlighted in [36] by discussion of the ethical issues surrounding data privacy in AI and computer science.

To address these difficulties, a thorough grasp of the complex data privacy and ethics issues is necessary, requiring cooperation among practitioners, researchers, and policymakers. To ensure that technological gains do not come at the expense of ethical standards, this cooperative approach is essential for creating solutions that meet the ethical concerns offered by computer science and AI. The different ethical issues that come up during the creation and application of AI systems are examined by [37]. The study emphasizes the significance of openness, accountability, and privacy in AI applications and the necessity of responsible governance to reduce adverse effects and foster favorable results. To solve these issues and guarantee that AI technologies are created and applied in ways that benefit society, ethical standards and

governance frameworks must be established. Adhering to GDPR principles like data minimization, purpose limitation, and user control, institutions can also build trust with customers and protect individual rights as AI technologies advance in finance [38].

The participants also point to the expertise of the human stakeholders who will be interacting with and overseeing the AI systems. This aligns with recent research that as AI becomes increasingly integrated into the financial sector; it is imperative for researchers and industry leaders to comprehensively examine the expertise level of the human stakeholders who will be interacting with and overseeing these AI systems [39]. Additionally, the transparency and interpretability of the AI systems themselves must be carefully evaluated, alongside a diligent assessment of the cost-benefit trade-offs associated with the implementation of these advanced technologies [40]. Ensuring a good understanding of AI capabilities and limitations among all relevant stakeholders, as well as maintaining transparency around the inner workings of AI models, will build trust and mitigate potential risks in the deployment of AI within the finance sector. Also, careful consideration should be given to data privacy and protection, as the aggregation and analysis of vast troves of consumer financial data by AI systems raises important ethical concerns around individual rights and consent [41,42].

Furthermore, in response to the cost of implementing AI-driven systems in the finance sector, thorough cost-benefit analysis is essential, to ensure the responsible and ethical deployment of these systems in the financial industry [43,44]. Some studies on cost analysis have revealed that the implementation of AI-based systems in the finance sector can incur significantly higher upfront expenses compared to traditional methods. This includes the initial investment required for hardware, software, and other technological infrastructure. A thorough evaluation of the long-term benefits and potential risks associated with their deployment is needed. Also, specialized talent often exceeds the expenses associated with these legacy systems (Fig. 2). Additionally, the ongoing maintenance and update requirements for AI-driven technologies can add substantial long-term costs that should be factored into the overall cost-benefit analysis. Therefore, careful consideration of the cost implications is a necessary aspect that must be addressed to promote the responsible and sustainable implementation of AI in the finance sector [45].



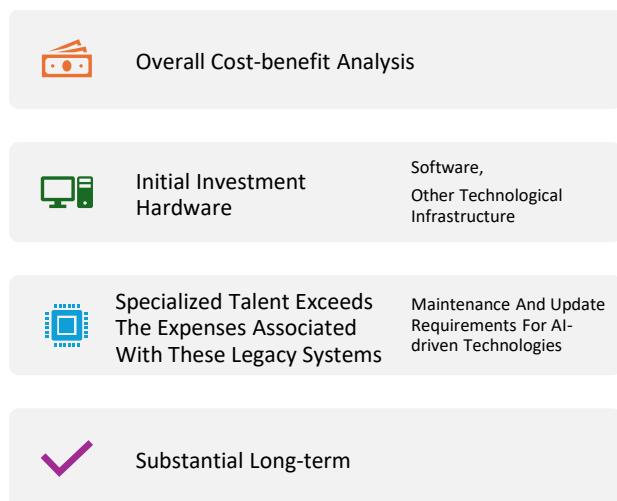


Figure 2. Cost-Benefit Analysis

The need to address issues of climate change in HCAI deployment was also raised by the participants. This aligns with current research on how AI could be utilized to facilitate more sustainable and environmentally conscious practices. Studies suggests that deploying AI-powered systems in financial institutions can enable optimization of energy consumption, reduction in waste and resource utilization, as well as the development and implementation of environmentally conscious investment strategies and financial products [46,47]. This highlights the potential for the finance sector to leverage AI capabilities to drive positive environmental impact, aligning their operational and investment decisions with the goal of transitioning towards a sustainable, low-carbon economy [48]. By integrating AI-enabled solutions to enhance energy efficiency, minimize waste, and facilitate green financing, the finance sector could play a significant role in accelerating the transition to a more sustainable future [42].

The identification of policy regulation and governance as one of the gaps is corroborated in the literature. Additionally, the difficulties in maintaining ethical standards in AI applications highlight how difficult it is to create universal ethical frameworks in the face of swift technology breakthroughs and a wide range of cultural norms.

B. Key Areas to Prioritize in Research on HCAI in FinTech

In response to the question raised in this regard, the participants identified areas such as trust, cyber-security, bias, and governance as those to be prioritized.

One of the key areas the participants hope is prioritized is the area of trust. The position of the participants aligns with previous research in this regard. Since trust is essential to the social capital that keeps society together and is a requirement for the sustainable data economy and usage of AI, it is crucial for societies, communities, and cultures developing social rules for implementing AI to understand the requirements for trust. According to Sutrop [44], there are two types of trust: social trust is created by having faith in AI service creators, while non-personal systemic trust is created by trustworthy procedures, structures, values, and culture.

Social and technical frameworks that guarantee AI systems' responsibility even in complicated use cases with unpredictable consequences are essential to establishing and preserving confidence. Trust is contextual and needs to be

considered in relation to the local environment, institutions, stakeholders, and technologies [45]. This implies that to build confidence in AI systems, it is crucial to consider organizational procedures, structures, and technical elements [46]. Technical robustness, explainability, transparency, traceability, and accountability are therefore necessary for developing reliable AI systems at the organizational and technical levels.

Trustworthy AI systems are necessary for both informed public discussion and critical public inspection [47,48]. To create stronger pillars for mutual trust, communication opportunities, and group decision-making, however, interdisciplinary discussion and a comprehensive grasp of the many viewpoints on the effects of AI are also required.

The participants equally raised the need to prioritize focus on cyber-security. The need to focus more on cyber security has been raised in previous studies as well. Suffice that by enabling the processing of ever-larger data sets with more complex analytics, AI models can strengthen cyber security. By using AI techniques, users can put more proactive fraud prevention and cyber security measures into place. Because of our increasing reliance on increasingly sophisticated digital systems, the interconnected globe is more vulnerable to cybersecurity breaches and criminality, and as a result, cyberthreats are outpacing our existing capacity to effectively prevent and manage them [49]. As a result of more advanced algorithms, cyberattacks are becoming more frequent, faster, and more complicated as AI technologies advance [50]. Threats include malware attacks for data leaks, zero-day attacks, and social engineering produced by AI. As a result, cyberattacks themselves are growing more common, complex, and damaging [51]. But concentrating on cyber defense alone is insufficient; instead, attention should be directed toward creating and routinely testing resilience to successful cyberattacks.

The adoption of HCAI broadens the scope for cyberthreats and introduces unique, specific risks [52]. In addition to the usual cyberthreats arising from software vulnerabilities or human error, HCAI systems face new forms of exploitation. These threats target inherent weaknesses in HCAI algorithms by altering data at various stages of the AI/ML lifecycle [53]. Such manipulations allow attackers to evade detection, extract sensitive information, or lead HCAI systems to produce incorrect conclusions. Given their complexity and the potential impact on financial sector organizations, HCAI models require continuous oversight to promptly identify and mitigate these attacks [54]. Cyberthreats to HCAI pose significant risks to the reliability and integrity of the FinTech industry. Corrupted systems may undermine the sector's ability to accurately assess, price, and manage risks, potentially resulting in the accumulation of hidden systemic vulnerabilities [55]. Moreover, attackers could gain access to training data sets containing private and sensitive financial information [56]. Prior research has also emphasized the critical need to address bias in HCAI within the FinTech industry. Bias in training data—often originating from preexisting biased processes and datasets—can lead HCAI models to replicate and perpetuate these biases in decision-making [57].

Inaccurate and inadequate information, or data biases, may lead to increased financial exclusion and foster mistrust of the technology, particularly among the poorest [58]. Bias could arise from data gathering in two ways. The system may have

been trained on incomplete or non-representative data. For instance, because there would be less uncertainty involved in the predictions made by predictive algorithms (like those for loan approval), they give preference to groups that are more represented in the training data [59]. When designing and training HCAI systems, human bias can lead to bias in the algorithm [60]. For example, a variety of psychological, social, emotional, and cultural factors can influence a researcher's decision regarding which features to include or exclude in the HCAI model.

Despite the possibility of prejudice, AI systems could aid in lessening existing biases. Miller [61] points out that while AI systems are prone to embedded bias, they can nevertheless enhance decision-making by reducing human bias. Lastly, even though many ML or AI systems may be seen as black boxes, biases could be recognized and lessened by closely examining their prediction and decision-making processes rather than those of people [62,63].

Participants in the IM session also suggested the need to prioritize governance and regulations. The need for governance has been a subject of earlier studies. Without a doubt, an autonomous system will eventually encounter a scenario where it must make a difficult ethical choice in addition to deciding whether to follow a certain rule [64]. The need for commercial possibilities, the need to safeguard customers and society from gadgets that could injure or negatively affect them, and the requirement for manufacturers to understand a legal framework within which they can function dependably are, therefore, some of the motivations for regulation [65].

The lack of a uniform definition in domestic regulations is criticized as it fails to ensure compliance [66]. Although, domestic regulations only apply nationally when it comes to the deployment of HCAI, the regulation of the risks posed by AI should have a global dimension. Stakeholders, such as academics, attorneys, industry professionals, and national and international policymakers, must be involved in the process. The ultimate objective is to take business interests into account while striking a balance between safe innovation and public objectives. International cooperation is crucial since the HCAI sector is global, with networks and computer resources dispersed across numerous nations. Since HCAI entities are functioning legally under human supervision, states and companies should not be allowed to decide how they wish to use them since they might put their own interests ahead of other factors. Given that countries compete for AI development and may enact insufficient laws, relying only on national measures could result in fragmented global regulations. Hence, organizations started to acknowledge the necessity of international AI legislation.

V. CONCLUSION

Following what the findings from the IM workshop has revealed, one can simply tell that the concern of researchers and practitioners in HCAI application in the FinTech industry has been largely around trust, data privacy, ethics, and regulation. These have also formed the focus of earlier studies in this regard and the call for urgent efforts to plug the leakages in the application of AI. These issues have also constituted the challenges posed to studies targeted at this segment of the finance sector.

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